AN AUTOMATED SYSTEM FOR DETECTION, CLASSIFICATION AND REHABILITATION OF DEFECTS IN SEWER PIPES

Tariq Shehab-Eldeen

A Thesis in

The Department of Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy at Concordia University
Montreal, Quebec, Canada

2001

0-612-68210-2

ABSTRACT

AN AUTOMATED SYSTEM FOR DETECTION, CLASSIFICATION AND REHABILITATION OF DEFECTS IN SEWER PIPES

Tariq Shehab-Eldeen, Ph.D.
Concordia University, 2001

The poor status of sewer pipes in North America has been reported by many researchers, revealing the presence of many defects that impact their performance. Inadequate inspection is considered as one of the main causes behind the declining condition of this class of pipes. This could be attributed to high cost of inspection and inadequate funds allocated to this purpose. The high cost is due to the current manual and high labor intensive inspection practice. Sewer rehabilitation methods are numerous and are constantly being developed. One of the rapidly expanding fields in the sewer rehabilitation industry is trenchless technology. Due to the large number of methods associated with this field, selecting the most suitable method manually can be a challenging task. Selection in this environment may also suffer from the limited knowledge and/or experience of the decision-maker.

This research presents two developed automated systems: AUTO-DETECT and AUTO-SELECT. AUTO-DETECT detects and classifies defects in sewer pipes automatically. The system utilizes image analysis techniques, artificial

intelligence (AI) and Visual Basic programming language for performing its task. A multiple classifier module encompassing a total of fifteen classifiers was developed to counter-check the results generated by the system. A solution strategy was also developed for efficient utilization of the developed specialized classifiers in an effort to improve the system's performance. The automated system was validated using actual data from randomly selected sections of the sewer network of a major Canadian municipality. The system's accuracy was found to range from 80% to 100%.

AUTO-SELECT is essentially a multi-attribute decision support system designed to select and rank the most suitable trenchless rehabilitation methods for sewer pipes. The system utilizes two modules: 1) database management system (DBMS) and 2) decision support system (DSS). The developed relational database assists in identifying suitable trenchless rehabilitation techniques that satisfy a total of sixteen factors which account for technical, contractual and cost requirements of projects as well as user specified preferences. In case of having more than one suitable rehabilitation method, a DSS was developed to evaluate and rank them and, accordingly, suggest the most suitable one. A case example has been worked out to demonstrate the use and capabilities of the developed system.

ACKNOWLEDGMENTS

I wish to express my deepest gratitude and sincere appreciation to my supervisor Dr. Moselhi, O. for his solid support and valuable guidance throughout all stages of this research. My heartfelt thanks to him for his continuous encouragement and inspiration. I will always be indebted to him for teaching me how to make dreams come true.

I wish also to acknowledge the cooperation of Mr. Gilles St Denis, consultant, Mr. Leo Gohier, Director of water and wastewater division of regional municipality of Hamilton, Ontario, Canada and Mr. Antonio Pistilli, Project Manager of sewer rehabilitation projects for Enviroform Inc., for providing the data used in this research.

Very special thanks to my parents for instilling in me the curiosity and inquisitiveness that brought me this far.

My deepest appreciation to my wife for her patience and encouragement.

The financial support for this research provided by the Natural Science and Engineering Research Council of Canada (NSERC) is greatly acknowledged.

TABLE OF CONTENTS

CHAPTER 3

NOMENCLATURE

SSET:	Sewer scanner and evaluation technique
CCTV:	Closed circuit television
SASW:	Spectral analysis of surface waves
PIRAT:	Pipe inspection real time assessment technique
PCES:	Pavement condition evaluation service
CREHOS:	Crack recognition holographic system
KARO:	Kanalroboter (i.e. canal robot)

LIST OF FIGURES

CHAPTER 1

CHAPTER 2

CHAPTER 3

CHAPTER 4

CHAPTER 5

CHAPTER 6

LIST OF TABLES

CHAPTER 2

CHAPTER 3

CHAPTER 4

CHAPTER 5

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Deterioration of underground infrastructure facilities such as sewer pipes poses a serious problem to most developed urban centers today. Sewer pipes form one of the six most capital intensive infrastructure systems in North America (Reyna et al. 1994). Their poor status has been reported by many researchers (Siddiqui and Mirza 1996 and Thomson 1991), revealing the presence of many defects that impact their performance. It has been documented that the condition of 40 % of the total Canadian sewer system has declined over the last ten years (Siddiqui and Mirza 1996). It has also been documented that 68 % of the sewer networks of all Canadian municipalities are described as either in need of repair or not acceptable (Siddiqui and Mirza 1996). Probably, the first question that comes to mind, after identifying the overall condition of sewer pipes in Canada, is how much does it cost to bring the condition of this class of pipes to an acceptable limit. It has been estimated that Canada needs to spend $ 5-7 Billion to restore the condition of its sewer network (Siddiqui and Mirza 1996 and Semenak 1999).

The decline in the condition of sewer pipes could, generally, be attributed to two main factors: 1) inadequate preventive maintenance and inspection programs and 2) deterioration of pipes. Inadequate maintenance and inspection is mainly attributed to high cost and inadequate funds received from the governmental agencies. Interviews conducted with several municipal engineers and consultants in Quebec and Ontario revealed that the cost of sewer inspection is about CDN $1.5 per linear meter. The breakdown of this cost is depicted in Figure 1-1. As can be noticed from this figure, about 30 % of the total cost is spent on inspection of videotapes. This high percentage is attributed to the current inspection practice that is followed by all municipalities. This current practice is performed manually and is fully dependent on human inspectors.

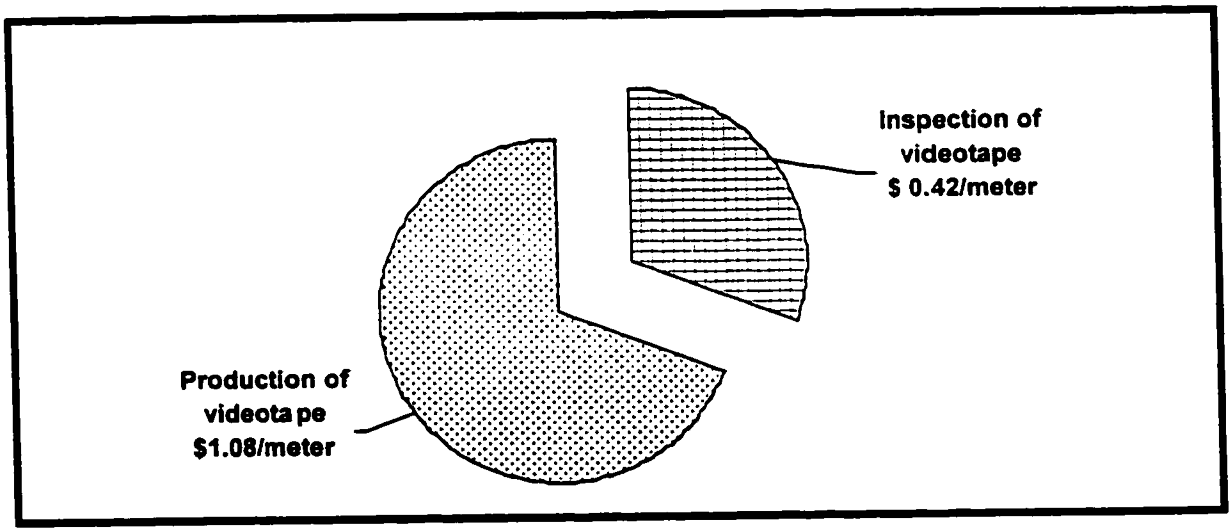


Figure 1-1: Cost Breakdown of Sewer Pipes Inspection Process

On the other hand, deterioration of pipes could be due to the aging process. The aging process is attributed to the age of pipes and their design life. As the age of pipe approaches the maximum design life, it deteriorates and may ultimately fail to fulfill their intended functions. It has been estimated that the average useful life of most commonly used sewer pipes is about 70 years (Siddiqui and Mirza 1996 and Hadipriono 1987). Most sewer pipes in North America have been in use for the last 40-50 years (McKim 1997). Figure 1-2 depicts the condition of sewer pipes over time (Shehab-Eldeen and Moselhi 2000). In this figure, the condition of a pipe is represented on a scale of 1-5, with 5 and 1 indicating superior performance and failure, respectively. It can be noticed that inadequate inspection and maintenance programs accelerate the rate of deterioration until the pipe ultimately fails. But, if regular inspection and maintenance programs are conducted, then the performance and lifetime of the pipes can be significantly improved.

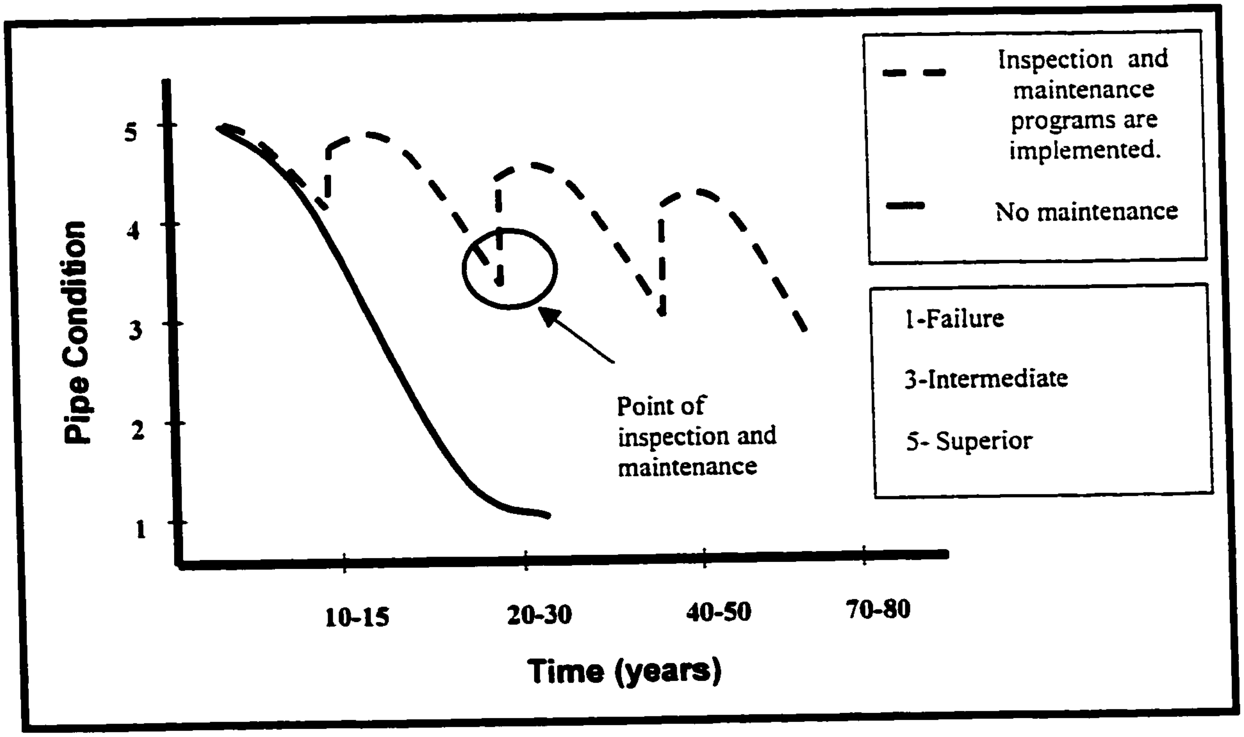


Figure 1-2: Behavior of Sewer Pipes Over Time

Rehabilitation of sewer systems poses a major challenge for most municipalities as they embark on providing quality service and preserving their infrastructure assets. Sewer rehabilitation methods are numerous and are constantly being developed, benefiting from emerging technologies. The implementation of these methods is driven by the need to improve quality, reduce cost and project duration. One of the rapidly expanding fields in the sewer rehabilitation industry is trenchless technology. Due to the large number of methods associated with emerging new technologies in this field, selecting the most suitable method manually can be a challenging task. Selection in this environment may also suffer from the limited knowledge and/or experience of the decision-maker, and could result in overlooking some of the suitable methods that could do the job at less cost.

Clearly, if sewer pipes inspection process can be automated, then significant time and money can be saved. Automating this process can also provide an incentive for checking this class of pipes more regularly; this will help municipality engineers to plan ahead and avoid unpleasant surprises. Automating the selection process of the most suitable trenchless rehabilitation techniques will also help in saving the construction industry a considerable amount of money. It will also facilitate transfer of knowledge and experience to new engineers who are involved in sewer pipes rehabilitation projects.

This research presents a developed automated system, designed to detect and classify defects in sewer pipes and recommend the most suitable rehabilitation techniques for the detected defects. The system utilizes image analysis techniques, artificial intelligence (AI), database management systems (DBMS), decision support system (DSS) and Visual Basic programming language for performing its task, including the development of the user interface.

1.2 CURRENT PRACTICE

Up until the sixties, inspection of sewer pipes has been a challenging task. The reason is that 95% of this class of pipes is too small for effective manual, i.e. walk-in, inspection (Reyna et al. 1994). The need to assess the condition of sewer pipes led to the development of new techniques for inspection. In an effort to develop new techniques, the closed-circuit television (CCTV) camera was first introduced in the 1960s (Reyna et al. 1994). Later on, other techniques were also introduced such as laser-based scanning and ultrasound inspection systems (Rens and Greimann 1997, Makar 1999, Pla-Rucki and Eberhard 1995 and Wirahadikusumah 1998). Despite the development of other inspection techniques, the CCTV inspection remains to be the most commonly used technique by most municipalities (Makar 1999). The use of CCTV inspection system is depicted in Figure 1-3.

As depicted in Figure 1-3, the process of CCTV inspection is usually accomplished by mounting the camera on a small robot to facilitate its movement in a pipe, or, alternatively, it could be winched between two manholes. As the robot moves along the pipe, the camera scans its inner surface to capture and record any existing defects. This process yields a videotape. This videotape is played back using a VCR and visually inspected to check the structural and serviceability conditions of the inspected pipe. After defects have been identified and classified, a report is prepared and forwarded to an engineer who recommends, based on his/her own experience, the most suitable rehabilitation techniques.

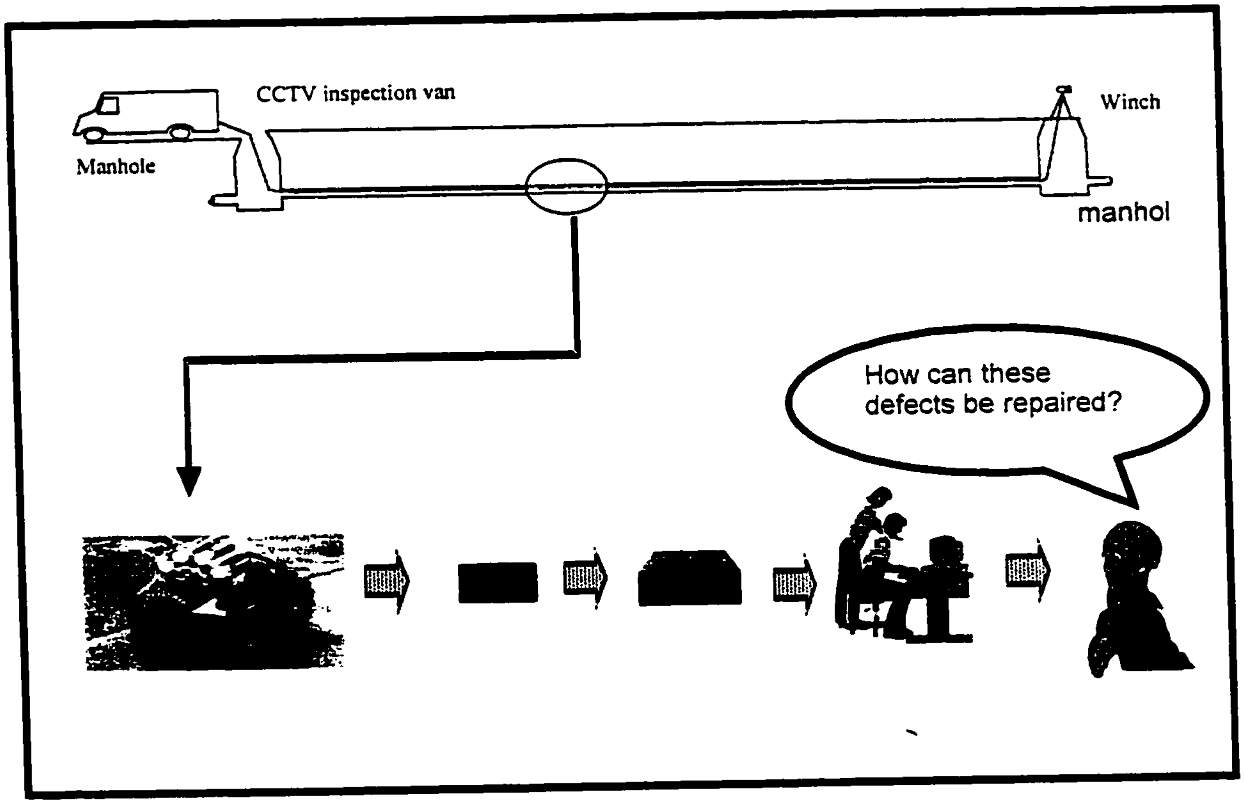


Figure 1-3: Current Practice

1.3 LIMITATIONS OF CURRENT PRACTICE

To protect the investment made in sewer pipes and to safeguard them against sudden collapses, municipalities inspect them using the CCTV camera, and repair them using various techniques. As described earlier, the techniques by which pipes are inspected and methods of repair are selected are currently performed manually. Performing these activities in this manner is usually associated with a number of limitations. The following is a description of these limitations and their effects on the overall performance of the process.

1.3.1 Manual CCTV Inspection Process

The manual CCTV inspection process of sewer pipes suffers from a number of limitations. The following is a description of these limitations and their effects on the overall performance of the process.

Costly: based on various interviews conducted with several municipal engineers and consultants in Quebec and Ontario, it was estimated that the cost of sewer inspection is about CDN $1.5 per linear meter. This total cost can be grouped into two main categories: 1) cost to produce the videotape and 2) cost to inspect the videotape. These categories constitute $1.08/m and $0.42/m of the total cost, respectively. The cost of producing videotapes includes robots, CCTV (closed circuit television) camera, cables, monitors operators and truck. The cost of videotape inspection includes cost of engineers or other trained personnel required to prepare a report on inspected pipes.

Time consuming: While acquiring data (i.e. producing videotapes) takes only few hours, analyzing them is a very time consuming process. The time needed to analyze videotapes is variable, depending on whether the process is conducted in house (i.e. at a municipality) or at a consultant's office.

Tedious: the nature of the inspection process requires inspectors to watch videotapes for long numbers of hours. This is considered a very tedious and boring process for most engineers and practitioners.

Fertile source of diagnostic errors: the process may lead to diagnostic errors due to lack of concentration and/or experience of inspectors.

1.3.2 Selection of Suitable Rehabilitation Techniques

Manual selection of suitable rehabilitation techniques, i.e. not computer assisted, suffers from a number of limitations. The following is a description of these limitations.

- Large pool to select from: numerous sewer rehabilitation techniques are available in the market; each is considered suitable for a certain application. Knowing the various limitations and applications of each method is considered a challenge to engineers and practitioners in this field.

- Rapidly developing field: due to the rapidly developing nature of the sewer rehabilitation field, evaluating new products as they come available in the market is not performed promptly by municipal engineers and consultants. This is considered as a major drawback that leads to overlooking new products that could do a better job and/or reduce cost.

- Overlooking other feasible techniques: the manual selection process, by nature, is heavily dependent on human memory. This could result in overlooking some of the suitable methods that could do the job at less cost and /or better quality.

- Localized source of information: usually the decision to be made, as to which rehabilitation technique should be selected, is limited to senior engineers who have good experience in sewer rehabilitation projects. This does not give the opportunity to new engineers to be easily involved in this domain of projects.

Clearly, if identification and classification of defects in sewer pipes could be automated, then not only significant time and money could be saved, but also more reliable and productive working environment could be achieved. Automating these processes could also provide an incentive for assessing sewer networks more regularly as a part of preventive maintenance programs. This could help municipality engineers to plan ahead and avoid unpleasant surprises. Providing a computer-assisting tool in selecting suitable rehabilitation techniques is expected to help new engineers to benefit from the experience and knowledge gained by others. It will also help senior and experienced engineers to be more updated about new technologies that are constantly being developed in the domain of sewer rehabilitation. It will ensure selecting the most suitable rehabilitation technique that satisfies job and user requirements.

1.4 RESEARCH OBJECTIVES

The objective of this research is to develop a methodology that facilitates and eases the rehabilitation process of sewer pipes. In order to fulfill this main objective, the following sub-objectives are identified:

1- Develop a methodology to identify and classify defects in sewer pipes.
2- Utilize the suggested methodology to develop an automated system that can automatically detect and classify defects in sewer pipes.
3- Develop a methodology to recommend the most suitable rehabilitation technique for sewer pipes.
4- Utilize the suggested methodology to develop a computer-assisted tool that can recommend the most suitable rehabilitation technique based on a specific project's conditions.
5- Utilize field collected data to validate and illustrate the use and capabilities of the developed systems.

1.5 THESIS ORGANIZATION

Chapter Two presents a literature review on various tools utilized in inspection of infrastructure facilities. It demonstrates the importance of image analysis techniques and neural networks as tools in pattern recognition tasks. It explains various image analysis techniques and a number of factors that should be considered in design and application of neural networks. It presents also various techniques utilized in trenchless construction. Research on automated inspection of various infrastructure facilities is also presented.

Chapter Three presents the development of the automated inspection system. It presents the overall modules and configuration of the proposed system. It explains the various steps followed in developing the system such as, data acquisition, data preparation, data processing and results validation. A detailed design of the proposed system embracing methods of detection and a total of fifteen classifiers is presented. Case examples are presented to demonstrate the use and capabilities of the developed system.

In Chapter Four, a full design of the rehabilitation system is presented. It presents the overall modules and configuration of the proposed system.

In Chapter Five, the developed systems are validated. Two case studies are presented.

In Chapter Six, the results of this research are summarized, the main limitations are highlighted, the main contributions are stated, and the recommendations for future research are presented.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The construction industry faces problems in productivity, quality, safety and skilled labor availability (Moselhi et al. 1992 (a)). Automation is often proposed as solutions to these problems. Despite the need for automation in the construction industry, it has not been implemented on a large scale as in the case of the manufacturing industry. This could be attributed to the complex and varying work environment in construction. Other reasons for the limited use of automated machines on construction sites are threat of losing jobs, fear of handling new requirements and inadequate understanding of the need for change (Navon et al. 1992). These reasons have been also emphasized by a study made by Everett and Saito in1996, in which the demand for automation has been measured in the United States and Japan. The demands were measured in accordance to managers, workers and social perspectives. The results of this study revealed the difference in attitude toward automation in the construction industry in these two countries (Table 2-1). The apparent difference was attributed to the above reasons.

Table 2-1: Demand for Construction Automation in the United States and Japan (Everett and Saito 1996)

GROUP	UNITED STATES	JAPAN
Managers/ Owners	Weak	Moderate
Workers	Weak	Moderate
Social	Weak	Strong

Despite these problems, automation gained great momentum in the construction industry during the last decade, and considerable efforts have also been made to emphasize its importance in enhancing the construction industry (Moselhi et al. 1992 (a)). This could be partially due to the different methodology that is followed by most researchers and construction authorities in promoting automation. In the new methodology, automation is perceived to improve wages, safety and work conditions (Everett and Saito 1996).

2.2 AUTOMATED INSPECTION SYSTEMS

Automatic inspection and maintenance of civil engineering structures gained great momentum during the past 10 years (Hason 1994 and Moselhi 1998(b)). Automation in this field implies the use of pattern recognition techniques. Pattern recognition is defined as the science that concerns the description and or classification of measurements (Schalkoff 1992). The process of pattern recognition has been explained by some researchers as being composed of two definite tasks: 1) feature extraction and 2) classification (Setiono and Liu 1997). A more comprehensive description was given by Schakoff (1992) and Looney

(1997) who explained the different processes that a pattern recognition task should pass through. Figure 2-1 depicts these processes.

As can be seen from figure 2-1, the process starts by collecting information about the utility needed to be inspected. This is accomplished by utilizing different types of sensors, depending on the nature of defect and availability of equipment, such as cameras. The collected information is then processed to obtain feature vectors. The process ends by classifying these obtained features into different categories by utilizing a recognizer. It should be noted that the purpose of the pre-processing unit is to ease the process of feature extraction. For pattern classification problems, the recognizer is considered to be a classifier module. There are different methods of classification, among which is neural networks. Neural networks proved their capabilities in classification tasks and are considered to be very versatile in different civil engineering applications (Ortiz et al. 1997, Ritchie 1991, Moselhi et al. 1994, Faghri et al. 1997 and Kaseco).

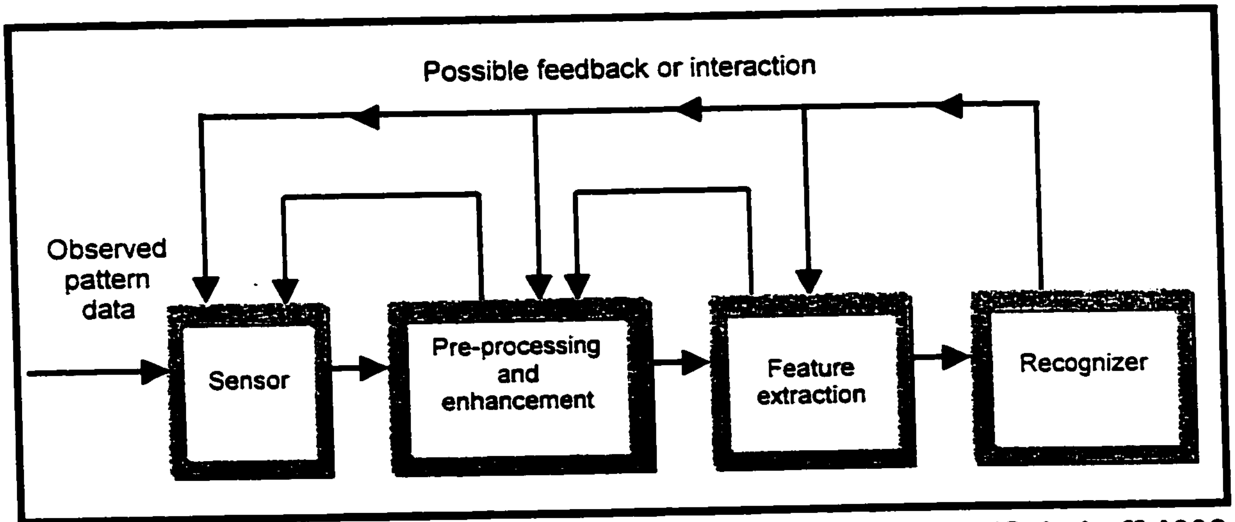


Figure 2-1: Typical Structure of Pattern Recognition System (Schakoff 1992 and Looney 1997)

Collins (1998) identified five general steps for detection and classification of defects. These steps are 1) image acquisition, 2) frame grabber, 3) image enhancement, 4) image analysis and 5) defect classification. He discussed various classification techniques. These techniques can be divided into two categories. These categories are traditional such as algorithmic and statistical and non-traditional such as neural networks. He identified various problems that are usually associated with traditional systems. These problems are: 1) the boundaries between different categories are often highly non-linear, 2) techniques which attempt to model these boundaries require an adequate number of examples, 3) the boundaries are usually fuzzy.

On the other hand, neural networks were described as a feasible alternative to the traditional techniques as they do not suffer from most of the problems listed above such as linearity and restriction with respect to number of examples. A case example was presented in which a surface defect detection system was developed. The system was designed to detect defects in rolled metal products. It extracts feature vectors composed of geometry and pixel intensities (i.e. gray level values). The results of the automated system were compared to an already existing manual one and the conclusion was in favor of the automated system.

The concepts outlined by Schakoff (1992), Looney (1997) and Collins (1998) have been utilized by a number of researchers to develop automated inspection systems for various civil engineering infrastructure facilities. The majority of these systems were developed to detect defects in pavements. Other systems were developed to detect defects in other infrastructure facilities such as sewers and bridges. Image analysis techniques were also utilized to study the internal structure of some construction materials such as asphalt and cement-based materials. It has been also utilized to develop as-built drawings automatically. The following presents the development made in each area.

In the inspection of infrastructure facilities field, Weil (1998) utilized infrared technology to inspect sewer pipes. In so doing, an infrared thermographic scanning system was used to measure the surface temperature. The resulting data were displayed as computer images with areas that have different temperatures. These areas are distinguished either by different gray levels in a black and white image or by various colors in a colored image. The varying energy areas, represented by different gray levels or colors, showed various aspects such as presence of voids in the supporting soil or a leak in a utility pipe. The system consists of four modules: 1) infrared scanner, 2) a microprocessor, 3) data analysis software package and 4) image recording and retrieving devices. The infrared scanner is similar in appearance to a video camera and is utilized to acquire data (i.e. images) about pipes needed to be inspected. The microprocessor will process the images so that different energy areas are represented by different colors. The data analysis software is to grab frames from the videotaped infrared images and to analyze them in a manner to extract information about the different energy areas. The image recording and retrieving device serves to store images for later use. It should be noted that the system does not require digging or intervention in sewer pipes. The developed system was tested in two locations. The result of one test showed 12 x 12 x 6 (ft) void around one sewer line. The other test covered a 415000 (ft^2) area. In this test, 14 voids were detected.

Wirahadikusumah et al. (1998), Gokhale et al. (1998) and (2000) described three systems that were developed for inspection of sewer pipes. These are the German KARO, the Australian PIRAT and the Japanese SSET systems. It should be noted that all these systems are still under development. The KARO system utilizes ultrasound, microwave and an optical sensor. The ultrasonic sensor measures defects covered by debris or mud and wall thickness, the microwave sensor detects defects behind the pipe wall and the optical sensor is utilized to detect surface defects. The system works by performing two passes. The first one defines damage candidates detected by any of the three sensors (i.e. suggests the presence of defect, but does not tell what type it is). In the second one, the operator goes back to these damage candidates and activates the proper sensor to identify the type of defect encountered. As can be noticed, the system is not fully automated. This is due to the fact that it does not interpret the data generated by different sensors automatically and relies heavily on the operator's experience in activating proper sensors for identifying the types of defects. The system can detect deformation, obstacles, cracks and leakage holes in the adjacent soils.

The PIRAT system utilizes two sensors. These sensors are laser and sonar scanners. The laser sensor projects a radial beam of light, while the sonar scanner emits sound waves. The light and sound waves are reflected back and recorded. The reflected sound waves are utilized to determine the pipe radius. This is achieved by calculating the travel time and knowing the sonic velocity. The laser beams are utilized to detect surface defects in a pipe wall. This is achieved by utilizing image processing techniques, neural networks and management information systems. The image processing performs two main tasks. These tasks are: 1) to reduce the effect of in-pipe vehicle motion on the produced laser beams and 2) to identify potential defect regions. These potential defects are then fed to a neural network for classification. It should be noted that this system is limited to pipes with diameter of at least 600 mm. As can be noted, the system shows a number of limitations. These limitations are: 1) the utilized sensors are under development and are more expensive compared to other inspection tools, such as the CCTV camera, 2) the system can not be utilized in almost 95% of sewer pipes. This is due to the fact that 95% of sewer pipes are not man-entry type (i.e. their diameter is less than 600 mm) (Reyna et al. 1994).

The SSET system consists of optical scanners and gyroscope. The optical scanners provide information about the structure condition of a pipe (i.e. surface defects), while the gyroscope provides information about the shape of a pipe (i.e. deformation). It should be noted that the system unwraps the circumference of the scanned images and stores all collected images in a digital format. It should also be noted that the system has low inspection rate.

Abraham et al. (2000) and Chae and Abraham (2001) developed an automated system for detection of defects in sewer pipes. The system interprets the data collected by the video camera installed in the SSET system. It utilizes three modules. These modules are 1) video camera, 2) commercial neural network software package and 3) commercial image analysis software package. The video camera scans the inner surface of a pipe and stores the images in a digital format. These images are 638 x 1000 pixels. The original images are then reduced to one quarter of their original size (i.e. 39,750 pixels). The images will then be processed by utilizing an edge-detector operator. This image will then be fed to a neural network-driven fuzzy system for identifying the type and condition (i.e. poor/medium/good) of defects. It should be noted that the system detects cracks and joint displacement only. Other information provided by the system is the number of joints. It should be noted that the system's accuracy was reported to be 100%, 82 % and 73% for number of joints, joint displacements, and cracks respectively. The developed system shows a number of limitations. First, the system is limited to two types of defects only, namely cracks and joint displacements. Second, the system utilizes all attributes of the reduced video-image as an input to the neural network. This will impose some limitations on the analysis process such as long process time. It will also be an obstacle against online usage of the system. Having all image pixels being analyzed by the neural network is a waste of computing time and effort. This is due to the fact that many pixels do not necessary show signs of defects. Third, the system utilizes SSET camera as a main module. This system is not widely utilized by municipalities and many municipalities are not even aware of its existence. The system costs CDN $9/linear meter of pipes. This is considered to be very expensive compared to CDN $1.5/ linear meter for the CCTV camera. It should be noted that this cost includes production and analysis (i.e. producing the defect's report) of SSET images. It should also be noted that this high cost could be partially attributed to its low inspection speed, which has been documented to be up to 4.5m/ minute compared to 24m/ minute for the CCTV system.

Sinha (2001) developed an automated system for detection of defects in underground sewer pipes. In his system, he utilized SSET camera to scan the inner surface of the pipe. An image analysis software was developed to process these scanned images and to extract some feature vectors. The results of the processed images (i.e. feature vectors) are then further processed by a fuzzy system to smooth the variation in the calculated features. These modified feature vectors are then fed into a back-propagation neural network for classification. The overall system's accuracy was reported to range from 89.5% to 94.1%. This variation in the system's accuracy is mainly due to the variation in the type of membership function utilized by the fuzzy system. As can be noticed, the system shows a number of limitations. First, it was developed to detect and classify defects in concrete sewer pipes only. Second, the system can detect and classify joint displacements, laterals and cracks only. Third, the system utilizes a SSET camera for collecting images, which suffers from a number of problems such as high cost and low production rate.

Ritchie (1989) identified the potential of automating the inspection process of pavements. In his research, he identified some major concepts in the digital imaging field such as components of a digital image and various image processing techniques such as thresholding to isolate defects from their background. He identified several steps that should be followed to automate this process. These steps are: 1) image acquisition (i.e. video camera), 2) conversion of the video image to a digital format, 3) image enhancement to prepare it to the thresholding stage, 4) thesholding to isolate defects, 5) feature extraction, 6) image registration to account for problems that could arise due to the high speed of the vehicle carrying the video camera and 7) defect classification.

Ritchie et al. (1991) developed an automated system for detecting and classifying surface defects in pavements. The system utilized a video camera to acquire images. These images were digitized and feature vectors were extracted. The extracted features were the number and variance of gray level value of the distressed pixels per row and column in an image. It should be noted that the variance of the distressed pixels was used to identify any interrupted sequence of the distressed pixels. The features were then fed to a back-propagation neural network for classification. The system was capable of classifying three types of cracks: transverse, longitudinal and combined. The output of the classification process (i.e. type of defects) and their attributes (i.e. feature vector) were then fed into an expert system to determine the remaining life and safety of the pavement. It should be noted that the recognition rate of the system was reported to be 68%, 95% and 96% for combined, transverse, and longitudinal cracks, respectively.

Kaseco and Ritchie (1994) developed an automated system for detecting defects in pavements. The system performs its task in six steps: 1) image acquisition and digitization, 2) image thresholding, 3) feature extraction, 4) tile classification, 5) classification of crack type and 6) identification of crack severity. In this research, a 512x512 image was divided into a number of tiles each of which is 32 x32 pixels. The features were then extracted from each tile. These features are the relative number of distressed pixels as a proportion of the total number of pixels in the tile and the number of distressed pixels per line in the transverse, longitudinal and diagonal directions. Based on these features, the system was able to classify transverse, longitudinal, diagonal and combined cracks. It should be noted that dividing the image into tiles was made in order to make the process of classification easier, in case there are more than one defect per image. In this study, the authors compared two paradigms of classifiers. These paradigms are traditional (i.e. K-nearest approach) and neural networks. The results obtained from neural networks were found to be superior to those obtained from the traditional approach.

Tsao et al. (1994) developed an automated system to detect spalling and transverse cracks in pavement. The system is composed of image analysis and expert system modules. Image analysis techniques such as edge detection and smoothing were used to prepare the image for feature extraction. These features are gray level value of pixels and size of defects. The features are then fed into the expert system for classification. The accuracy of the system was reported to be 85% and 90% for spalling and transverse cracks, respectively.

Wang and Nallamothu (1998) developed an automated system for detecting defects in pavements in real-time. He utilized a ready-made special neural network chip (NI 1000) to accelerate the process of classification. With this particular chip, the system was able to classify 32000 input vectors per second. The system performs its task in six steps: 1) image capturing, 2) digitization, 3) adjustment of illumination, 4) thresholding, 5) preparing the image to fit 240 X 9 pixels, 6) feeding the 240x9 images into the NI 1000 chip as a feature vector for classification. Several neural network paradigms were incorporated into the chip. The highest obtained accuracy, which was 74%, was achieved utilizing the probabilistic paradigm. It should be noted that the author suggested some techniques to improve the obtained results such as utilization of feature vectors, rather than utilizing tiles of 240X9 pixels, and increasing the sample size. It should also be noted that the author suggested the use of orientation, length and width as a feature vector, but he preferred to feed into the neural network the multi-attributed tiles (240 X 9) to test the capability of NI 1000 chip.

Cheng and Miyojim (1998) developed an automated system for pavement distress detection. The system starts the detection process by removing the background noise (i.e. illumination) from the image. Then the image is thresholded. A developed algorithm is utilized to detect and classify cracks. This algorithm locates one end of the crack's skeleton and follows it through its neighbors until it reaches a branching point or an end is found. At the branching points, the algorithm proceeds recursively. When the crack is complex, it sometimes contains loops. The algorithm is capable of tracing these loops and calculating their parameters. Based on this algorithm, a number of features could be extracted. These features are 1) the number of pavement distressed pixels in the transverse, longitudinal and diagonal directions; and 2) the number of loops. Based on these features, the cracks are further classified into different types based on the following rules:

1- If there are only a few independent significant pavement distressed units with no loops, then the defect is considered a longitudinal, transverse or diagonal crack.
2- If there are no loops, but numerous pavement distress units are available, then the distress is an alligator crack.
3- If there are one or more long loops, then the distress is also an alligator crack
4- If there are no loops, but the pavement distress units intersect each other at two or more points, then the distress is a block crack.
5- If there are no loops and there is a single intersection, then the distress is a combination crack.

It should be noted that the system was reported to have 100 % accuracy.

Chen and Chang (2000) developed a system for detecting painting defects in bridges. The system utilizes fuzzy set theory, neural networks, an image processing software package and a digital camera. The system performs its task by acquiring images through a digital camera. The system then utilizes its image analysis software package to transform the acquired colored image to a gray scale image. After conversion to a gray scale image, illumination values of all pixels are calculated by the image processing software package. These illumination values are a function of the gray level value of each pixel and range between 0 for very dark to 1 for very bright pixels. Based on these calculated illumination values, all pixels of an image are separated into three areas. The system then utilizes its fuzzy application to adjust the illumination values of pixels along the boundaries of the three areas. This adjustment is in a range of +/- 10%. The average illumination values of the three areas are calculated. The calculated average illumination values are then fed into a neural network. The neural network will be utilized to determine the threshold value of the three areas. It should be noted that this threshold value ranges between 0 to 255. After each area has been thresholded, in accordance to the calculated threshold values by the neural network, all dark areas will be considered as defects and bright areas as background.

Wang (2000) described a number of automated systems that were developed for pavement inspection. These systems are 1) the Japanese Komatsu System, 2) the U.S. Pavement Condition Evaluation Service System, 3) the Swedish PAVUE System and 4) the Swiss Crack Recognition Holographic System.

1- Komatsu System

This system was developed in the late 1980s. It consists of a survey vehicle and data processing system. The system detects cracks. To survey a road, it is illuminated by a laser scanner. The reflected light from the road surface is detected by a Photomultiplier Tube (PMT). The change in the reading of the PMT indicates an existence of a crack. Digital image processing techniques are then used to determine the number, width and length of the cracks. It should be noted that the system does not classify cracks into categories (i.e. longitudinal and transverse) and it works only during night.

2- U.S. PCES System

This system was developed in the early 1990s. It utilized a line-scan device to collect pavement data. Digital signal processing was utilized to analyze the captured signals. It should be noted that the development of this system was not completed. One factor that contributed to this decision is that the necessary technologies associated with the image capturing and processing were not mature enough at that time. It should be noted that the system was processing the captured signal in real-time.

3- The Swedish PAVUE System

This system consists of four video cameras, a lighting system, four videocassette recorders and a speed compensation module. Each of the four video cameras cover one-fourth of the pavement surface. The speed compensator controls the van to drive at a speed of 5-55 mi/h. The captured images by video cameras are processed by removing noise such as trees and power lines by thresholding and applying morphological operators. Features are then extracted from the processed images. These features are area, perimeter, average width, and orientation. These features are then classified based on decision tree analysis to determine the type and severity of the cracks.

4- The Swiss CREHOS System

This system consists of three modules. These modules are 1) a scanning device, 2) a light recording system and 3) a processing system. The image scanning device emits laser light. The reflected light from the pavement surface is recorded. When the laser light falls in a crack, the strength of the signal decreases. These signals are then fed into the processing system for classification.

In the construction materials field, Darwin (1994) utilized image analysis techniques to isolate cracks in cement paste materials. Cracks were classified based on their gray level value and geometrical attributes. Landis et al. (1997) also developed a system that detects cracks and bolbs in Portland cement based components. The system performs its task utilizing the following steps: 1) X-ray image acquisition, 2) image digitization, 3) thresholding, 4) feature extraction and 5) classification. The extracted features are perimeter (P) and area (A). The classification is performed based on evaluating the term ($P^2/4\pi A$). If ($P^2/4\pi A$) is approximately equal to 1, then the object is a bolb and if it is greater than 2, then the object is a crack. It should be noted that the system was developed to study the properties of cracks under increasing loads rather than to function as an automated inspection system.

Masad et al. (1999) developed a system to describe the internal structure of asphalt pavement. The system uses X-ray images. Image analysis software to threshold the image and to extract features. These features are the angle between the object's major axis and the horizontal axis of the image, areas of voids between aggregates and area of aggregate. From these features, the system is capable of describing the orientation of the aggregate particles, specifying the percentage of air voids in the specimen and determining the gradation. It should be noted that the system was developed to study the internal structure of the specimens rather than to function as an automated inspection system.

In the transportation engineering field, Yuan et al. (1994) developed an automated system for automatic vehicle classification. The model performs its task using the following steps:

1- Acquiring image(s) by a video camera
2- Subtracting this image from another image that shows all surroundings, such as buildings. This is done to isolate the vehicle from its surrounding
3- Thresholding the image
4- Projecting the thresholded image on different plans to obtain the object's real measurements
5- Obtaining the vehicle length, width and height
6- Determine the vehicle profile (i.e. flat front or not)

Based on the extracted dimensions, the system is able to classify cars, pickups, vans, busses, trucks (i.e. signal or multi-trailers). The accuracy of the system was reported to be 94%.

In the construction engineering field, Smith and Raynar (1993) developed a system to produce as-built drawings. The system consists of three main modules. These modules are CAD, image storage, and a video camera. The system performs its task by acquired video images of constructed items on site. These images are processed utilizing edge detectors. The produced edge images are then compared to an electronic copy of the original CAD drawings. This comparison is performed by overlaying both images (i.e. the edge and CAD drawings). Once the comparison is performed, the system identifies the unmatched features (i.e. doors, windows and ducts). The system's operator then prepares the data necessary to update the original CAD drawing.

Based on the above discussion, image analysis techniques, computerized interpretation of data obtained from scanning devices and neural networks could be considered as the backbone of any automated inspection process. In the following sections, a literature review will be presented on each process that a typical pattern recognition task passes through (i.e. data acquisition, processing, feature extraction and classification). In so doing, inspection techniques for various infrastructure facilities will be presented. Image analysis techniques will be discussed to demonstrate their capabilities in extracting feature vectors, which will be further utilized to perform the classification task. Neural networks as a classifier module will also be discussed. The chapter will end by describing the most common trenchless rehabilitation techniques for sewer pipes and presenting the controlling factors that should be considered in selecting the most suitable technique based on specific job and/or user requirements.

2.3 INSPECTION OF INFRASTRUCTURE FACILITIES

Several inspection techniques were developed to inspect various infrastructure facilities; each is utilized to perform a certain task (Rens and Greimann 1997, Makar 1999, Pla-Rucki and Eberhard 1995 and Wirahadikusumah et al. 1998). As depicted in Figure 2-2, these techniques could be generally divided into two main groups: 1) destructive and 2) nondestructive. With the evolution of reliable nondestructive techniques, the use of many destructive ones started to vanish. The use and popularity of nondestructive techniques are function of their commercial availability, cost and the type of information and measurements they provide. Nondestructive techniques could be further grouped, based on their application, into two main groups: 1) techniques to inspect non-sewer pipes and 2) techniques to inspect sewer pipes. The first group includes, radiography, radioactive computed thermography, acoustic emission and magnetic techniques, while, the second group includes techniques such as ultrasound, vibration, infrared, microwave imaging (ground penetrating radar), closed circuit television cameras (CCTV) and laser-based scanning. It should be noted that techniques such as ultrasound vibration, infrared and CCTV, which fall within the second group (i.e. techniques for sewer pipes), could also be utilized for non-sewer applications.

Techniques to inspect sewer pipes could also be further grouped into three different categories: 1) techniques to perform internal inspection, 2) techniques to inspect the pipe wall and 3) techniques to inspect behind the pipe wall. Table 2-2 lists all methods utilized to inspect sewer pipes and summarizes their advantages and disadvantages (Rens and Greimann 1997, Makar 1999, Pla-Rucki and Eberhard 1995 and Wirahadikusumah et al. 1998). It should be noted that despite the development of other inspection techniques, the CCTV inspection remains the most commonly used by most municipalities (Makar 1999 and Wirahadikusumah et al. 1998). Different cameras are available and they all differ in size and capability. For applications concerned with pipe inspection, it has been recommended to use black and white cameras rather than colored ones (Morici 1997). The pictures captured in black and white are sharp and have good image contrast. The different types of CCTV cameras, regardless of being black and white or colored, could be grouped into two main categories. These categories are stationary and mobile.

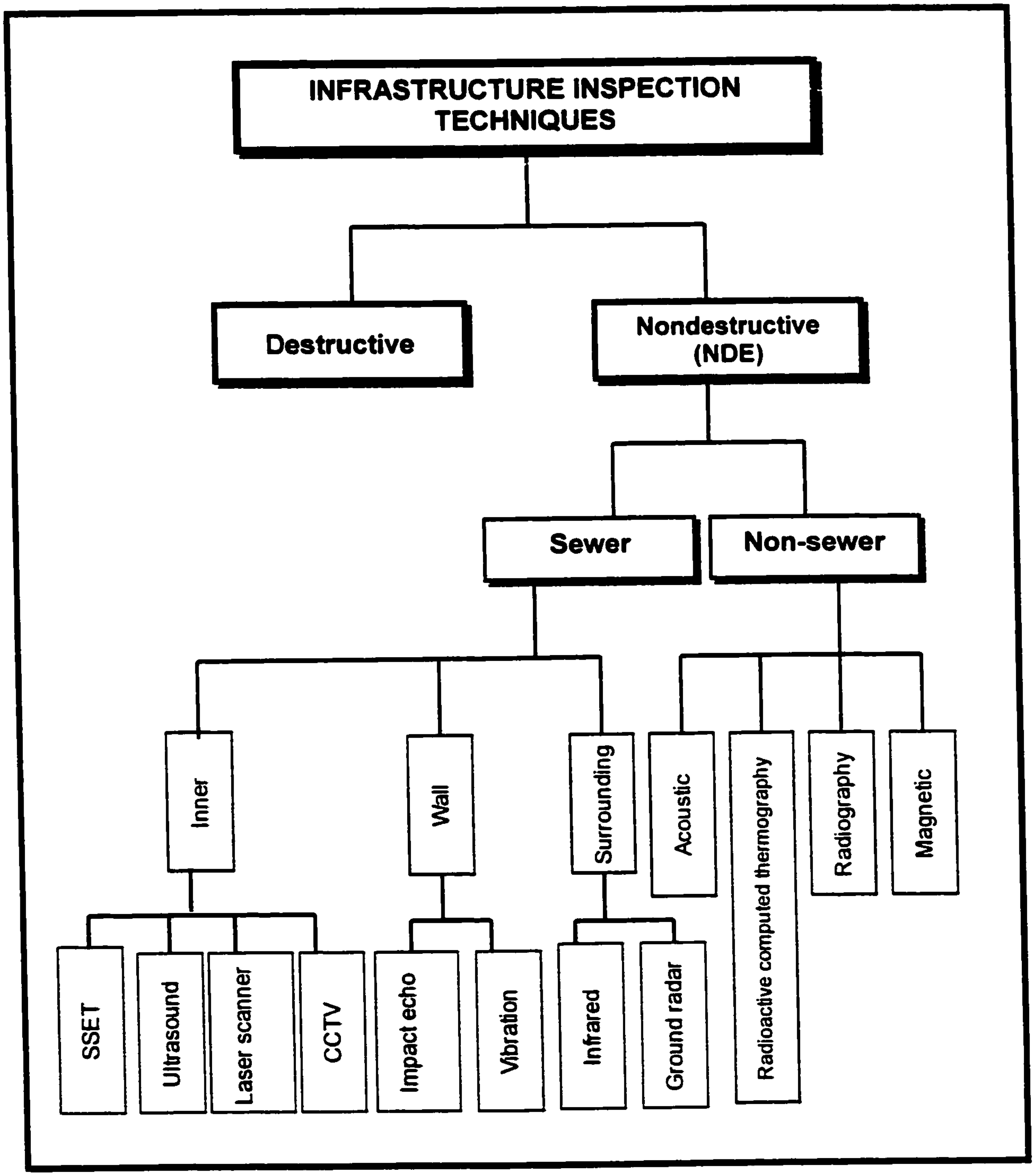


Figure 2-2: Infrastructure Inspection Techniques

Table 2-2: Summary of Sewer Pipes Inspection Techniques

METHOD	USES	ADVANTAGES	DISADVANTAGES
Mobile CCTV	Examines pipe wall surface.	1- Most commonly used technique. 2- Not expensive compare to other techniques.	1- Requires substantial effort in interpretation of data. 2- Misses defects hidden behind obstructions or under water.
Stationary CCTV	Examines pipe wall surface to select pipes for mobile CCTV examination.	1- Cheaper than mobile CCTV 2- Screening technique for other techniques.	1- Examines sewer near manhole. 2- Requires substantial effort in interpretation of data. 3- Misses defects hidden behind obstructions or under water.
Ground-penetrating radar	Determines the presence of voids and water in the surrounding soil and delamination in pipe wall.	1- Can be applied from surface or from inside the pipe (i.e. does require entry to the pipe). 2-Identifies depth of defects.	1- In the development stage. Field tests are required to prove the technique 2- More expensive than CCTV. 3- Data interpretation is very difficult .
Laser scanner	Examines pipe wall surface. It is considered as CCTV substitute.	1- Accurate geometry measurement. 2- Computer based analysis. 3- Digital storage.	1- In the development stage and not yet commercially available for large diameter pipes. 2- More expensive than CCTV. 3- Works only above the water line.
Ultrasound	Examines pipe wall surface and quantifies deformation. Considered as CCTV substitute.	1- Can measure defects above and below water line. 2- Computer based analysis. 3- Digital storage.	1- Very difficult to identify cracks. 2- Cleaning of sewer is necessary for accurate measurement. 3- More expensive than CCTV.

Table 2-2: Summary of Sewer Pipes Inspection Techniques (Continued)

Light line CCTV	Measures deformation only.	1- Good estimation of pipe deformation.	1- More expensive than CCTV.
Vibration	Measures pipe wall and bedding conditions.	1- Can assess single section of a pipe or the full length of pipe.	1- In the development stage. 2- Applicable for limited types of defects.
Infrared	Detects voids and leaks.	1- High production rate. 2- Can be utilized during day and night.	1- Needs experience to interpret the thermogram.
SSET	Examines pipe wall surface.	1- Measures deflection of pipes. 2- Unwraps the circumference of the scanned images. 3- Stores images in a digital format.	1- More expensive than CCTV. 2- Slow inspection rate.
Impact echo and SASW	Measures pipe wall integrity and surrounding soil conditions.	1- Detect voids behind pipes.	1-Available for large diameter pipes only. 2-Will not locate individual defects. 1- More expensive than CCTV. 2- Results combine pipe wall and bedding behavior.

Stationary CCTV cameras are mounted at manholes (Figure 2-3). They utilize their zooming capabilities to search for defects. They are limited with respect to what they can see. Defects that are close to the manhole will be detected, but the farther away the defect is, the harder it is to identify and evaluate. Defects beyond the range of the camera would be missed entirely. It was suggested that this technique could be used as a part of a screening process to determine which sewer sections should be thoroughly examined by the mobile CCTV system.

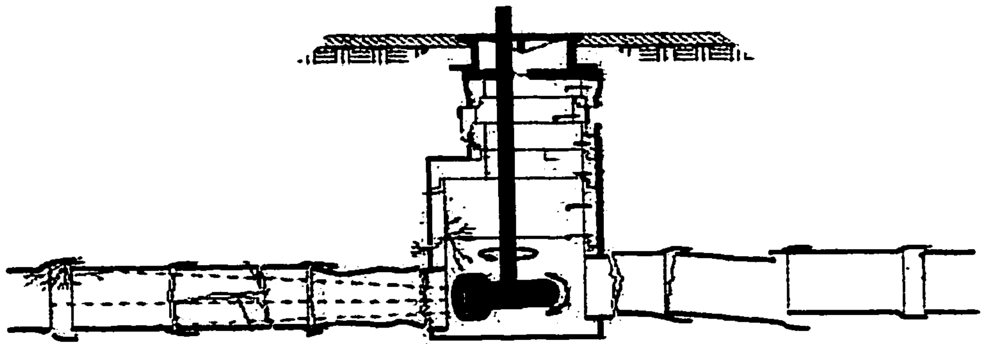


Figure 2-3: Stationary CCTV Cameras (Aqua Data 2001)

Mobile CCTV cameras are considered the most commonly utilized technique for inspecting sewer pipes (Makar 1999 and Wirahadikusumah et al. 1998). This technique uses a camera mounted on a robot or winched between two manholes (Figure 2-4). The camera enters the sewer system through manholes. It looks forward and may tilt as the robot system moves along the sewer pipe. Some of the CCTV equipment is equipped with a "light line" attached to assist in quantifying the pipe deformation. This light line system simply projects a line of light around the circumference of the sewer being examined.

Figure 2-4: Mobile CCTV Cameras

2.4 IMAGE ANALYSIS AND PROCESSING TECHNIQUES

Image processing refers to techniques that are applied to images to improve their quality for analysis purposes. Some of the useful techniques are: dilation, edge detection, inverse transformation, segmentation and thresholding (Gose et al. 1996 and Gonzalez and Wintz 1987). Image analysis techniques have been recently introduced to the civil engineering discipline. They provide civil engineers with tools to evaluate images quantitatively rather than qualitatively, as has been the case for several decades. They also enable them to perform automatically many tasks that were extremely labor intensive in the past (Moselhi and Shehab-Eldeen 1999 (a) & 2000 (b), Ritchie 1989, Ritchie et al. 1991, Kaseco and Ritchie 1994, Weil 1998, Wirahadikusumah et al. 1998, Gokhale et al. 2000, Abraham et al. 2000, Chen and Chang 2000, Chae and Abraham 2001 and Sinha 2001).

2.4.1 Edge Detection

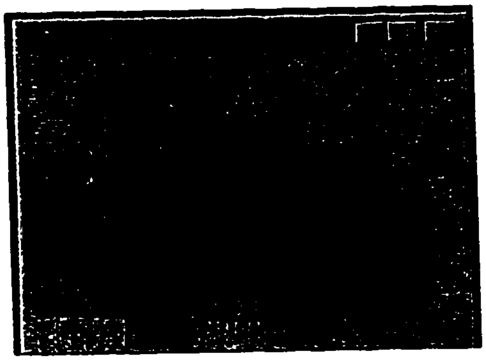


Figure 2-5: Original Image

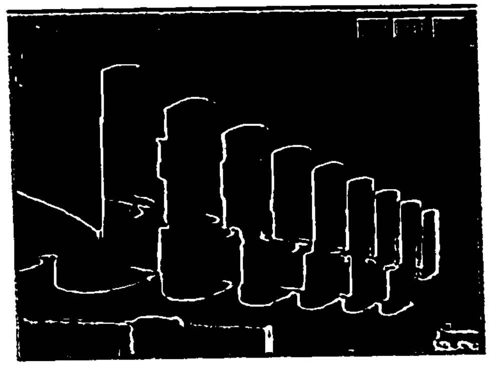


Figure 2-6: Edge Detection

Edge detection (Figure 2-6) is performed by measuring the change in the gray level intensity between pixels. The rate of change in gray level in both the vertical and horizontal direction is set equal to the derivative in X and Y direction, respectively. Of course, for a digitized image, a continuous derivative can not be performed. Instead, the difference in value between adjacent pixels is calculated as a finite derivative using popular masks such as Robert's, Prewitt's and Sobel's operators (Gose et al. 1996, Russ 1992, and Batchelor Whelan 1997). These operators are basically sets of weights and are arranged in 3X3 masks as shown in Figures 2-7, 2-8, 2-9 and 2-10.

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -1 \end{pmatrix} \quad \begin{pmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{pmatrix}$$

Figure 2-7: Robert's Edge Operator Masks

These operators will be applied to a grid of 3x3 pixels and the resulting gray level value of each pass (i.e. operation), as calculated per Equation no. 1, will be assigned to the central pixel. It should be noted that the neighborhood pixels in 3X3 pixels are denoted as shown in Figure 2-8.

$$\{|A-I|+|C-G|\}/2 \tag{1}$$

A	B	C
D	E	F
G	H	I

Figure 2-8: Neighborhood Pixels

Figures 2-9 and 2-10 depict the masks utilized to perform edge detection operations as per Sobel and Prewitt operators, respectively. It should be noted that these operators are evaluated as per equation 2 and 3, respectively.

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Figure 2-9: Sobel's Edge Operator Masks

$$\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \qquad \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

Figure 2-10: Prewitt's Edge Operator Masks

$$\{|[A+(2.B)+C] - [G+(2.H)+I]| + |[A+(2.D)+G] - [C+(2.F)+I]|\}/6 \qquad \textbf{(2)}$$

$$\{|(A-C) + (D-F)+(G-I)| + |(A+B+C) - (G+H+I)|\}/6 \qquad \textbf{(3)}$$

2.4.2 Inverse Transformation

Inverse Transformation is a process by which the color table of each image is inverted, i.e. the dark becomes light and light becomes dark (Figure 2-11) (Gose et al. 1996). This process is sometimes needed when the object's gray level intensity is lighter than the background. It may also ease and enhance the thresholding and segmentation processes by converting the background to white and the objects to black.

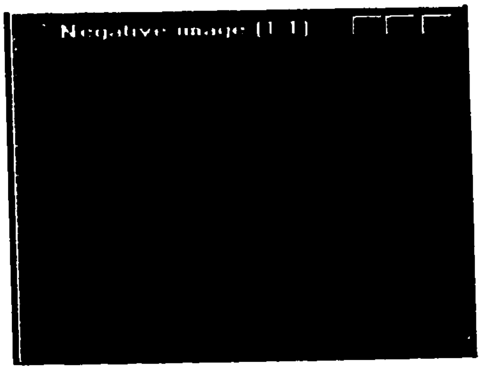


Figure 2-11: Inverted Image

2.4.3 Dilation

Dilation is defined as the process of adding boundary pixels to an object. This process is very helpful in connecting discontinuous objects and filling in holes within objects themselves. In this operation a 3X3 operator is utilized to scan the original image. During this scanning process, the origin of the operator (i.e. pixel E in Figure 2-8) is placed at each object pixel in the image in succession. If the operator can be placed at object's pixels and part of it is not fully included with in the object, then this part of the background pixels near the object is converted into object pixels (Batchelor and Whelan 1997). This process is explained in Figure 2-12. The result of this operation as applied to the image shown in Figure 2-5 is demonstrated in Figure 2-13.

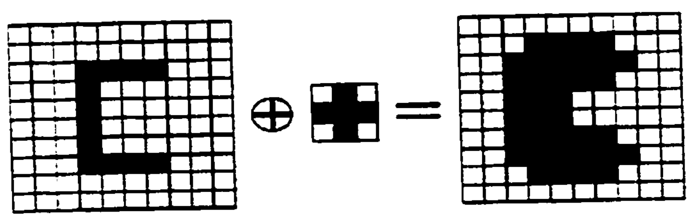


Figure 2-12: Dilation Process

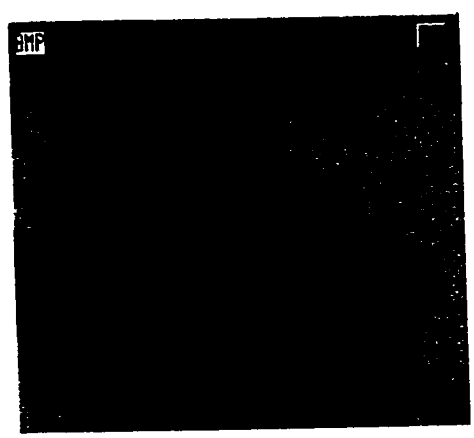


Figure 2-13: Dilated Image

2.4.4 Background Subtraction

As the name implies, this is a technique by which the background is subtracted from the original image. This technique is very important to reduce the noise resulting from poor illumination or non-uniformity response of certain camera lenses to light across their field of view. In some circumstances, poor illumination and non-uniform response of certain camera lenses to light across their field of view cause severe problems in isolating objects (Vernon 1991). To benefit from this technique, the Rolling Ball filter is utilized (Russ 1992). In applying this filter, a ball is visualized to role over the gray level histogram of an image. As it roles, it is in contact with several pixels. These pixels could be divided into two groups, one is inner and one is outer. The inner group has a small number of neighborhood pixels, while the outer group has a larger number. The shape of both groups is considered to be approximately circular. When the ball roles, if any point is darker than both groups and corresponds to points that the ball can not touch, then this point is considered to be a noise point. The gray level of this noise point is replaced by the lightest gray level in the inner group (Russ 1992). Figure 2-14 depicts the result of applying this technique to the image shown in Figure 2-5.

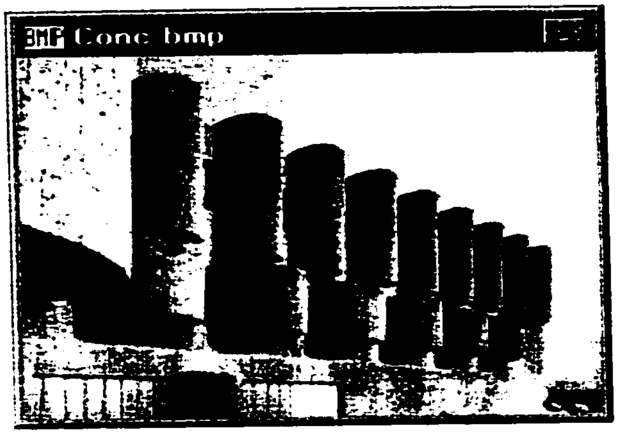


Figure 2-14: Background Subtraction

2.4.5 Thresholding

Thresholding is a process that sets each gray level that is less than or equal to some value T (threshold value) to black and each gray level greater than T to white (Gose et al. 1996). This threshold value (T) is determined from the gray level histogram that depicts the gray level distribution in an image (Figure 2-15). The gray level is the brightness value associated with each pixel and it ranges from 0 for black to 255 for white. One way to establish the threshold value (T) is to set it equal to the gray level that corresponds to the minimum point between two peaks (Gose et al. 1996). Referring to Figure 2-15, the Threshold value was found to be equal to the gray level of 121. It should be noted that this value (T) was used in developing the thresholded image shown in Figure 2-16.

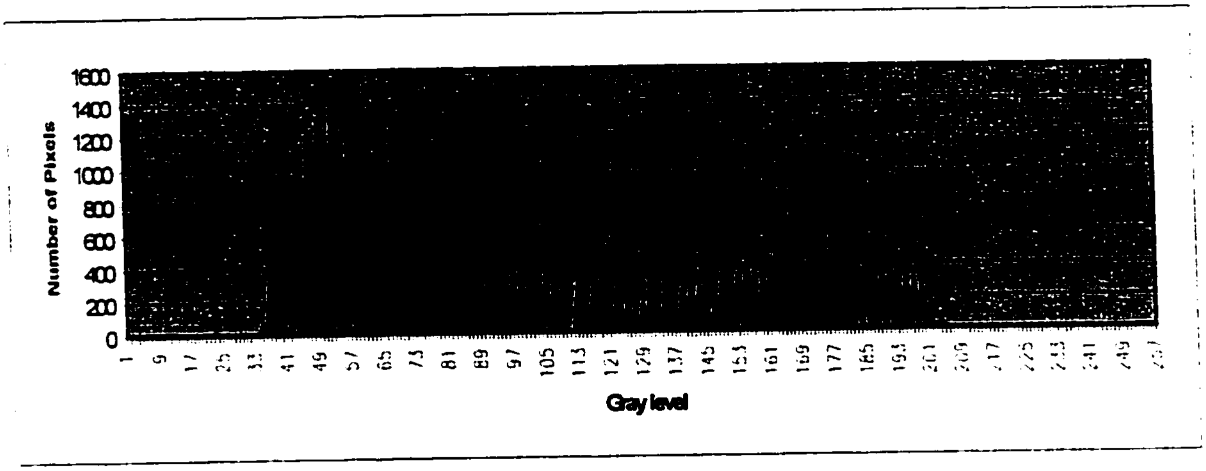


Figure 2-15: Gray Level Histogram

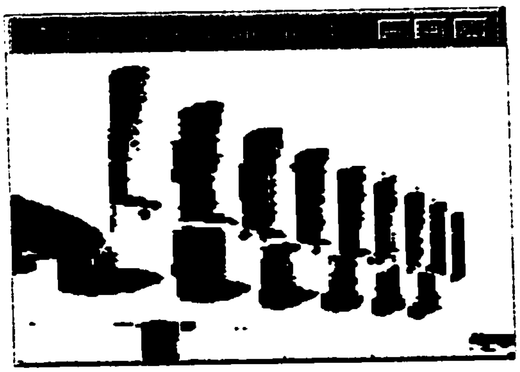


Figure 2-16: Thresholded Image

2.4.6 Image Segmentation and Feature Extraction

Segmentation refers to the division of an image into a number of regions, each of which is reasonably uniform in some characteristics such as the gray level value (Gose et al. 1996). The simplest method of segmenting an image is to threshold it and then to consider each connected region as an object as shown in Figure 2-

17 (Gose et al. 1996). Once the image has been segmented, the different parameters of the identified objects can be measured and analyzed.

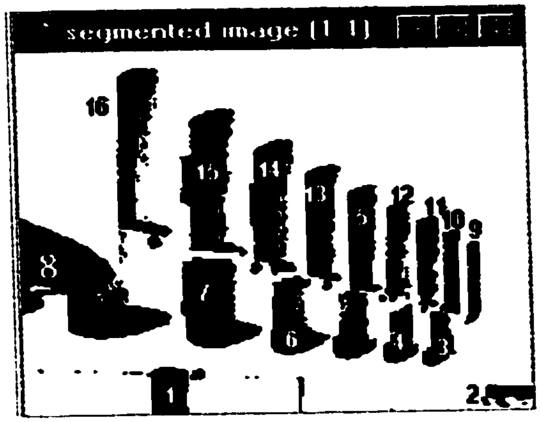


Figure 2-17: Segmented Image

2.5 NEURAL NETWORKS

2.5.1 Background

Neural networks can be thought of as "man made brains". They were built to mimic the human brain. Developing neural networks was an attempt to build computers to function in a manner similar to the human brain, and perhaps can do few things that the brain can not do (Anderson 1995). They were first introduced by McCulloch & Pitts in 1943 (Fausett 1994). By the mid 1980s the back-propagation neural network was developed by Rumelhart and McClelland (Zhao et al. 1998). During this period neural network research started to flourish. During the 1990s, neural networks became more widely utilized in engineering and were found to have a great potential in various civil engineering applications (Moselhi et al. 1991& 1994 and Flood and Kartam 1994 (a) & (b)).

2.5.2 Neural Networks as a Tool in Civil Engineering

The need for automation and decision making, among other reasons, has led civil engineers to seek the help of other engineering disciplines to achieve their objectives. Artificial intelligence (AI), which is a flourishing and active area of research in computer science, has shown some promising results that encouraged civil engineers to utilize it and adopt its techniques to their field. Neural networks are considered one of the key areas of AI. They can be defined as information processing systems that have certain performance characteristics in common with the human brain (Fausett 1994). This distinctive characteristic of neural networks enabled the development of systems for performing tasks that are considered challenging, and only human beings could perform.

Several researchers such as Moselhi et al. 1991, 1992 (b), Moselhi 1998 (a) and Flood and Kartam 1994 (a) & (b) illustrated the great capabilities and potential use of neural networks in various civil engineering applications. Their early pioneering work paved the way for others to think more seriously about utilizing this new tool in developing various systems that are in use today. These systems perform different tasks in areas such as cost estimating (Al-Tabtabi et al. 1999) and (Siqueira 1999), detection of structural damages in concrete structures (Zhao 1998), detection of cracks in pavements (Ritche et al. 1991), roadway classification (Faghri and Hua 1995), prediction of pile capacity (Teh et al. 1997), design of concrete mixes (Cheng 1999) and river flow prediction (Karunanithi et al. 1994).

2.5.3 Components and Characteristics

There are several paradigms of networks; each is considered suitable for a certain type of application (Moselhi et al. 1991). Some of these paradigms are back-propagation, regression, self-organizing and probabilistic. Despite having different paradigms of neural networks, they all consist of similar components. Neural networks have an input layer to which the input data is presented and an output layer that holds the response of the network to a given input. Layer(s) between the input and output layer are called hidden layers. It should be noted that some paradigms such as self-organizing networks do not have hidden layers (Caudill and Butler 1992). Each layer of neural networks consists of processing elements. These processing elements are called neurons. The neurons in different layers are connected by weighted connections. These weights represent the network's state of knowledge and are established during the training process.

Neural Networks, regardless of their types, share several characteristics. Some of these characteristics include:

- Learn by examples.
- Produce fast response.
- Suited for pattern recognition where a large number of attributes has to be considered in parallel.
- Generalize from limited size sample.

- Respond in parallel to a set of input rather than executing instruction sequentially.

2.5.4 Network Training

Training a neural network is the process of changing the values of weights, using certain training algorithms, until satisfactory results are obtained. When satisfactory results are obtained, the training process is terminated and the calculated weights are saved. There are various algorithms; each is considered suitable for a certain paradigm of neural networks. Neural networks can be trained using two main techniques: 1) supervised and 2) unsupervised (Caudill and Butler 1992, Fausett 1994 and Looney 1997). In the supervised technique, a set of inputs and desired outputs is presented to the network. The network then applies its training algorithm and calculates its output. This output is compared to the desired one and an error term, if any, is calculated. This error term is then used to calculate the adjustment that should be made to the network's weights so that the actual output matches or becomes as close as possible to the desired one.

As the name implies, unsupervised training does not require supervision during training (i.e. there is no desired output to which the network's calculated output is compared to while training). In this type of training, all input patterns are presented to the network. The network then arbitrarily organizes the patterns into categories. When other patterns are later presented to the network, it provides an output response indicating the category to which the input belongs. If a suitable category can not be found for an input pattern, a new category is generated.

2.5.5 Back- Propagation Neural Networks

Back-Propagation neural networks are recognized for their superior performance in pattern recognition and classification tasks (Kaseco and Ritchie 1994 and Nekovei and Sun 1995). They are also the most commonly used paradigm of networks in civil engineering applications (Moselhi 1998 (a) and Zhao et al. 1998). Figure 2-18 depicts a back-propagation neural network. Essentially, it consists of an input layer, an output layer and one or more hidden layers. Each layer consists of one or more neurons. These different layers are linked to each other by weighted connections. The weights associated with these connections are calculated during the training process and represent the network's state of knowledge.

Back-Propagation neural networks gain their problem solving capabilities by learning from cases encountered, in a similar manner to a human gaining work experience. These cases are called training examples. For each case of training example, the input parameters form an input pattern and the desired output parameters form an associated output pattern. In training this type of neural networks, the different input patterns (i.e. $x_1, x_2, x_3, \ldots x_n$) are presented to the neurons in the input layer (Figure 2-18). Each input is then multiplied by its weight (w_{in}) and broadcasts the result to the hidden layer. Upon receiving the result, each neuron in the hidden layer sums its weighted inputs and applies its activation function to compute its output. Those computed outputs are then multiplied by their respective weights (w_{jn}) and sent to the output layer. The output layer processes its received inputs in a similar manner to the hidden layer. Upon completion of these calculations, the network compares its calculated outputs to the desired values. The weights are then adjusted so as to minimize the difference between the output generated by the network and the desired output (Fausett 1994).

2.5.6 Design of Back-Propagation Neural Networks

In view of the proven capabilities of back-propagation neural networks in classification tasks (Kaseko and Ritchie 1994 and Nekovei and Sun 1995) and their wide versatility in different civil engineering applications (Moselhi 1998 (a) and Zhao et al. 1998), this paradigm will be utilized in developing the proposed system for detection and classification of defects in sewers. It should be noted that in designing back-propagation neural networks, several questions need to be answered: 1) how many neurons should be in the input and output layers, 2) how many hidden layers should be used, 3) how many neurons should be used in each hidden layer, 4) what type of activation and scaling functions should be used and 5) how different network parameters (i.e. learning rate, momentum factor and initial weights) should be selected. Probably the most straightforward question to address is the one regarding the number of neurons in input and output layers. The number of neurons in the input layer should be equal to the number of features that significantly impact and govern the output generated by the neural network. The number of neurons in the output layer should be equal to the desired number of output generated by the neural network.

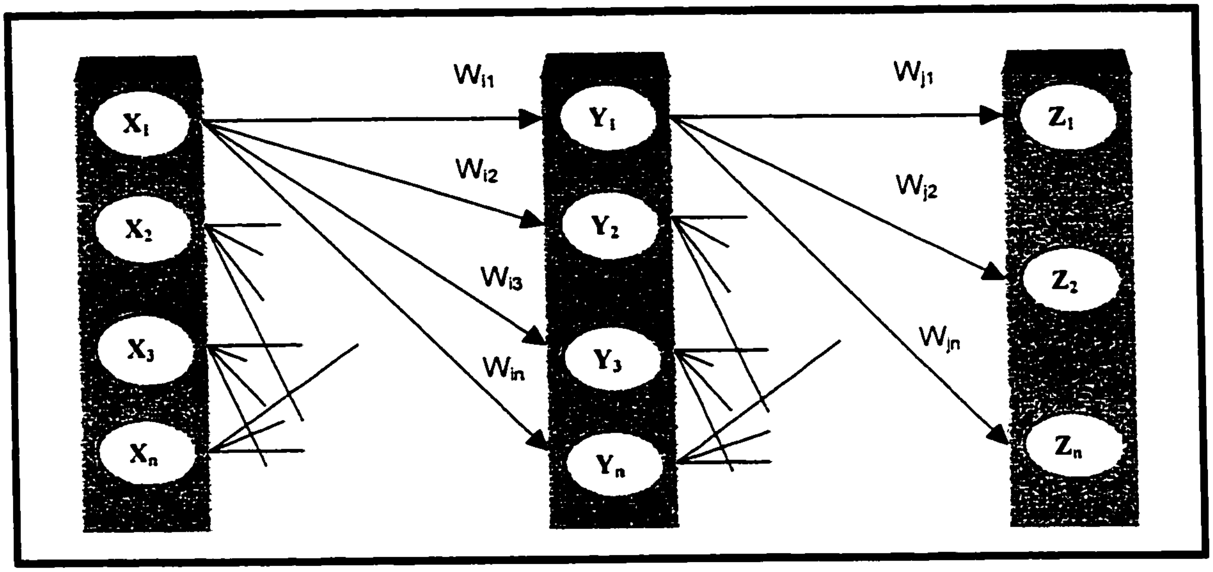


Figure 2-18: General Model for Back-Propagation Neural Networks

To make a decision regarding how many hidden layers should be used, one should consider the overall performance of the network (i.e. its generalization and mapping capabilities) as the final goal. Essentially, the choice is limited between one or two hidden layers. Theoretically, if an infinite number of hidden neurons were used, then three and four layer networks (i.e. one or two hidden layers) were reported to have equivalent performance (Tamura and Tateishi 1997). Villiers and Barnard studied the generalization capability of three and four layer networks for classification tasks. Their conclusion was against the use of four layer networks in all but the most esoteric applications (Tamura and Tateishi 1997). On the other hand, Obradovic and Yan indicated that four layer neural networks are superior to the three-layer ones with regard to their mapping capabilities (Tamura and Tateishi 1997). Tamura and Tateishi (1997) found that three-layer networks can exactly represent, with N-1 hidden neurons, any N input-output relationship. Despite the above differences, it has been documented that three-layer neural networks are sufficient to perform any non-linear mapping, with only very few exceptions (Simpson 1996). It was also reported that three-layer networks have been used in 95% of the working applications and that they can be trained much more quickly than four layer networks (NeuroShell-2 1996).

As for the number of neurons that should be used in the hidden layer, it has been documented that selecting the proper number is a process of trial and error (Hegazy et al. 1994 and Looney 1997). In other words, there is no definite number that can be selected beforehand that guarantees good results. Nevertheless, others such as Looney (1997) and Neuroshell-2 (1996) have suggested a number of formulas that predict an approximate number of neurons in a hidden layer. One of these equations is:

$$N = 0.5\,(X + Y) + (Z)^{1/2} \tag{1}$$

Where;

N = Number of neurons in the hidden layer

X = Number of input patterns

Y = Number of output patterns

Z = Number of patters in training set

Scaling and activation functions are used to bind the input and output to a specific range. Scaling functions are usually referred to as those functions that are utilized with the input neurons, while activation functions are referred to as those functions that are utilized with the hidden and output neurons. The bounded range in both cases is usually between 0 to 1 or 1 to -1. These functions are either linear or non-linear. Some of the most commonly used non-linear functions are: Sine = Sin (x), Hyperbolic Tangent = tanh (x), Logistic =1/[1+exp (-x)], Symmetric Logistic = [(2/1+exp.(-x))]-1 and Gaussian = exp. ($-x^2$) (Neuroshell-2 1996). The shapes of these functions are depicted in Figures 2-19 to 2-23 (Neuroshell-2 1996).

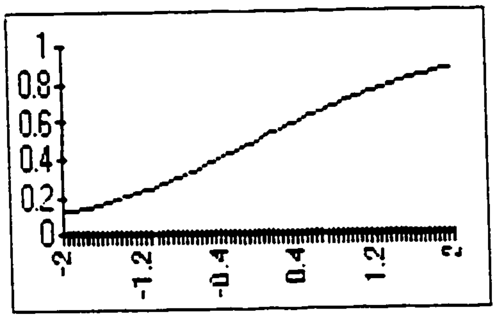


Figure 2-19: Logistic Function (Neuroshell-2 1996)

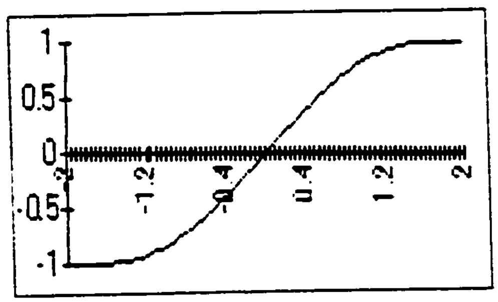


Figure 2-20: Tanh Function (Neuroshell-2 1996)

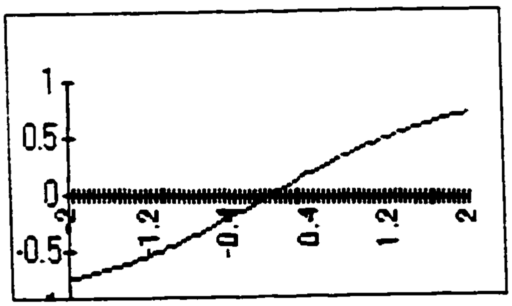


Figure 2-21: Symmetric Logistic Function (Neuroshell-2 1996)

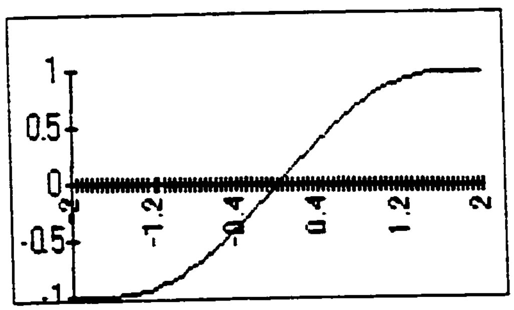


Figure 2-22: Sine Function (Neuroshell-2 1996)

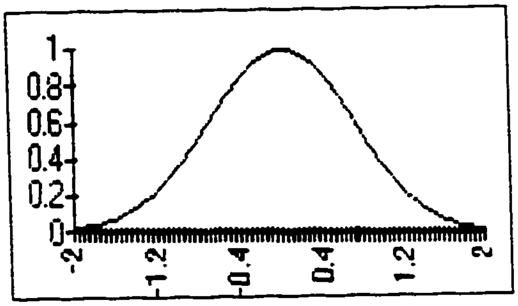


Figure 2-23: Gaussian Function (Neuroshell-2 1996)

Selecting the best activation and scaling functions that yield satisfactory results is also a process of trial and error. Some guidelines can only be suggested, such as to scale the input data to –1 to 1 rather than 0 to 1 whenever Sine or Hyperbolic Tangent activation functions are used in the hidden layer. Logistic function has also been recommended whenever classification networks are developed (Neuroshell-2 1996).

Selecting proper initial weights is important so that reasonable convergence performance of neural networks is achieved. Two different initial weight sets can lead to different convergence behaviors. Initial weights have to be small enough to prevent saturation. Saturation occurs when a point enters a region of weight space that has an activation function's slope equal to/or near zero (Figure 2-24) (Looney 1997). Some researchers suggested that [–0.5 to 0.5] is a feasible starting range (Looney 1997 and Fausett 1994). Some other references suggested a range of [-0.3 to 0.3] (Neuroshell-2, 1996).

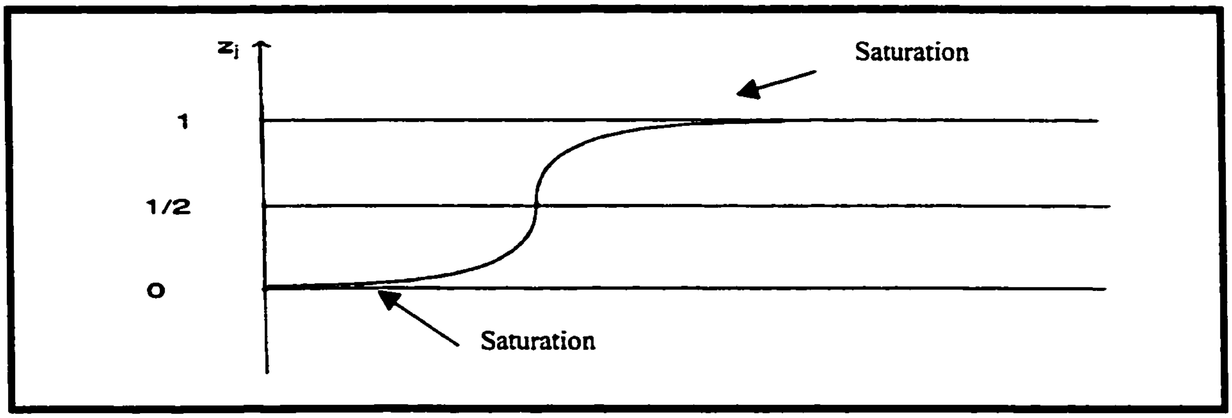


Figure 2-24: The Saturation Region of a Logistic Sigmoid Activation Function (Looney 1997)

Other parameters found to have an effect on the training behavior of neural networks are learning rate and momentum. Learning rate is a parameter that controls the amount by which weights are changed during training (Fausett 1994). If a small learning rate is used, then slower convergence is expected. On the other hand, if a large learning rate is used, then oscillation is also expected. The solution to this problem is to use a momentum factor. Momentum is a parameter that smoothes the behavior of neural networks and prevents oscillation while training (Looney 1997). Some researchers recommended 0.7 and 0.15 as starting values for momentum and learning rate, respectively (Al-Tabtabai et al. 1999). Other references such as (Neuroshell-2 1996) have also recommended 0.1 and 0.1 as starting values for learning rate and momentum, respectively. It should be noted that other values should be tried if those recommended ones do not yield satisfactory results.

2.6 TRENCHLESS TECHNOLOGY

The condition of sewer pipes in North America has severely deteriorated, over the last few decades, creating a need for rehabilitation (Siddiqui and Mirza 1996 , Thomson 1991). Sewer rehabilitation methods are numerous and are constantly being developed. Implementation of these newly developed methods is driven by the need to improve quality, reduce cost and project duration. One of the rapidly expanding fields in the sewer rehabilitation industry is trenchless technology. The use of this emerging new technology has dramatically increased over the past few years. It has been documented that over the past five years, utilization of the various methods associated with the trenchless technology, in Canada, for new construction and rehabilitation of underground facilities has increased by 180% and 270%, respectively (Ariaratnam et al. 1999). In general, the utilization of trenchless technology and the involvement of more consulting firms and specialists in this domain of projects have also increased in North America. Figure 2-25 depicts the growth of the trenchless industry in North America between 1996 to 1998 (Miller 1998). As can be noticed, the number of projects, firms and specialists increased by 150%, 300% and 270%, respectively.

Trenchless technology can be defined as the technology for placing new pipe, cables, or conduits in the ground between two defined points without continuous, open-cut excavation between them, or for renovating, replacing, and rehabilitating (Kramer et al. 1992). There are various trenchless techniques that are available in the market and their use has been expanded over the last few years. The most commonly used one is the lining technique (i.e. sliplining, cured in place, fold and formed and spiral winding), which was reported to account for 94% of the total length of pipes rehabilitated during 1996-1997 construction season in Canada (Ariaratnam et al. 1999). The following sections describe the various lining techniques.

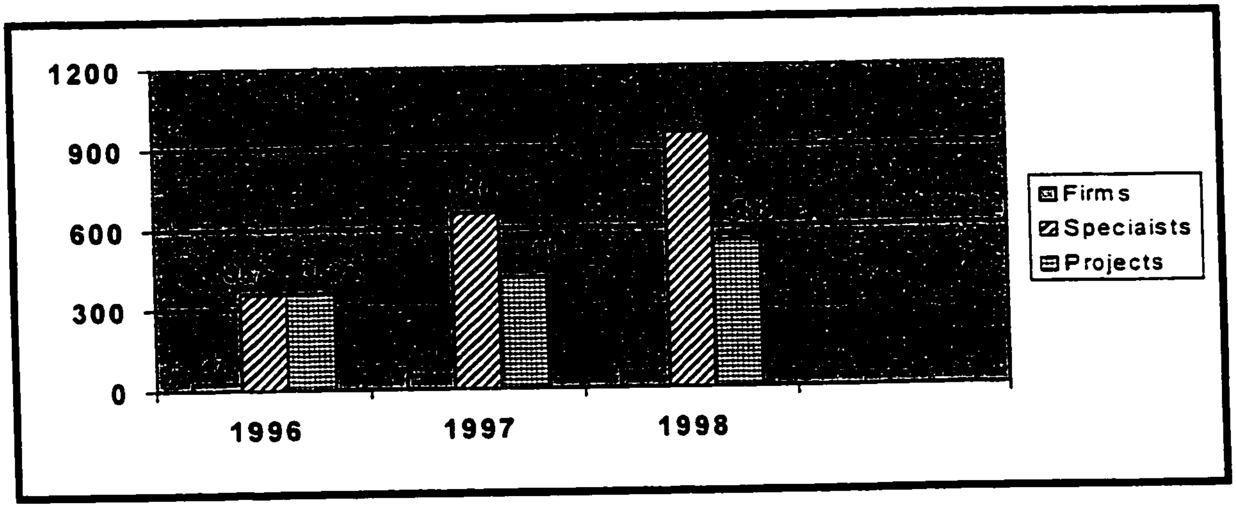


Figure 2-25: Growth of Trenchless Industry in North America

2.6.1 Sliplining

Sliplining is the process of insertion of a new smaller pipe into the old by pulling or pushing (Kramer et al. 1992). Figure 2-26 depicts the insertion process by pulling technique. As can be seen in this figure, a towing head is connected to the liner. This towing head transmits the pulling force, delivered by the winch, to the pipe and prevents stress concentrations that could damage the liner. After the insertion process is completed, annular grout is utilized to fill in the gap between the liner and the host pipe. It should be noted that butt-fused joints are used between pipe sections if the pulling insertion techniques are utilized. This is to prevent sections from pulling apart during insertion (ISTT 1998). It should be noted that this process has been claimed to cause a loss of cross-sectional area of host pipe and accordingly reduction in capacity (Kramer et al. 1992 and Reyna et al. 1994). Since this process involves the insertion of an already cured pipe into the host pipe, it suffers from some limitations with regard to its negotiation of bends (Reyna et al. 1994).

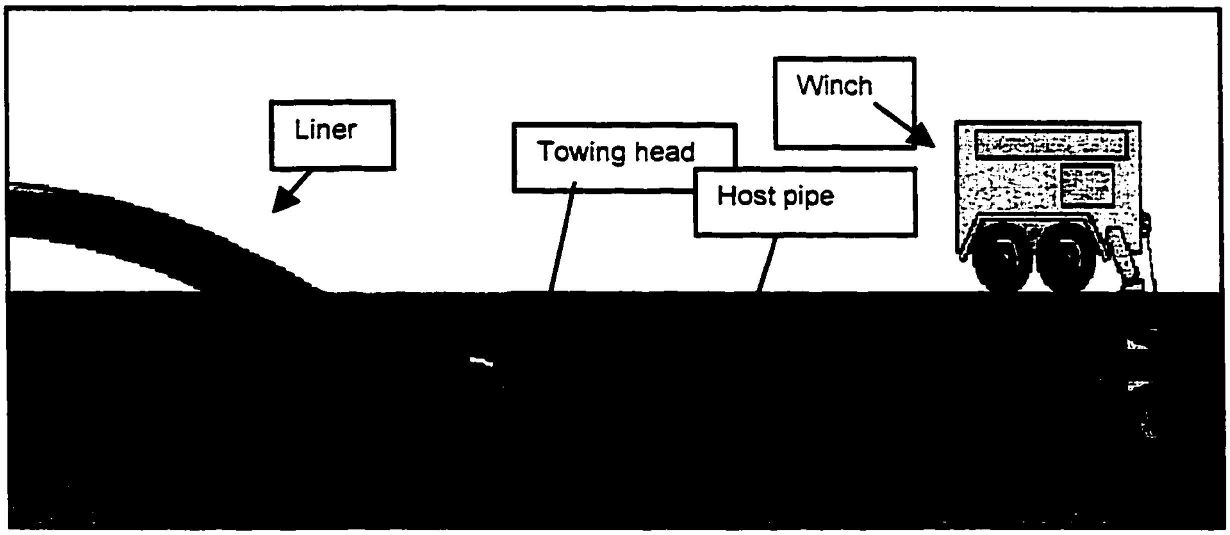


Figure 2-26: Sliplining Using Pulling Technique

2.6.2 Fold and Formed Lining

This technique involves forming the liner into a "U" or "C" shape prior to insertion (Figure 2-27) (ISTT 1998 and Kramer et al. 1992). The liner is installed by inserting it into the host pipe utilizing a pulling technique. Once the liner is inserted, it is restored to its original shape again. The restoration process is accomplished by utilizing hot air or water (Figure 2-28) (ISTT 1998 and Kramer et al. 1992). It should be noted that this method of repair should not be used if the host pipe shows excessive joint displacements (i.e. misalignments) that will causes deformation to the installed liner (Larsen et al. 1997). This is due to the reason that this deformation will eventually cause loss of the structural strength of the liner over time (Larsen et al. 1997).

Figure 2-27: "U" Fold and Formed Liner

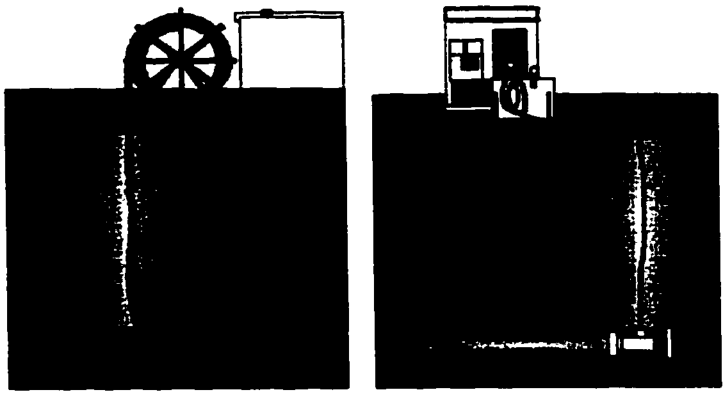


Figure 2-28: Insertion of a Fold and Formed Liner

2.6.3 Spiral Winding

This technique involves the formation of a liner by spirally winding interlocking strips (Kramer et al. 1992) (Figure 2-29). There are two types of spiral winding liners: 1) original and 2) expandable. The original liner has a smooth interior and ribbed exterior. The annular gap between the liner and the host pipe is filled with grout. The expandable liner is formed so that its diameter is considerably smaller than the host pipe. After completion of the winding process, the liner is then wound in reverse. This will allow the liner to expand to the inside of the host pipe

(Kramer et al. 1992). If a gap between the liner and the host pipe exists, then a grout could be used. It should be noted that liners installed utilizing this particular technique have low stiffness values, which could be an obstacle against using them for structural repairs (ISTT 1998).

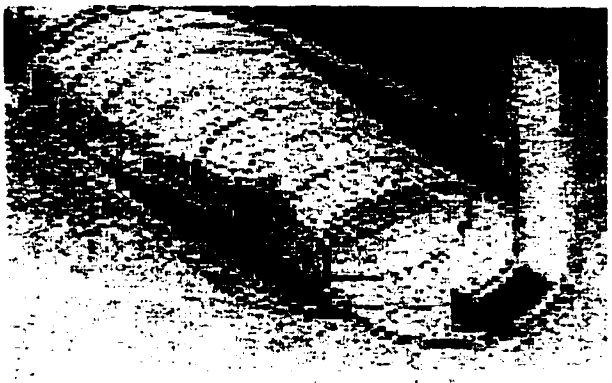


Figure 2-29: Spiral Winding Liner

2.6.4 Cured in Place Liner

In this method of lining, a resin impregnated tube is inserted into the host pipe and inflated against the pipe wall. The tube is then cured using an ambient temperature, steam or ultra-violet light (ISTT 1998) (Figure 2-30). To install this liner, the liner is first wetted with resin and the leading end is turned inside-out for a few meters. Then water is introduced, which will cause the whole liner to be inverted. When the inversion process is completed, the water inside the liner is circulated through a boiler unit to cure the resin (ISTT 1998). It should be noted that this process requires bypass pumping during installation (Reyan et al. 1994). This is due to the reason that the presence of water during the installation process will severely affect the curing process. For the same reason, this technique can not also be utilized when infiltration takes place into the host pipe (Kramer et al. 1992).

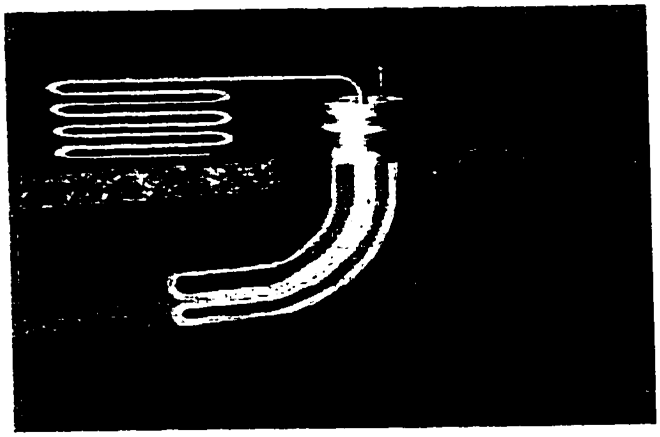


Figure 2-30: Installation of Cured in Place Liner

2.6.5 Swaged Liner

In this process the diameter of the liner is reduced temporarily so that it can be pulled into the host pipe. This is achieved by rolling the liner through rolldown machine. Once the diameter of the liner has been reduced, it is inserted through the host pipe. Then the liner's diameter reverts to its original size. The reversion process is accomplished by utilizing hot air or water (Figure 2-31) (ISTT 1998 and Kramer et al. 1992). It should be noted that this process is not commonly used in sewers that have displaced joints (i.e. misalignments) or dimensional irregularities (ISTT 1998). This is due to the reason that these irregularities impose excessive stress concentrations that could damage the installed liner. It should also be noted that this process does not cause any damage (i.e. breakage) to the host pipe after the reversion of liner. This is due to the reason that the liner is usually custom-made for each project in a manner that its outer diameter equals to the inner diameter of the host pipe. This will prevent the development of significant tensile forces within the wall of the host pipe that might cause failure.

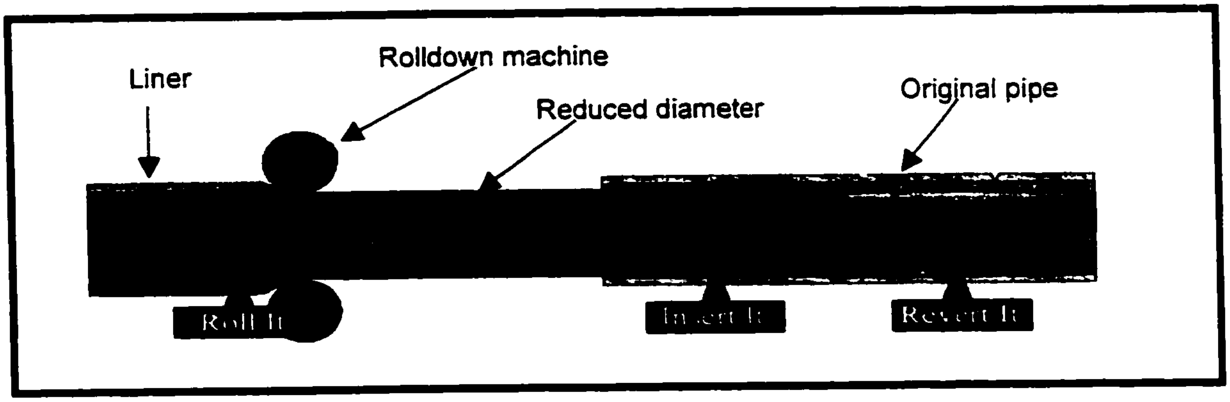


Figure 2-31: Installation of Swaged Liner

2.7 FACTORS AFFECTING SELECTION OF TRENCHLESS TECHNIQUES

Various rehabilitation techniques are available in the market, each of which is considered suitable for certain job/user requirements. To select a suitable rehabilitation technique, it is necessary to consider all contributing attributes that help in performing the selection process. Based on literature review, number of contributing attributes were selected (Duggan et al. 1995, Keefe and Phillips 1993, Moselhi and Sigurdardottir 1998, Najafi et al. 1997). The following is a description of each attribute and its significance in the selection process (Shehab-Eldeen and Moselhi 2001).

1- *Type of repair*: there are numerous products available on the market. Some are considered effective for repairing structural defects and others are not.

2- *Diameter of pipe:* products may be applicable only for a certain range of diameters.

3- *Degree of bends:* certain products allow for bends and others do not. The products that allow for bends could also have restrictions on the degree of bend (i.e. 45° or 90°) that could be applied. This could be a major factor to consider in case of having a pipeline with bends.

4- *Ability to improve hydraulic characteristics:* the desired hydraulic characteristics of pipes after rehabilitation have a bearing on which trenchless method could be applied. This could be due to the fact that some techniques, such as sliplining, result in reduction of the cross-sectional area of the original pipe, and accordingly impact its discharge characteristics (Kramer et al. 1992). Most suppliers of this technique, on the other hand, deny this argument. Their argument is whatever effect could happen to the hydraulic characteristics of the original pipe due to the reduction of the cross-sectional area will be compensated by the improvement that will occur to the flow rate and velocity. This improvement will be obtained by reducing the Manning coefficient as a result of introducing the lining.

5- *Distance between access points:* each product has limitations on the length of its pipe that can be installed per one stretch (i.e. without the intervention of a human or a machine through another manhole or an excavation pit). These limitations could be due to the limited capabilities of pushing or pulling equipment as in the case of the sliplining technique. Other limitations could be attributed to the required supporting technologies (i.e. curing methods) or weight of pipes as in the case of cured in-place or fold and formed technique. It should be noted that heavier pipe weight requires larger pressure equipment to maintain constant pressure and to avoid any problem during the inversion process. This factor is important to consider in case the municipality requires all access points to be through manholes.

6- *Ability to accommodate future settlement:* this factor could have a bearing on which product could be used. This is due to the fact that some products can not accommodate differential settlements. If pipe breakage is expected to happen due to certain soil conditions, then some products could be discarded.

7- *Duration of project:* project schedule could pose a major limitation on the selected product. This is due to the fact that different products require different installation periods. It should be noted that to ensure consistency of different suppliers in answering this question, a 500 (m) of pipe was considered as a reference unit.

8- *By-pass requirement:* certain techniques, such as sliplining, can be applied while the original pipe is running. Others, such as cured in-place, can not. This is due to the fact that they require a controlled environment, in terms of temperature and dryness, necessary for curing the resin used.

9- *Years in business and length of product installed:* the number of years that a certain product has been in use, and the number of linear meters that have been actually installed using that product could increase/decrease the confidence in applying it. This factor is believed also to assist municipalities in experimenting with new technologies.

10-*Life expectancy of products:* design life is a factor that could increase/decrease the desirability of using certain products.

11-*Locality of suppliers:* this factor could be of concern to those municipalities that prefer dealing with local suppliers. Dealing with local suppliers could be imposed, in some cases, by contractual requirements due to economical and/or political reasons. Dealing with non-local suppliers, in some cases, could cause future maintenance or manufacturer's technical support problems. Maintenance problems could occur if sudden failure happens and replacement parts are required immediately.

12- *Type of access to the original pipe:* some trenchless techniques require excavation pits in addition to manholes for installing pipes. If a municipality limits the access of the new pipe to manholes only due to limitations on location or traffic problems that could be caused by excavation pits, then a number of techniques could be discarded.

13-*Method* of *service connections:* the ability to reconnect laterals to the rehabilitated pipe without digging is considered an advantage. Some trenchless techniques have this advantage and others do not.

14-*Degree of innovation:* the ability of suppliers to accommodate new client requirements that are not part of their design or production standards. It also indicates the ability of suppliers to come up with new fabrication or installation procedures. This factor is introduced to account for new products and for the ability of suppliers to accommodate non-standard field conditions.

15- *Cost effectiveness of products:* many products could be discarded if they do not fulfill the budgetary limitations of a project. It should be noted that to ensure consistency of suppliers in answering this question, the price per centimeter of diameter per linear meter of pipe was considered as a reference unit. It should also be noted that the cost considered in this system is the direct material cost only.

CHAPTER 3

DEVELOPMENT OF AN AUTOMATED INSPECTION SYSTEM

3.1 INTRODUCTION

This chapter presents the development of an automated system for detection and classification of defects in sewer pipes. The system is designed to support, enhance and improve the current practice for inspecting this class of pipes. An attempt to identify common types of defects in this class of pipes is conducted. Based on the defects identified, the automated system was developed utilizing image analysis and artificial intelligence techniques.

3.2 TYPES OF DEFECTS IN SEWER PIPES

Knowing prior information about types, nature and frequency of occurrence of defects could probably be considered a corner stone in developing a system that detects them automatically. It helps to identify the characteristic features of defects, which will be considered as the basic criteria in classifying them automatically. A recent survey by the regional municipality of Hamilton, Ontario, Canada, was conducted to identify the defective sections within its sewer network (Regional municipality of Hamilton 1997). The survey covered approximately 25% of the total sewer network in the region, which is approximately 5659 sections. Each section is about 80 (m). The age of pipes ranged between 2 and 100 years, and their materials are concrete and clay. The burial depth of pipes ranged between 2 and 10 m and their diameter ranged from 250 to 1950 mm. The results of the survey are summarized in Table 3-1 (Moselhi and Shehab-Eldeen 1999 (b) and Regional Municipality of Hamilton 1997). As can be noticed from this table, the most common defects are dirt deposits (23.8%) and offset joints (13.7%). Longitudinal cracks, water infiltration at the joint, sign of infiltration at the joint are also reported to have percentage occurrence of more than 5%, which are considered to be high compared to other types of defects. It should be noted that due to the fact that neither the flow nor structural soundness of pipes are adversely affected by the presence of right or left lateral deviations, they could be considered non-serious problems. It should also be noted that having a water level over 25% of pipe diameter was not considered as an independent type of defect due to the fact that it could be attributed to other defects, such as opposite slopes.

Depending on the nature, shape and common features of defects, they could be grouped into major categories as shown in Figure 3-1. In this grouping scheme, the various defects were grouped into seven different categories. These categories are misalignment, roots, deposits, infiltration, cracks, side effects and others.

Table 3-1: Types of Defects in Sewer Pipes

Defect type	Number of sections	% of existence
Offset joint over 3 cm	523	13.670
Open joint over 5 cm	1	0.026
Broken joints	12	0.314
Opposite slopes	13	0.340
Visible soils	25	0.653
Visible armature along the pipe	2	0.052
Visible armature at joint	3	0.078
Broken pipes	16	0.418
Sagging pipes	5	0.131
Circular cracks	10	0.261
Longitudinal cracks	218	5.698
Multiple cracks	60	1.568
Water infiltration	25	0.653
Water infiltration at the joint	221	5.776
Sign of infiltration	15	0.392
Sign of infiltration at the joint	311	8.129
Right lateral deviation	487	12.729
Left lateral deviation	543	14.192
Visible rubber gasket at the joint	15	0.392
Grease accumulations	9	0.235
Light roots	38	0.993
Medium roots	31	0.810
Heavy roots	9	0.235
Mineral accumulations	44	1.150
Water level over 25% of pipe diameter	279	7.292
Dirt Deposits	911	23.811
Total	**3826**	**100**

Defects that are included in the misalignment category are offset joints over 3 cm, open joints over 5 cm, opposite slopes, visible soil, sagging pipes, right lateral deviation, left lateral deviation and visible rubber gasket at the joint. This category is suggested due to the fact that a crescent shape is usually formed at the joint when any of the mentioned defects exists. Infiltration category includes sign of infiltration, sign of infiltration at the joint, water infiltration, water infiltration at the joint and mineral accumulation. This category is suggested due to the fact that they all share the same effect of having a wetted area around the defect. Dirt deposits result in building up of foreign materials on the bottom of a pipe, and accordingly it was considered to fall in a separate category. Cross-sectional reduction category includes all objects that obstruct the flow in pipes such as roots. Longitudinal and circular cracks were grouped in one category (i.e. Cracks) due to their common geometrical features (i.e. length and width). Defects such as broken pipes, broken joints, visible armature along the pipe, visible armature at the joint, multiple cracks and grease accumulation were grouped in one category due to the fact that their possibility of existence is very minimum. Category of side effects includes increasing of water level over 25% of pipe diameter. This is due to the fact that this phenomenon could be attributed to more than one defect. These defects are opposite slopes, existence of roots or solid deposits at the bottom of a pipe.

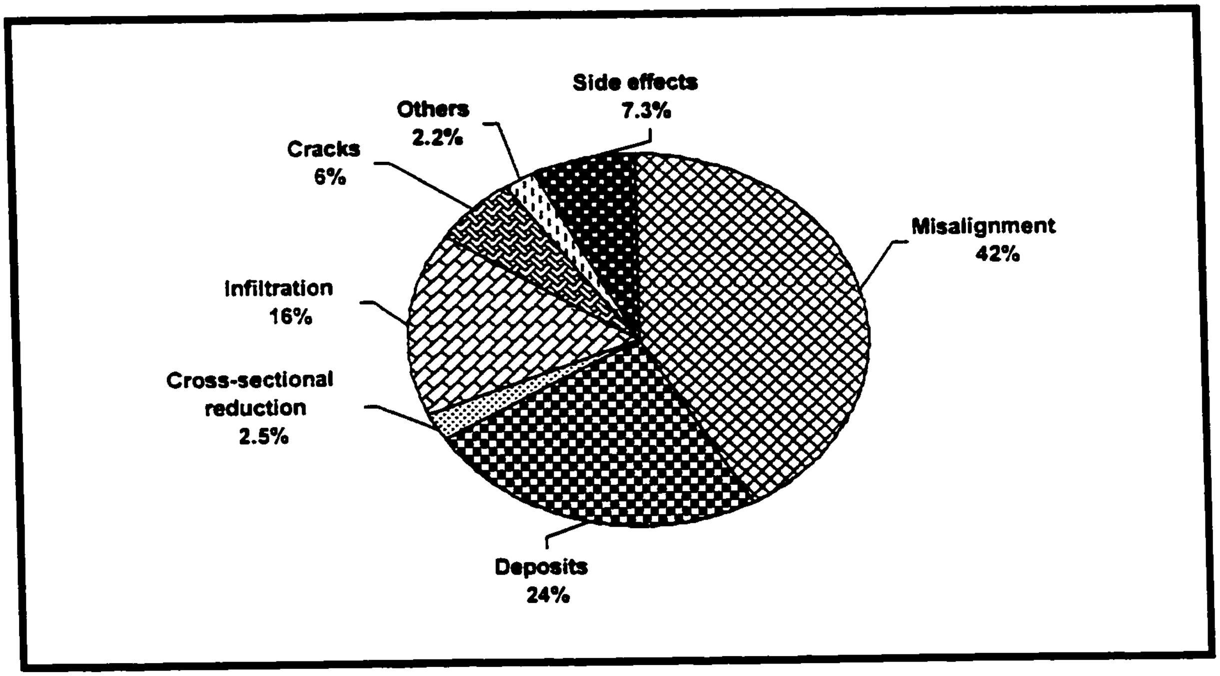


Figure 3-1: Categories of Defects in Sewer Pipes (Moselhi and Shehab-Eldeen 1999 (b))

It should be noted that defects such as roots, infiltration and deposits are considered to be serious problems by many municipalities in North America. It has been reported that the intrusion of roots to sewers (Figure 3-2) is the most important factor contributing to their blockage in North America (Hogan 1998). It has also been reported that the blockage of sewer pipes caused by root intrusion increases by 3% yearly (Schrock 1985). Naturally, roots search for a nutritious source for survival. Once a sewer pipe is found, it is considered to be a perfect environment. The roots then penetrate the pipe through any opening, such as an open or broken joint. After penetration, they grow in until they reach the flow. Once they reach the flow, they grow more and collect solids until they form a blockage. Beside roots being a major factor contributing to blockage of sewer pipes, they could also cause structural and functional failure to these pipes. This is due to their ability to uplift pipes, which could result in creation of cracks or opening of joints (Casey 1989).

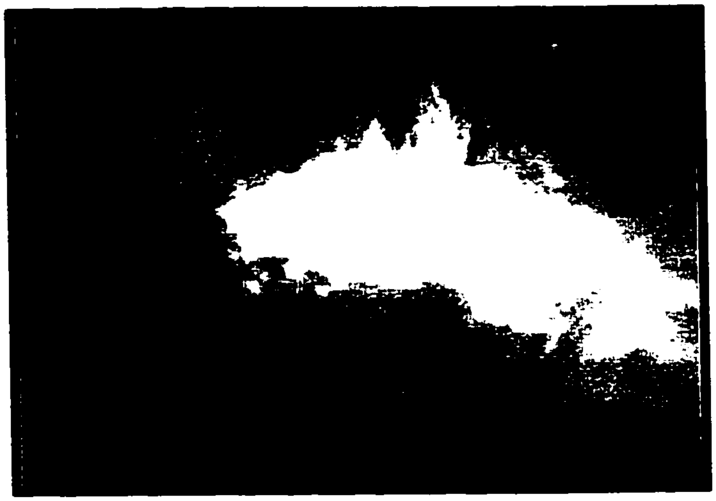


Figure 3-2: Root Intrusion

Deposits in sewer pipes (Figure 3-3) have been reported to be a worldwide problem (Skipworth et al. 1999). A recent survey in the United Kingdom has revealed the presence of large amounts of deposits in their sewer pipes (Tait et al. 1998). Usually, deposits consist of a mixture of coarse sediments, fine sediments and organic material. The coarse and fine sediments find their way into sewer pipes through defects in manholes or joints. These deposits have been reported to cause erosion of pipes as well as loss of discharge capacity (Skipworth et al. 1999).

Figure 3-3: Dirt Deposits

Infiltration of ground water into sewer pipes (Figure 3-4) is a major problem that faces most municipalities. Infiltration has been reported to account for 40 % of the total flow in sewer pipes (Aguiar et al. 1996). This unnecessary extra flow contributes to serious problems such as overloading of sewer pipes and wastewater treatment plants. This phenomenon has also been documented to account for an additional 10%, at least, to treatment cost (deMonsabert and Thornton 1997). It should be noted that water infiltrates sewer pipes through defected joints, manholes or cracks (Cutts 1986).

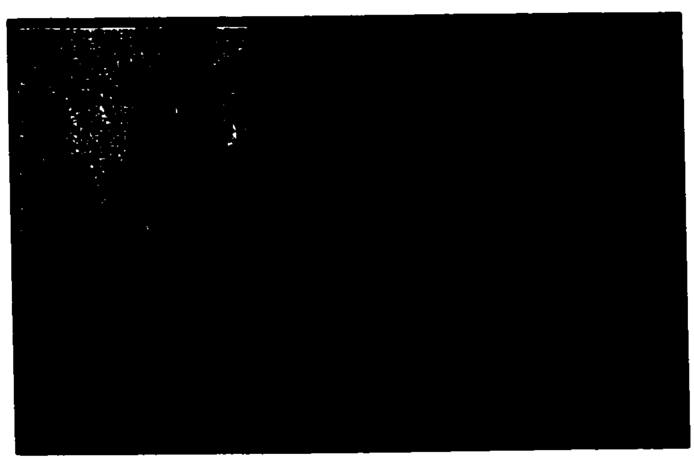


Figure 3-4: Infiltration

The two common types of cracks are longitudinal and circular (Table 3-1). These cracks are mostly caused due to two main reasons. These reasons are frequent overload and/or presence of uneven pipe support (Lofthouse 1983 and Najafi et al 1997). Cracks are considered to be the preliminary stage of sewer pipe fracture (Lofthouse 1983). This is due to the fact that once they are developed, water could exfiltrate or infiltrate from/to the surrounding soil. If side supports are lost due to washing out of soil particles, caused by exfiltration or infiltration processes, cracks will be developed into fractures. It should also be noted that if a pipe further moves outwards, due to absence of enough side support, it eventually collapses (Lofthouse 1983).

Figure 3-5: Cracks

Defective joints (Figure 3-6) were found to be one of the main categories of defects in sewer pipes (Moselhi and Shehab-Eldeen 1999 (b)), see also Figure 3-1. They are mostly caused due to loss of supporting soil. This is usually initiated by having a defective gasket. These defective gaskets allow for the infiltration or exfiltration process to take place, which will eventually cause the supporting soil to be disturbed. This disturbance of the supporting soil causes pipes to settle and their joints open. It should be noted that once open joints are created, cracks could also be initiated which could eventually result in pipe failure (Lofthouse 1983).

Figure 3-6: Misalignments

3.3 PROPOSED SYSTEM

Figure 3-7 depicts the overall configuration of the proposed automated inspection system. As depicted in Figure 3-7, a CCTV, or a zooming, camera first scans the inner surface of a pipe and produces a videotape which is played back using a VCR. The VCR then feeds the information captured on the tape to a computer equipped with a frame grabber, image analysis and neural network software. The frame grabber captures and digitizes the frames of the acquired images. The image analysis software analyzes those digitized images and processes them in a manner so as to prepare a suitable input to a neural network. Based on those analyzed images, some feature vectors are extracted, using different image analysis techniques, and are fed to several neural networks for training. The trained networks can then be used to classify new set of defects based on their extracted features.

As can be noticed, the system utilizes a CCTV camera as its main component for scanning and collecting information about pipes. This technique of video imaging was selected to benefit from the long experience gained by municipalities and practitioner engineers in using this particular data collection device. This particular data collection device was also preferred, compared to others, due to its availability, affordable cost and proven capabilities. Utilizing the CCTV camera, as a data collection device in the developed system, also builds on the experience gained by municipalities in inspecting sewer pipes, and does not overburden them with purchasing new data collection devices that might be expensive, under development or not available in local markets. By keeping the momentum gained by municipalities in utilizing the CCTV camera, the proposed system will facilitate the detection and classification processes of most common defects in sewer pipes, namely cracks, misalignments, infiltration, cross-sectional reduction and deposits by using an automated process. The system is designed to speed up the detection and classification processes so that minimum processing time is required. This is achieved by extracting from video images all necessary and essential information required for performing its task. This will minimize the processing time to a degree that the system could be utilized in on-line inspection tasks.

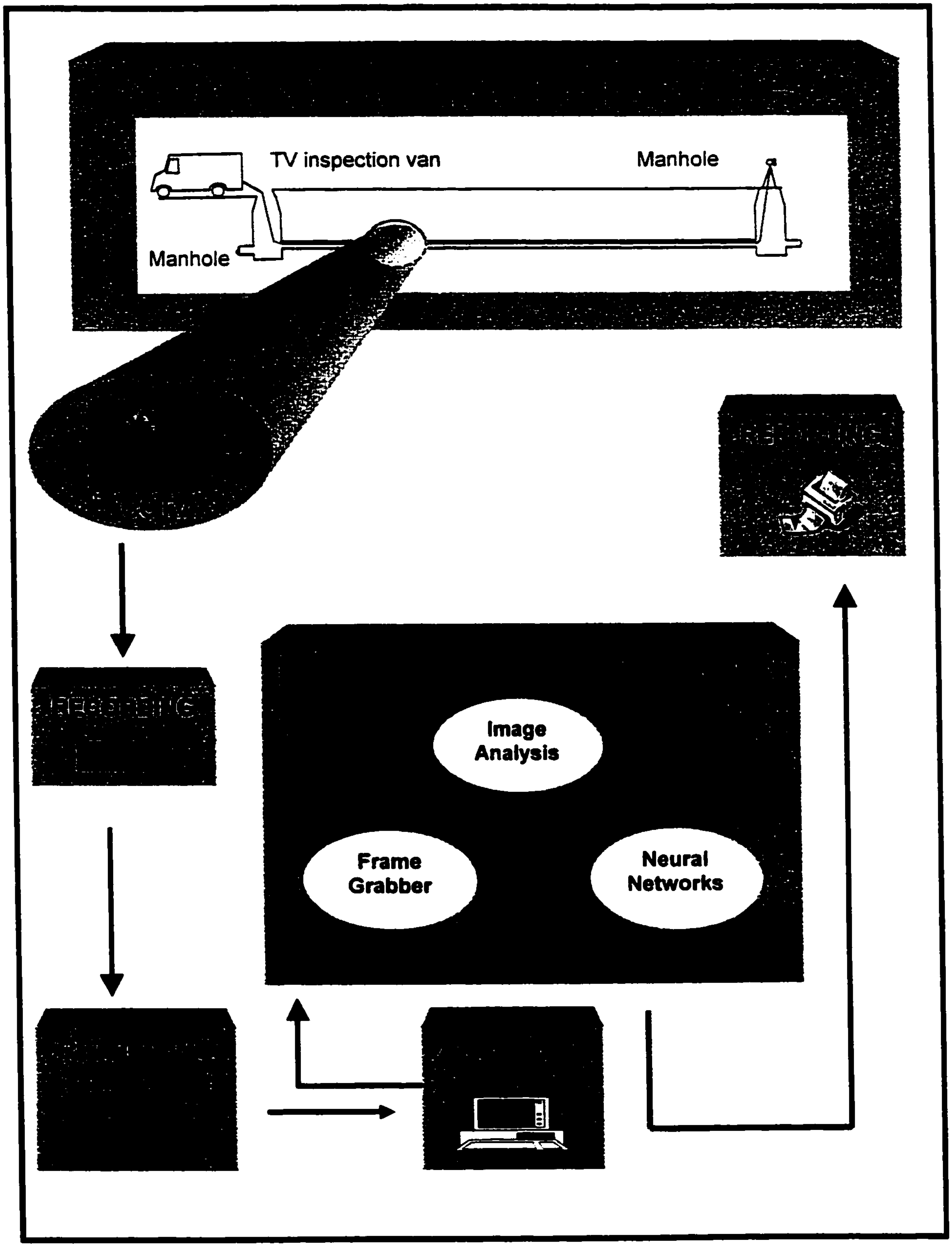


Figure 3-7: Proposed Automated Detection and Classification System

3.4 DEVELOPMENT METHODOLOGY

Figure 3-8 depicts the methodology followed in developing the automated inspection system. As can be seen, four main steps were followed: 1) data acquisition, 2) data preparation, 3) data processing and 4) performance validation. In the following sections, a detailed description of each step is presented.

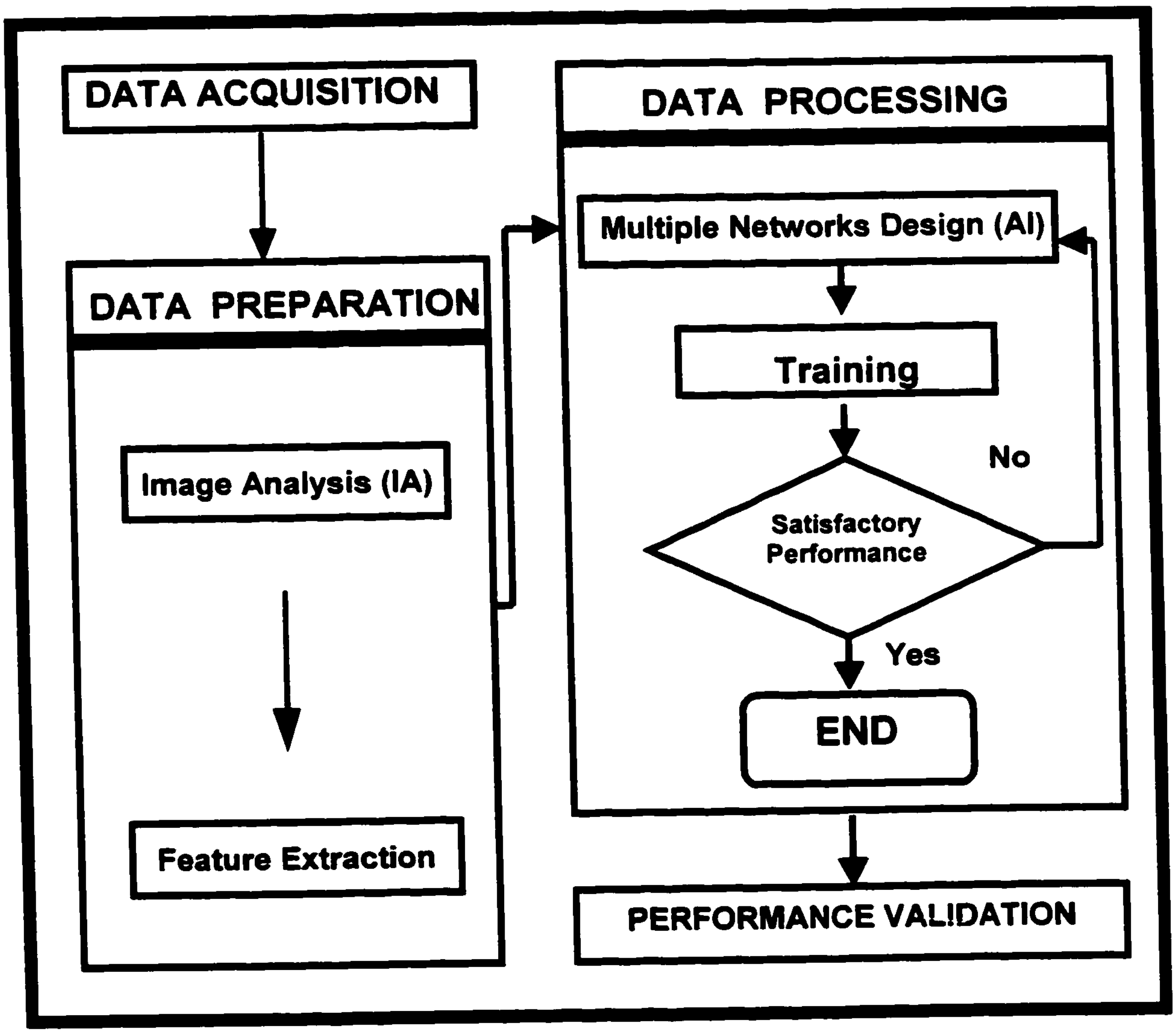


Figure 3-8: Methodology for Developing Automated Detection System

3.4.1 Data Acquisition

A total of five videotapes were collected from several municipalities and sewer rehabilitation contractors. These videotapes depict the condition of sewer pipes in several cities such as Montreal and Hamilton, Canada. They also depict all common types of defects that exist in sewer pipes. These defects are cracks, misalignments, infiltration, deposits and cross-sectional reductions. Moreover, images depicting all various defects were extracted from these collected videotapes and presented to consultants in the domain of sewer rehabilitation for verification of their types.

3.4.2 Data preparation

Neural networks are recognized for their superior performance in pattern recognition and classification capabilities. As a rule of thumb, the number of neurons in the input layer has to be minimized so that the computation and conversion speed can be maximized (Looney 1997). Reducing the number of neurons can also help in improving the learning process of neural networks (Looney 1997).

Data captured on video images were utilized to train neural networks on classifying various defects in sewer pipe. A typical video image may consist of 760 X 480 pixels. If this image is to be processed using neural networks, then at least two alternatives could be considered. First is to digitize and feed one image or frame at a time with its huge number of pixels into the neural network. The second is to extract feature vectors that represent the different objects in the image and then feed them into the neural network. It should be noted that a feature vector is defined as a set of geometrical and statistical attributes that describe an object (i.e. defect) and its surroundings in a video image.

Clearly, the first alternative is impractical since one neuron will be needed for each single pixel in the image. This requires a huge number of neurons in the input layer that could not be handled efficiently by the neural network and, accordingly, could degrade the classification performance or delay the processing time. The second alternative appears to be promising and will be considered in subsequent developments of the proposed system. This alternative has been found useful in pattern classification using neural networks (Ritchie et al 1991, Ritchie 1989, Mashford 1995, Kaseco and Ritchie 1994, Darwln 1994, Taso et al. 1994, Landis et al. 1997 and Masad et al. 1999). The technique basically minimizes the amount of data that has to be fed into a neural network and, accordingly, reduces significantly the number of neurons in the input layer of that network. It ultimately results in improving the learning speed as well as the classification capabilities of the network.

In preparing the data, all acquired videotapes were digitized. A commercial software package was utilized for this task. This software package is Adobe PhotoShop (Adobe PhotoShop 1999). Once all images have been digitized, they were processed and analyzed utilizing a commercial image analysis software package. This software package is Scion Image (Scion Image 1998). Various image analysis techniques were utilized in processing and analyzing the digitized video images. It should be noted that the aim of these techniques is to detect and isolate defects from image background. Once defects were detected and isolated, they were analyzed to determine their relevant attributes (i.e. geometrical and pixels intensities). It should be noted that the process of determining defect attributes is called feature extraction.

3.4.3 Data Processing

3.4.3.1 Selecting a neural network paradigm

Back-propagation neural networks are recognized for their superior performance in classification tasks (Moselhi et al. 1994, Faghri et al. 1997, Kaseko and Ritchie 1994 and Tamura and Tateishi 1997). They are also considered the most commonly used type of neural network in civil engineering applications (Moselhi et al. 1994, Flood 1994 (a)&(b)). It should also be noted that this type of network was previously used in developing an automated system for classification of defects in pavements and proved its superior capabilities (Kaseco and Ritchie 1994). Accordingly, this type of network will be utilized in developing the automated system.

3.4.3.2 Network design and training

Contrary to developing traditional algorithmic computer programs, designing and developing neural network applications is heavily dependent on trial and error. Although there are some guidelines for selecting reasonable initial values for these parameters, there are no rules that assure selection of most suitable values before hand. Accordingly, the process involves a lot of trials until satisfactory performance is obtained. Basically, in designing neural networks, the following parameters are considered:

- Activation and scaling functions
- Number of hidden layers
- Number of neurons in input, hidden and output layers
- Learning rate and momentum coefficients

Techniques that were presented in Chapter Two (Section. 2.5.6) will be utilized in selecting reasonable initial values for these parameters. Other values will be tried if unsatisfactory results are obtained.

The total acquired data will be randomly divided into three sets: 60% for training, 20% for testing and another 20% for production. It should be noted that the testing set is a set of patterns that are used to test the generalization capabilities of the network while in training. In so doing, the training process temporarily stops, after a pre-specified number of training iterations (calibration interval), and computes the average error for the training set. The production set is a set of patterns that are not exposed to the network while training or testing and is used to test the performance of the trained network.

3.4.3.3 Result validation

Once the neural networks have been designed and trained, their capabilities will be tested on a different set of defects that they were not exposed to during development. This will be achieved by utilizing the production set. It should be noted that the satisfactory performance of each developed neural network will be measured based on several parameters. These parameters are (R^2), mean square error, mean absolute error, minimum absolute error, maximum absolute error and correlation coefficient (NeuroShell-2 1996). In addition, the recognition rate will also be considered as suggested by Ritchie et al. 1991, Taso et al. 1994. and Batchelor 1997.

3.5 DEVELOPMENT OF A MULTIPLE CLASSIFIER SYSTEM

In an effort to improve the overall accuracy of the developed inspection system, three neural networks will be developed for each category of defects. These neural networks will be developed in a manner to ensure full independence among them. This will be achieved by changing the order of patterns in the training set and/or utilizing different attributes in the input layer. The networks are designed to counter-check the results obtained from each other, embracing a multiple classifier strategy (Moselhi and Shehab-Eldeen 2001). In essence, they function in a similar way to a team of human experts. It should be noted that the decision to use three neural networks was made so that in case of having disagreement in the results obtained from two nets, the third is used to confirm one of the classifications made. As such functioning as a team of experts. Figure 3-9 depicts the proposed methodology of comparing the output of the three networks. As depicted in Figure 3-9, when the multiple classifiers system is activated, it first compares the output of two networks (i.e. neural network no.1 and no.2). If their results are in agreement, then a report will be issued stating the classification of defect agreed upon by both networks. If their results are not in agreement, then a third network will be consulted. If the results obtained from the third network match the results obtained from any of the previously applied networks, then a report will be issued confirming the two matched classifications. If the results obtained from the three networks are different, then the defect features will be compared with the upper and lower boundaries of each network (i.e. the range in which the neural networks have been trained). If the defect features are outside the boundary limits of the three networks, then a message will be given to the user to consult a human expert to identify the actual type of defect encountered. If the features of the defect in question fall within the boundary limits of one network only, then the results obtained from that network will be reported. This is due to the reason that it is believed that the results obtained from neural networks are more reliable if they are applied to similar pattern to those trained on. If the features of the defect in question fall within the boundary limits of more than one network, then the results obtained from the network with the highest accuracy (i.e. recognition rate) will be reported. If more than one network were found to have the same accuracy, then a human intervention is needed. It should be noted that the recognition rate is measured as the percentage of correctly classified cases out of a number of cases that were not encountered by the neural network during the training stage (i.e. production set). Figure 3-10 depicts the utilization of the proposed multiple classifier system and its integration with the main detection and classification system.

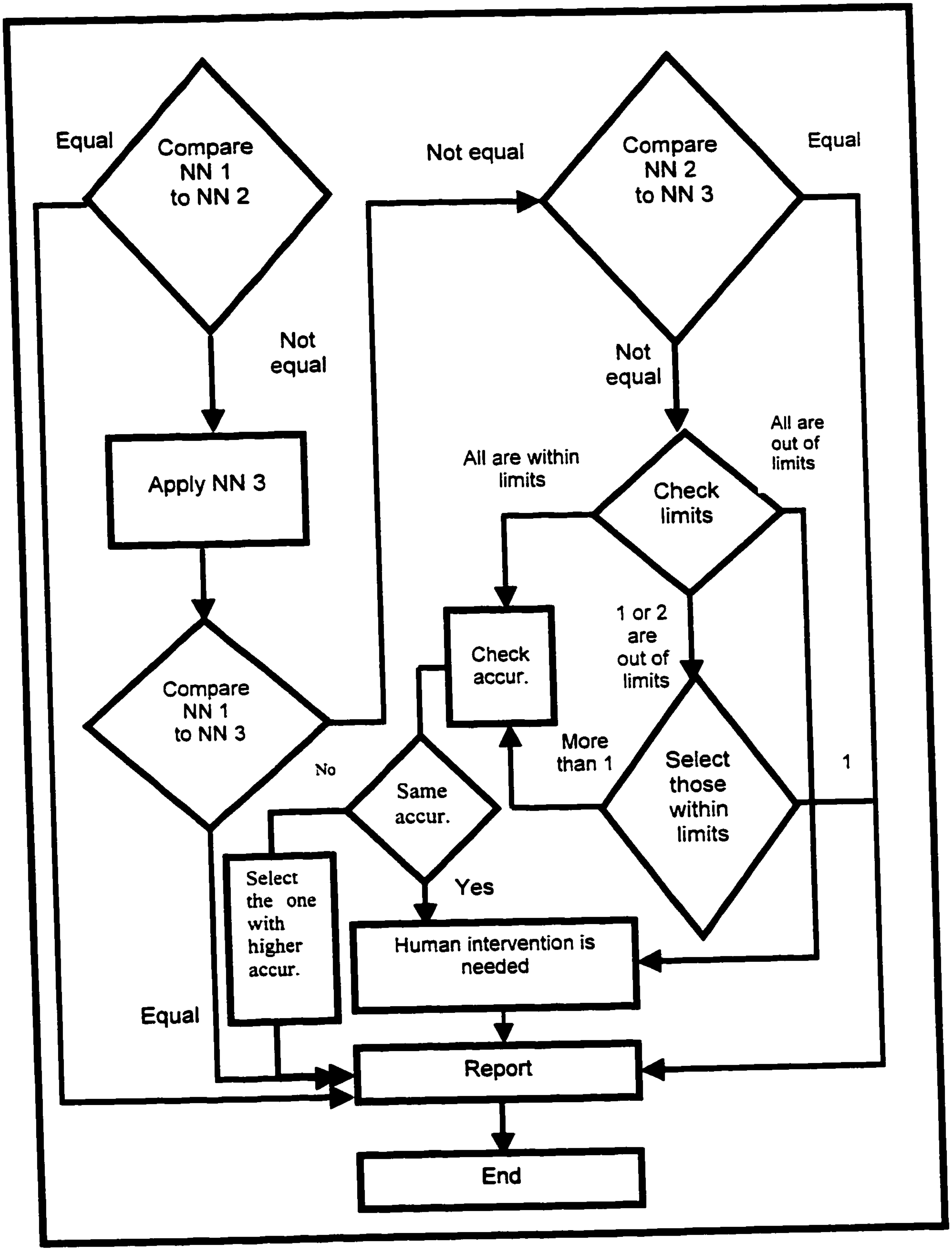


Figure 3-9: Algorithm of the Multiple Classifier System

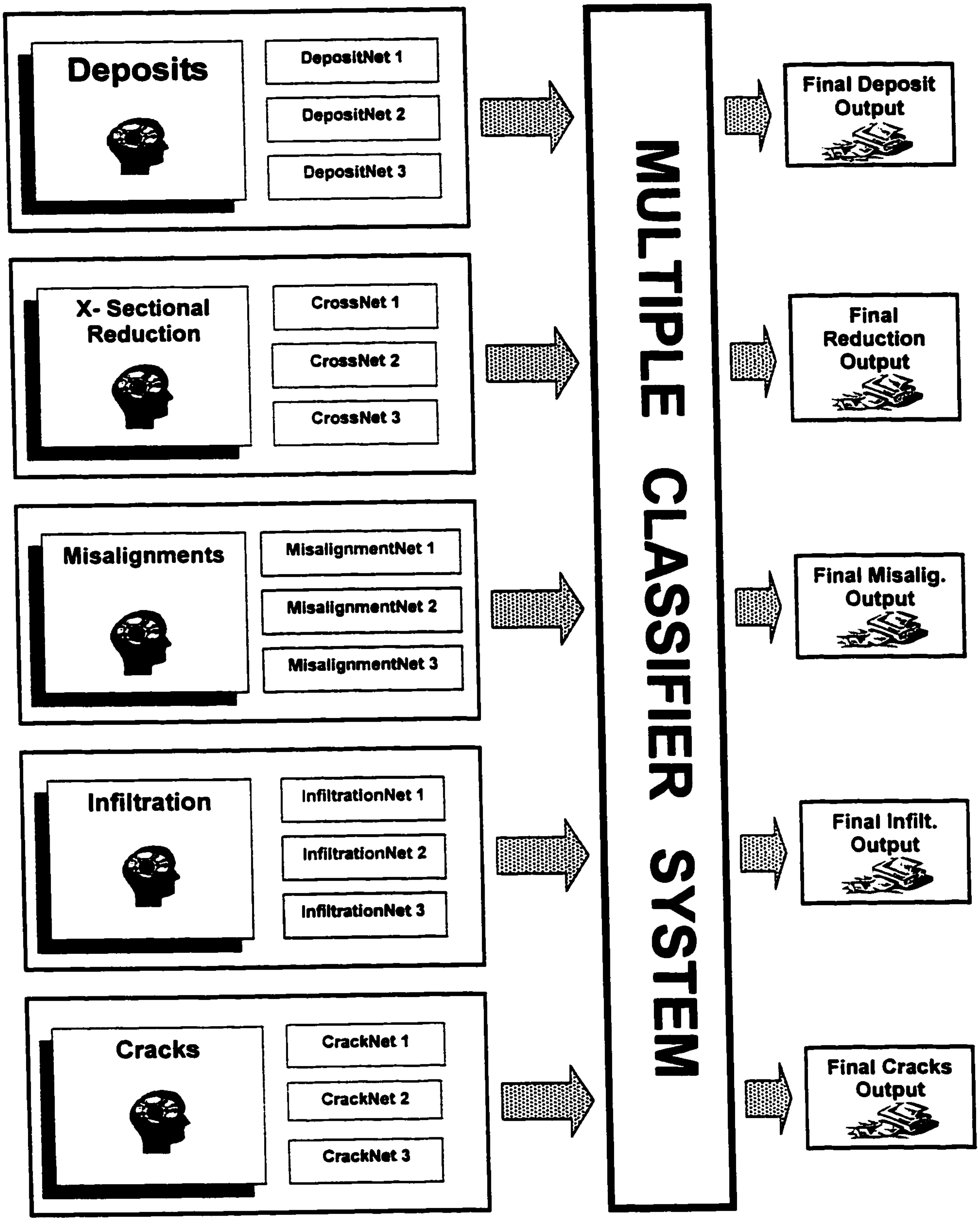


Figure 3-10: Utilization of the Multiple Classifier System

3.6 SOLUTION STRATEGY

Neural networks work in an analogous way to human experts. The more focused the expert is in a specific domain of application, the higher are the expectations to solve difficult problems. In this chapter, several classifiers (i.e. neural networks) are developed; each is considered suitable for a certain category of defects. This was considered advantageous, as opposed to one network that classifies more than one type of defect, in order to express and demonstrate the importance of specialty in classification tasks. Although diversity of networks is advantageous, it leads to a problem of guiding the detected patterns in the proper direction that will ensure that each category of defect is received by its corresponding specialized classifier. In this section, a solution strategy is presented to organize data traffic so as to guide the patterns in their proper directions and accordingly improve the system's performance.

Figure 3-11 depicts the proposed solution strategy. As depicted in this figure, all images will be processed three times. In the first pass (i.e. inverted images), all images will be inverted, dilated, background subtracted, thresholded, segmented and finally analyzed. In the second pass (i.e. non-edge detection), images will be subjected to the same image processing techniques except inversion. In the third pass (i.e. edge detection), all images will be subjected to a number of operations. These operations are background subtraction, edge detection, dilation, thresholding and analysis. The sequence of these image processing operations and their associated outputs are summarized in Table 3-2. The reason behind subjecting the same videotape to a number of passes is to benefit from all image processing techniques that are necessary to detect all categories of defects recognized by the system.

Table 3-2: Sequence of Image Processing Operations and Detected Defects

Pass #	Sequence of Operation	Detected Defects
1	Inversion, dilation, background subtraction, thresholding, segmentation and analysis	Deposits, Cross-sectional reductions and misalignments
2	dilation, background subtraction, thresholding, segmentation and analysis	Infiltration
3	background subtraction, edge detection, dilation, thresholding and analysis	Cracks

As can be seen in Figure 3-11, results of the first pass (i.e. inverted images) will first be processed by set of networks number 1, specialized in detecting deposits. This set consists of three networks: DepositNet 1, DepositNet 2 and DepositNet 3. These networks will classify the input data (i.e. patterns) into two categories: "Deposits" and "Else" (i.e. non-deposits). All patterns classified as "Else" will be screened based on their X and Y coordinate and will be further processed by another two sets of networks (i.e. sets no.2 and 3), each is specialized to deal with a specific set of defects. Patterns with X and Y coordinates equal to (1,1) will be fed into these networks specialized in classifying cross-sectional reductions and misalignments (i.e. set no. 2 and 3, respectively). It should be noted that set number 2 and 3 consist of three networks each. These networks are Cross-sectionalNet 1, Cross-sectionalNet 2, Cross-sectional 3, MisalignmentNet 1, MisalignmentNet 2 and MisalignmentNet 3. It should be noted that all patterns classified as "Else" by set # 2 and 3 will be ignored since they could be non-defects or defects that are not recognized by the system.

The results of the second pass of image processing (i.e. non-edge detection) will be fed into those networks specialized in classifying infiltration (i.e. set no 4). This set consists of three networks: InfiltrationNet 1, InfiltrationNet 2 and InfiltrationNet 3. Each network is capable of classifying patterns into two categories: "Infiltration" and "Else" (i.e. non-infiltration). It should be noted that all patterns classified as "Else" will be ignored since they could be non-defects or defects that are not recognized by the system.

The results of the third pass of image processing (i.e. edge detection) will be fed into the networks specialized in classifying cracks (i.e. set no 5): CrackNet 1, CrackNet 2 and CrackNet 3. Each network is capable of classifying patterns into two categories. These categories are "Crack" and "Else" (i.e. non-crack). It should be noted that all patterns classified as "Else" will be ignored since they could be non-defects or defects that are not recognized by the system.

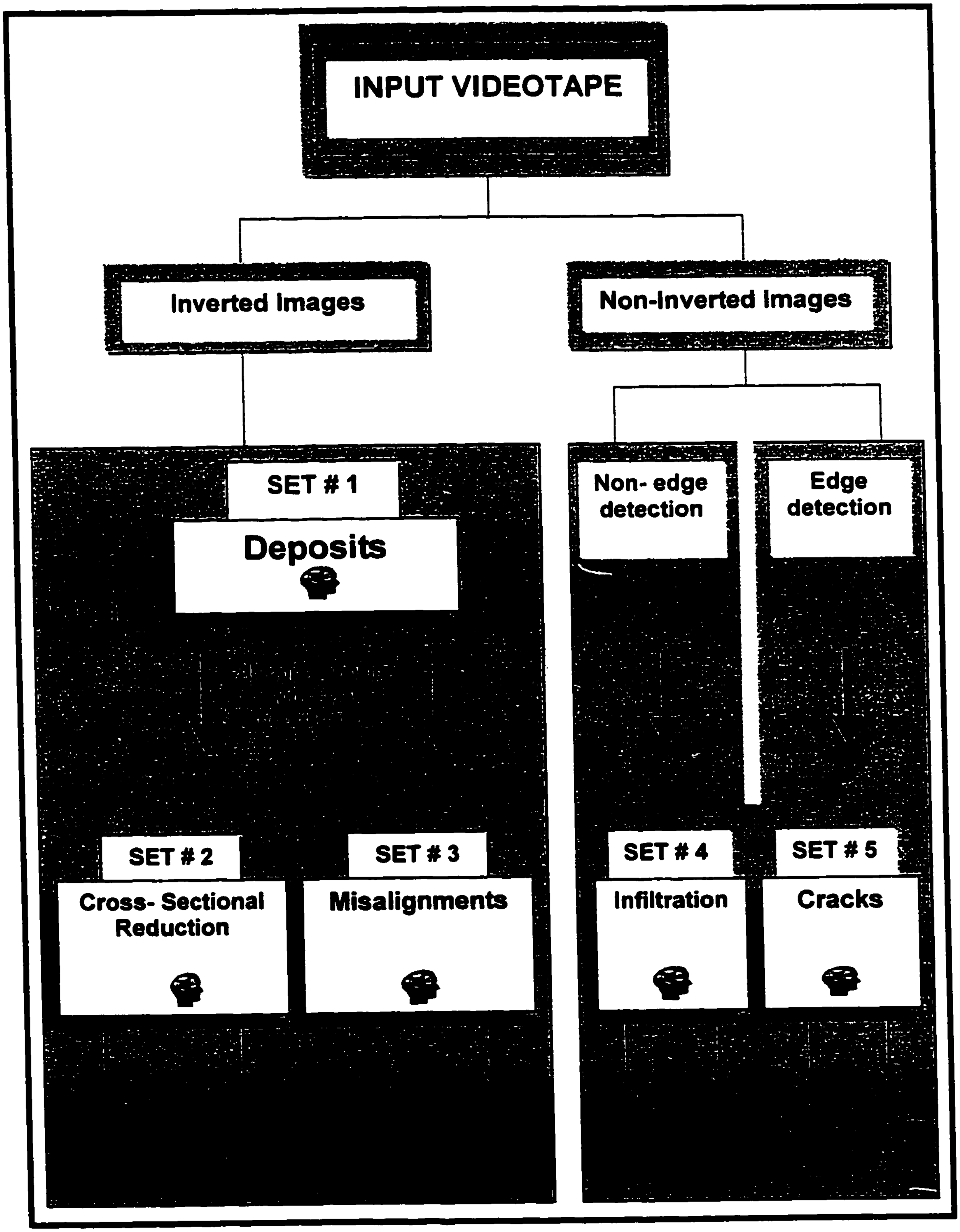


Figure 3-11: Solution Strategy

3.7 SYSTEM DEVELOPMENT

3.7.1 General

As described earlier, there are five major categories of defects. These categories are cracks, misalignments, deposits, infiltration and cross-sectional reductions. Since a human expert, by definition, is specialized in a specific domain of application, and neural networks function in an analogous way to a human expert, it was believed that it would be advantageous to develop separate neural networks, each is specialized in classifying a specific type of defect. Accordingly, the methodology described previously in Section 3.4 will be utilized to develop five sets of neural networks, each consisting of three networks. The first, second, third, fourth and fifth sets will be designated to cracks, cross-sectional reductions, deposits, misalignments and infiltration, respectively. The following sections describe the development of each set of neural networks. Case examples will also be presented to demonstrate the use and capabilities of the developed neural networks.

3.7.2 Cracks

There are two types of cracks considered in this system, longitudinal and circular. They all posses the same attributes, except orientation (i.e. angle). Longitudinal cracks run parallel to the pipe axis, while circular ones run along the circumference of the pipe. They are characterized by distinctive features. These features are small width, large length and large length to width ratio. In order to extract these distinguishing features, image analysis techniques will be applied utilizing Scion Image software package (Scion Image 1998). Image analysis techniques will process defects so as to enhance and isolate them from their background, and finally analyze them to determine their attributes. These attributes are area, mean density, standard deviation, X-coordinate, Y-coordinate, modal density, perimeter, major axis, minor axis, angle, integrated density, modal value of background, minimum gray value, maximum gray value, the ratio of major axis length to the minor axis length, the ratio of perimeter to area and the ratio of mean gray level value of defect to mean gray level value of image. These parameters are defined below:

Gray value: the brightness value of a pixel (0 for black, and 255 for white).

Pixel: picture element (Figure 3-12).

Area: area of defect in pixels.

Mean density: average gray value of all pixels within the defect.

Standard deviation: standard deviation of the gray values referred to in "Mean density" above.

X-Y coordinate: X-Y coordinates of the center of defect.

Perimeter: Parameter of the "area" in pixels referred to above (Figure 3-12).

Modal value: most frequent occurring gray level value referred to in the "mean density" above

Major axis length: length of the major axis of the "area" in pixels referred to above (Figure 3-12).

Minor axis length: length of the minor axis of the "area" in pixels referred to above (Figure 3-12).

Angle: angle between the major axis and a line parallel to the x-axis of the image.

Integrated density = N * (mean density – modal value of background)

Where N is the number of pixels within the area of the defect.

Modal value of background: most common gray value of image background.

Minimum gray value: minimum gray value within the defect.

Maximum gray value: maximum gray value within the defect.

Ratio of major axis length to minor axis length (Maj./Min.): major axis length (as defined above) / minor axis length (as defined above).

Ratio of perimeter to area (L/A): Perimeter of defect (as defined above)/ area of defect (as defined above).

Ratio of mean to mean(Mean/Mean): mean gray level of defect/ mean gray level of image.

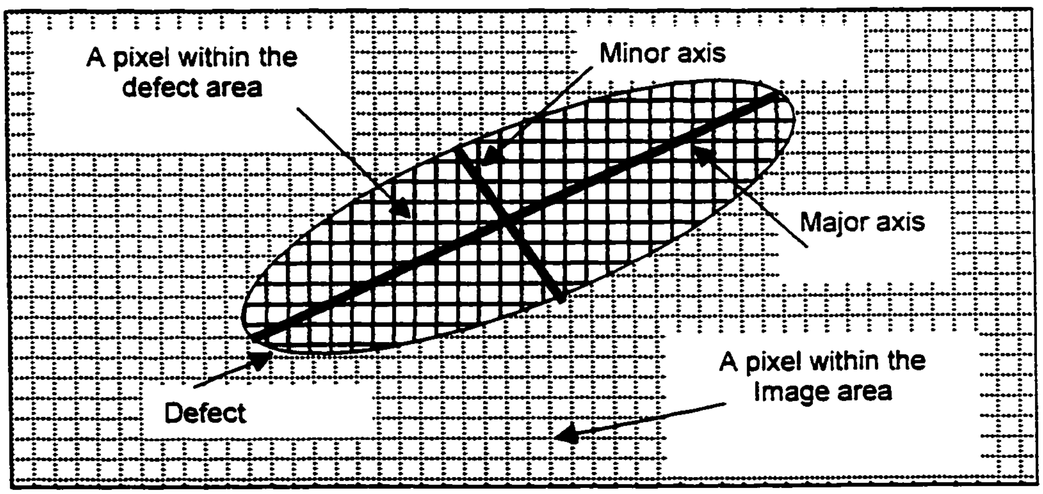


Figure 3-12: Geometrical Attributes of Defects

Various image analysis techniques were tried and analyzed, aiming to enhance the image of defects and isolate them from background, such as inversion, dilation background subtraction, threshholding, smoothing, erosion and edge detection. Finding a set of techniques that could be applied to all types of cracks, regardless of their gray level value, was a challenge. This is due to the fact that some cracks were found to have a high gray level value (i.e. white or close to white) and others were found to be vice versa (i.e. black or close to black). The techniques found to yield best results are background subtraction, edge detection, dilation and threshholding. Background subtraction is utilized to isolate cracks from the background of an image (Figure 3-13). This was found very helpful in obtaining good results form the thresholding operation. In this operation, all background pixels are deleted from the image and only cracks remain. Edge detection is utilized to outline the cracks regardless of being black or white (Figure 3-14). Dilation is utilized to fill in the gaps and connect discontinuous pixels (Figure 3-15). This is achieved by filling in these gaps by pixels with gray level value similar to their neighborhood dark pixels. It should be noted that these gaps are created due to discontinuity of gray level values (i.e. a group of light pixels in between two groups of dark pixels). Thresholding is utilized to isolate cracks and prepare them for the analysis stage (Figure 3-16). Once the image has been thresholded, it becomes ready for analysis. In this step, all above described attributes are measured (Figure 3-17 and 3-18). It should be noted that the values of geometrical attributes such as area, perimeter, major axis length and minor axis length are greater than zero, otherwise they will not be detected. It should also be noted that several sequences of operation were tried and thesequence found to yield the best results is sequence number 3 as detailed in Table 3-2. This sequence of operations was conducted on the collected images. Three hundred and seventy one cracks were detected, isolated and analyzed. The results obtained from this analysis were utilized in developing three neural networks. The purpose of these networks is to classify cracks from non-cracks, based on their attributes calculated in the analysis process.

Figure 3-13: Background Subtracted Image of Cracks

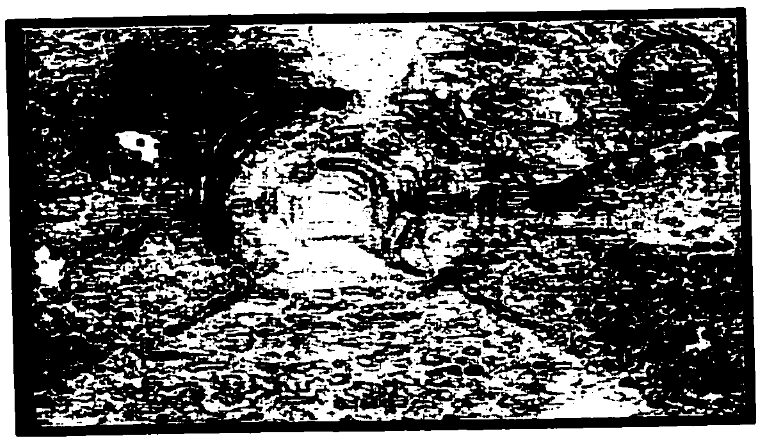


Figure 3-14: Edge Detected Image of Cracks

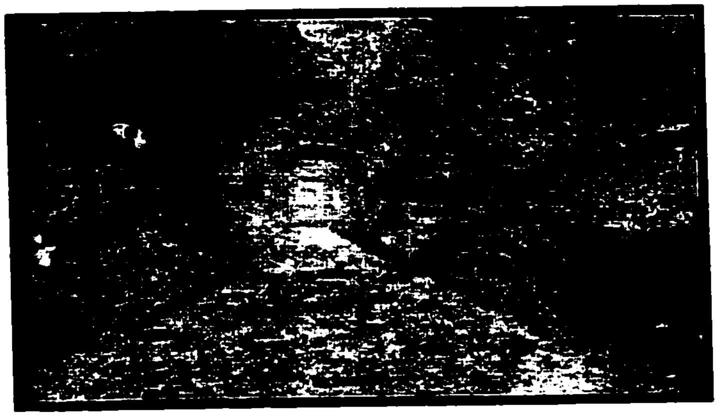


Figure 3-15: Dilated Image of Cracks

Figure 3-16: Thresholded Image of Cracks

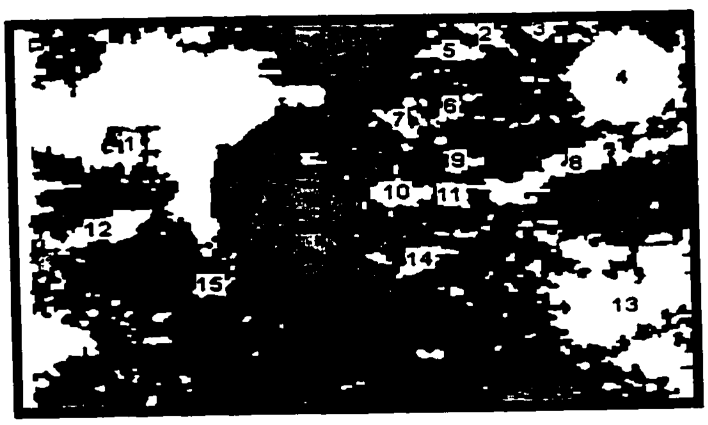


Figure 3-17: Segmented Image of Cracks

Results

	Area	Mean	S.D.	X	Y	Length	Major
1.	10298.00	190.81	66.39	53.65	71.71	1524.50	158.94
2.	243.00	128.24	43.82	219.07	7.41	104.81	29.39
3.	136.00	111.10	21.24	244.56	4.30	65.70	17.86
4.	2159.00	188.20	70.57	282.51	35.62	368.13	61.65
5.	292.00	131.72	32.81	202.45	17.68	89.01	31.38
6.	192.00	109.64	23.06	202.17	51.82	119.71	24.13
7.	241.00	130.94	42.37	178.54	59.96	101.64	23.34
8.	1345.00	168.22	65.38	259.09	87.75	399.50	95.43
9.	195.00	140.76	49.97	205.39	84.36	68.87	17.46
10.	356.00	143.16	44.28	176.45	103.95	96.43	29.89
11.	177.00	137.53	39.02	201.72	105.62	56.63	18.03
12.	591.00	142.98	50.42	37.24	123.74	175.10	51.35
13.	4009.00	145.72	47.18	281.45	174.64	761.11	88.82
14.	251.00	136.23	42.46	186.72	144.71	90.08	30.47
15.	136.00	119.99	31.48	88.65	158.98	59.84	22.41

Figure 3-18: Analysis Results of an Image Depicting Cracks

Based on the extracted feature vectors of various defect types, it was noticed that misalignments might have almost the same attributes as cracks. This is due to the difference in distance between the CCTV camera and each type of defect. In other words, misalignments away from the camera tend to have similar attributes to cracks closer to the camera. These similar attributes are small minor axis length, small area and large ratio of major axis length to minor axis length. The only factors that differentiate between the apparently similar attributes are the X and Y coordinates (i.e. location). It was noticed, from the collected sample of video images, that the center of an image is darker than its surrounding area. This is due to the fact that the lighting effect vanishes as the distance from the lighting source gets larger. It was also noticed that misalignments tend to be illuminated at this specific area (the center of an image). This is due to the fact that these defects tend to project from the surface of the pipe and reflect back the beam of light they are exposed to. Other defects such as cracks do not exhibit the same phenomena. This was utilized to facilitate the classification process by assigning the coordinates of objects located outside this dark area to (0,0) (Moselhi and Shehab-Eldeen 1999 (b) & 2000 (a)). It should be noted that this assignment was made by changing the original coordinates of objects to (0,0) manually.

In view of the proven capabilities of back-propagation neural networks in classification tasks and to their wide versatility in different civil engineering applications, this paradigm was utilized in developing the automated inspection (detection and classification) system. The literature review discussed in Chapter Two was carefully considered to set the initial values of all training parameters of the preliminary designed neural networks. Described below are the parameters used in designing the preliminary neural networks.

- Since the number of neurons in the input layer should equal the number of attributes in the feature vector that was selected to represent the input patterns, it was decided to use seventeen neurons in that layer.

- Since the number of neurons in the output layer should equal the desired number of categories, the output layer of the developed network was built consisting of two neurons (i.e. one for each class of defects). These classes are "Cracks" and "Else".

- In the developed network, a three-layer network was used (i.e. one hidden layer).
- For the number of neurons that should be used in the hidden layer, the following equation has been applied in selecting initially 30 neurons in the hidden layer (Neuroshell-2 1996).

$$N = 0.5\,(X + Y) + (Z)^{1/2} \qquad (1)$$

Where;

N = Number of neurons in the hidden layer

X = Number of input parameters

Y = Number of output categories

Z = Number of patterns in training set (i.e. 560 patterns)

- Other parameters such as the type of activation and scaling functions, initial weights, learning rate and momentum factor are listed in Table 3-3.

Table 3-3: Initial Parameters Used in Designing a Preliminary Neural Network for Classification of Cracks

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	17
Number of neurons in output layer	2
Number of neurons in hidden layer	30
Number of hidden layers	1
activation function in hidden layer	Sine
Activation function in output layer	Logistic
Initial weight	0.4
Learning rate	0.3
Momentum	0.4
Calibration interval	50
Saving of network	At the best testing set

The developed three-layer back-propagation network was trained to classify two categories. These categories are "Cracks" and "Else". The network was developed and trained using NeuroShell-2 software package. The process was implemented on a Pentium II computer with 233 MHz processor and 64 MB RAM. A total of 966 patterns were used in developing the network. The total number of patterns was randomly divided as follows: 580 patterns (60%) for training, 193 patterns (20%) for testing and 193 patterns (20%) as a production set. These different sets have been defined earlier in Section 3.4.3.2. It should be noted that the training algorithm was set to save the trained network at the best test set and limit the calibration interval to 50. This was done so that over-training of the network is monitored and prevented. It should be noted that over training causes the network to memorize rather than generalize (Fausett 1994). Various combinations of hidden neurons, activation and scaling functions were tried and the near optimum design was found to be 17 neurons in the input layer, 34 neurons in the hidden layer and 2 neurons in the output layer. Linear scaling, Gaussian and Logistic activation functions were selected for the input, hidden and output layers, respectively. The results obtained using the developed network are shown in Table 3-4. It should be noted that these results are for the 193 patterns not seen by the network during training (i.e. production set). Based on this trained network, the contribution of each input variable was calculated (Figure 3-19). These contributions illustrate the relative importance of each variable to the performance of the network.

Table 3-4: Performance Results of a Preliminary Neural Network for Classification of Cracks

Performance Criteria	Crack	Non-Cracks
R^2	0.82	0.82
Mean squared error	0.042	0.042
Mean absolute error	0.095	0.095
Min. absolute error	0	0
Max. absolute error	1.0	1.0
Correlation coefficient (r)	0.90	0.90
Recognition rate	98.6%	93.3%

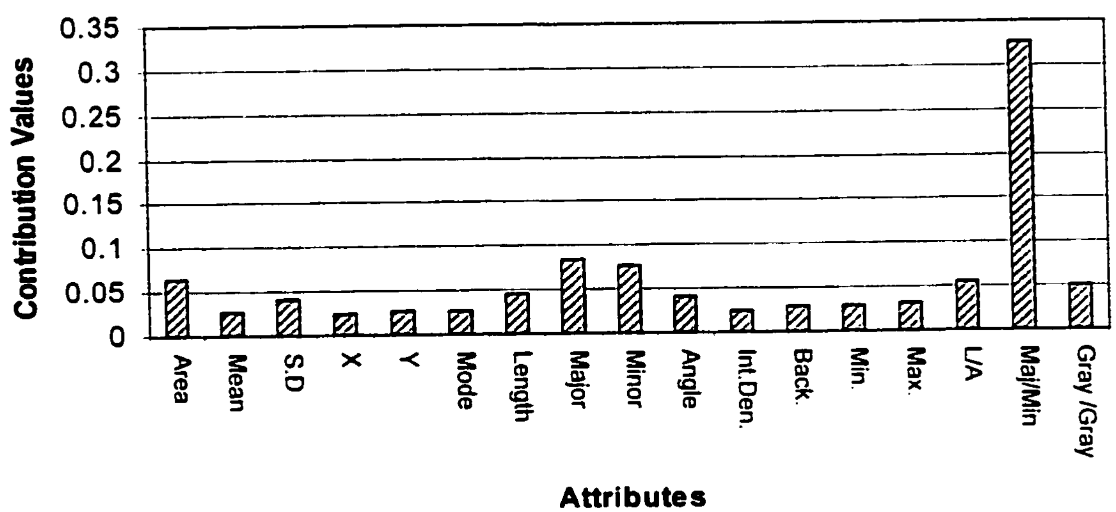


Figure 3-19: Contribution Values of Attributes Utilized in Designing the Preliminary Neural Network for Classification of Cracks

In an effort to improve the performance of the network, a sensitivity analysis was carried out to study the effect of reducing the number of attributes on the overall performance of the network. The general performance of the network was measured in accordance to the values of the coefficient of multiple determination

(R^2), the correlation coefficient (r) and recognition rate. In this analysis, several networks with different input attributes were developed and their performance was compared. Based on the analysis of the results obtained, 6 attributes were used in the input layer of the developed network (Moselhi and Shehab-Eldeen 2000 (a)). These attributes are area, X-coordinate, Y-coordinate, major axis length, minor axis length and the ratio of major axis length to the minor axis length. Figure 3-20 depicts the contribution values for the selected attributes. The developed network (i.e. CrackNet 1) was tested on the production set (193 cases, not seen by the network during training). The performance of the developed network is shown in Table 3-5. Table 3-6 also lists the final parameters that were considered in designing this network.

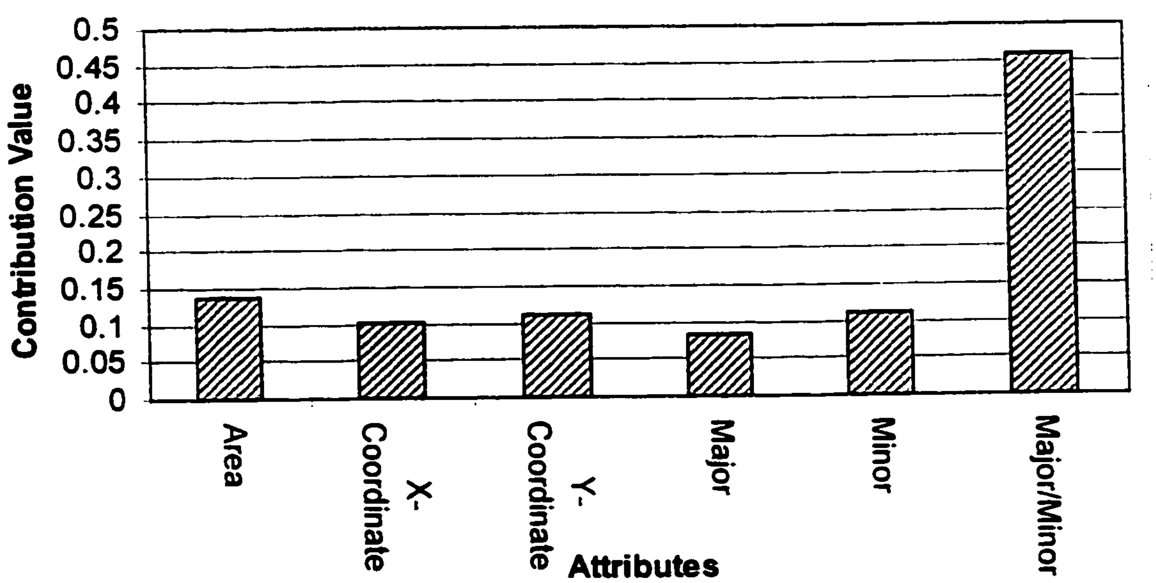


Figure 3-20: Contribution Values of Attributes Utilized in Designing Neural Network # 1 for Classification of Cracks

Table 3-5: Performance Results of CrackNet 1

Performance Parameters	Crack	Non-Cracks
R^2	0.92	0.92
Mean squared error	0.016	0.016
Mean absolute error	0.047	0.047
Min. absolute error	0	0
Max. absolute error	0.82	0.82
Correlation coefficient (r)	.96	0.96
Recognition rate	97.2%	100%

Table 3-6: Final Parameters Used in Designing CrackNet 1

Parameter	Value
Network paradigm	Back-propagation
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Number of neurons in input layer	6
Number of neurons in output layer	2
Number of neurons in hidden layer	31
Number of hidden layers	1
Initial weight	0.7
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

As can be noticed, all attributes considered by CrackNet 1 are geometrical. Although these geometrical attributes were found to be sufficient for the classification task, it was felt that introducing attributes related to intensity of pixels would be advantageous. This is due to the fact that any photographed object is described by two main parameters: geometry and color. If one of them is missing, an incomplete description could be expected. Accordingly, another sensitivity analysis was conducted aiming at introducing as many attributes as possible related to intensity of pixels. The challenge was to keep the performance of the newly developed neural networks as high and as close as possible to performance of the network that considers geometrical attributes only. The results of this sensitivity analysis revealed that introducing the mean gray level value will not dramatically affect the performance of classification (Tables 3-7 and 3-9). Tables 3-7 and 3-9 show the performance of CrackNet 2 and CrackNet 3, respectively. The contribution values of attributes for these two developed networks are shown in Figure 3-21 and 3-22. Tables 3-8 and 3-10 list also the parameters utilized in designing and developing these two networks.

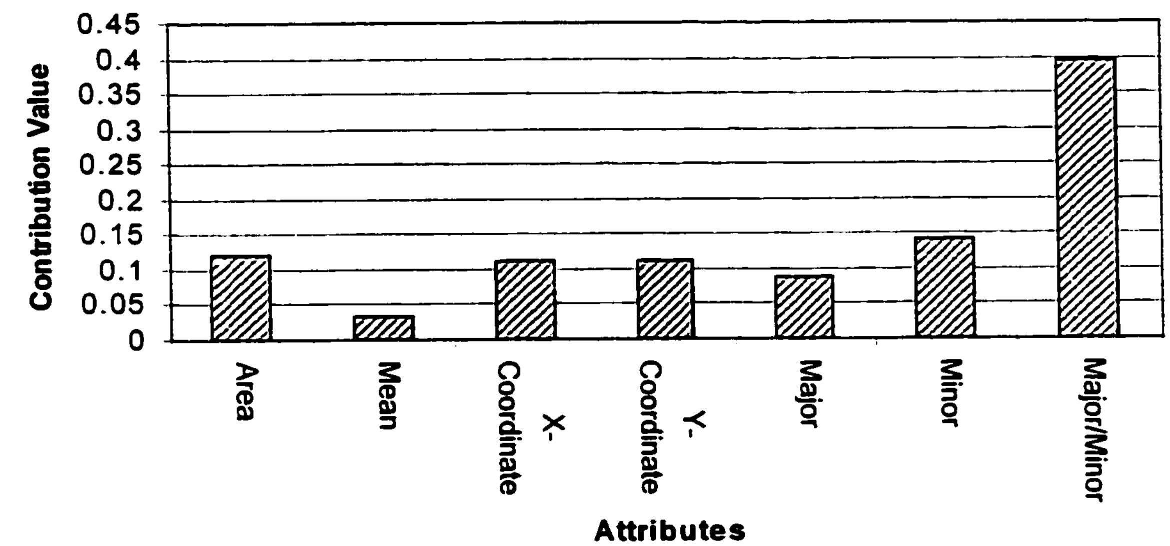


Figure 3-21: Contribution Values for the Selected Attributes Utilized in Designing CrackNet 2

Table 3-7: Performance Results of CrackNet 2

Performance Parameters	Crack	Non-Cracks
R^2	0.90	0.90
Mean squared error	0.022	0.022
Mean absolute error	0.049	0.049
Min. absolute error	0	0
Max. absolute error	1.0	1.0
Correlation coefficient (r)	.95	0.95
Recognition rate	98.6%	98%

Table 3-8: Final Parameters Used in Designing CrackNet 2

Parameter	Value
Network paradigm	Back-propagation
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Number of neurons in input layer	7
Number of neurons in output layer	2
Number of neurons in hidden layer	41
Number of hidden layers	1
Initial weight	0.7
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

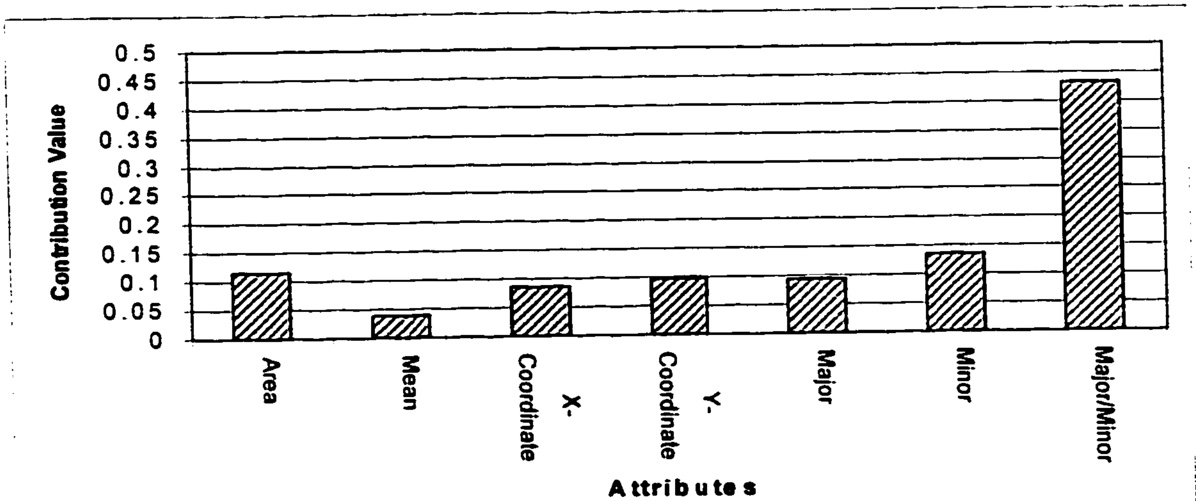


Figure 3-22: Contribution Values for the Selected Attributes Utilized in Designing CrackNet 3

Table 3-9: Performance Results of CrackNet 3

Performance Parameters	Crack	Non-Cracks
R^2	0.87	0.87
Mean squared error	0.029	0.029
Mean absolute error	0.059	0.058
Min. absolute error	0	0
Max. absolute error	1.0	1.0
Correlation coefficient (r)	0.93	0.93
Recognition rate	94%	98.6%

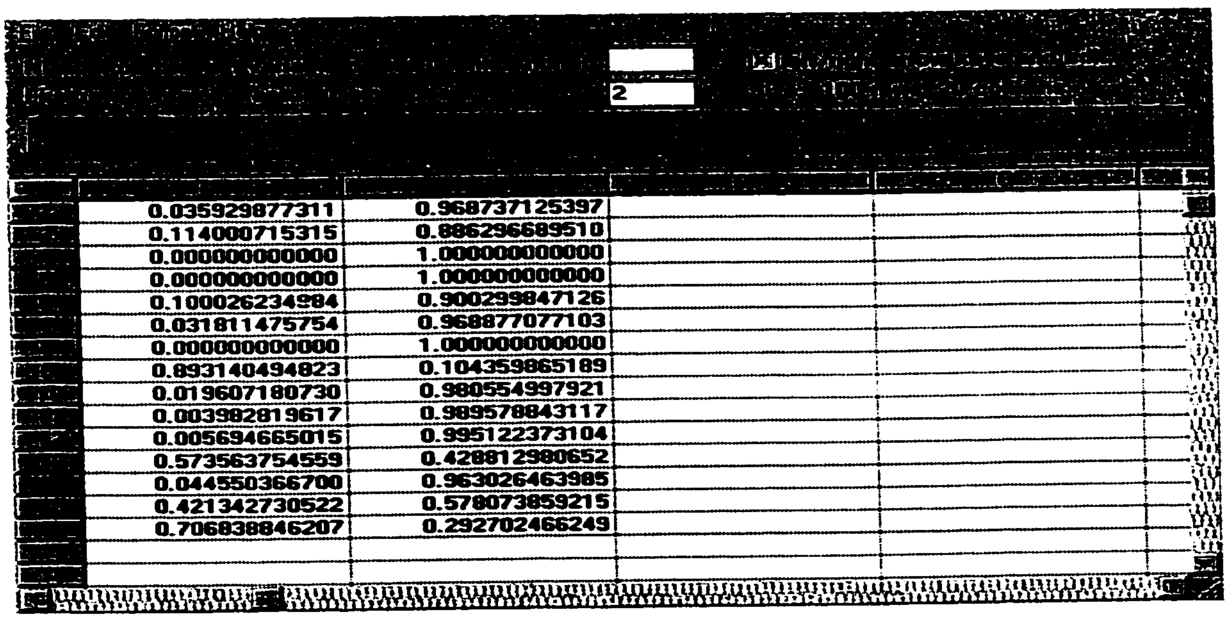
Table 3-10: Final Parameters Used in Designing CrackNet 3

Parameter	Value
Network paradigm	Back-propagation
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Number of neurons in input layer	7
Number of neurons in output layer	2
Number of neurons in hidden layer	25
Number of hidden layers	1
Initial weight	0.7
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

To demonstrate the use and capabilities of the developed neural networks, the image shown in Figure 3-5 was considered. Note that the image depicts longitudinal cracks. To detect and classify these defects, the image was processed in the same manner as shown in Figures 3-13 to 3-18. It should be noted that the segmented image is shown below for easy reference (Figure 3-23). As can be noticed, the segmented image depicts 15 objects. The parameters of these objects are shown in Figure 3-18. Based on location, all objects were assigned (0,0) and (1,1) for their X and Y coordinates. These objects were then fed into the already trained neural networks for classification purpose. The results obtained from a sample network are shown in Figure 3-24.

As can be noticed from Figure 3-24, the output values range from 0 to 1. These values can be considered as the probability that a certain object belongs to either of the two categories recognized by the developed network (i.e. Cracks and Else). For example, the probability of object number 6 being classified as a Crack and Else is 10% and 90%, respectively. A threshold value of 50% was considered sufficient for positive classification. As such, if the probability that a certain object belongs to a certain category exceeds 50%, then this object is considered to fall in that category. Although a default value of 50% was used for classification, the developed system allows the user to specify such a threshold value. It should be noted that if the probability of a certain object does not exceed the preset threshold value (i.e. 50%) in any of the categories recognized by the developed neural network, then the object will be classified as neither "Crack" nor "Else", indicating uncertainty in classifying this particular object. After defining the selected threshold value to the developed network, the data was processed and the final output results were obtained (Figure 3-25). By comparing objects in Figure 3-23 and results shown in Figure 3-25, it can be noticed that the developed neural network was able to classify all objects, as being "Cracks" or "Else", with 100% and 92.3% accuracy, respectively. As can be noticed that although object number 10 in Figure 3-23 is a crack, it was not correctly classified by the developed neural networks. This is due to the fact that in designing these neural networks, the current practice followed by human inspectors were considered. In this practice, the cracks are not reported until they are reached by the CCTV camera. This is to expose them to as much light as possible to prevent misclassification.

Figure 3-23: Segmented Image of a Case Example on Cracks



0.035929877311	0.968737125397
0.114000715315	0.886296689510
0.000000000000	1.000000000000
0.000000000000	1.000000000000
0.100026234984	0.900299847126
0.031811475754	0.968877077103
0.000000000000	1.000000000000
0.893140494823	0.104359865189
0.019607180730	0.980554997921
0.003982819617	0.989578843117
0.005694665015	0.995122373104
0.573563754559	0.428812980652
0.044550366700	0.963026463985
0.421342730522	0.578073859215
0.706838846207	0.292702466249

Figure 3-24: Output Results of a Case example on Cracks

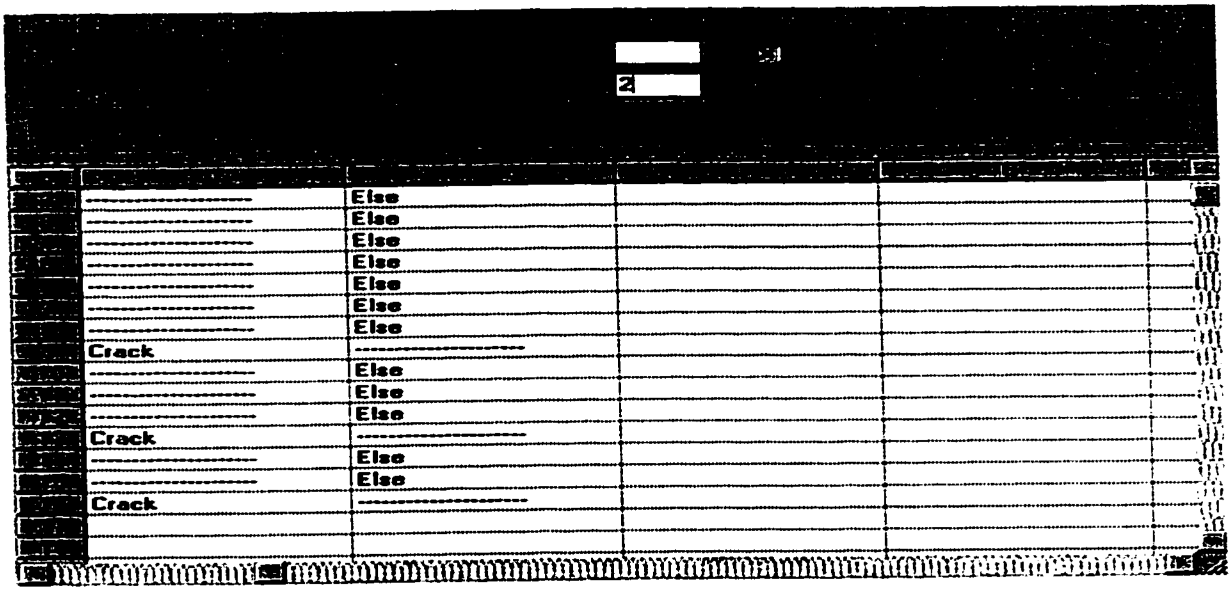


Figure 3-25: Thresholded Output Results of a Case example on Cracks

3.7.3 Infiltration

The infiltration category includes several defects: sign of infiltration, sign of infiltration at the joint, water infiltration, water infiltration at the joint and mineral accumulation around the joints. They all share the same effect of having a wetted area on the wall of pipe. This wetted area is characterized by distinctive attributes, such as dark color compared to surroundings, relatively large width and length. In order to extract these distinguishing features and other attributes that will prove their contribution to the classification process, image analysis techniques were applied. Various image analysis techniques were tried, but the techniques found to yield the best results are summarized in group number 2 shown in Table 3-2. It could be noticed that the inversion process was not applied to images depicting defects falling under the infiltration category. This is due to the reason that their color, being darker than the surroundings, creates enough contrast for further operations.

Similar to the methodology used for the design and training of classifiers for cracks, three neural networks were developed for classification of infiltration (i.e. InfiltrationNet 1, 2 and 3). In the development of these three classifiers, a total of 868 patterns were used. The developed networks were trained to classify two categories. These categories are "Infiltration" and " Else" (i.e. non-infiltration). It should be noted that the total number of patterns was randomly divided as follows: 540 patterns (60%) for training, 174 patterns (20%) for testing and 174 patterns (20%) as a production set. The extracted features from these patterns were first utilized to develop a back-propagation neural network (i.e. InfiltrationNet 1). The literature review discussed in Chapter Two was carefully considered in designing this neural network. The results obtained from InfiltrationNet 1 are summarized in Table 3-11. It should be noted that these results are for the 174 patterns not seen by the network during training (i.e. production set). The contribution values of attributes utilized in developing this network are shown in Figure 3-26.

Although the results obtained from InfiltrationNet 1 are considered to be in the high range, an effort was made to minimize the number of attributes while keeping such high performance unchanged. This was done to reduce the processing time as much as possible. This is due to the fact that as input parameters decrease, processing time also decreases (Looney 1997). Accordingly, two more neural networks (i.e. InfiltrationNet 2 and 3) were developed in a similar way to that discussed in Section 3.5.2. The results for the two networks are shown in Tables 3-12 and 3-13. As can be seen from these tables a noticeable reduction in the input parameters was achieved while keeping the high performance of network # 1 almost the same. The design parameters considered in developing the three networks are shown in Tables A-1 to A-3 in Appendix A.

Table 3-11. Performance Results of InfiltrationNet 1

Performance Parameters	Infiltration	Non-infiltration
R^2	0.8245	0.8245
Mean squared error	0.013	0.013
Mean absolute error	0.025	0.025
Min. absolute error	0	0
Max. absolute error	0.96	0.96
Correlation coefficient (r)	.9093	0.9092
Recognition rate	92.8%	100%

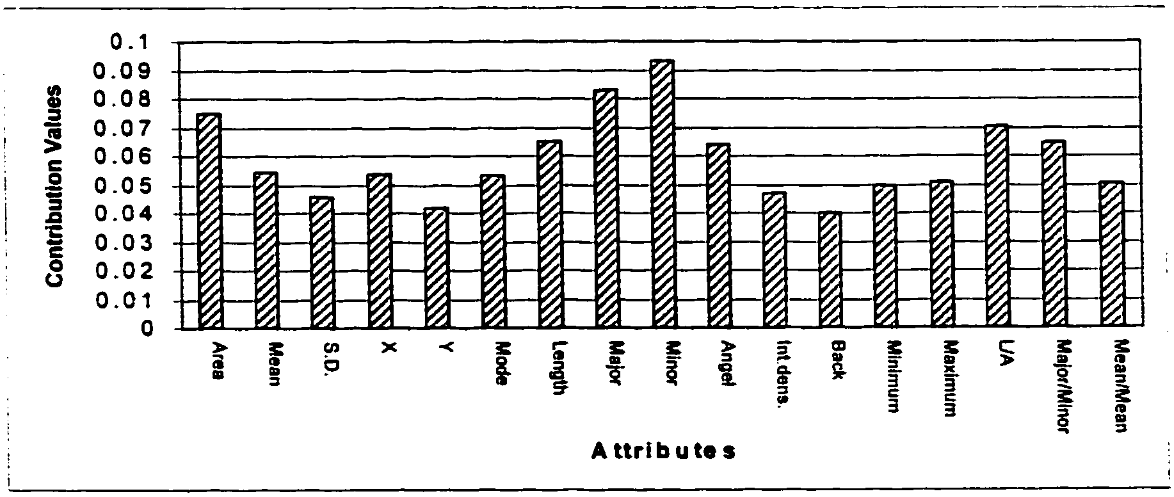


Figure 3-26: Contribution Values of Attributes Utilized in Designing InfiltrationNet 1

Table 3-12. Performance Results of InfiltrationNet 2

Performance Criteria	Infiltration	Non-infiltration
R^2	0.9206	0.9205
Mean squared error	0.003	0.003
Mean absolute error	0.024	0.024
Min. absolute error	0	0
Max. absolute error	0.335	0.334
Correlation coefficient (r)	0.9684	0.9684
Recognition rate	100%	100%

Table 3-13. Performance Results of InfiltrationNet 3

Performance Parameters	Infiltration	Non-infiltration
R^2	0.9023	0.9022
Mean squared error	0.004	0.004
Mean absolute error	0.018	0.018
Min. absolute error	0	0
Max. absolute error	0.741	0.738
Correlation coefficient (r)	.95	0.95
Recognition rate	100%	99.4%

To demonstrate the use and capabilities of the developed neural networks in this category, the image shown in Figure 3-4 was considered. As can be noticed from this figure, the image depicts infiltration. To detect and classify this defect, the image was processed following the sequence of operations summarized in Table 3-2. The results of this process are shown in Figures 3-27 to 3-30. As can be seen in Figure 3-30, the image depicts four objects. Objects number 1 and 2 are infiltration, while objects number 3 and 4 are not. The attributes of these objects, which are shown in Figure 3-31, were then fed into the already trained neural networks for classification. A sample of obtained results are shown in Figure 3-32. It should be noted that a threshold value of 50% was considered for positive classification.

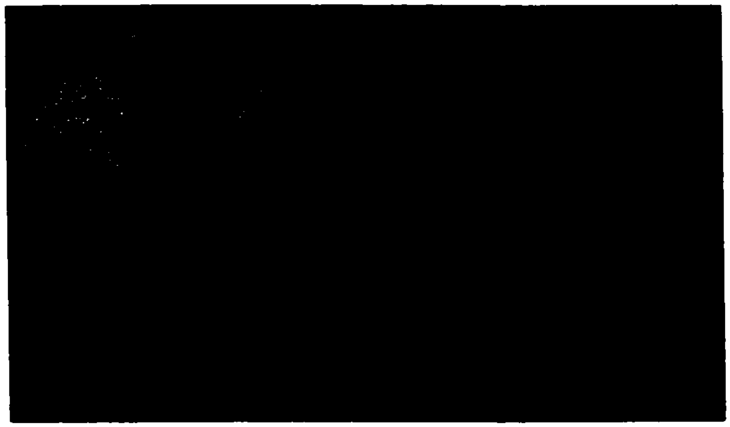


Figure 3-27: Dilated Image of Infiltration

Figure 3-28: Background subtracted Image of Infiltration

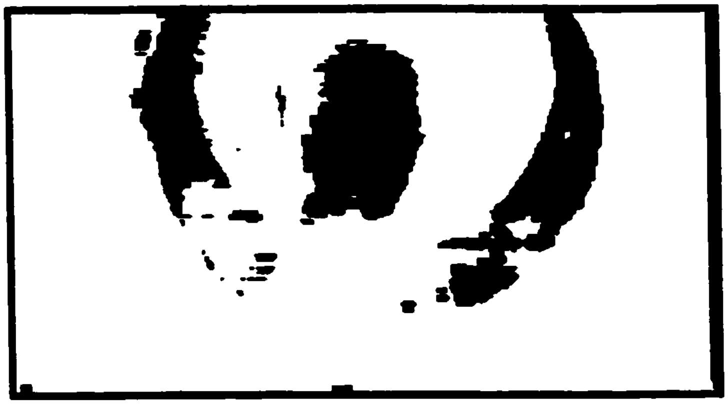


Figure 3-29: Thresholded Image of Infiltration

Figure 3-30: Segmented Image of Infiltration

Results

	Area	Mean	S.D.	X	Y	Length	Major
1.	2390.00	57.95	26.30	79.89	52.34	371.30	97.58
2.	3032.00	44.43	9.70	240.70	73.93	516.32	118.22
3.	492.00	55.05	34.63	318.00	81.50	332.24	185.05
4.	3609.00	49.03	13.20	159.46	56.57	343.61	87.67

Figure 3-31: Analysis Results of an Image Depicting Infiltration

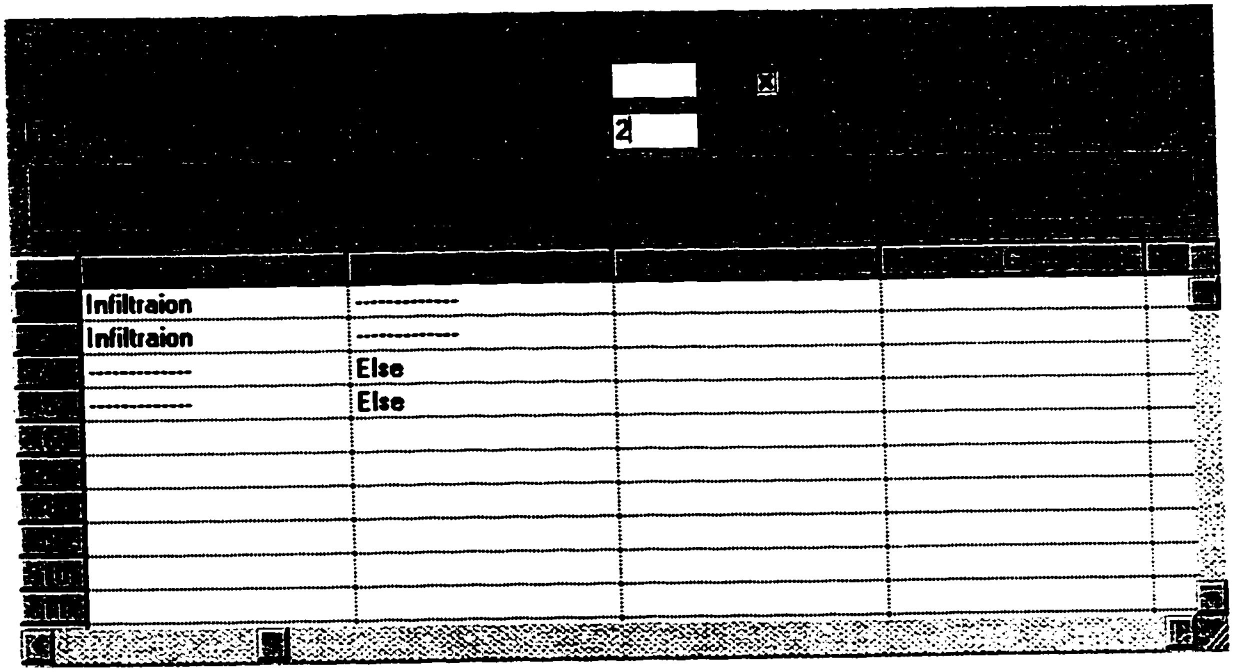


Figure 3-32: Classification Results of a Case Example on Infiltration

3.7.4 Deposits

The deposits category includes all materials that buildup on the bottom of a pipe. Regardless of their source being organic or non-organic, they all share one common feature: their location. Their location is at the invert level of pipes (i.e. bottom of pipe). In order to extract this distinguishing feature and other features that will prove their contributions to the classification process, image analysis techniques were applied.

Various image analysis techniques were analyzed and tried to enhance images of defects in order to isolate deposits from their background. The techniques found to yield the best results are detailed in group number 1 shown in Table 3-2.

These techniques were applied on all collected images that showed defects within the deposits group. Based on the extracted features obtained from the analysis of collected images, it was noticed that deposits might share some attributes with other defects such as cross-sectional reductions. These attributes are large minor axis length, relatively large area and small ratio of major axis length to minor axis length. The only factors that differentiate between the apparently similar attributes are the X and Y coordinates (i.e. location). It was noticed also from the collected sample of video images that the location of cross-sectional reductions is in the central area of the pipe. This is in contrast to the location of deposits, which are at the bottom of the pipe. These observations have been utilized to facilitate the classification process by assigning the coordinates of objects located at the bottom of pipe to (2,2). It should be noted that this assignment was made by changing the original coordinates of objects to (2,2) manually.

Using a set of 760 patterns, a set of three neural networks was developed to classify deposits (i.e. DepositNet 1, 2 and 3). This was carried out following the same methodology described in the two previous sections (Sections 3.5.2 and 3.5.3). The developed networks were trained to classify two categories: "Deposits" and "Else" (i.e. Non deposits). It should be noted that the total number of patterns was randomly divided as follows: 456 patterns (60%) for training, 152 patterns (20%) for testing and 152 patterns (20%) as a production set. It should also be noted that the training algorithm was set to save the trained network at the best test set and limit the calibration interval to 50 to prevent and monitor over-training.

In developing DepositNet 1, various combinations of hidden neurons, activation and scaling functions were tried and the near optimum design was found to be 17 neurons in the input layer, 40 neurons in the hidden layer and 2 neurons in the output layer. The results obtained using this developed network are shown in Table 3-14. It should be noted that these results are for the 152 patterns not seen by the network during training (i.e. production set). The contribution values of all attributes utilized in developing this network are shown in Figure 3-33.

Although the results obtained from DepositNet 1 are in the high range, an effort was made to minimize the number of attributes while keeping such high performance unchanged. This was done to reduce the processing time as much as possible. Accordingly, two more neural networks were developed (i.e. DepositNet 2 and 3). The results for these two networks are shown in Tables 3-15 and 3-16. It should be noted that these results are for the 152 patterns that were not presented to the network while training (i.e. the production set). As can be seen from Tables 3-15 and 3-16, a noticeable reduction in the input parameters was achieved while keeping the high performance almost the same. The design parameters considered in developing the three networks are listed in Tables A-4 to A-6 in Appendix A.

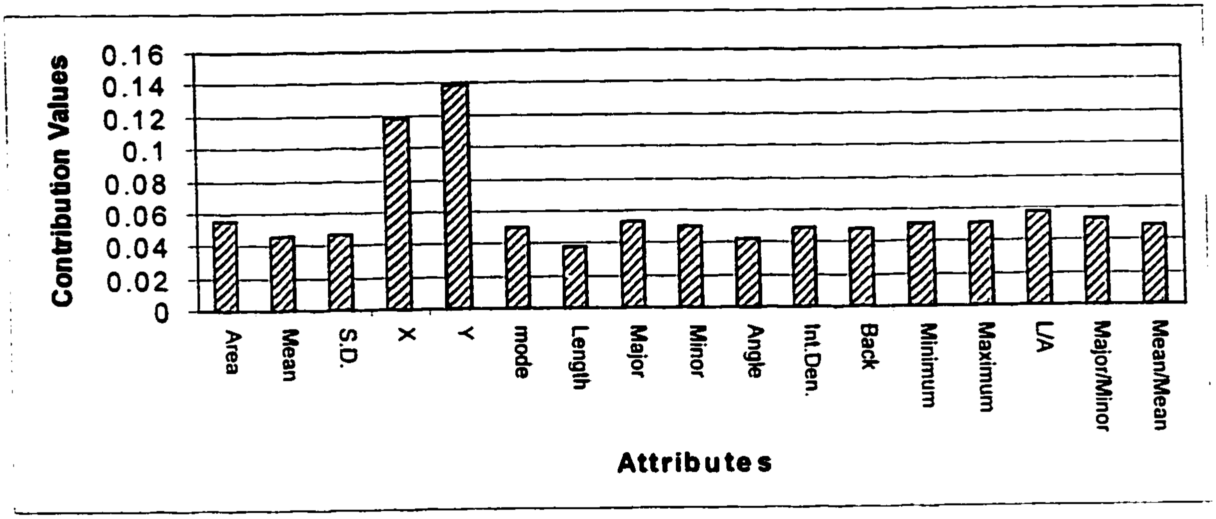


Figure 3-33: Contribution Values of Attributes Utilized in Designing DepositNet 1

Table 3-14: Performance Results of DepositNet 1

Performance Criteria	Non-Deposits	Deposits
R^2	0.9912	0.9915
Mean squared error	0.0	0.0
Mean absolute error	0.005	0.005
Min. absolute error	0	0
Max. absolute error	0.106	0.112
Correlation coefficient (r)	0.9985	0.9988
Recognition rate	100%	100%

Table 3-15: Performance Results of DepositNet 2

Performance Criteria	Non-Deposits	Deposits
R^2	0.9981	0.9983
Mean squared error	0.0	0.0
Mean absolute error	0.002	0.002
Min. absolute error	0	0
Max. absolute error	0.050	0.046
Correlation coefficient (r)	0.9999	0.9999
Recognition rate	100%	100%

Table 3-16: Performance Results of DepositNet 3

Performance Criteria	Non-deposits	Deposits
R^2	0.9903	0.9854
Mean squared error	0.0	0.0
Mean absolute error	0.002	0.002
Min. absolute error	0	0
Max. absolute error	0.166	0.204
Correlation coefficient (r)	0.9952	0.9928
Recognition rate	100%	100%

To demonstrate the use and capabilities of the developed neural networks, the image shown in Figure 3-3 was considered. As can be seen, the image depicts a number of objects. These Objects are deposits and a number of non-defects. To detect and classify these objects, the image was processed in the same manner as explained earlier. The results of this process are shown in Figures 3-34 to 3-38. The extracted feature vectors shown in Figure 3-39 were then fed into the already trained neural networks for classification. The results obtained from a sample network are shown in Figure 3-40. It should be noted that a threshold value of 50% was considered for positive classification.

Figure 3-34: Inverted Image of Deposits

Figure 3-35: Background Subtracted Image of Deposits

Figure 3-36: Dilated Image of Deposits

Figure 3-37: Thresholded Image of Deposits

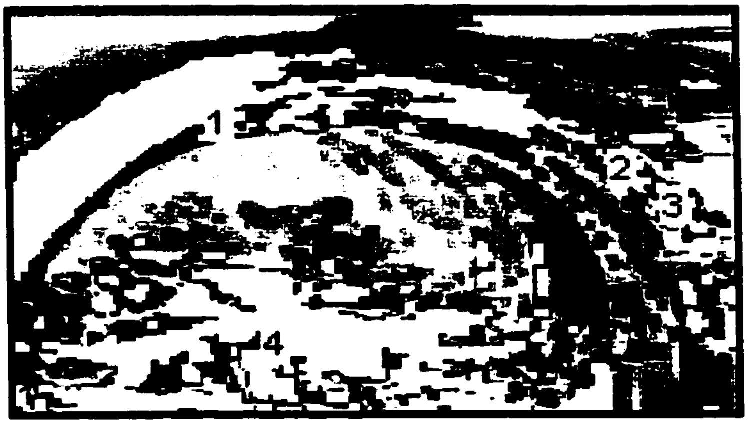


Figure 3-38: Segmented Image of Deposits

Results

	Area	Mean	S.D.	X	Y	Length	Major
1.	2652.00	80.03	22.30	55.52	37.85	715.94	109.63
2.	108.00	68.61	14.66	161.80	53.11	55.60	17.59
3.	144.00	71.94	16.32	175.35	66.67	70.43	18.30
4.	2972.00	96.81	34.10	69.02	114.82	870.18	98.21

Figure 3-39: Analysis Results of an Image Depicting Deposits

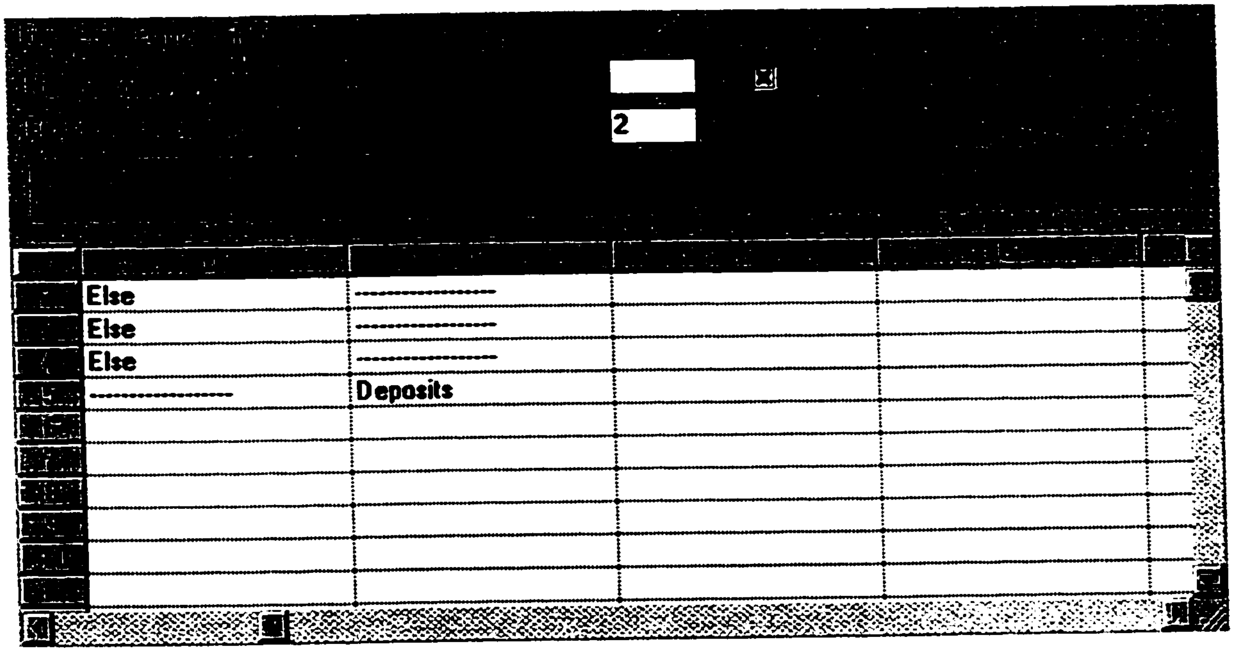


Figure 3-40: Classification Results of a Case Example on Deposits

3.7.5 Cross-sectional Reductions

The cross-sectional reductions category includes all materials that obstruct flow in pipes. Regardless of their nature, roots or buildup of deposits, they all share a common feature: location. Their location is at the central area of pipes. To detect and classify this particular type of defect, similar techniques to those utilized in detecting and classifying deposits were utilized (i.e. sequence # 1 in Table 3-2).

A sample of 273 cross-sectional reductions and non-cross-sectional reductions was analyzed. Based on the extracted feature vectors from this analysis, it was noticed that cross-sectional reductions might have similar attributes to those obtained from other types of defects such as deposits. This is due to the difference in distance between the CCTV camera and each type of defects. The only factors that differentiate between the apparently similar attributes are the x and y coordinates (i.e. location). It was noticed from the collected sample of video images that the center of an image is always darker than its surrounding areas. This is due to the fact that the lighting effect vanishes as the distance from the lighting source gets greater. It was also noticed that cross-sectional deductions tend to be illuminated at this specific area (the center of an image). This is due to the fact that these defects tend to project from the surface of the pipe and reflect back the beam of light they are exposed to. These observations have been utilized to facilitate the classification process by changing the coordinates of objects located in center of images to (1,1). It should be noted that this assignment was made by changing the original coordinates of objects to (1,1) manually.

The results obtained from the analysis conducted on the collected images were utilized to develop a back-propagation neural network. The developed network was trained to classify two categories: "Cross-sectional reduction" and " Else" (i.e. Non-cross-sectional reductions). The results obtained using this developed network are shown in Table 3-17. It should be noted that these results are for the 54 patterns not seen by the network during training (i.e. production set). The contribution values of attributes utilized in developing this network are shown in Figure 3-41.

In an effort to improve the performance of this developed network, three neural networks were developed in a similar method to that explained in Section 3.5.2 (i.e. CrossNet 1, 2 and 3). The results of these networks are shown in Tables 3-18, 3-19 and 3-20. It should be noted that these results are based on the production set. The final design parameters considered in designing these networks are listed in Tables A-7 to A-10 in Appendix A.

Table 3-17: Performance Results of a Preliminary Neural Network for Classification of Cross-sections Reductions

Performance Criteria	Cross-sectional reduction	Non-cross-sectional reductions
R^2	0.8319	0.8288
Mean squared error	0.023	0.024
Mean absolute error	0.053	0.053
Min. absolute error	0	0
Max. absolute error	0.808	0.824
Correlation coefficient (r)	0.9125	0.9107
Recognition rate	88%	97.8%

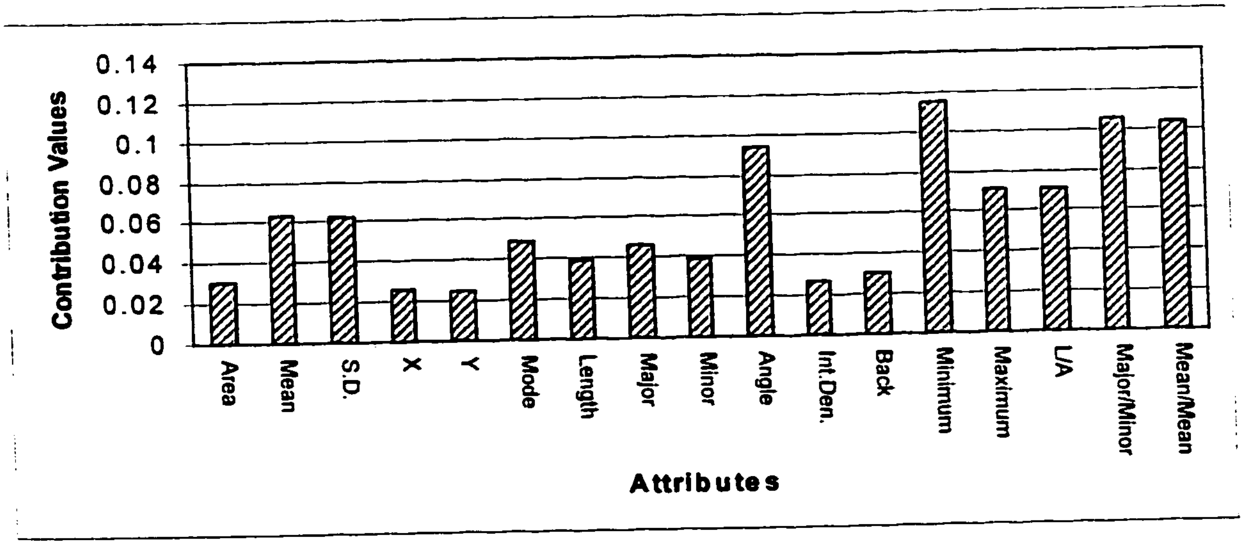


Figure 3-41: Contribution Values for all Attributes Utilized in Designing a Preliminary Neural Network for Classification of Cross-sectional Reductions

Table 3-18: Performance Results of CrossNet 1

Performance Criteria	Cross-sectional reductions	Non-cross-sectional reductions
R^2	0.8203	0.8257
Mean squared error	0.025	0.024
Mean absolute error	0.058	0.052
Min. absolute error	0	0
Max. absolute error	0.826	0.823
Correlation coefficient (r)	0.9064	0.9096
Recognition rate	88%	100%

Table 3-19: Performance Results of CrossNet 2

Performance Criteria	Cross-sectional reductions	Non-cross-sectional reductions
R^2	0.8679	0.8600
Mean squared error	0.020	0.021
Mean absolute error	0.072	0.075
Min. absolute error	0	0
Max. absolute error	0.614	0.621
Correlation coefficient (r)	0.9375	0.9375
Recognition rate	90%	94%

Table 3-20: Performance Results of CrossNet 3

Performance Criteria	Cross-sectional reductions	Non-cross-sectional reductions
R^2	0.9072	0.9091
Mean squared error	0.013	0.013
Mean absolute error	0.049	0.049
Min. absolute error	0	0
Max. absolute error	0.640	0.626
Correlation coefficient (r)	0.9553	0.9564
Recognition rate	88%	100%

To demonstrate the use and capabilities of the developed neural networks, the image shown in Figure 3-2 was considered. Note that the image depicts a cross-sectional reduction in a form of roots. To detect and classify this defect, the image was processed as shown in Figures 3-42 to 3-47. As can be noticed, the segmented image depicts five objects. Object number 2 is a root intrusion, while objects 1, 3, 4 and 5 are not. Based on location, all objects were assigned (0,0) and (1,1) for their X and Y coordinates. These objects with (1,1) (i.e. located inside the central area of pipe) were then fed into the already trained neural networks for classification. The results of classification for a sample network are shown in Figure 3-48.

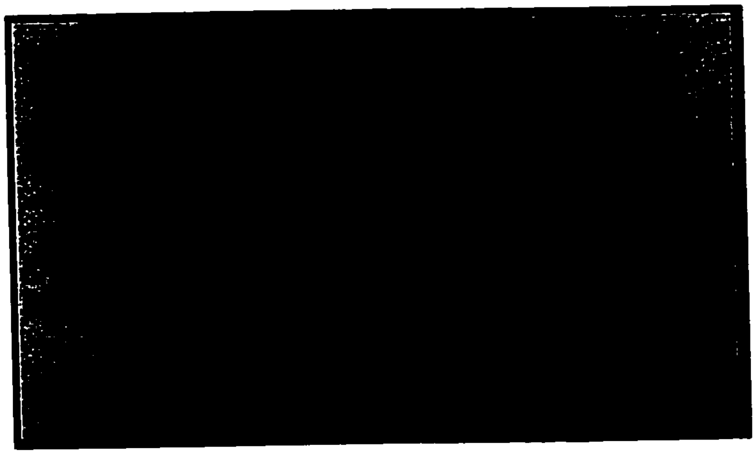


Figure 3-42: Inverted Image of cross-sectional Reductions

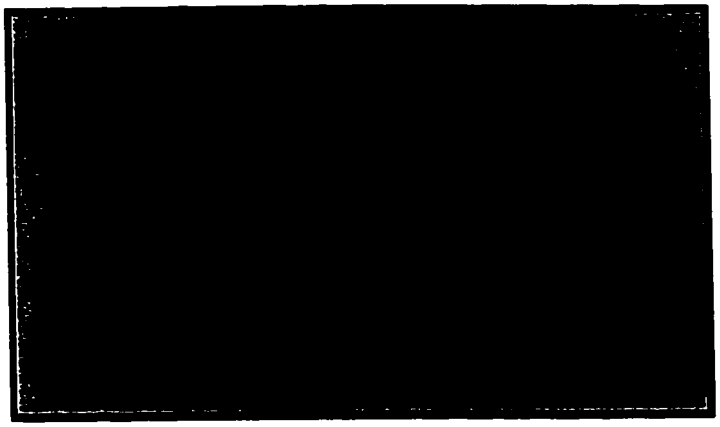


Figure 3-43: Dilated Image of cross-sectional Reductions

Figure 3-44: Background subtracted Image of Cross-sectional Reductions

Figure 3-45: Thresholded Image of Cross-sectional Reductions

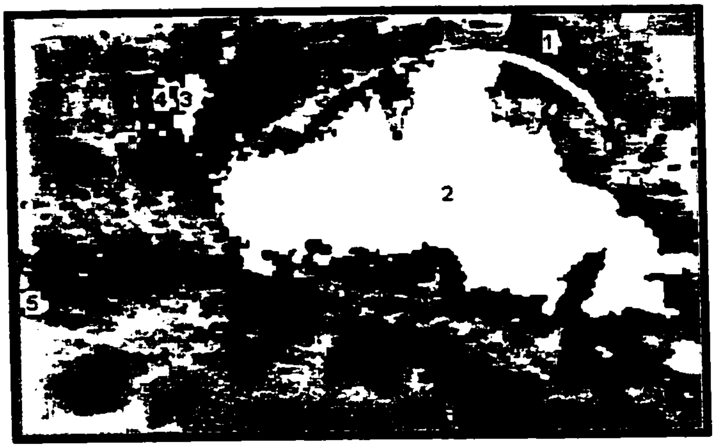


Figure 3-46: Segmented Image of Cross-sectional Reductions

Results

	Area	Mean	S.D.	X	Y	Length	Major
1.	76.00	90.84	55.80	256.92	16.22	38.04	12.60
2.	17141.00	77.01	17.65	206.03	102.46	1347.63	196.15
3.	433.00	51.68	4.15	82.04	47.86	149.88	32.95
4.	63.00	49.22	2.34	70.62	47.83	36.38	13.25
5.	105.00	53.85	6.10	6.34	162.71	45.56	15.40

Figure 3-47: Analysis Results of an Image Depicting Cross-sectional Reductions

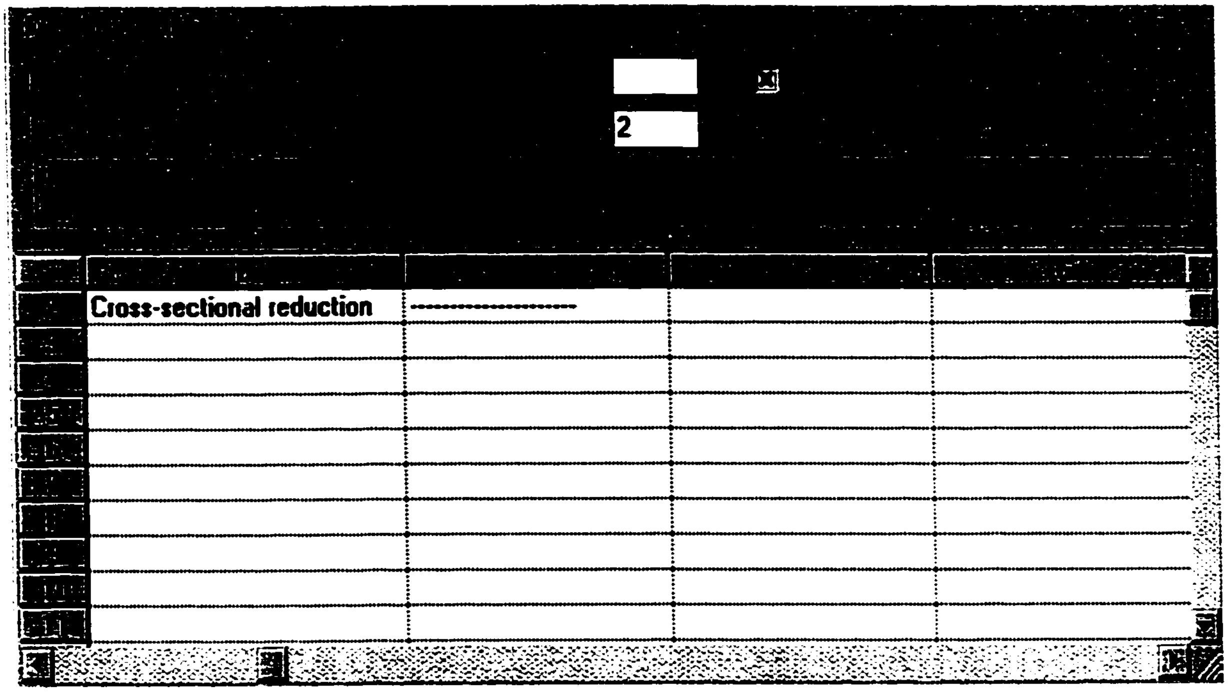


Figure 3-48: Classification Results of a Case Example on Cross-sectional Reductions

3.7.6 Misalignments

The misalignment category includes several defects. These defects are offset joint over 3 cm, open joint over 5 cm, opposite slope, visible soil, sagging pipes, right lateral deviation, left lateral deviation and visible rubber gasket at the joint. They all share the same effect of having a crescent shape at the joints. This crescent shape is characterized by distinctive attributes, such as relatively small area and bright color. In order to extract this distinguishing feature and other features that will prove their contributions to the classification process, image analysis techniques were applied. These image analysis techniques are the same as those utilized in detecting and classifying deposits and cross-sectional reductions (i.e. sequence # 1 in Table 3-2).

A sample of 275 patterns was analyzed and their feature vectors were extracted. Based on this analysis, it was noticed that misalignments might have similar attributes to those obtained from other defects such as cracks. This is due to the difference in distance between the CCTV camera and each type of defect. In other words, misalignments away from the camera tend to have similar attributes to cracks closer to the camera. Those similar attributes are small minor axis length, small area and large ratio of major axis length to minor axis length. The only factors that differentiate between the apparently similar attributes are the X and Y coordinates (i.e. location). For example, it was noticed from the collected sample of video images that the center of an image is always darker than its surrounding areas. As has been explained earlier in the case of cross-sectional reductions, misalignments are also illuminated at this specific area of pipes. This is due to the reason that these two objects are projected from the surface of pipes, and they both reflect back the beam of light they are exposed to. Other defects such as cracks do not exhibit the same phenomena. This was utilized to facilitate the classification process by assigning the coordinates of objects located in this dark spot to (1,1).

The collected sample of video images was then utilized to develop a back-propagation neural network. The developed network was trained to classify two categories: "Misalignments" and "Else". The results obtained using the developed network are shown in Table 3-21. It should be noted that these results are for the

55 patterns not seen by the network during training (i.e. production set). The contribution of each attribute is shown in Figure 3-49. In an effort to improve the performance of this network, three neural networks were developed in a similar way to that explained in Section 3.5.2 (i.e. MisalignmentNet 1, 2 and 3). The results obtained from these networks are shown in Tables 3-22, 3-23 and 3-24. It should be noted that these results are based on the production set. The final design parameters considered in designing and developing these networks are listed in Tables A-11 to A-14 in Appendix A.

Table 3-21: Performance Results of a Preliminary Neural Network for Classification of Misalignments

Performance Criteria	Misalignments	Non-misalignments
R^2	0.8319	0.8288
Mean squared error	0.023	0.024
Mean absolute error	0.053	0.053
Min. absolute error	0	0
Max. absolute error	0.808	0.824
Correlation coefficient (r)	0.9125	0.9107
Recognition rate	88%	97.8%

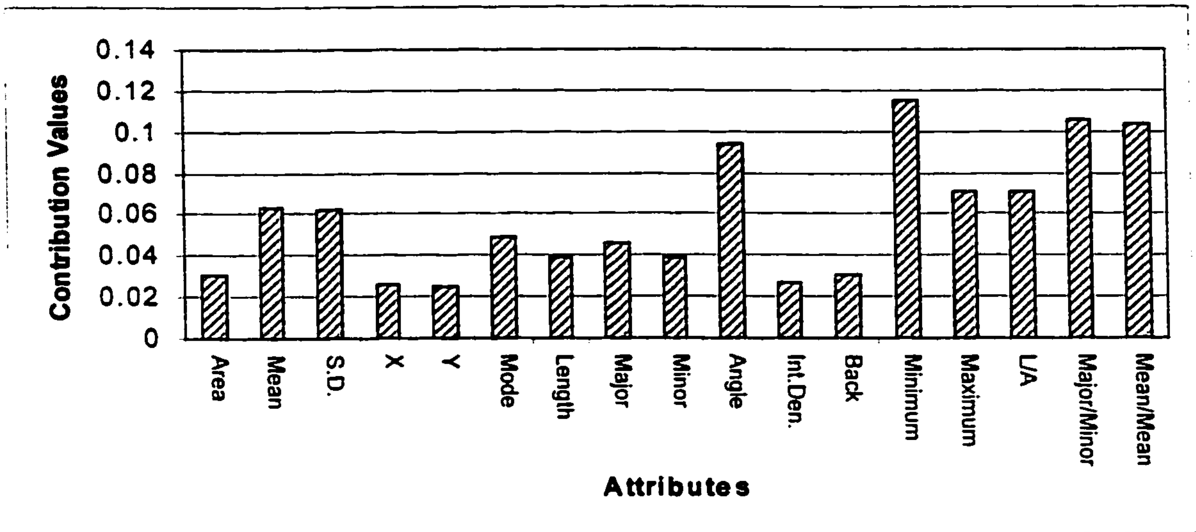


Table 3-49: Initial Parameters Used in Designing a Preliminary Neural Network for Classification of Misalignments

Table 3-22: Performance Results of MisalignmentNet 1

Performance Criteria	Misalignments	Non-misalignments
R^2	0.8776	0.8823
Mean squared error	0.018	0.018
Mean absolute error	0.051	0.053
Min. absolute error	0	0
Max. absolute error	0.599	0.574
Correlation coefficient (r)	0.9378	0.9405
Recognition rate	90%	97.8%

Table 3-23: Performance Results of MisalignmentNet 2

Performance Criteria	Misalignments	Non-misalignments
R^2	0.9458	0.9484
Mean squared error	0.008	0.008
Mean absolute error	0.031	0.030
Min. absolute error	0	0
Max. absolute error	0.430	0.421
Correlation coefficient (r)	0.9749	0.9761
Recognition rate	100%	100%

Table 3-24: Performance Results of MisalignmentNet 3

Performance Criteria	Misalignments	Non-misalignments
R^2	0.8514	0.8550
Mean squared error	0.022	0.022
Mean absolute error	0.059	0.058
Min. absolute error	0	0
Max. absolute error	0.767	0.758
Correlation coefficient (r)	0.9254	0.9272
Recognition rate	100%	97.8%

To demonstrate the use and capabilities of the developed neural networks, the image shown in Figure 3-6 was considered. As can be seen, the image depicts a number of objects. These objects are misalignments and non-misalignments. To detect and classify these objects, the image was processed in the same manner as was shown in Figures 3-50 to 3-55. As can be noticed, the segmented image depicts 22 objects. Object number 10 is a misalignment, while other objects are not. Based on location, all objects were assigned (0,0) and (1,1) for their X and Y coordinates. Objects with (1,1) were then fed into the already trained neural networks for classification. The results of classification for a sample network are shown in Figure 3-56.

Figure 3-50: Inverted Image of Misalignments

Figure 3-51: Dilated Image of Misalignments

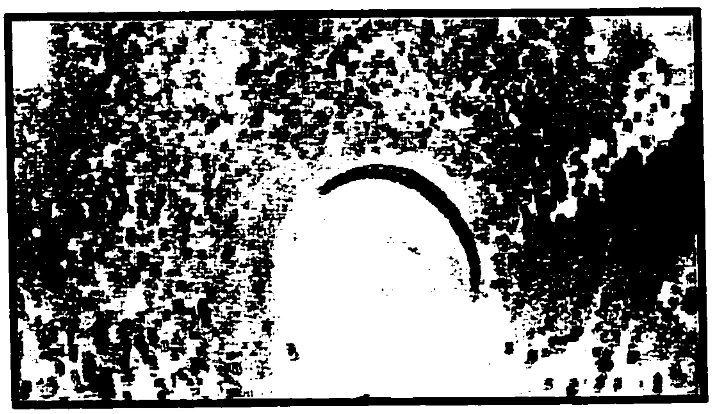


Figure 3-52: Background Subtracted Image of Misalignments

Figure 3-53: Thresholded Image of Misalignments

Figure 3-54: Segmented Image of Misalignments

Results

	Area	Mean	S.D.	X	Y	Length	Major
1.	2661.00	47.26	8.76	45.90	42.65	940.85	92.06
2.	75.00	46.45	12.18	158.67	5.32	49.36	12.07
3.	73.00	46.25	9.46	171.18	3.55	48.28	15.81
4.	6979.00	65.86	23.03	254.26	56.42	1431.09	127.44
5.	151.00	50.42	10.84	234.46	6.10	76.77	16.84
6.	63.00	42.86	3.46	24.00	7.59	43.46	14.36
7.	147.00	52.41	17.64	148.17	18.16	73.60	16.54
8.	315.00	49.34	12.66	113.77	25.18	172.99	22.07
9.	77.00	45.30	10.39	166.31	20.26	51.46	11.32
10.	524.00	61.37	24.96	181.44	75.00	212.65	46.55
11.	77.00	44.99	6.90	47.45	72.77	49.46	16.56
12.	51.00	43.12	3.41	34.14	92.31	34.97	11.00
13.	96.00	61.27	22.01	303.91	113.18	44.73	15.06
14.	61.00	44.38	3.60	2.20	112.74	31.90	12.69
15.	186.00	51.23	16.69	52.42	129.34	115.15	19.32
16.	86.00	55.33	14.79	39.26	125.14	39.80	15.82
17.	82.00	43.87	5.03	25.78	126.00	52.87	15.35
18.	97.00	44.66	5.31	15.62	128.27	57.46	12.62
19.	187.00	53.84	19.02	302.75	136.37	98.77	24.82
20.	170.00	60.12	19.48	37.32	142.69	65.94	21.02
21.	59.00	60.66	30.58	262.57	136.07	33.21	10.31
22.	89.00	46.31	7.62	2.34	144.67	55.31	17.46

Figure 3-55: Analysis Results of an Image Depicting Misalignments

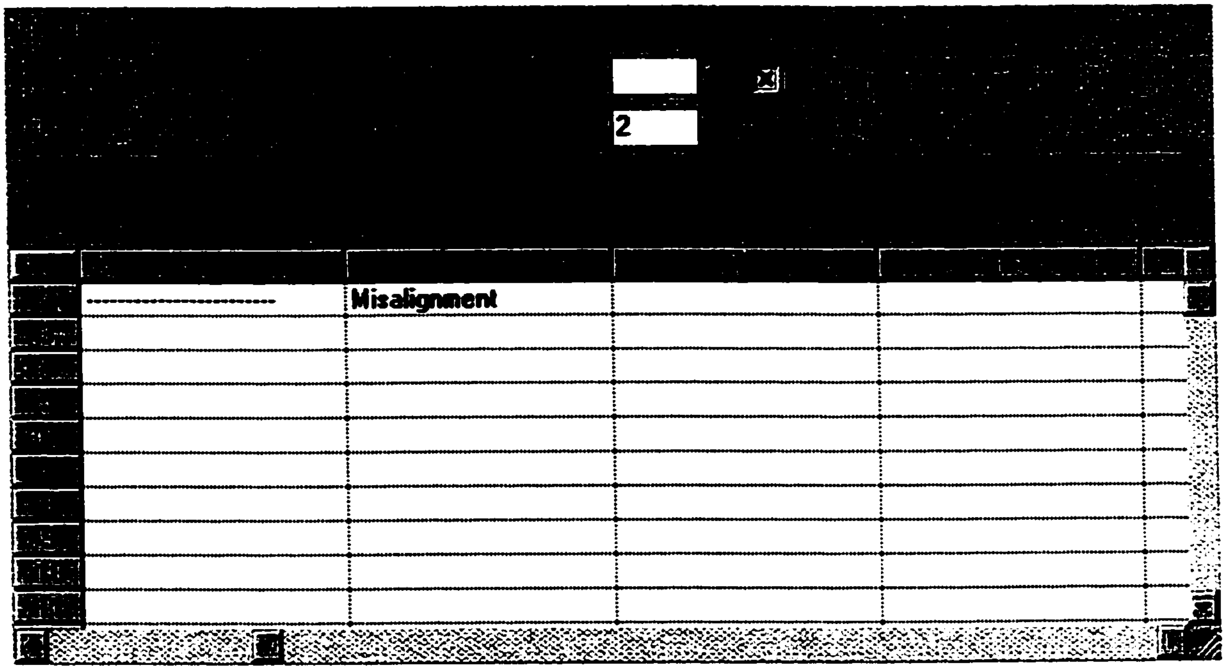


Figure 3-56: Classification Results of a Case example on Misalignments

3.8 EXAMPLE APPLICATION ON THE MULTIPLE CLASSIFIER SYSTEM AND SOLUTION STRATEGY

To demonstrate the use and capabilities of the proposed multiple classifier system and solution strategy, images shown in Figure 3-2 to 3-6 were considered. As can be seen cross-sectional reductions in a form of roots, deposits, infiltration, cracks and misalignments are depicted in Figures 3-2, 3-3, 3-4, 3-5 and 3-6, respectively. To classify these defects, the images were processed three times. In the first pass, the images were processed by sequence of operation number 1 shown in Table 3-2. The purpose of this pass is to detect and classify deposits, cross-sectional reductions and misalignments. The segmented images of these images are shown in Figures 3-57 to 3-61 below. As can be noticed from Figures 3-57, 3-58,3-59, 3-60 and 3-61, 4, 22, 5, 14 and 6 objects were detected, respectively. The extracted features of the images were processed using DepositNet 1, DepositNet 2 and DepositNet 3. The results of these networks are shown in Figures 3-62 to 3-64. As can be noticed, all developed networks were able to classify "Deposits" and "Else" with 100% accuracy. The multiple classifier system was then applied to counter-check the results obtained from the different neural networks. The results obtained from the multiple classifier system are shown in Figures 3-65. As shown in Figures 3-65, the overall performance of the system, with respect to "Deposits" and "Else", is concluded to be 100% for the considered sample of patterns.

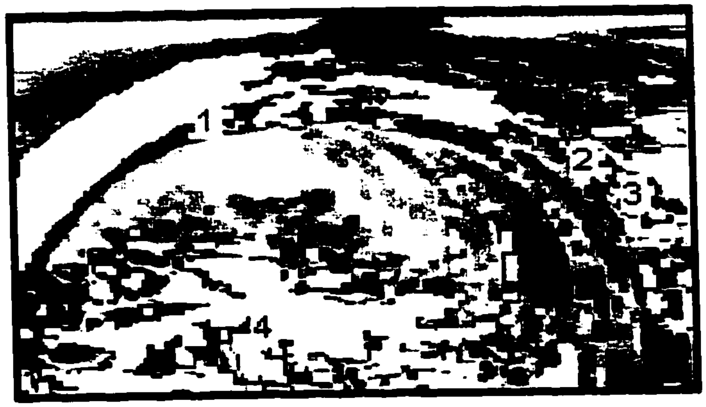


Figure 3-57: Segmented Image of Deposits

Figure 3-58: Segmented image of Misalignments

Figure 3-59: Segmented Image of Cross-sectional Reductions

Figure 3-60: Segmented Image of Cracks

Figure 3-61: Segmented Image of Infiltration

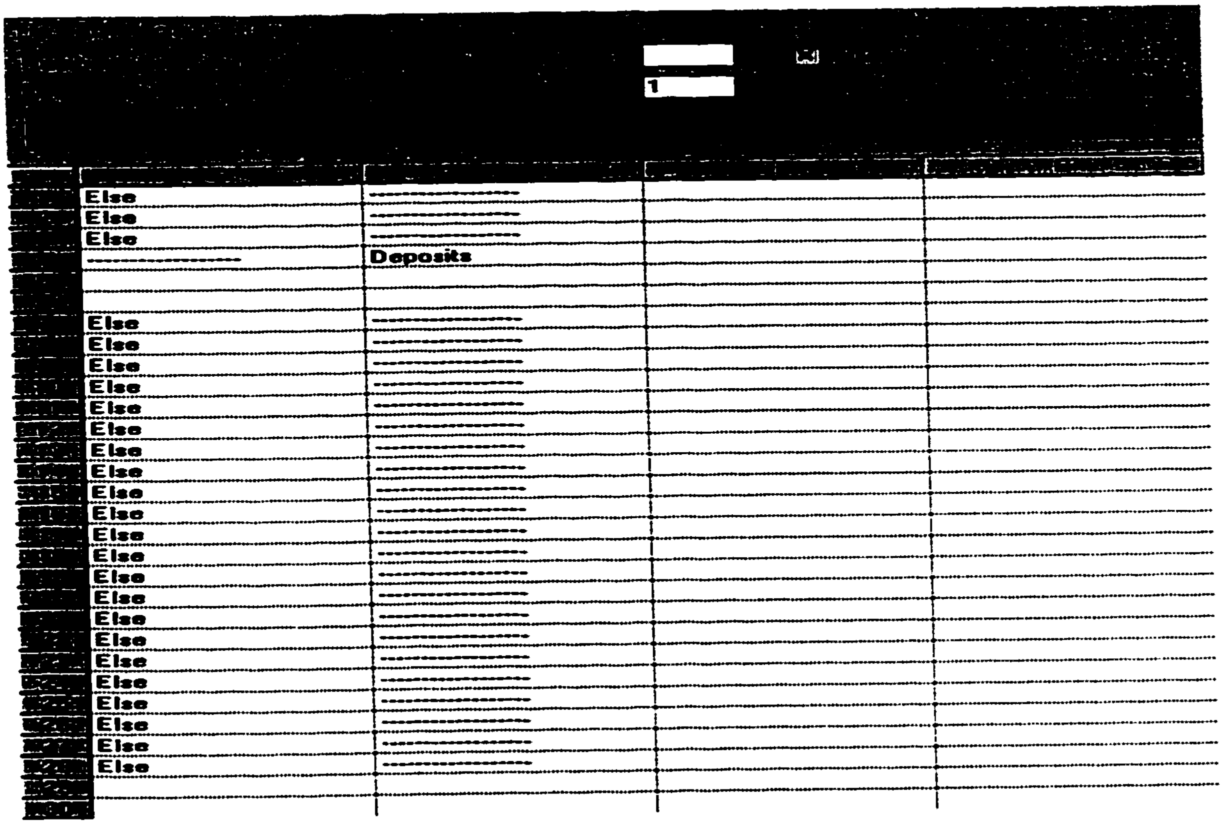


Figure 3-62: Output Results of a Case Example on Deposits Utilizing DepositNet 1 and the Solution Strategy Module

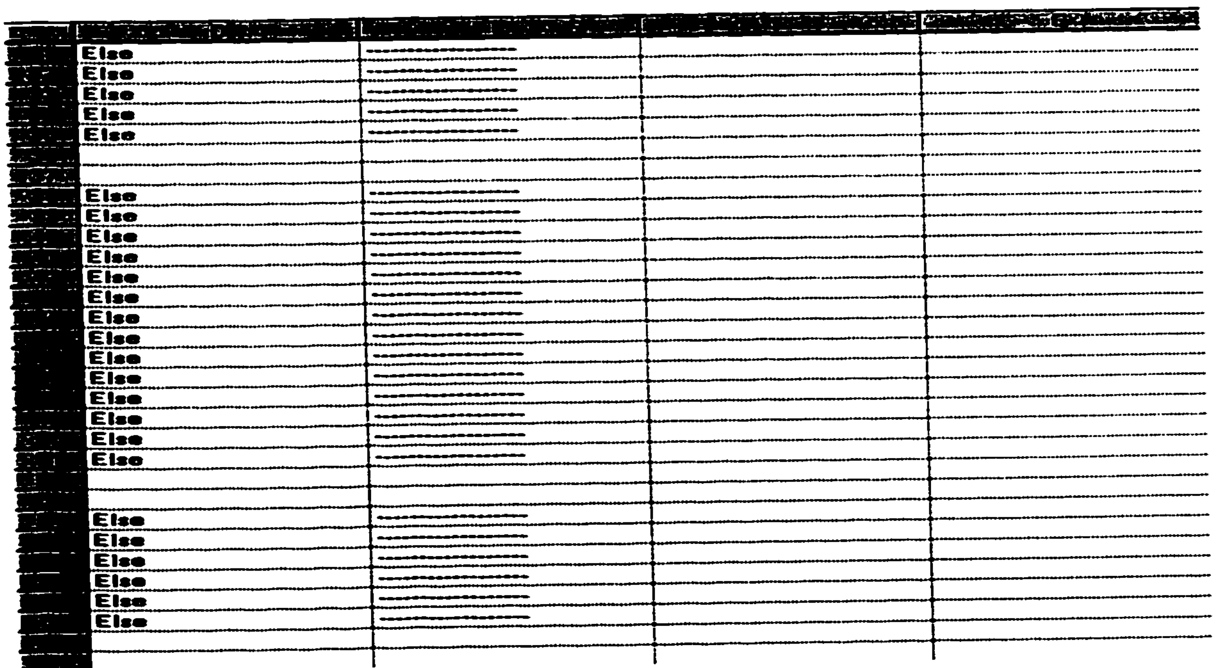


Figure 3-62: Output Results of a Case Example on Deposits Utilizing DepositNet 1 and the Solution Strategy Module (Continued)

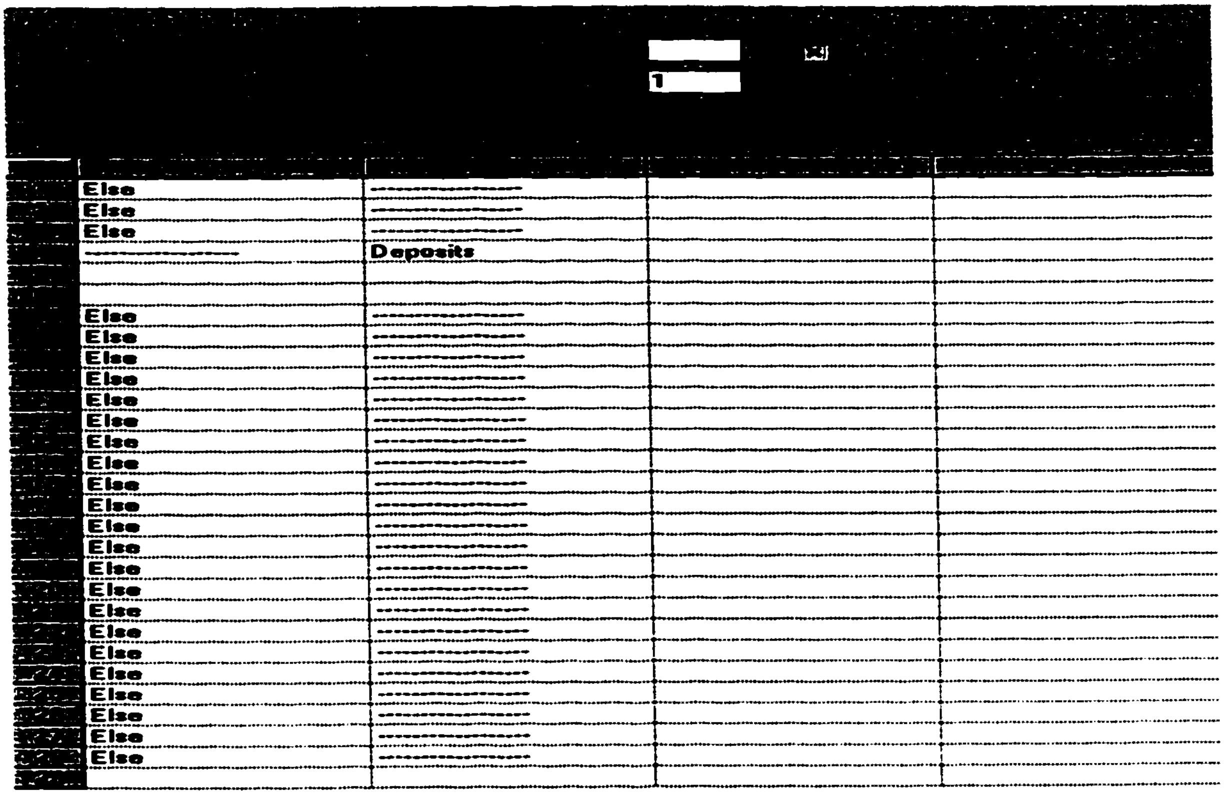


Figure 3-63: Output Results of a Case Example on Deposits Utilizing DepositNet 2 and the Solution Strategy Module

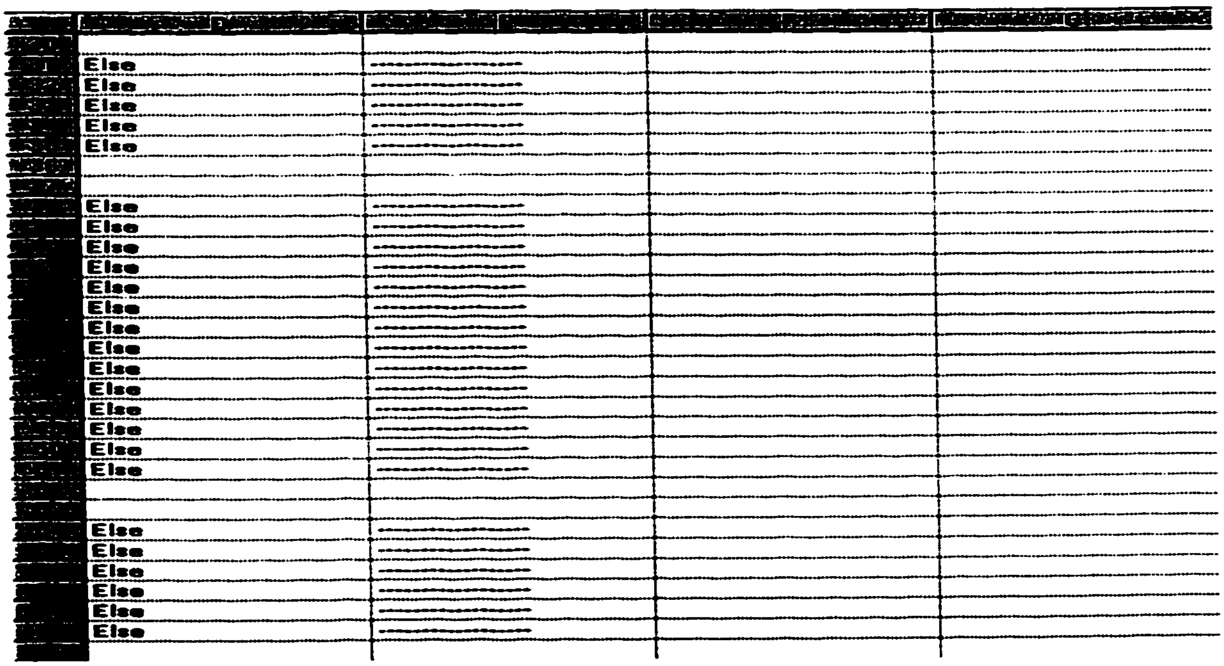


Figure 3-63: Output Results of a Case Example on Deposits Utilizing DepositNet 2 and the Solution Strategy Module (Continued)

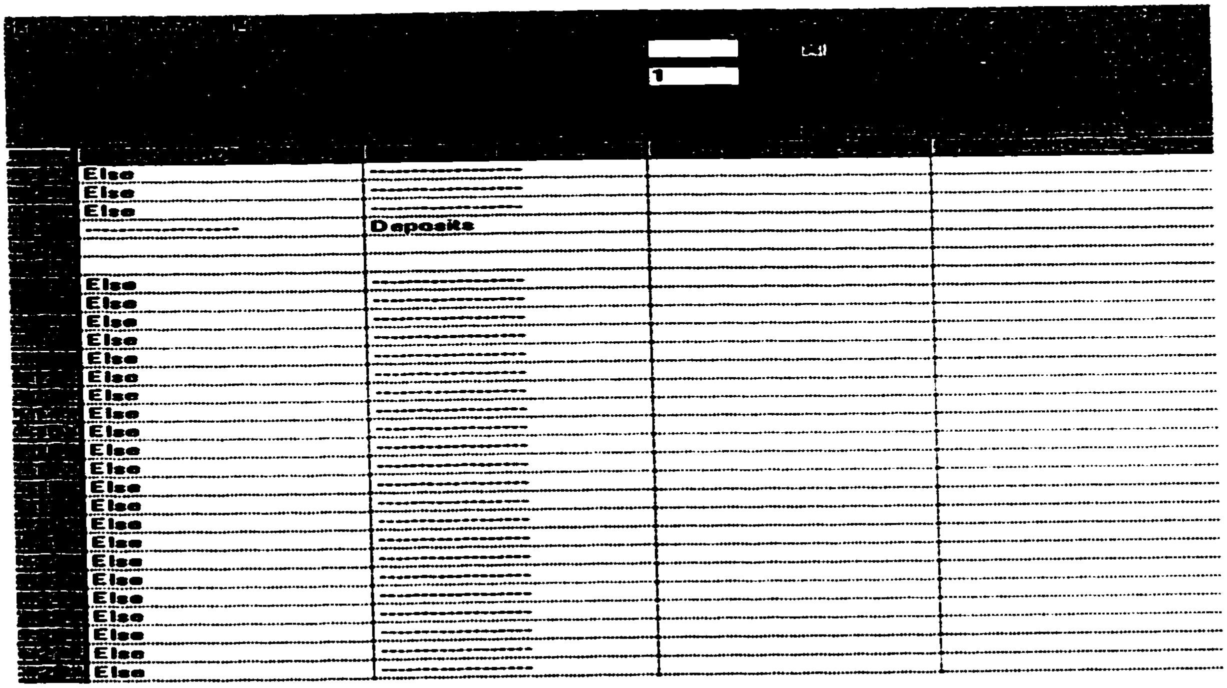


Figure 3-64: Output Results of a Case Example on Deposits Utilizing DepositNet 3 and the Solution Strategy Module

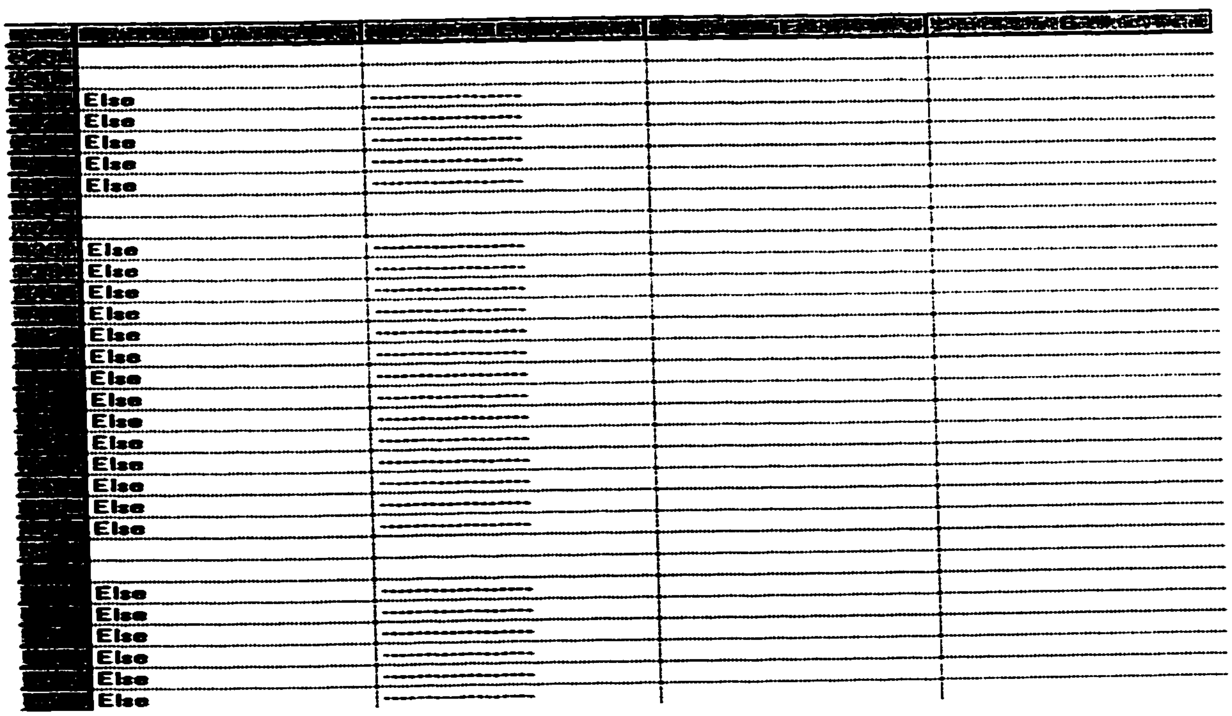


Figure 3-64: Output Results of a Case Example on Deposits Utilizing DepositNet 3 and the Solution Strategy Module (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Deposits			
[illegible]								
[illegible]								
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			

Figure 3-65: Comparison of Output Results of DepositNet 1-3 Utilizing the Multiple Classifier Module

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]								
[illegible]								
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]								
[illegible]								
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			
[illegible]					Else			

Figure 3-65: Comparison of Output Results of DepositNet 1-3 Utilizing the Multiple Classifier Module (Continued)

All non-deposits were then segregated based on their locations. Those with (1,1) coordinates were fed into CrossNet 1, CrossNet 2 and CrossNet 3 for classification of cross-sectional reductions. The results of these networks are shown in Figures 3-66 to 3-68. As can be noticed, CrossNet 1 was able to classify "Cross-sectional reductions" and "Else" with 100% and 0% accuracy, respectively. On the other hand, CrossNet 2 and CrossNet 3 classified both categories with 100% accuracy. To counter-check the results obtained from the different neural networks, the multiple classifier system was applied (Figure 3-69). As shown in Figure 3-69, the overall classification performance of the system is concluded to be 100% for "Cross-sectional reduction" and "Else". This is due to the fact that the misclassification that was reported by CrossNet 1 was confirmed by neither CrossNet 2 nor CrossNet 3.

Further, the same file (i.e. those defects with (1,1) coordinates) was also fed into MisalignmentNet 1, MisalignmentNet 2 and MisalignmentNet 3. The purpose of this step is to classify misalignments. The results of this process are shown in Figures 3-70 to 3-72. As can be noticed, MisalignmentNet 1 was able to classify "Misalignment" and "Else" with 100% and 0% accuracy, respectively. On the other hand, MisalignmentNet 2 and MisalignmentNet 3 classified both categories with 100% accuracy. By considering the results shown in Figures 3-73, the overall classification performance of the system is concluded to be 100% for "Misalignment" and "Else". This is due to the fact that the misclassification that was reported by MisalignmentNet 1 was confirmed by neither MisalignmentNet 2 nor MisalignmentNet 3.

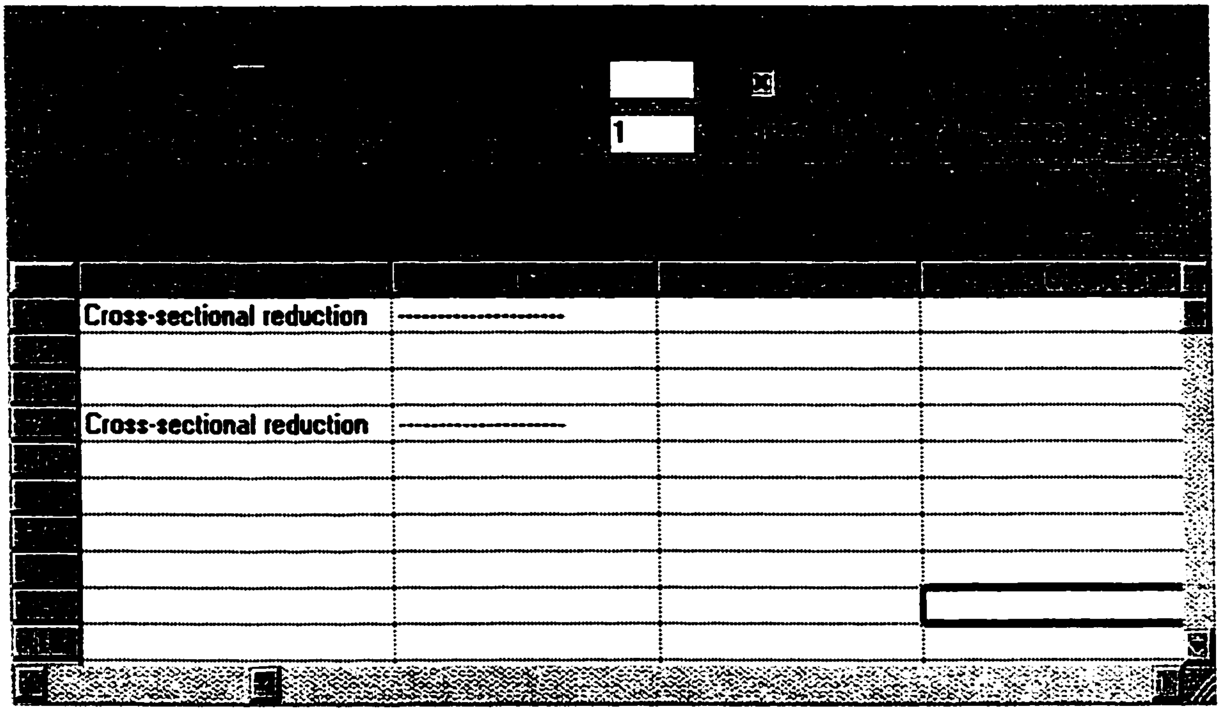


Figure 3-66: Output Results of a Case Example on Cross-sectional Reductions Utilizing CrossNet 1 and the Solution Strategy

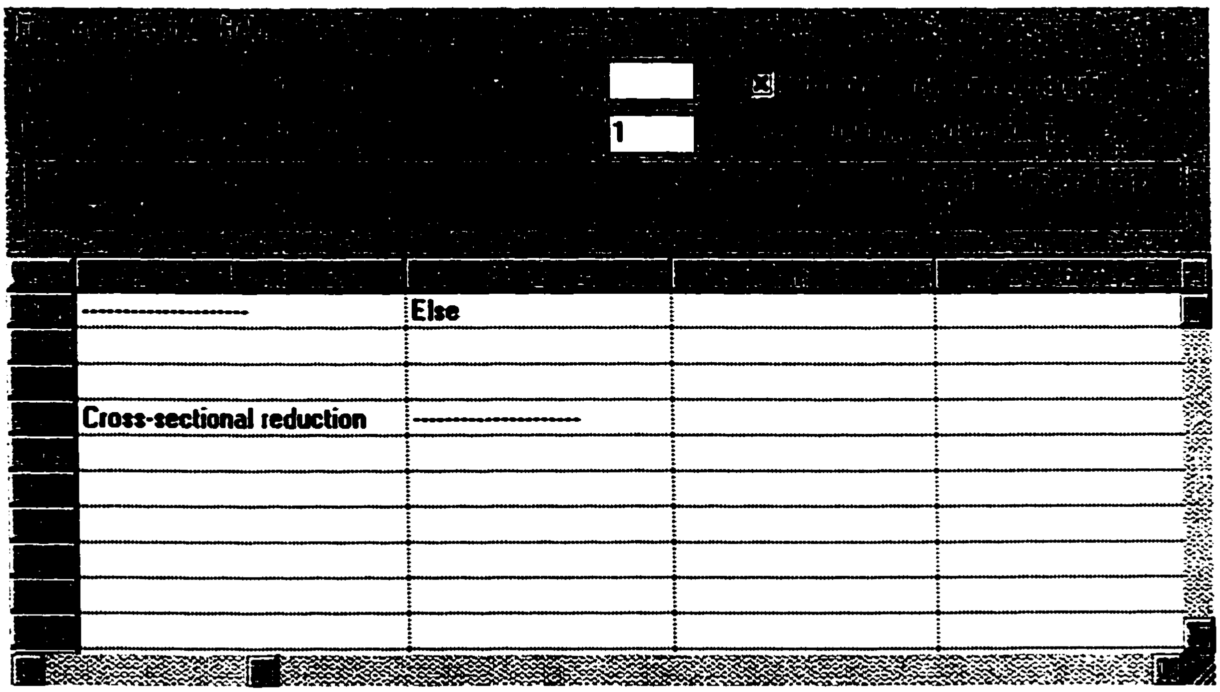


Figure 3-67: Output Results of a Case Example on Cross-sectional Reductions Utilizing CrossNet 2 and the Solution Strategy

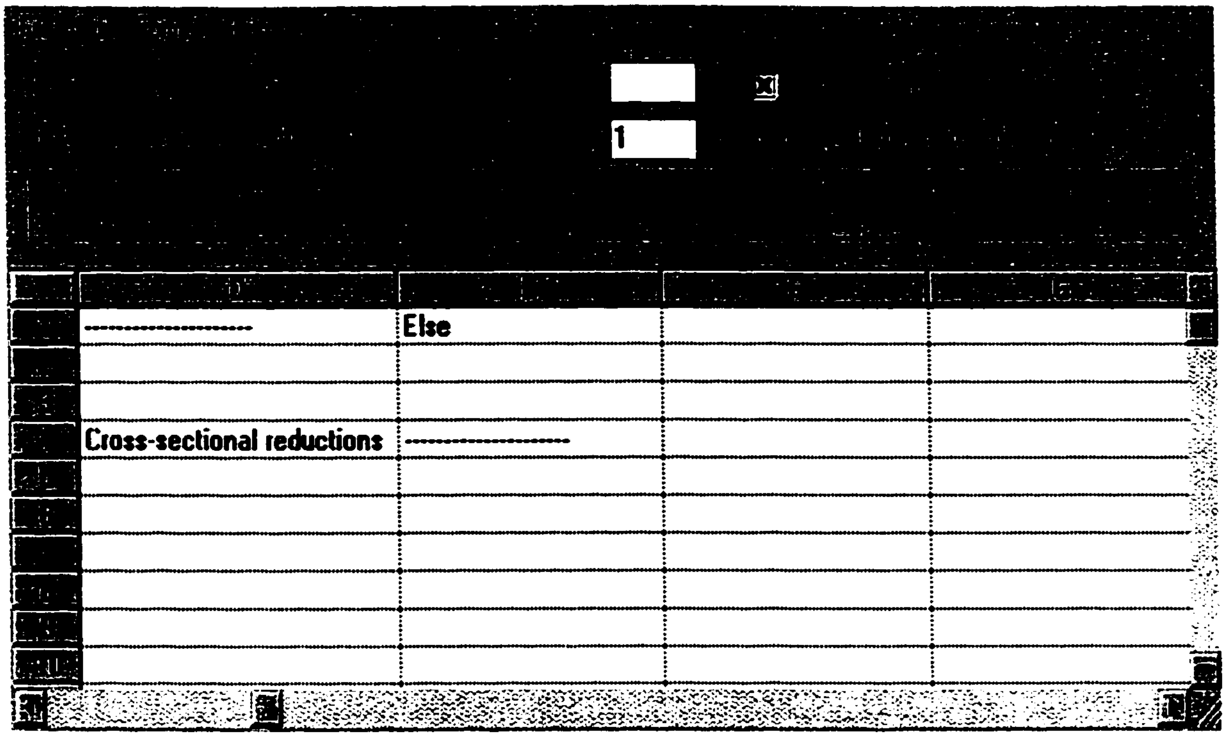


Figure 3-68: Output Results of a Case Example on Cross-sectional Reductions Utilizing CrossNet 3 and the Solution Strategy

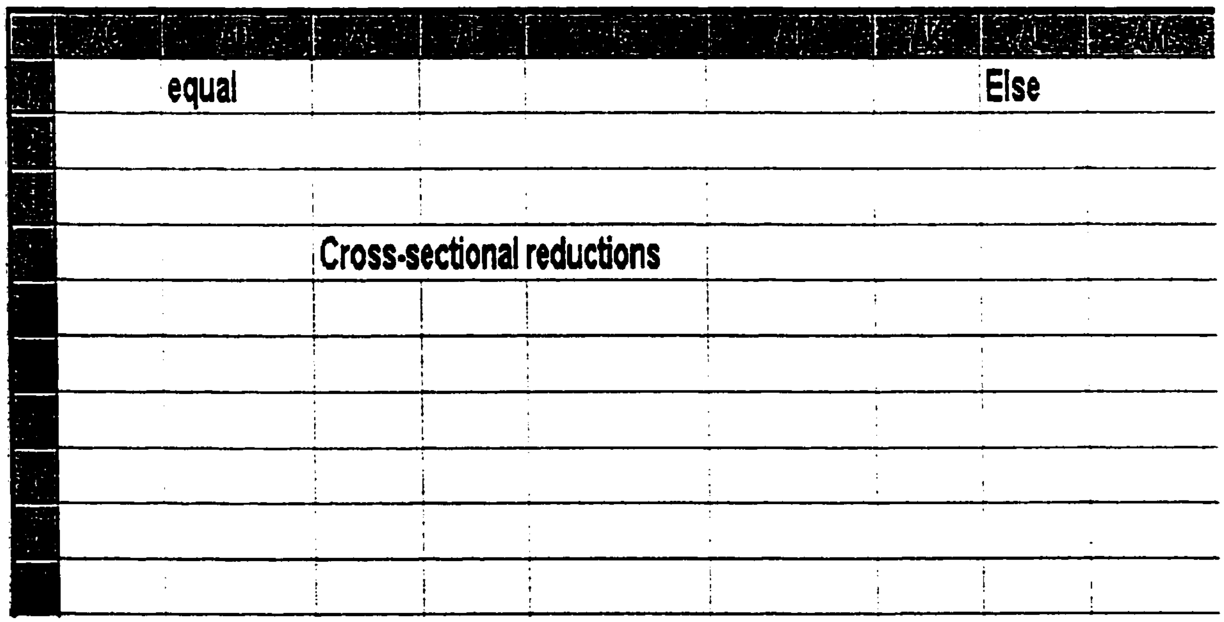


Figure 3-69: Comparison of Output Results of CrossNet 1-3 Utilizing the Multiple Classifier Module

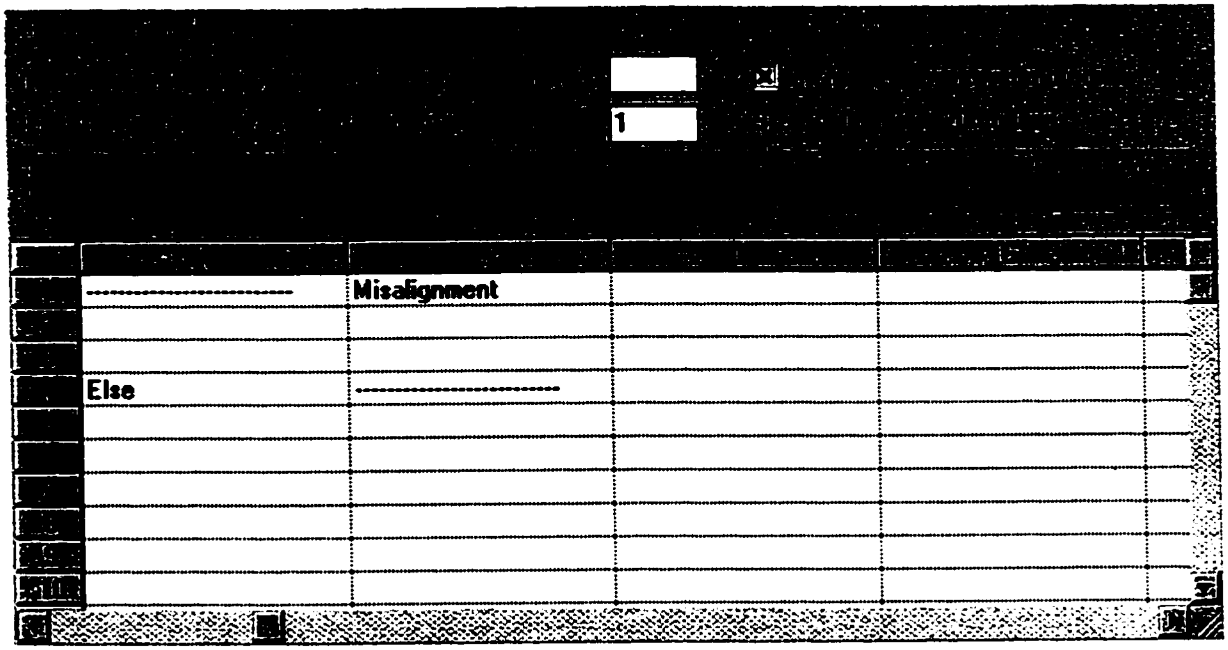


Figure 3-70: Output Results of a Case Example on Misalignments Utilizing MisalignmentNet 1 and the Solution Strategy Module

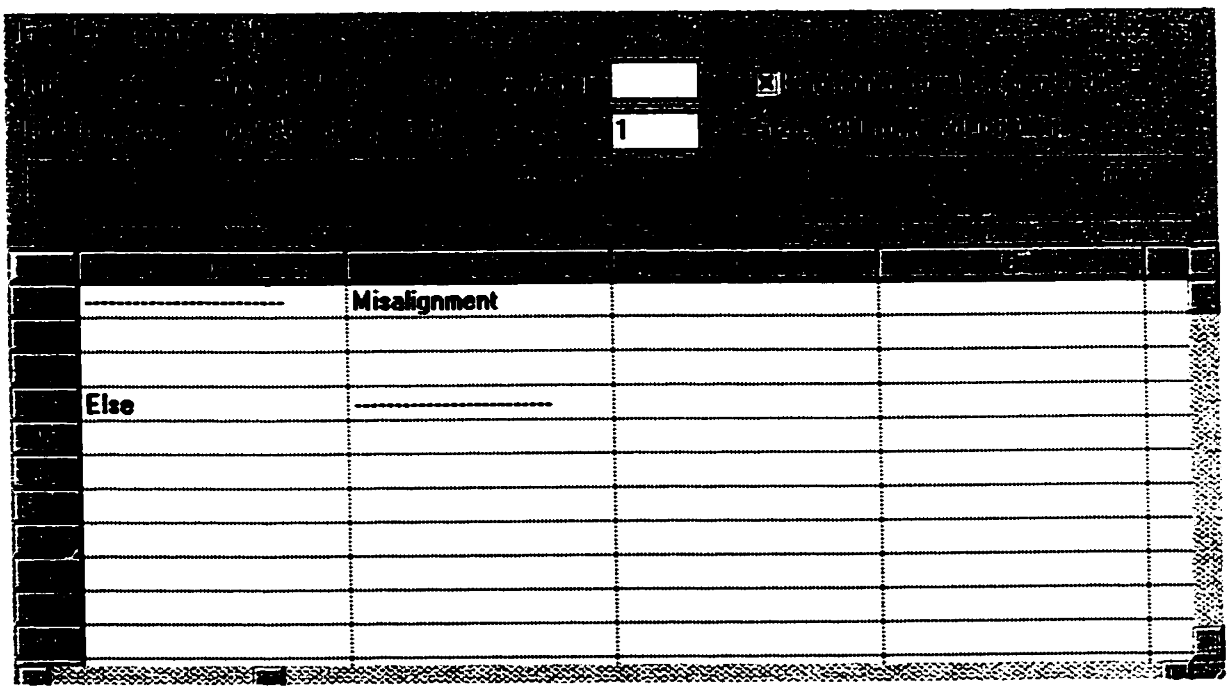


Figure 3-71: Output Results of a Case Example on Misalignments Utilizing MisalignmentNet 2 and the Solution Strategy Module

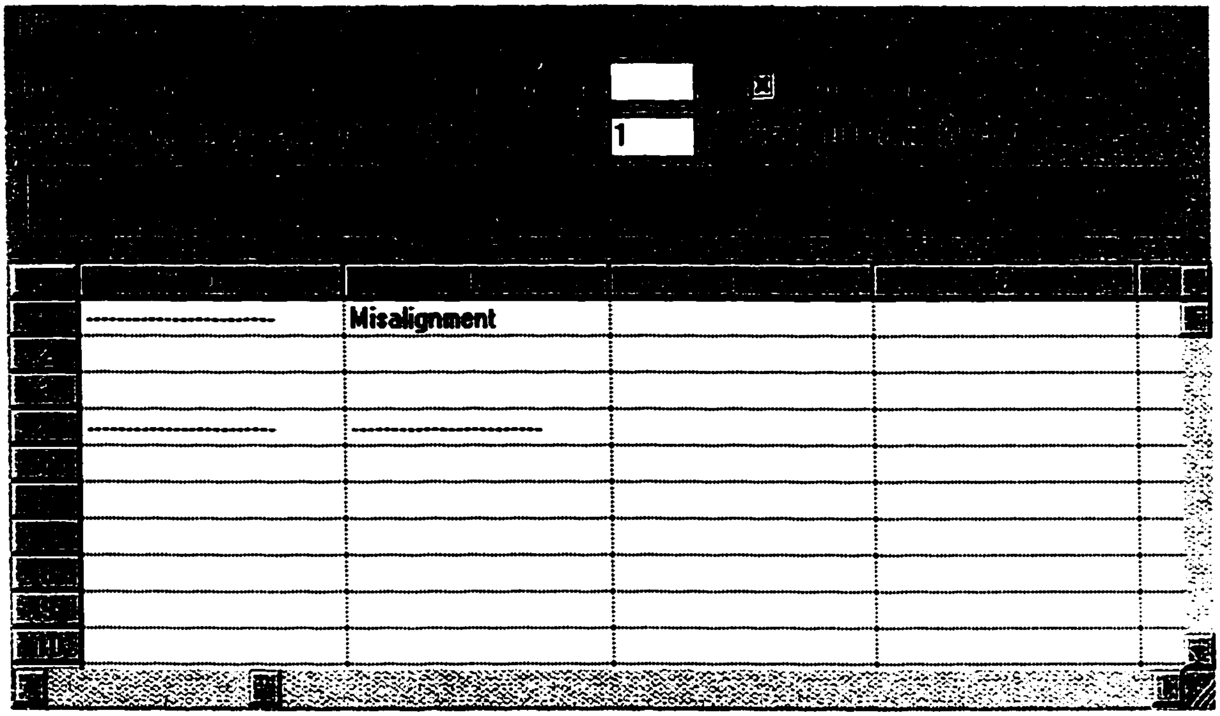


Figure 3-72: Output Results of a Case Example on Misalignments Utilizing MisalignmentNet 3 and the Solution Strategy

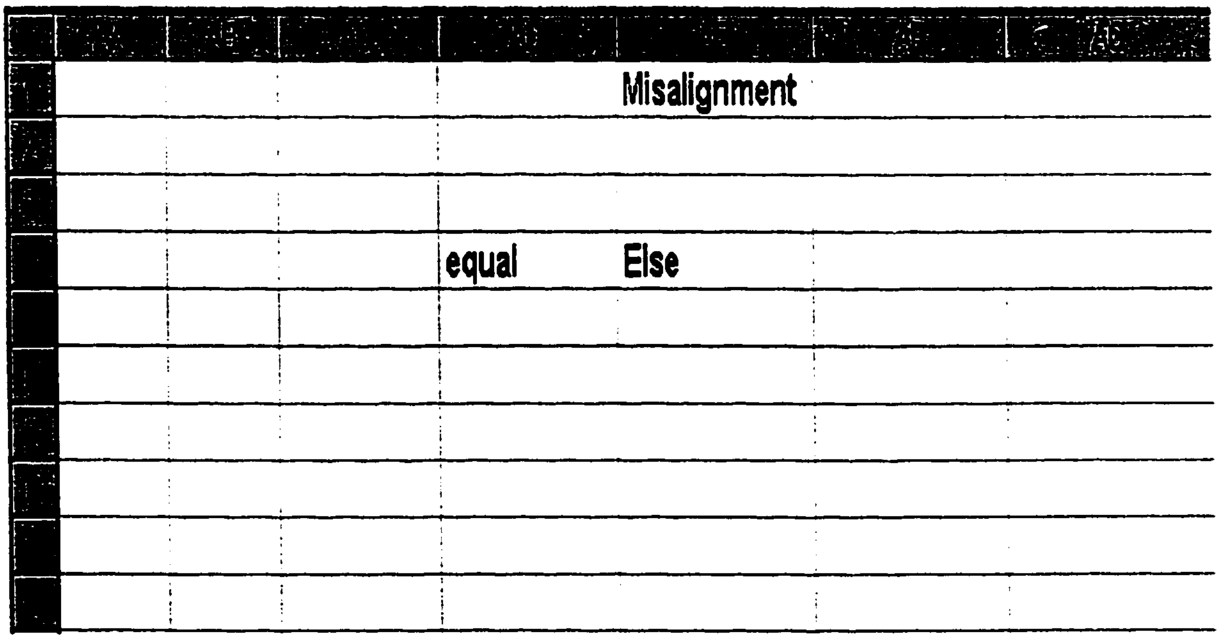


Figure 3-73: Comparison of Output Results of MisalignmentNet 1-3 Utilizing the Multiple Classifier Module

To detect and classify infiltration, the images were processed using sequence of operations number 2 rather than number 1 used in the first pass (Table 3-2). The segmented images are shown in Figures 3-74 to 3-78 below. As can be noticed from Figures 3-74, 3-75, 3-76, 3-77 and 3-78, 6, 7, 7, 3 and 4 objects were detected, respectively. The extracted features of these images were then processed using InfiltrationNet 1. The results of this network are shown in Figures 3-79. By comparing objects in Figures 3-74 to 3-78 and results shown in Figure 3-79, it can be noticed that the developed neural network was able to classify "Infiltration" and "Else" 100% and 96% accuracy, respectively.

Figure 3-74: Segmented Image of Cracks

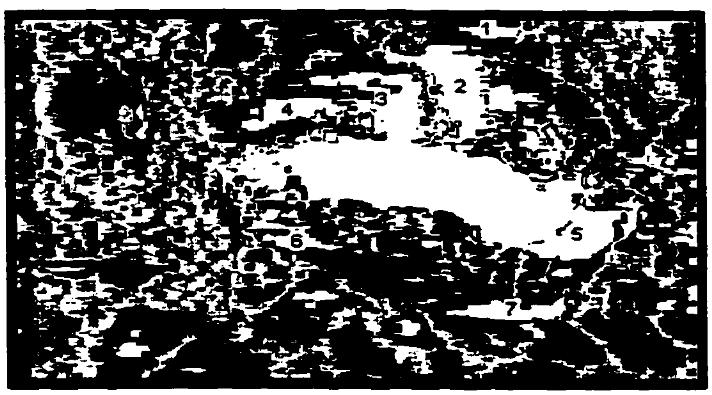


Figure 3-75: Segmented Image of Cross-sectional Reductions

Figure 3-76:Segmented Image of Misalignments

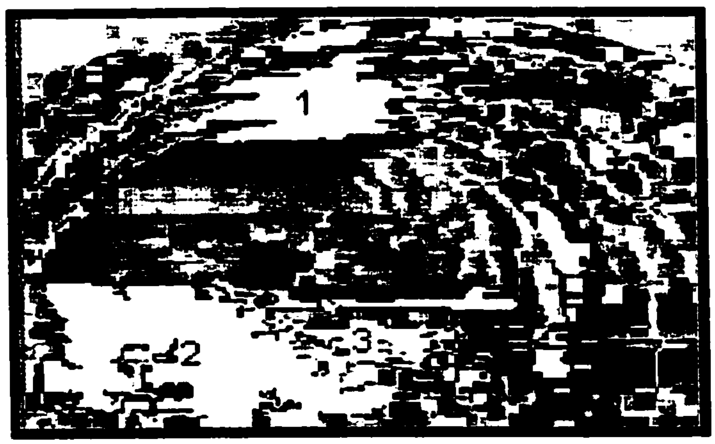


Figure 3-77: Segmented image of Deposits

Figure 3-78: Segmented Image of Infiltration

The same process was repeated utilizing InfiltarationNet 2 and InfiltrationNet 3 networks. The outputs of these two networks are shown in Figures 3-80 to 3-81. As can be noticed from Figure 3-80, InfiltrationNet 2 was able to classify "Infiltration" and "Else" with 100% and 92% accuracy, respectively. On the other hand, InfiltrationNet 3 was able to classify the same categories with 100% and 96% accuracy, respectively (Figures 3-81). By considering the results obtained from the three classifiers, it can be concluded that the overall performance of the system is 100% for "Infiltration" and 100% for "Else" categories, respectively. This is due to the fact that no object was misclassified by more than one neural network (Figure 3-82).

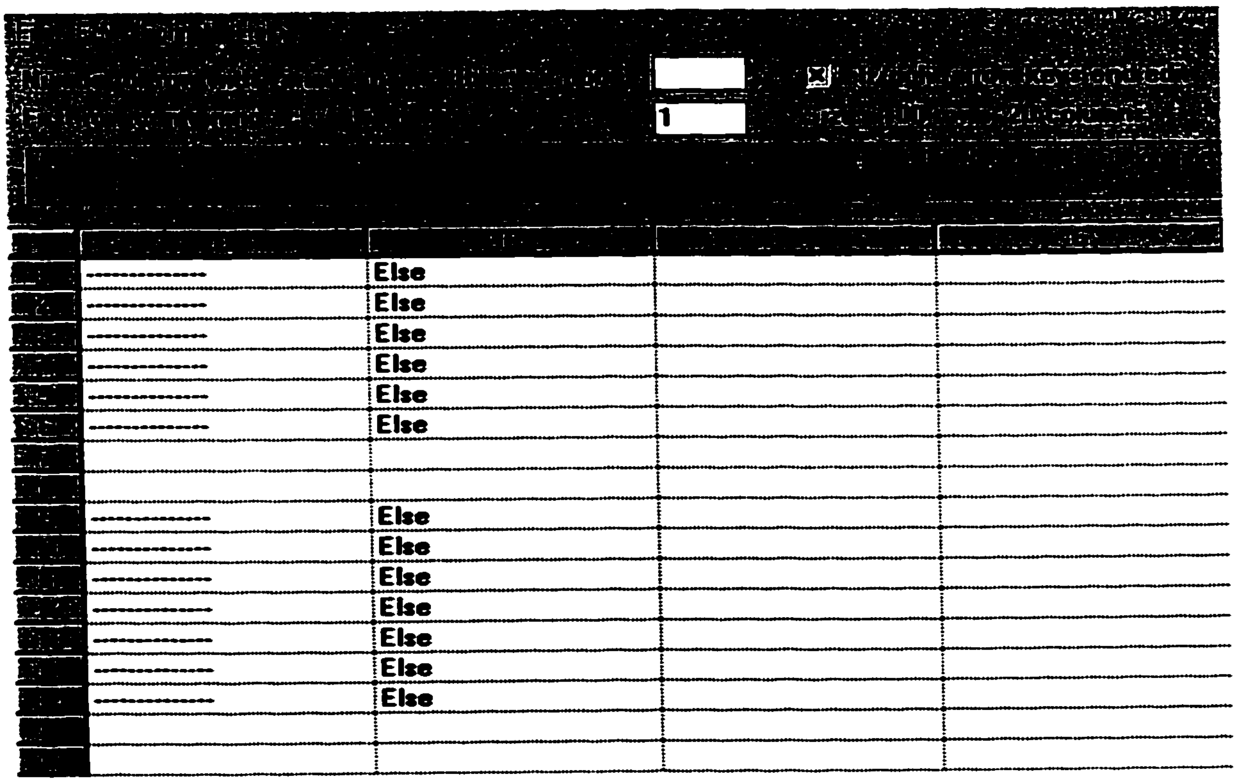


Figure 3-79: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 1 and the Solution Strategy Module

-------------	Else		
-------------	Else		
-------------	Else		
-------------	Else		
Infiltration	-------------		
-------------	Else		
-------------	Else		
-------------	Else		
-------------	Else		
-------------	Else		
Infiltration	-------------		
Infiltration	-------------		
-------------	Else		
-------------	Else		

Figure 3-79: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 1 and the Solution Strategy Module (Continued)

------------------	Else		
------------------	Else		
------------------	Else		
Infiltration	------------------		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		

Figure 3-80: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 2 and the Solution Strategy Module

-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
Infiltration	-------------------		
-------------------	Else		
Infiltration	-------------------		
Infiltration	-------------------		
-------------------	Else		
-------------------	Else		

Figure 3-80: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 2 and the Solution Strategy Module (Continued)

1

Infiltration	-------------------		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		
-------------------	Else		

Figure 3-81: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 3 and the Solution Strategy Module

	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	-----------------	Else		
	Infiltration	-----------------		
	Infiltration	-----------------		
	-----------------	Else		
	-----------------	Else		

Figure 3-81: Output Results of a Case Example on Infiltration Utilizing InfiltrationNet 3 and the Solution Strategy Module (Continued)

		Else				
		Else				
		Else				
	equal			Else		
		Else				
		Else				
		Else				
		Else				
		Else				
		Else				
		Else				
		Else				
		Else				

Figure 3-82: Comparison of Output Results of InfiltrationNet 1-3 Utilizing the Multiple Classifier Module

[illegible]			Else							
[illegible]			Else							
[illegible]			Else							
[illegible]			Else							
[illegible]		equal								Else
[illegible]			Else							
[illegible]			Else							
[illegible]										
[illegible]										
[illegible]			Else							
[illegible]		equal				Else				
[illegible]			Else							
[illegible]										
[illegible]										
[illegible]			Infiltration							
[illegible]			Infiltration							
[illegible]			Else							
[illegible]			Else							
[illegible]										

Figure 3-82: Comparison of Output Results of InfiltrationNet 1-3 Utilizing the Multiple Classifier Module (Continued)

To detect and classify cracks, the images were processed for the third time. In this pass, the images were processed by applying sequence of operations number 3 (Table 3-2). The segmented images of these images are shown in Figures 3-83 to 3-87 below. As can be noticed from Figure 3-83, 3-84, 3-85, 3-86 and 3-87, 15, 4, 2, 2 and 9 objects were detected, respectively. The extracted features of these images were then fed into CrackNet 1. The results of this neural network are shown in Figures 3-88. By comparing objects in Figures 3-83 to 3-87 and results shown in Figures 3-88, it can be noticed that the developed neural network was able to classify "Cracks" and "Else" 100% and 93.3% accuracy, respectively.

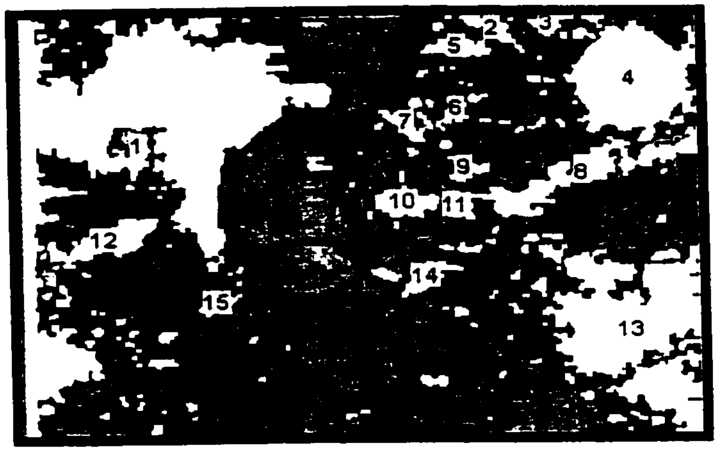


Figure 3-83: Segmented Image of Cracks

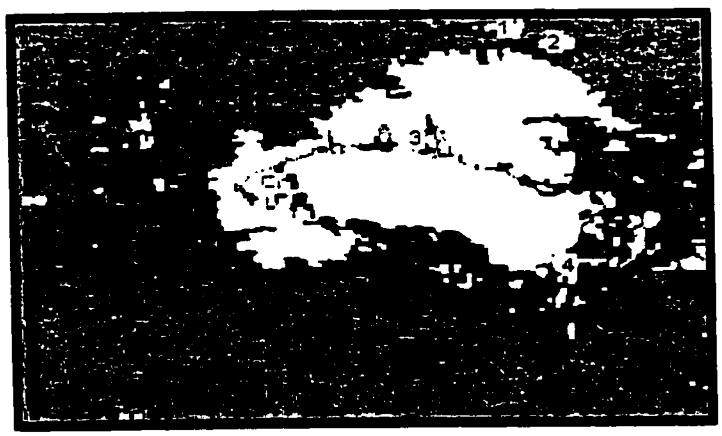


Figure 3-84: Segmented Image of Cross-sectional Reductions

Figure 3-85: Segmented Image of Misalignments

Figure 3-86: Segmented Image of Deposits

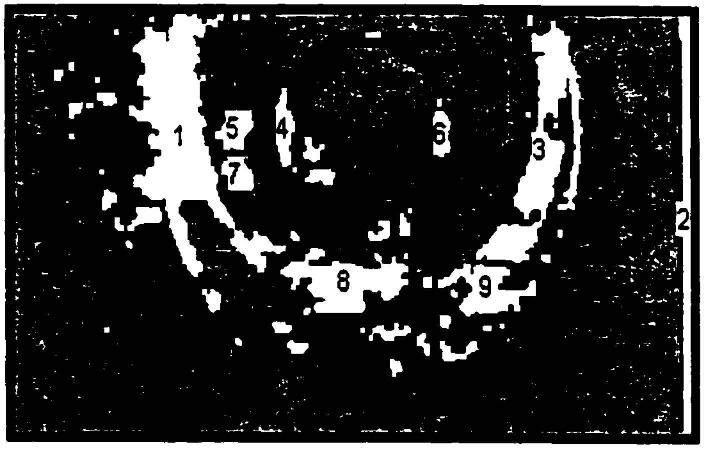


Figure 3-87: Segmented Image of Infiltration

The same process was repeated utilizing CrackNet 2 and CrackNet 3 neural networks. The outputs of these two networks are shown in Figures 3-89 and 3-90. As can be noticed from Figures 3-89, CrackNet 2 was able to classify "Cracks" and "Else" with 100% and 90% accuracy, respectively. On the other hand, CrackNet 3 was able to classify the same categories with 100% and 96% accuracy, respectively (Figures 3-90). By considering the results obtained from the three classifiers, it can be concluded that the overall performance of the system is 100% for "Crack" and 93.3% for "Else" categories, respectively (Figures 3-91).

----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		

Figure 3-88: Output Results of a Case Example on Cracks Utilizing CrackNet 1 and the Solution Strategy Module

D	E	F	G
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		

Figure 3-88: Output Results of a Case Example on Cracks Utilizing CrackNet 1 and the Solution Strategy Module (Continued)

----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		

Figure 3-89: Output Results of a Case Example on Cracks Utilizing CrackNet 2 and the Solution Strategy Module

Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
Crack	----------------		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		
----------------	Else		

Figure 3-89: Output Results of a Case Example on Cracks Utilizing CrackNet 2 and the Solution Strategy Module (Continued)

------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
Crack	------------------		
------------------	Else		
------------------	Else		
------------------	Else		
Crack	------------------		
------------------	Else		
------------------	Else		
Crack	------------------		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		

Figure 3-90: Output Results of a Case Example on Cracks Utilizing CrackNet 3 and the Solution Strategy Module

------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
Crack	------------------		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		
------------------	Else		

Figure 3-90: Output Results of a Case Example on Cracks Utilizing CrackNet 3 and the Solution Strategy Module (Continued)

			Else							
			Else							
			Else							
			Else							
			Else							
			Else							
			Else							
			Crack							
			Else							
			Else							
			Else							
			Crack							
			Else							
			Else							
	equal								Crack	
			Else							
			Else							
			Else							
			Else							

Figure 3-91: Comparison of Output Results of CrackNet 1-3 Utilizing the Multiple Classifier Module

		equal				Else				
			Else							
		equal								Else
			Else							
			Else							
			Crack							
			Else							
			Else							
			Else							
			Else							
			Else							
			Else							
			Else							

Figure 3-91: Comparison of Output Results of CrackNet 1-3 Utilizing the Multiple Classifier Module (Continued)

CHAPTER 4

DEVELOPMENT OF AN AUTOMATED REHABILITATION SYSTEM

4.1 INTRODUCTION

A typical rehabilitation process of underground sewer pipes usually starts by collecting information about the project requirements and constraints (i.e. diameter, type of defect and cost). This set of information is then processed to select the most suitable rehabilitation method(s) that satisfy the project and the decision-maker's requirements. As discussed in Chapter 1, currently, this selection process is done utilizing the decision-maker's experience without computer assisted tools. Due to the rapidly expanding field of sewer rehabilitation, selection in this manner may suffer from the limited knowledge and/or experience of the decision-maker and could result in overlooking technically feasible and cost effective methods.

This chapter describes a developed system for selecting the most suitable rehabilitation technique(s) for those defects recognized by the automated inspection system (Shehab-Eldeen and Moselhi 2000 & 2001). The system can assist municipal engineers and contractors in selecting the most suitable trenchless rehabilitation technique that satisfies job conditions and user's requirements. The system is also believed to help new and less experienced engineers to benefit from the experience gained by others. In this rehabilitation system, the user is required to input a set of information that describes the project and user's requirements. Based on this input data, the system utilizes two modules, namely database management system (DBMS) and decision support system (DSS), to select the product(s) and method(s), along with their supplier(s), that satisfy the project and user's requirements.

4.2 DEVELOPED SYSTEM

Rehabilitation of sewer pipes poses a major challenge to most municipalities. This challenge is demonstrated by two main tasks. The first is to satisfy all constraints that are imposed by specific job conditions and/or user requirements, and the second is to select the most suitable rehabilitation technique that satisfies those constraints. Various rehabilitation techniques are available in the market, each is considered suitable for certain job/user requirements. To recommend a suitable rehabilitation technique, it is necessary to consider all contributing attributes that help in performing the selection process. Given the availability of large number of rehabilitation techniques and their associated contributing attributes, the importance of developing a system that eases the challenging task of selecting a suitable rehabilitation technique for specific job conditions and/or user requirements can not be overemphasized.

To assist municipality engineers in carrying out this challenging task, an automated rehabilitation system has been developed. The system consists of two main modules, a DBMS and a DSS, developed in Microsoft Access and Visual Basic environments, respectively. Figure 4-1 depicts the main modules of the developed system. As depicted in Figure 4-1, the selection process of a suitable rehabilitation technique starts by feeding the system with a report on the status of defects. If the report indicates no sign of defects, then the rehabilitation system will not be executed and a report will be issued accordingly. Otherwise the user will be required to input necessary information, such as pipe diameter and degree of bends, to activate the DBMS module. Upon processing the input data by the DBMS, the system will suggest a suitable method for rehabilitation. If the system suggests one method only, then a report will be issued accordingly. But, if more than one method is suggested, then the DSS module will be activated to rank all suggested methods based on multi-attributed criteria. The following sections describe each module.

4.2.1 Database Management System (DBMS)

Developing a database encompasses the utilization of database management systems (DBMS) to support the process of defining, constructing and manipulating data (Elmasri and Navathe 1994). Defining a database involves specifying the data types and their associated constraints (i.e. text, number and format). Constructing a database is the process of building a conceptual model showing all entities and attributes, transferring this conceptual model to a physical one (i.e. tables and relationships) and populating the database tables with all required information, and defining relationships among them. Manipulating a database includes designing and building a supporting search system (i.e. query) that retrieves specific information based on user needs. There are different database models, of which the relational model is the most commonly used in engineering applications (Udo-Inyang and Chen 1997 and Johnson 1997). This model was utilized to design and build the database of the rehabilitation system. In this model, the data are organized in tables. These tables are related to each other by different types of relationships such as one-many, many-one and many-many.

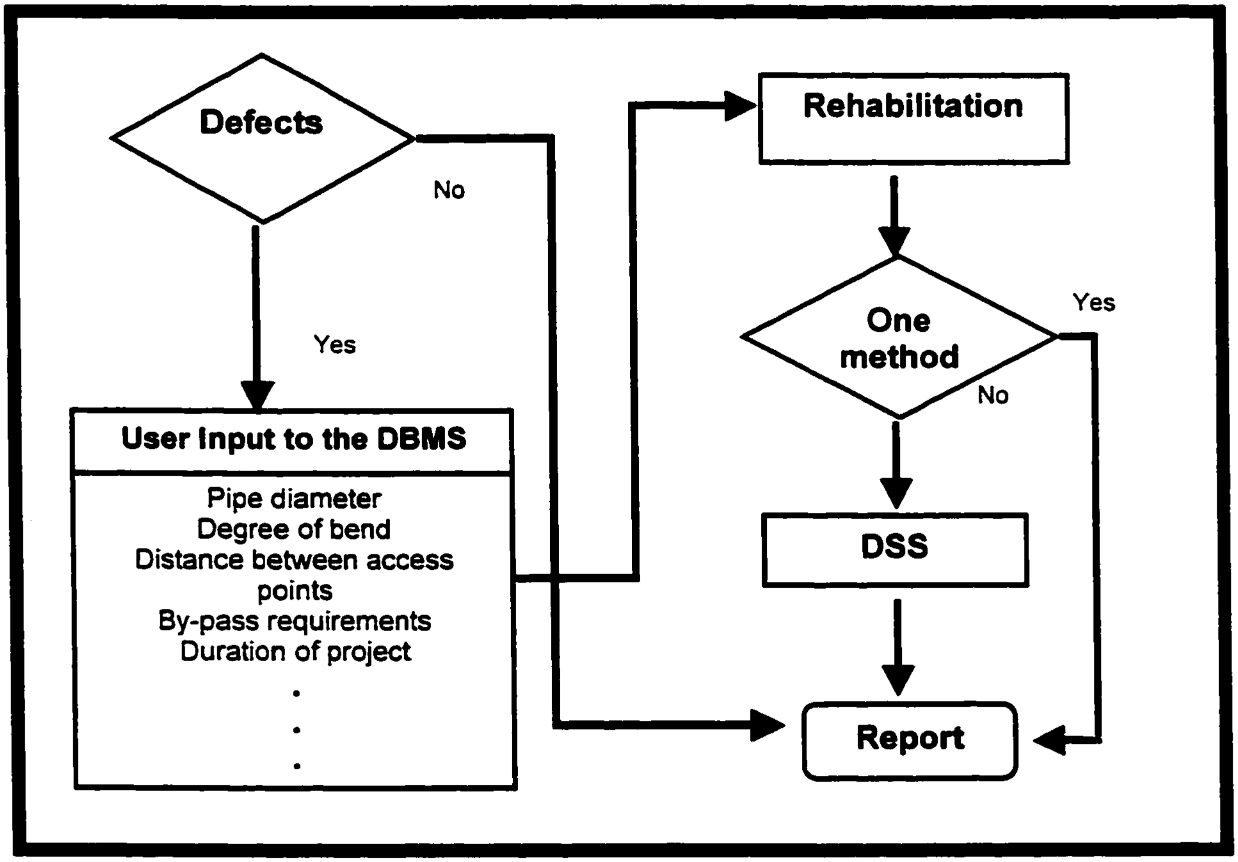


Figure 4-1: Developed Rehabilitation system

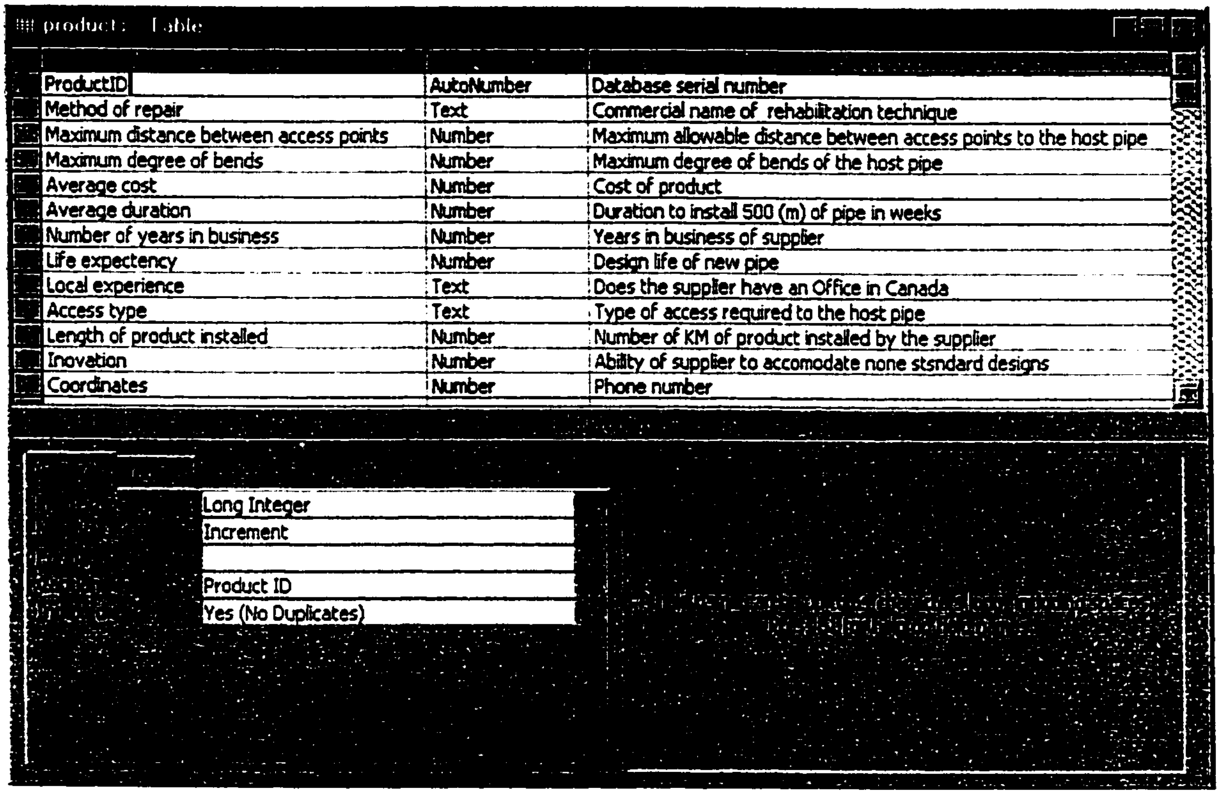
Various rehabilitation techniques are available in the market, each of which is considered suitable for certain job/user requirements. To recommend a suitable rehabilitation technique, it is necessary to consider all contributing attributes that help in performing the selection process. Based on the discussion presented in Section 2.7, a number of contributing attributes were considered. These attributes could be grouped into three main categories (see Table 4-1). These categories are technical requirements, contractual requirements and cost effectiveness. Technical requirements are defined as those attributes that determine the feasibility of the rehabilitation technique being considered and are independent of any personal preference or contractual obligations. They include type of repair, diameter of pipe, degree of bends, ability to improve hydraulic characteristics, distance between access points, ability to accommodate future differential settlement. Contractual requirements include attributes that ensure compliance of the rehabilitation technique with all terms and conditions of contract. They include duration of project, by-pass requirements, number of years in business of supplier and length of product installed, life expectancy, locality of suppliers, type of access to the original pipe (i.e. the host-pipe), method of service connections, degree of innovation. Cost effectiveness is defined as the ability of the technique to fulfill the budgetary limitations of a certain project.

Table 4-1 . Selection Attributes

GROUP I: TECHNICAL REQUIREMENTS	UNITS AND LIMITS
Type of repair	"Structural" or "Non-structural"
Diameter of pipe	2.5(cm) – 350(cm)
Degree of bends	0°-90°
Ability to improve hydraulic characteristics	"Improved" or "Not improved"
Distance between access points	Unlimited (m)
Ability to accommodate future differential settlement	"Yes" or "No"
Group II: CONTRACTUAL REQUIREMENTS	
Duration of project	Unlimited (Weeks)
By-pass requirements	"Yes" or "No"
Years in business and length of product installed	Unlimited (Year) and unlimited (km), respectively
Life expectancy	Unlimited (year)
Locality of suppliers	"Yes" or "No"
Type of access to the original pipe	"Manhole" or "Manhole & excavation pits"
Method of service Connections	"Excavation pits are not required" or "Excavation pits are required"
Degree of innovation	1-5, indicating poor and excellent, respectively
Group III: COST EFFECTIVENESS	
Cost of product	Unlimited ($/cm of diameter/m of length)

The conceptual design of a database is usually represented utilizing an entity relationship (ER) diagram, as shown in Figure 4-3 (Johnson 1997). It provides a comprehensive description of the database structure, highlighting its entities and attributes. As depicted in Figure 4-3, the ER diagram consists of eight main entities: type of defect, products, ability to accommodate future differential settlement, method of lateral connection, by-pass requirements, diameter, type of repair and ability to improve hydraulic characteristics. The attributes associated with type of defect are I.D. and name. Attributes associated with products are I.D., distance between access points, years in business of supplier, length of product installed, design life, access type, duration, innovation, locality, cost and name of product. Attributes associated with diameter are I.D. and diameter. Attributes associated with hydraulic characteristics are I.D. and improvement. Attributes associated with settlement are I.D. and settlement. Attributes associated with type of repair are I.D. and structural requirements. Attributes associated with lateral connections are I.D. and lateral connection requirements and attributes associated with by-pass are I.D. and by-pass requirements. As could be noticed from Figure 4-3, entities representing type of defect, ability to accommodate future differential settlement, method of service connection, by-pass requirements, diameter, type of repair and ability to improve hydraulic characteristics are connected by many-to-many relationships to the Products' table.

In order to implement the design suggested in the previously described ER diagram, each entity was mapped into a table. Each table was structured and its related attributes were added. Each attribute was then assigned its data-type (i.e. text or numeric) and constraints. A sample of this process is shown, for the "Products" table, in Figure 4-2. Similarly, all entities and attributes were mapped into tables, with each table having its own function. The descriptions of various tables are listed in Table 4-2.



product : Table

ProductID	AutoNumber	Database serial number
Method of repair	Text	Commercial name of rehabilitation technique
Maximum distance between access points	Number	Maximum allowable distance between access points to the host pipe
Maximum degree of bends	Number	Maximum degree of bends of the host pipe
Average cost	Number	Cost of product
Average duration	Number	Duration to install 500 (m) of pipe in weeks
Number of years in business	Number	Years in business of supplier
Life expectency	Number	Design life of new pipe
Local experience	Text	Does the supplier have an Office in Canada
Access type	Text	Type of access required to the host pipe
Length of product installed	Number	Number of KM of product installed by the supplier
Inovation	Number	Ability of supplier to accomodate none stsndard designs
Coordinates	Number	Phone number

Long Integer
Increment

Product ID
Yes (No Duplicates)

Figure 4-2: Products Table

Table 4-2: Description of Various Tables in the Database

TABLE'S NAME	DESCRIPTION
Products	Contains relevant technical, contractual and cost information about different rehabilitation techniques.
Type of defect	Contains information about the ability of various rehabilitation techniques to repair various categories of defects.
Settlement	Contains information about the ability of various rehabilitation techniques to accommodate differential settlements.
Lateral connection	Contains information about the ability of each rehabilitation technique to reconnect laterals to the rehabilitated pipe without digging.
By-pass requirements	Contains information about the ability of each rehabilitation technique to be applied while the original pipe is in service.
Diameter	Contains the range of diameters for various products.

Table 4-2: Description of Various Tables in the Database (Continued)

Type of repair	Contains information about the applicability of various rehabilitation techniques for repairing structural/non-structural defects.
Hydraulics	Contains information about the effectiveness of various rehabilitation techniques to improve the hydraulic characteristics of the host-pipe.
Junction	Connect "Products" and "Defects" tables through their primary keys.
Junction 1	Connect "Products" and "Diameter" tables through their primary keys.
Junction 2	Connect "Products" and "Hydraulics" tables through their primary keys.
Junction 3	Connect "Products" and "Structural requirements" tables through their primary keys.
Junction 4	Connect "Products" and "By-pass requirements" tables through their primary keys.
Junction 5	Connect "Products" and "Settlement" tables through their primary keys.
Junction 6	Connect "Products" and "Service connection" tables through their primary keys.

The schema of the developed database is shown in Figure 4-4. As depicted in this Figure, the developed database includes eight main tables and seven junction tables that describe all entities, attributes and relationships described in the ER diagram. The eight main tables represent the eight entities highlighted in the ER diagram: type of defect, products, ability to accommodate future differential settlement, method of lateral connection, by-pass requirements, diameter, type of repair and ability to improve hydraulic characteristics. It should be noted that the attributes associated with each entity are also shown in Figure 4-3. As could be noticed from this figure, tables representing type of defect, ability to accommodate future settlement, method of lateral connection, by-pass

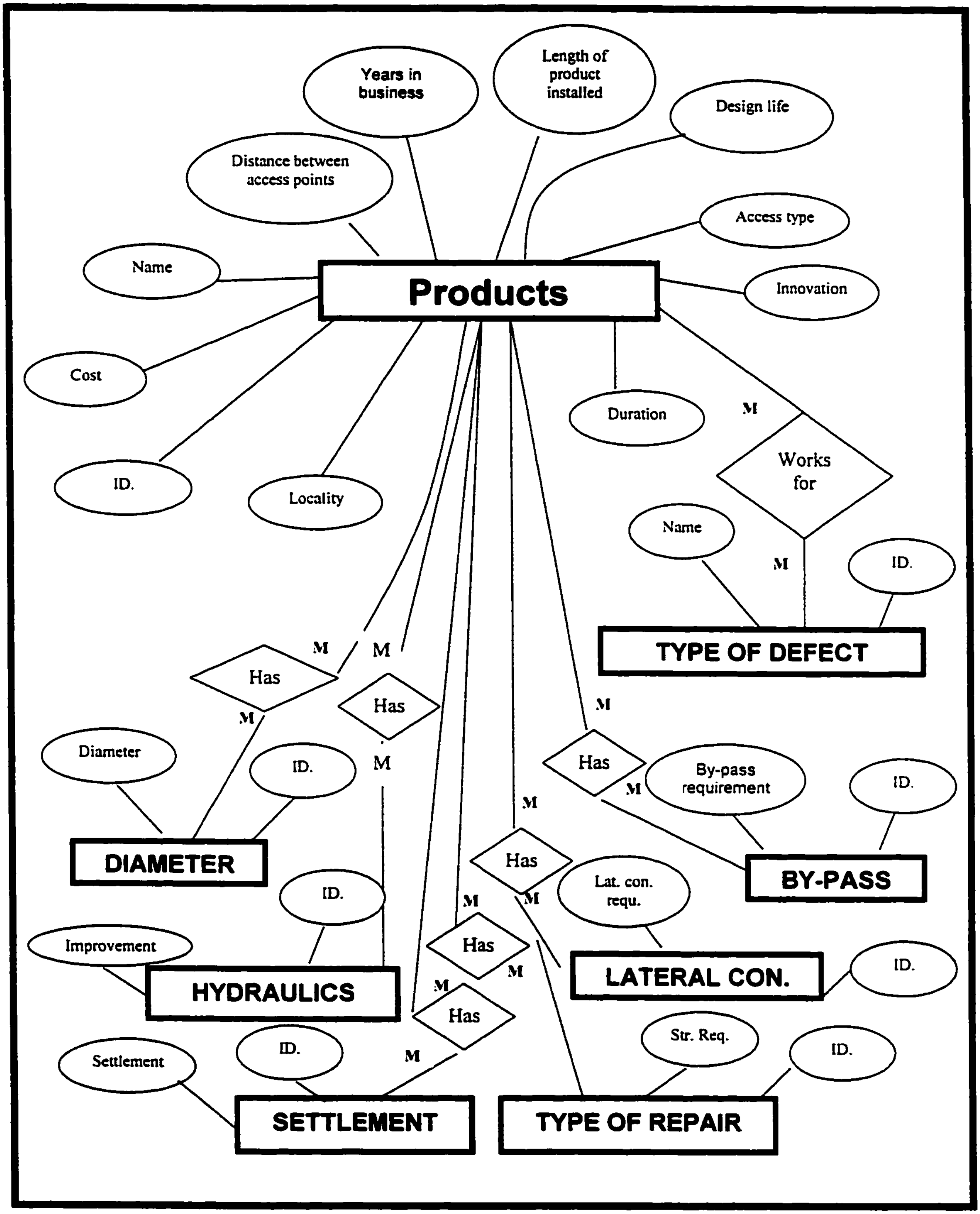


Figure 4-3: Entity Relationship Diagram

requirements, diameter, type of repair and ability to improve hydraulic characteristics are connected by many-to-many relationships to the Products' table. It should be noted that Access (Freeman 1997) does not directly support this type of relationship, except through the creation of what is known as junction tables (see Figure 4-4). Basically, these junctions work as intermediate tables that are related to the two main tables with many-to-one relationships. The information utilized to populate the database was acquired from 13 interviews with the manufacturers and suppliers of various methods of repair (see Appendix B). These manufacturers were located in Canada and the United States. A sample of collected information is shown in Appendix B. It should also be noted that the information delivered by suppliers for attributes such as cost, duration and ability to accommodate future settlement is based on average conditions and could be changed based on any particular project requirements.

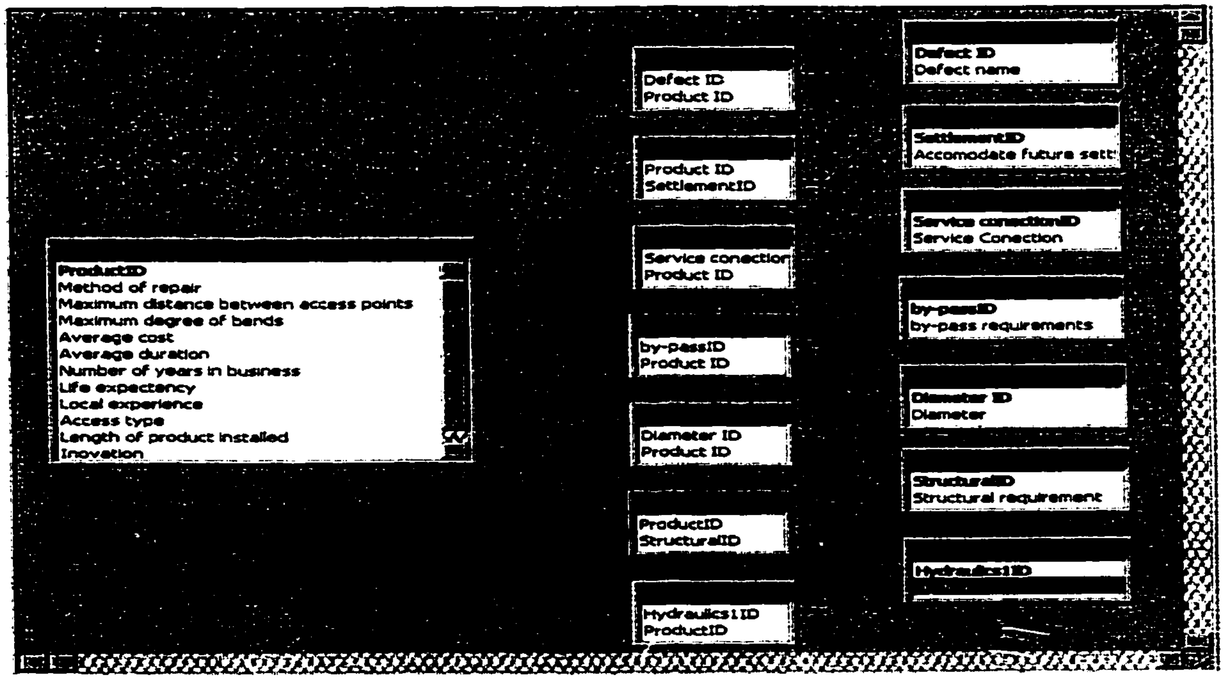


Figure 4-4: Schema of the Developed Database

To facilitate data entry and retrieval of information by users, a user-friendly form was designed (Figure 4-5 & 4-6). These forms were developed in Visual Basic environment. As Shown in Figure 4-6, the form consists of two sections: 1) input data and 2) output results. The input data section contains all technical, contractual and cost required information to run a query designed to search for the most suitable rehabilitation technique(s). The output results section contains the name of product(s) and suppliers' coordinates (i.e. telephone number). The suppliers' coordinates could be utilized in forwarding a request for a detailed quotation and/or analysis of the project, if needed. The form is designed with scroll-down menus to facilitate data entry.

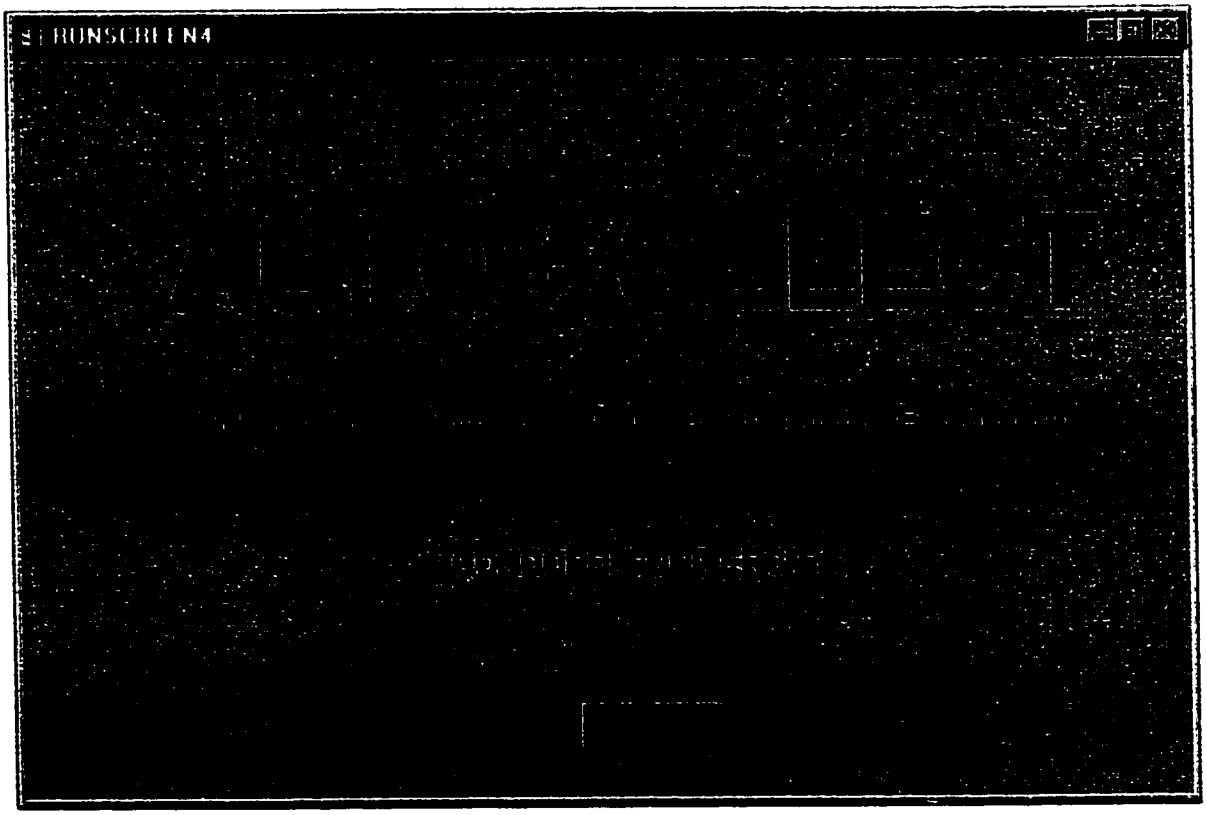


Figure 4-5: Database Execution Form

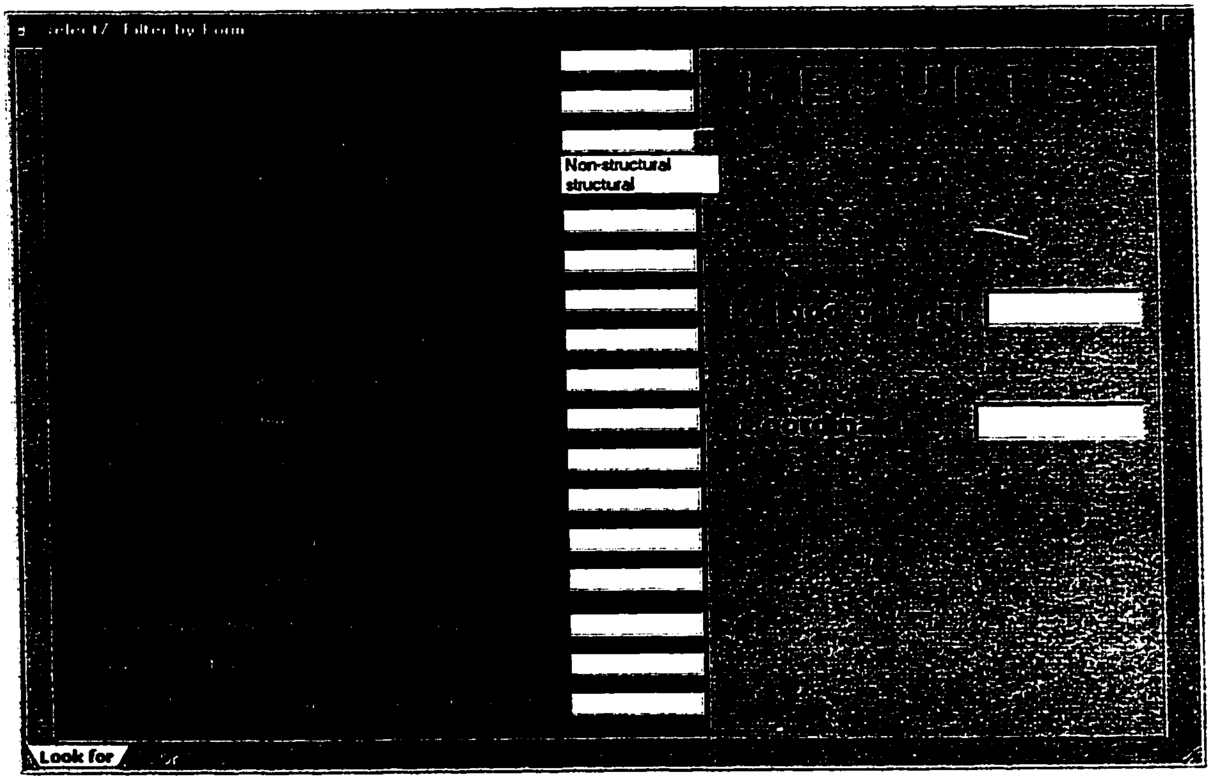


Figure 4-6: Data Entry and Retrieval Form

4.2.2 Decision Support System (DSS)

As depicted in Figure 4-1, the DSS will be activated only if more than one rehabilitation technique is suggested. The DSS utilizes multi-attribute utility theory (MAUT), which proved its effectiveness in comparing alternatives in a multi-attributed decision environment (Moselhi and Deb 1993 and Moselhi and Sigurdardottir 1998). In this method, the overall utility value of alternatives is expressed as follows (Keeney and Raiffa 1976):

$$U_i = \sum_{j=1}^{n} W_j \; U_{ij} \qquad (4\text{-}1)$$

In which

W_j = The relative weight assigned to the j^{th} attribute

U_{ij} = The value of the j^{th} attribute utility function (i.e. the utility value) associated with the i^{th} method of rehabilitation (i.e. the alternative being considered).

As can be noticed from Equation 4-1, there are two basic parameters necessary for calculating the overall utility values: the relative weight associated with each attribute (i.e. its priority or relative importance among all considered attributes), and the value of the utility function for each attribute. The relative weight is decided based on a pair-wise comparison of all attributes. This pair-wise comparison is performed on a scale of 1-9 (Table 4-3) and follows the process introduced by Saaty (1982).

Table 4-3: Pair-wise Comparison Scale (Saaty 1982)

SCALE	DEFINITION
1	Equal importance of both attributes
3	Weak importance of one attribute over the other
5	Strong importance of one attribute over the other
7	Demonstrated importance of one attribute over the other
9	Absolute importance of one attribute over the other
2,4,6,8	Intermediate values between two adjacent judgments

In conducting the pair-wise comparisons, it is important to be consistent in assigning the relative importance among the attributes. In other words, if attribute "A" is 4 times more important that Attribute "B", and Attribute "B" is twice as important as attribute "C", then, if the user is consistent, attribute "A" should be 8 times more important than attribute "C". If during the assignment of relative importance, attribute "C" was assigned a relative importance more than attribute "A", or alternatively, attribute "A" was assigned a relative importance more than 8 compared to attribute "C", then inconsistent assignment of importance was performed. This inconsistency could adversely affect the quality of the decision made, and ultimately the suitability of the selected rehabilitation technique. Accordingly, the consistency of relative importance should be monitored to prevent misleading conclusions. This consistency is monitored through evaluation of the consistency ratio (CR). The method of evaluation of CR is presented in Appendix C. It should be noted that values of CR in excess of 10% suggest inconsistent values entered by the user.

The utility functions of attributes are constructed based on the desirable values for each attribute. In so doing, utility values of 1.0 and 0.0 are assigned to the most and least desirable values, respectively. Intermediate utility values are assigned to express the degree of satisfaction of the decision maker as each attribute takes values between the two extremes.

In implementing the above described decision support technique, the developed system was designed in a manner that requires the user to specify the attributes for each project being considered (Figure 4-7). The decision is based on a maximum of 6 major attributes. These attributes are cost, duration, innovation, number of years in business, number of kilometers installed and life expectancy. The user can select a subset from that list of attributes for evaluating the various alternatives being considered. This design was implemented to expand the flexibility of the system and to accommodate different users' requirements. Once the user has specified the combination of attributes he or she would like to consider in the decision analysis, the system gets into an interactive dialogue designed to elicit the user preference. This dialogue is conducted through prompting the user to a set of questions. It should be noted that each dialogue consists of five questions. These questions are designed to elicit the user preference with respect to the most, least and intermediate values related to the attribute in question. A sample of these questions is shown in Figure 4-8. It should also be noted that this dialogue is executed for each attribute selected by the user.

After the system has determined various points representing user preference for each attribute, it generates various functions representing these points. These functions are linear, logarithmic, exponential, power, polynomial with second and third degrees. (Figure 4-9). It should be noted that the coefficient of multiple determination (R^2) is also calculated for each function. Once the system generates all possible functions, it prompts the user to select the one best depicting his preference. This is achieved by comparing the values of R^2 (Figure 4-10). The selected functions are used later to determine the user's satisfaction as these attributes take values between the most and least desirable values.

Figure 4-7: Available Attributes to Users

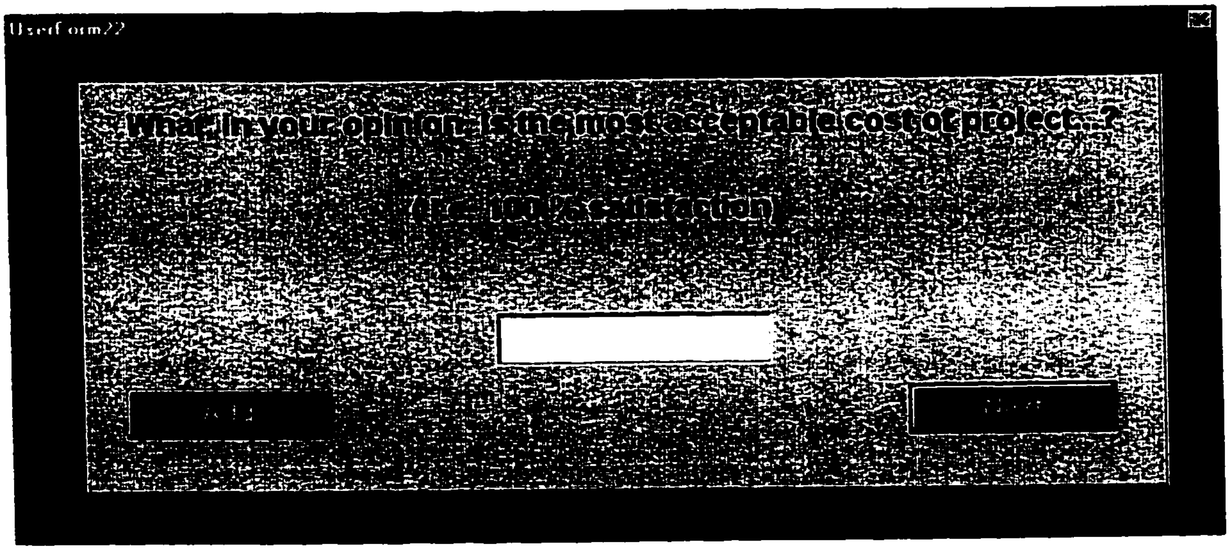


Figure 4-8: Sample Dialog Screen

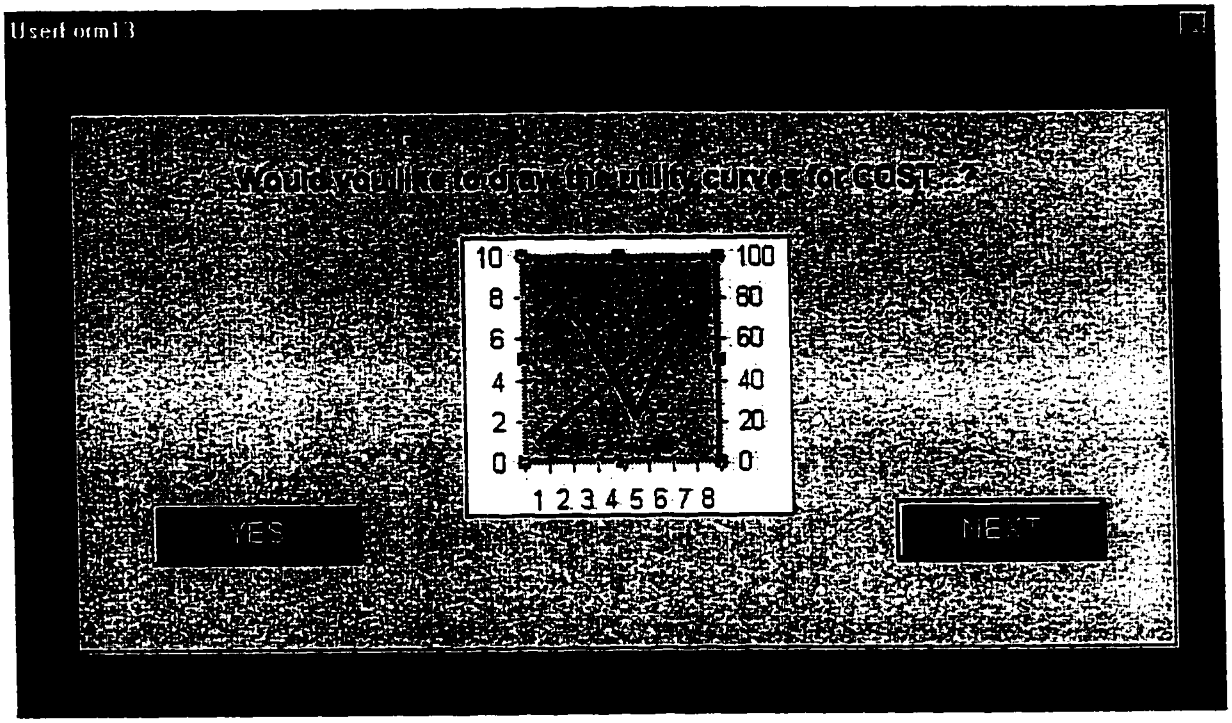


Figure 4-9: Plotting of Utility Functions

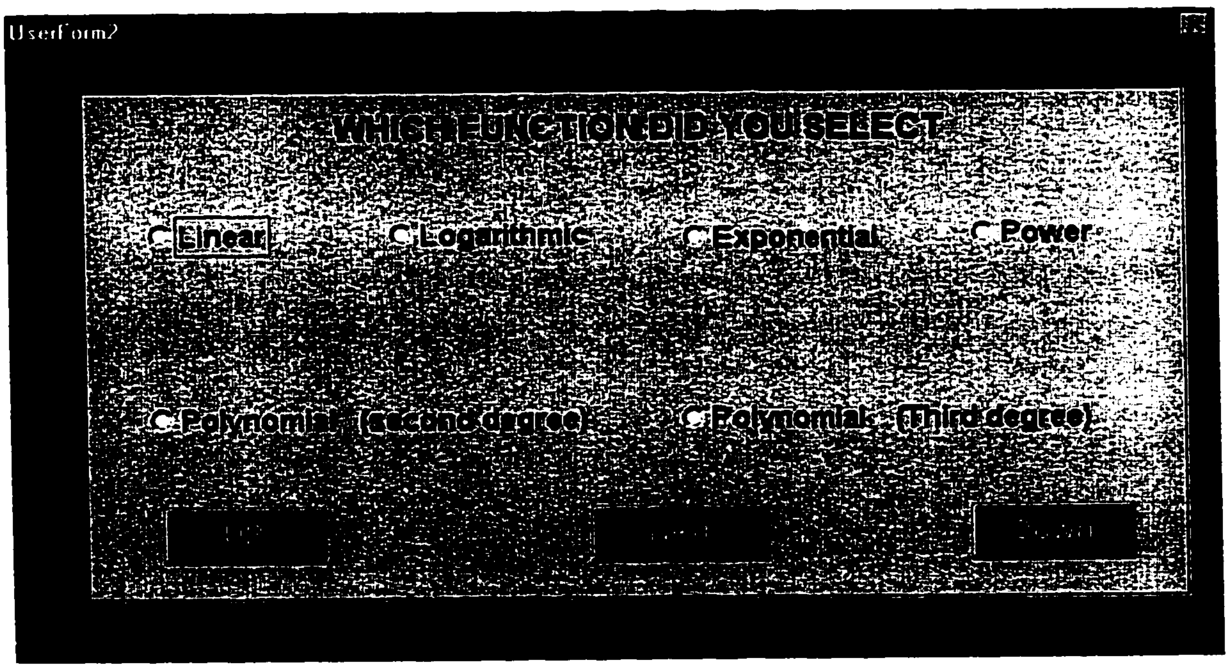


Figure 4-10: Selection of Utility Functions

Upon constructing the utility functions and calculating the various utility values of attributes, the system then establishes the relative weights for the decision criteria. In so doing, the system gives the choice to the user as to use pre-defined weights, or, alternatively, let the system calculate them automatically (Figure 4-11). This flexible design was made to accommodate different user requirements and to reduce the program execution time in case of frequent uses. In case the user selects the first choice (i.e. use pre-defined set of weights), the system prompts the user to specify the file name in which the weights are saved, or, alternatively, to feed in weights of his choice (Figures 4-12 and 4-13). But, if the user selects the second choice (i.e. the system is to calculate the weights), then the system prompts the user to a relative importance screen, in which he or she has to feed in the relative importance factors (Figure 4-14). It should be noted that these relative importance factors are based on a scale of 1-9. Since the relative importance factors are in a matrix form (i.e. the screen shown in Figure

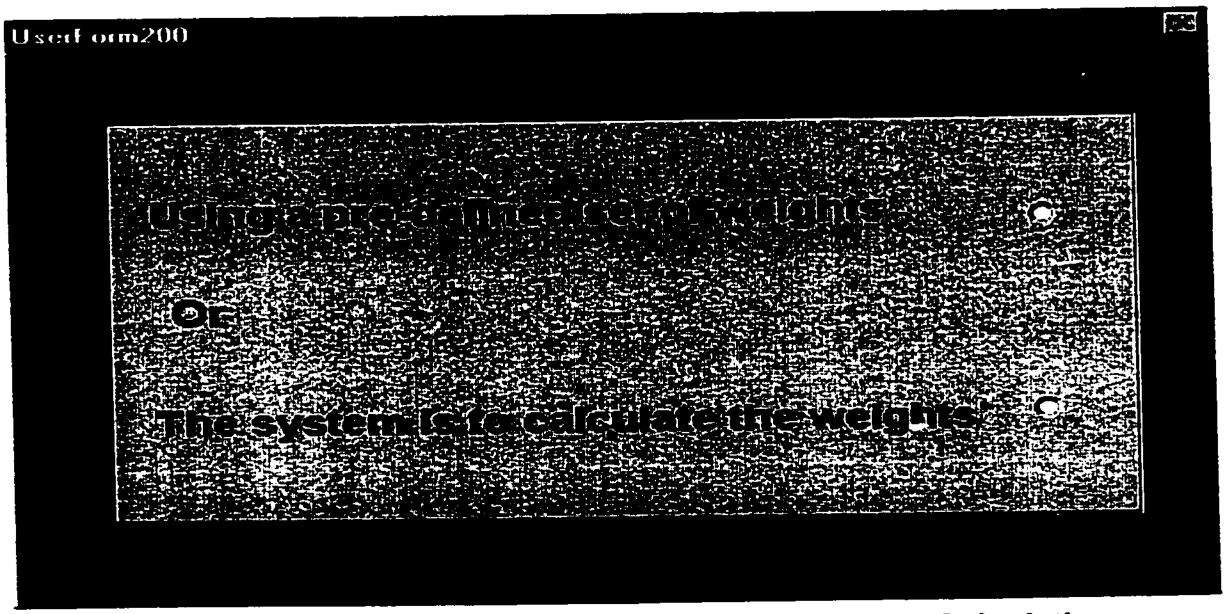


Figure 4-11: Selection of Required Mode of Weight Calculation

4-14), the user is required to fill in one triangle only (i.e. above or bellow the diagonal), and the other one is generated automatically. This was done to facilitate and ease the process of data entry. Once the relative importance factors have been decided by the user, the system calculates the weights of various attributes (Figure 4-15). As can be noticed From Figure 4-15, the CR is calculated for consistency monitoring. In case the CR value exceeds 10%, indicating inconsistency in assigning relative importance factors, the user is given the choice to revise his input data. Once the various weights of attributes are calculated, the system calculates the overall utility values using Equation 4-1 (Figure 4-16). To demonstrate the use and capabilities of the developed system, a case example has been designed and worked out in Chapter 5.

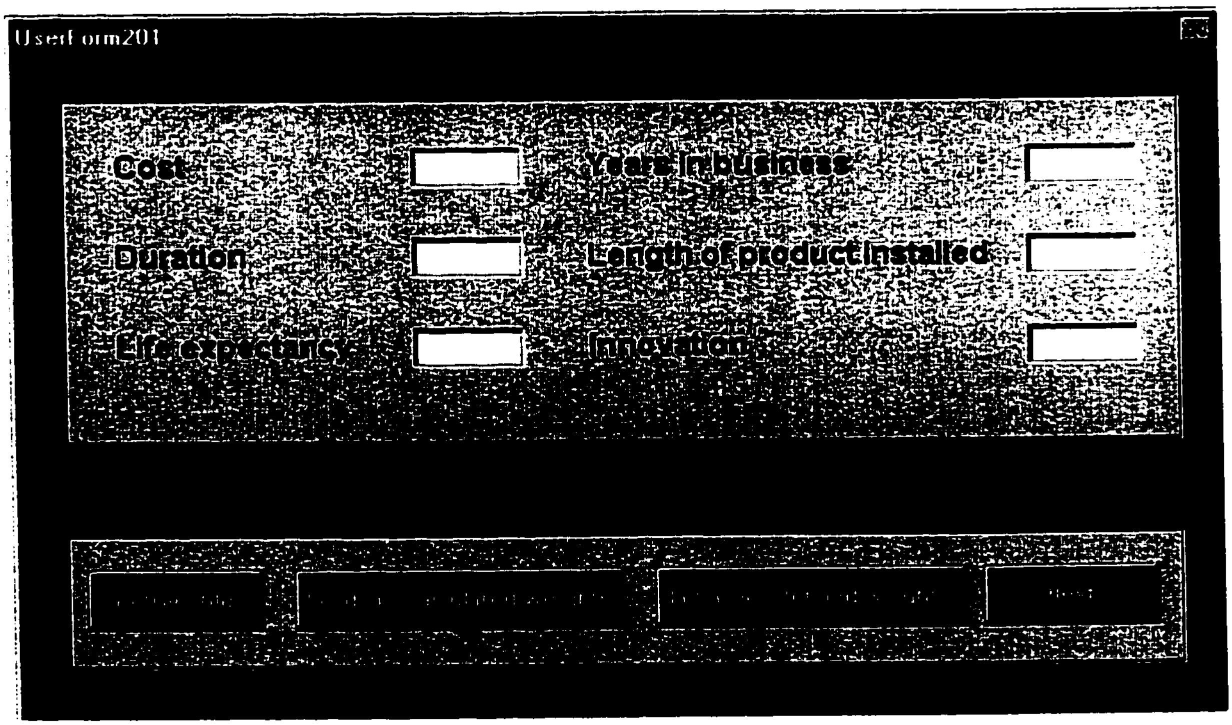


Figure 4-12: Feeding a Pre-Calculated Set of Weights

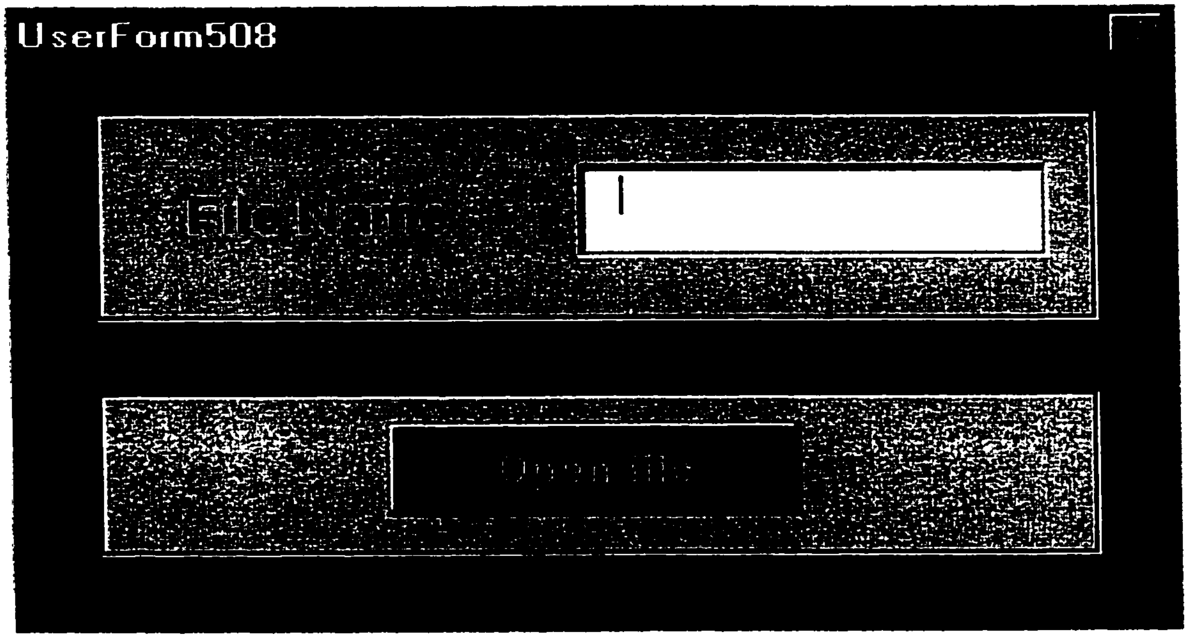


Figure 4-13: Retrieving a Pre-Defined Set of Weights

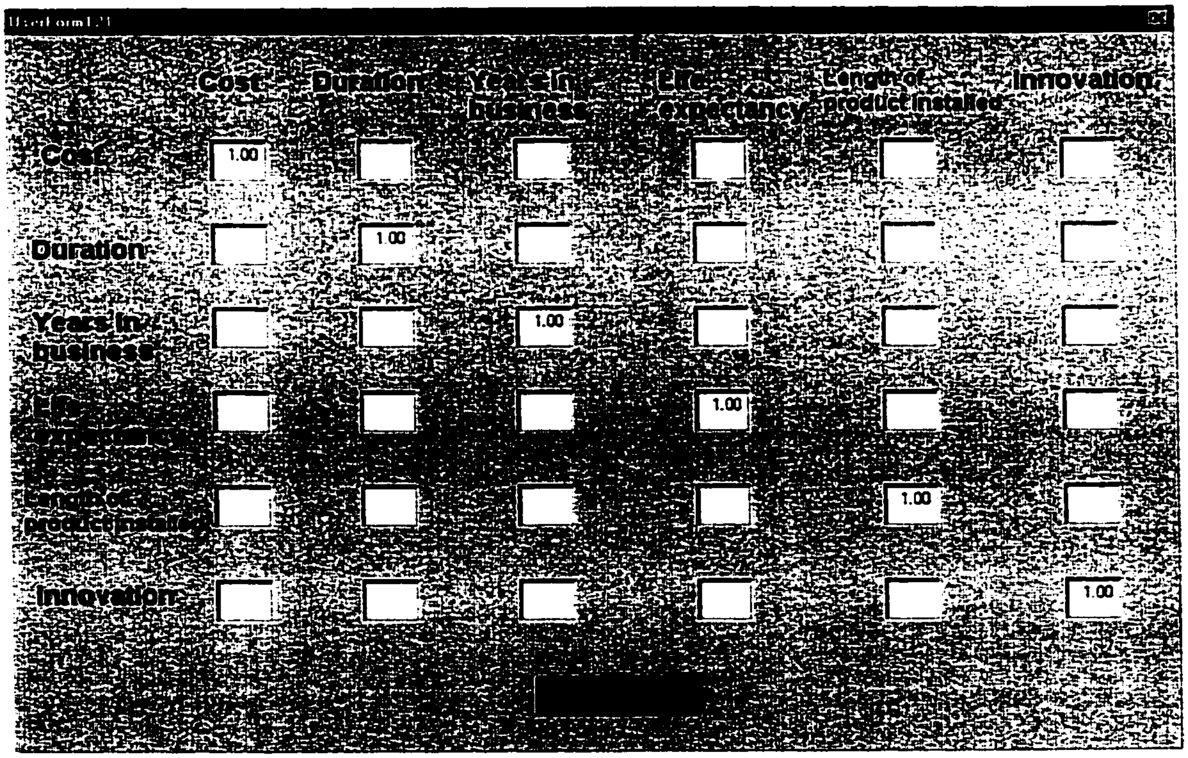


Figure 4-14: Relative Importance Screen

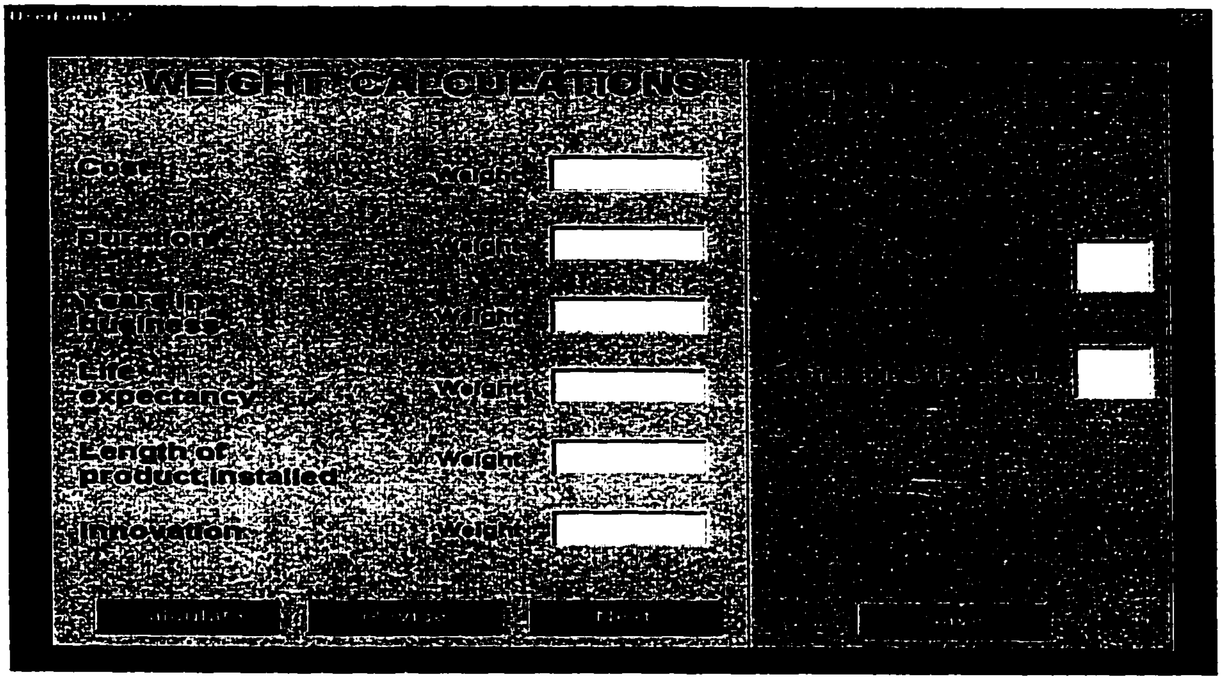


Figure 4-15: Weight Calculation Screen

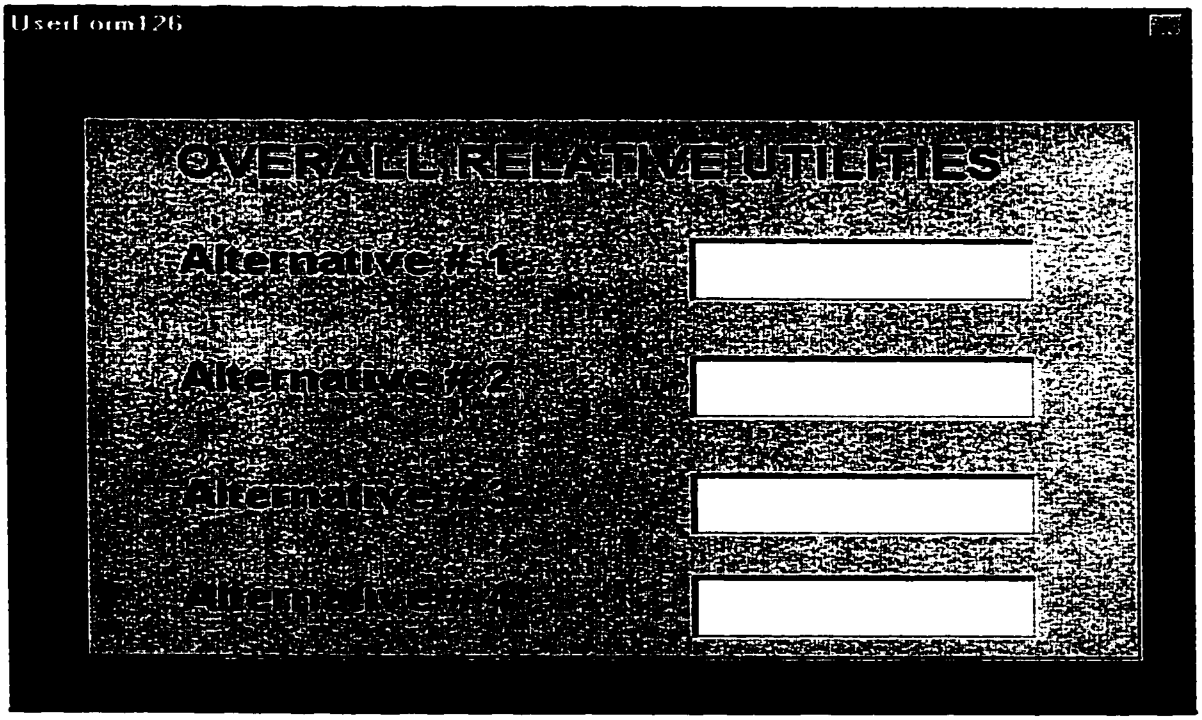


Figure 4-16: Overall Utility Values

CHAPTER 5

VALIDATION OF THE DEVELOPED AUTOMATED SYSTEMS

5.1 INTRODUCTION

This chapter presents application examples to test and validate the developed AUTO-DETECT and AUTO-SELECT systems. These examples also demonstrate the capabilities of the developed systems. The application example on AUTO-DETECT was randomly selected from the sewer network of Hamilton, Ontario, Canada. The application example on AUTO-SELECT demonstrates the capabilities of the developed system and the various uses of trenchless rehabilitation techniques (No-Dig construction).

5.2 APPLICATION OF AUTO-DETECT SYSTEM

Upon completion of AUTO-DETECT design, testing and training using the initial set of patterns, a videotape depicting the conditions of randomly selected segments of the sewer network at Hamilton municipality was considered.

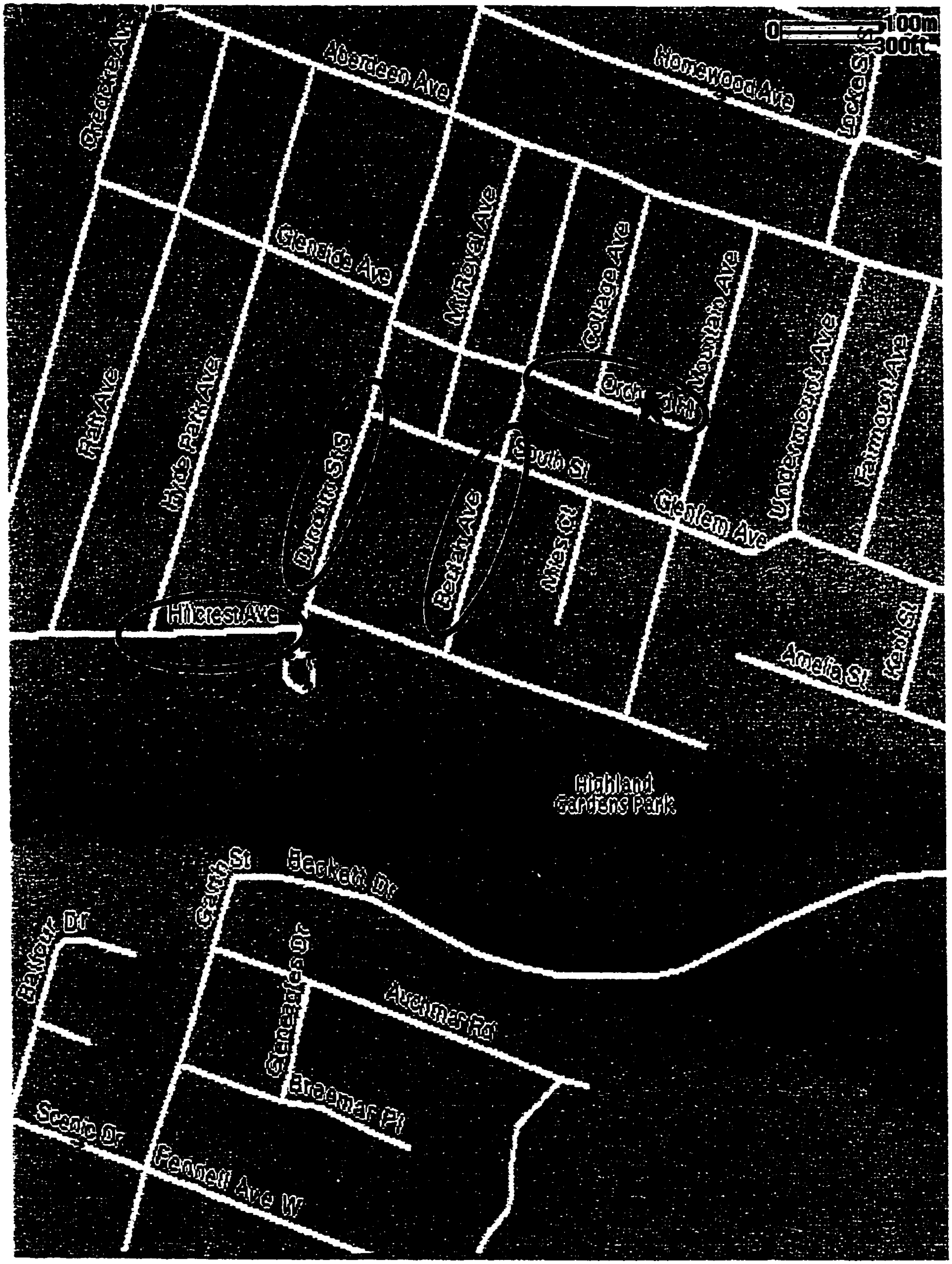


Figure 5-1: Location of Sewer Pipes

The videotape depicts the conditions of sewer pipes that were laid under Beulah, Orchard, Hillcrest and Dundurn Streets. The pipes are made of concrete and clay and their diameters range from 300 (mm) to 675 (mm). The total length of pipes is approximately 350 (m) and their burial depth ranged from 1.2 (m) to 3.7 (m). The locations of these sewer lines are shown in Figure 5-1. To detect and classify defects automatically, the videotape was processed three times as per the processes outlined in Table 3-2, utilizing Scion Image software package. The purpose of the first pass was to detect and classify three categories of defects: deposits, x-sectional reductions (i.e. root intrusions) and misalignments. It should be noted that the output of this process was a set of feature vectors (i.e. one for each detected object).

The extracted feature vectors of objects depicted in the various video images were fed into DepositsNet 1 for classification. The output values ranged from 0 to 1. A threshold value of 50% was considered for positive classification. After defining the selected threshold value to the developed network, the data was further processed and the final output results were obtained. Figures 5-2 depicts a sample of the obtained results. In this figure, the results of the automated classification process are presented in columns "D" and "E", while the actual classification is in columns "A" and "B". By comparing columns "A", "B", "D" and "E" in Figure 5-2, it was found that DepositsNet 1 was able to classify "Deposits" and "Else" with 100% and 93.3% accuracy, respectively. The complete output results of this classifier are shown in Figure D-1 in Appendix D.

To apply the multiple classifier system, the same file of feature vectors was further fed into DepositsNet 2 and DepositsNet 3 neural networks. By comparing the results obtained from DepositsNet 1, 2 and 3, it was found that the overall performance of the system is100% and 93.3% accuracy for "Deposits " and "Else", respectively. It should be noted that for all classifications, the accuracy is measured in comparison with the performance of a human inspector.

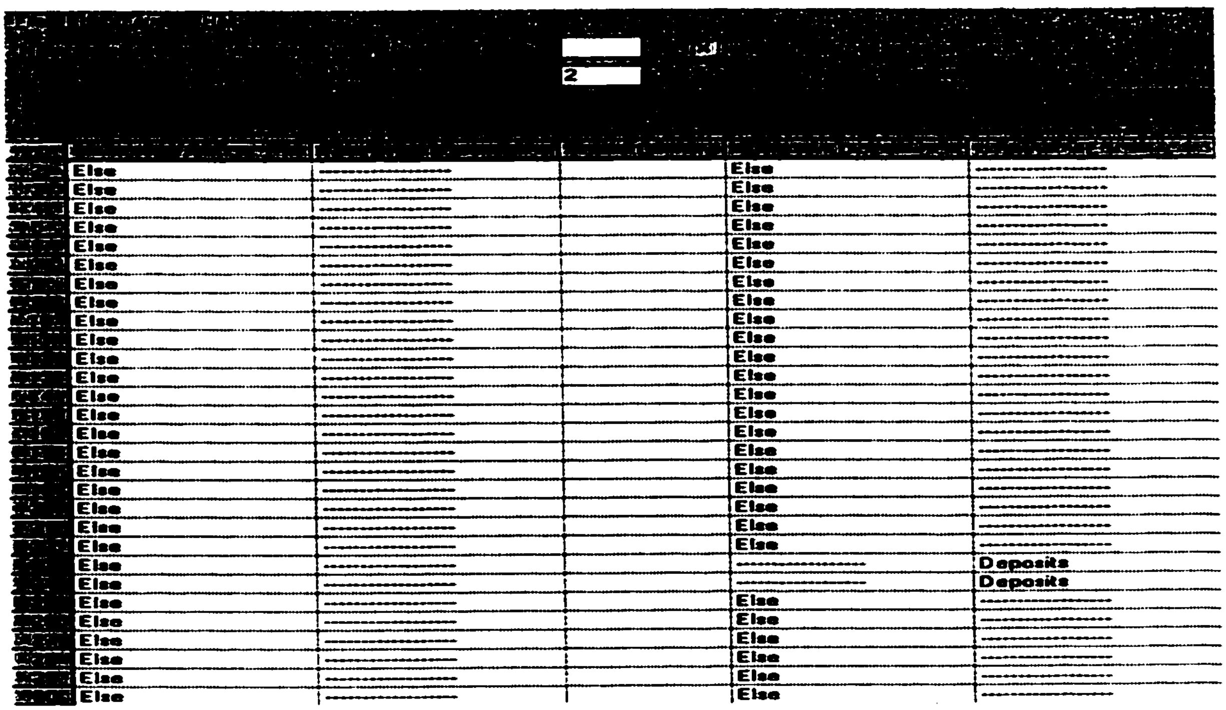


Figure 5-2: A Sample Screen Generated by DepositNet 1

Objects having coordinates (1,1) and classified as "Else" (i.e. not deposits) by DepositNet 1, 2 and 3 were then further processed by CrossNet 1. The purpose of this process was to classify x-sectional reductions. Upon classifying those objects it was found that the level of accuracy associated with "x-sectional reductions" and "Else" was 87.5 % and 60%, respectively. In an effort to improve the accuracy of this classifier, all objects that were misclassified by the system were re-visited with the aim of extracting a common feature among them. It was noticed that the majority of misclassified objects share one common feature: small areas. Although the area of objects is one of the parameters considered in designing and training the developed neural networks, it was also represented as a ratio to the cross-sectional area of pipe rather than an absolute term (i.e. "area of object / x-sectional area of pipe"). The performance and design parameters of these newly developed neural networks is shown in Tables A-15 to A-20 in Appendix A. It should be noted that these modified neural networks are designated as ModcrossNet 1, 2 and 3.

Upon testing the newly developed set of neural networks, a significant improvement was noticed. ModcrossNet 1 was able to classify both "X-sectional Reductions and "Else" with accuracy of 87.5% and 90.5%, respectively. To apply the multiple classifier system, the same process was also repeated utilizing ModcrossNet 2 and ModcrossNet 3 neural networks. ModcrossNet 2 was able to classify "X-Sectional Reductions" and "Else" with accuracy of 87.5% and 89%, respectively. Similarly, ModcrossNet 3 was able to classify the same categories with accuracy of 87.5% and 92%, respectively. By comparing the results obtained from ModcrossNet 1, 2 and 3, it was concluded that the overall accuracy of the system is 87.5% and 90.5% with respect to "X-sectional Reductions" and "Else", respectively. A sample output of ModcrossNet 1 is shown in Figure 5-3. A complete output results of ModcrossNet 1 is shown in Figure D-2 in Appendix D.

------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
X-sectional Reduction	------------------		X-sectional Reductions	------------------
X-sectional Reduction	------------------		X-sectional Reductions	------------------
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		X-sectional Reductions	------------------
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		------------------	Else
------------------	Else		X-sectional Reductions	------------------
X-sectional Reduction	------------------		------------------	Else

Figure 5-3: A Sample Screen Generated by ModcrossNet 1

To classify misalignments, all objects classified as "Else" (i.e. not deposits) by DepositsNet 1, 2 and 3, and their coordinates are (1,1), were further processed utilizing MisalignmentNet 1. The output values ranged from 0 to 1. A threshold value of 50% was considered for positive classification. After defining the selected threshold value to the developed network, the data was further processed and the final output results were obtained. Figure 5-4 depicts a sample output generated by MisalignmentNet 1. It was found that

MisalignmentNet 1 was able to classify "Misalignments" and "Else" with 93.3% and 68.5% accuracy, respectively. To apply the multiple classifier system, the same process was repeated utilizing MisalignmentNet 2 & 3. MisalignmentNet 2 was able to classify "Misalignments" and "Else" with accuracy of 73.3% and 79.6%, respectively. Similarly, MisalignmentNet 3 was able to classify the same categories with accuracy of 80% and 85.2%, respectively. By comparing the results obtained from MisalignmentNet 1, 2 and 3, it can be concluded that the overall accuracy of the system is 80% and 81.5% with respect to "Misalignments" and "Else", respectively. A sample output of MisalignmentNet 1 is shown in Figure 5-4. A complete output results of MisalignmentNet 1 is shown in Figure D-3 in Appendix D. As can be noticed from Figure D-3 that the system depicts many misalignments. This could be attributed, in part, to the solution strategy developed for analyzing videotapes. According to this strategy, all other defects, such as deposits, are sieved before reaching the stage at which misalignments

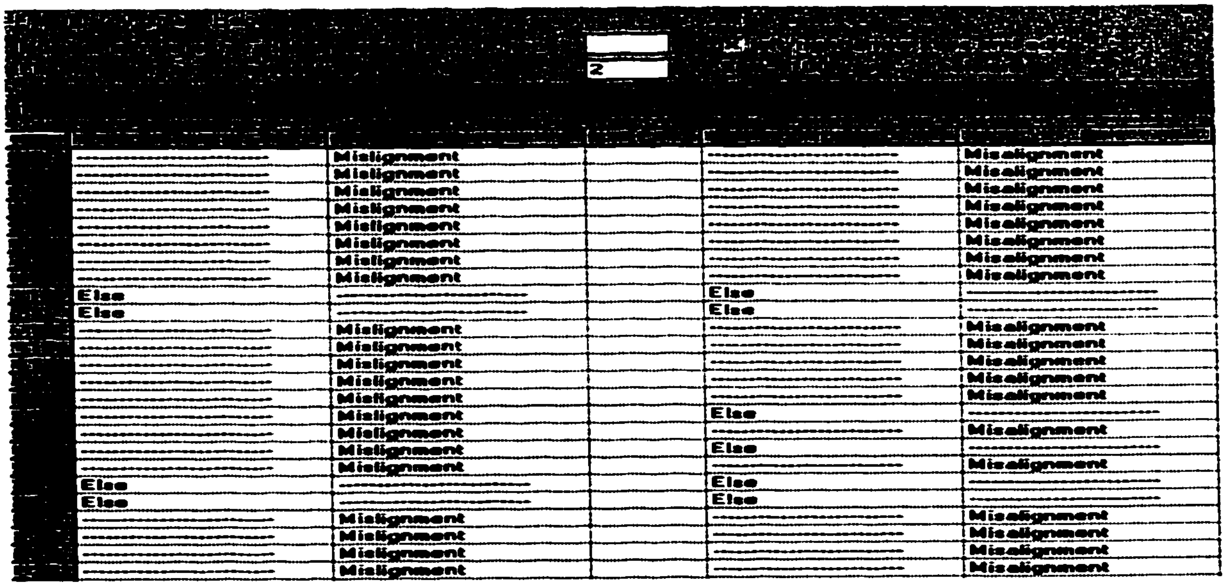
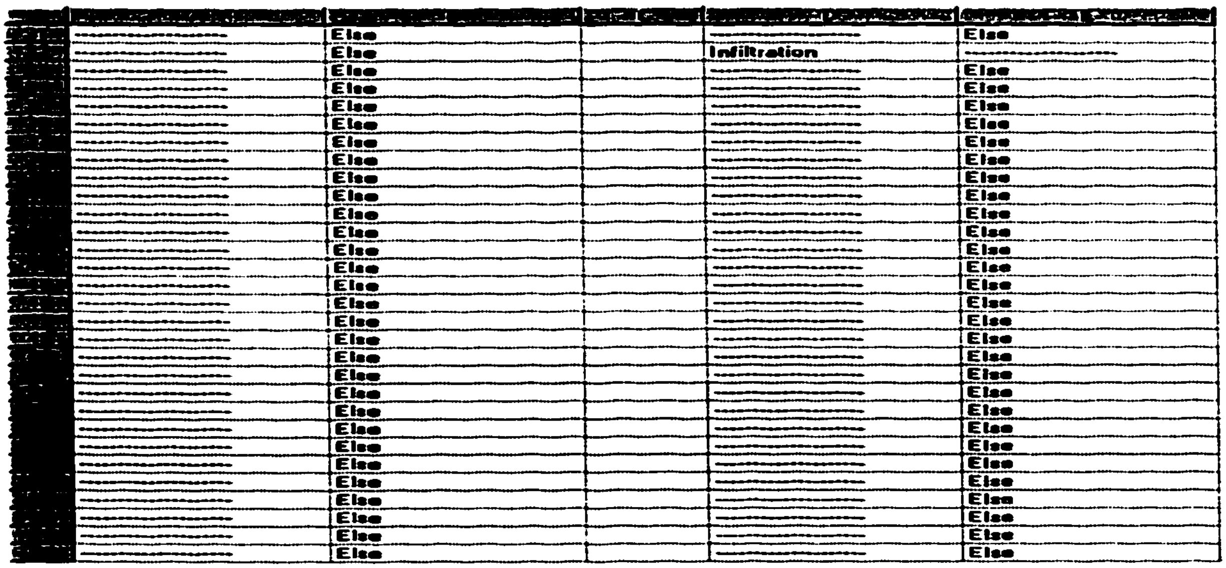


Figure 5-4: A Sample Screen Generated by MisalignmenttNet 1

and cross-sectional reductions are classified. So, by the time this stage is reached, most of the detected defects are either misalignments or cross-sectional reductions. Further, the most common type of defect in sewer pipes was found to be misalignments. This is in accordance to the survey conducted by the municipality of Hamilton as shown in Figure 3-1 (Regional municipality of Hamilton 1997).

To detect and classify infiltration, all images were processes for the second time as per the techniques outlined in Table 3-2. The extracted feature vectors of objects depicted in various video images were fed into InfiltrationNet 1 for classification. Figure 5-5 depicts a sample of the obtained results. This classifier was able to classify “Infiltration” and “Else” with accuracy of 54.5% and 91.6%, respectively. A complete output results of InfiltrationNet 1 is shown in Figure D-4 in Appendix D.



----------	Else		----------	Else
----------	Else		Infiltration	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else

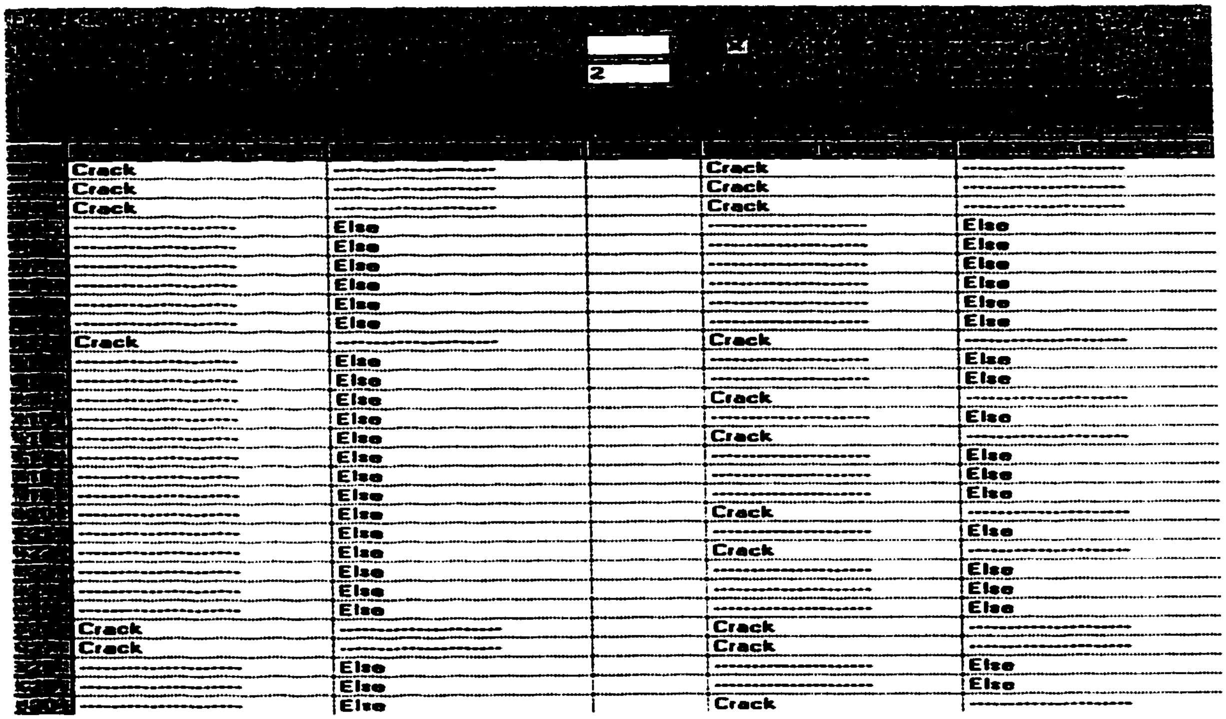
Figure 5-5: A Sample Screen Generated by InfiltrationNet 1

To apply the multiple classifier system, the same process was repeated utilizing InfiltrationNet 2 and InfiltrationNet 3 neural networks. InfiltartionNet 2 was able to classify "Infiltration" and "Else" with accuracy of 91% and 88.6%, respectively. Similarly, InfiltrationNet 3 was able to classify "Infiltration" and "Else" with accuracy of 91% and 90.2%, respectively. By comparing the results obtained from InfiltrationNet 1, 2 and 3, it can be concluded that the overall accuracy of the system is 91% and 92.7% with respect to "Infiltration" and "Else", respectively.

To detect and classify cracks, the images were further processed for the third time as per the techniques outlined in Table 3-2. The extracted feature vectors of objects depicted in various video images were fed into CrackNet 1 for classification. Figure 5-6 depicts a sample of the obtained results. CrackNet 1 was able to classify "Cracks" and "Else" with 82% and 80.3% accuracy, respectively. A complete output results of CrackNet 1 is shown in Figure D-5 in Appendix D.

To apply the multiple classifier system, the same file of feature vectors was further processed utilizing CracksNet 2 and InfiltrationNet 3 neural networks. CracksNet 2 was able to classify "Crack" and "Else" with accuracy of 82% and 80%, respectively. Similarly, CracksNet 3 was able to classify both categories with accuracy of 80%. By comparing the results obtained from CracksNet 1, 2 and 3, it can be concluded that the overall accuracy of the system is 82% and

80% with respect to "Crack" and "Else", respectively. It should be noted that this accuracy is measured in comparison with the performance of a human inspector.



Crack	-		Crack	-
Crack	-		Crack	-
Crack	-		Crack	-
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
Crack	-		Crack	-
-	Else		-	Else
-	Else		-	Else
-	Else		Crack	-
-	Else		-	Else
-	Else		Crack	-
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
-	Else		Crack	-
-	Else		-	Else
-	Else		Crack	-
-	Else		-	Else
-	Else		-	Else
-	Else		-	Else
Crack	-		Crack	-
Crack	-		Crack	-
-	Else		-	Else
-	Else		-	Else
-	Else		Crack	-

Figure 5-6: A Sample Screen Generated by CrackNet 1

5.3 APPLICATION OF AUTO-SELECT SYSTEM

Consider that a CCTV inspection of a 500(m) sewer line indicated major cracks in the wall of a pipe located in a commercial area, necessitating the use of trenchless rehabilitation technique, rather than the traditional open-cut. Consider further that the contract calls for the use of new innovative materials and methods, if required. It is required to select the most suitable repair method for this sewer line considering the technical specifications, contractual and user's requirements summarized in Table 5-1.

Upon completion of data entry, two methods of rehabilitation were suggested by AUTO-SELECT (see Figure 5-7). Due to the presence of more than one suggested method of rehabilitation, the decision support system was activated. Upon identifying the user preferences and levels of importance, through a set of interactive questions, the utility functions were generated, weights of attributes determined and the consistency ratio calculated as shown in Figure 5-8. Based on the R^2 value, second degree polynomial, linear, third degree polynomial, third degree polynomial, third degree polynomial and third degree polynomial functions were selected to best represent the utility functions for cost, duration, years in business, life expectancy, length of product installed and innovation, respectively. Based on the various levels of importance that were entered into the system, the consistency ratio was found acceptable (0.08), being < 0.1. It should be noted that the consistency ratio provides a measure for the degree of consistency in the data entered by the user, expressing the relative importance of various attributes considered in the decision hierarchy. Values in excess of 10% suggest inconsistent values entered by the user, and accordingly, the system prompts the user to reexamine the data entered. Based on the calculated overall utility value for each rehabilitation method, the decision was made to select rehabilitation method # 1 due to its higher overall utility value (Figure 5-9). It should be noted that the higher the utility value, the higher the degree of satisfaction with the selected method in fulfilling the selection criteria.

Table 5-1: Project Requirements

CRITERIA	REQUIREMENTS
Type of repair	Structural
Diameter of pipe	30 (cm) or (12 in)
Degree of bends	Up to 45°
Ability to improve the hydraulic characteristics	Improved
Distance between access points	100 (m)
Ability to accommodate future differential settlement	Yes
Duration of project	One week
By-pass requirements	Yes
Years in business and length of product installed	5 years and 200(km) (at least), respectively
Life expectancy	50 years (at least)
Locality of suppliers	Yes
Type of access to the original pipe	Manholes only
Method of service connections	Excavation pits are not required
Degree of innovation	Not less than 2
Cost of product	Not greater than $ 6 /cm of diameter/linear meter of pipe

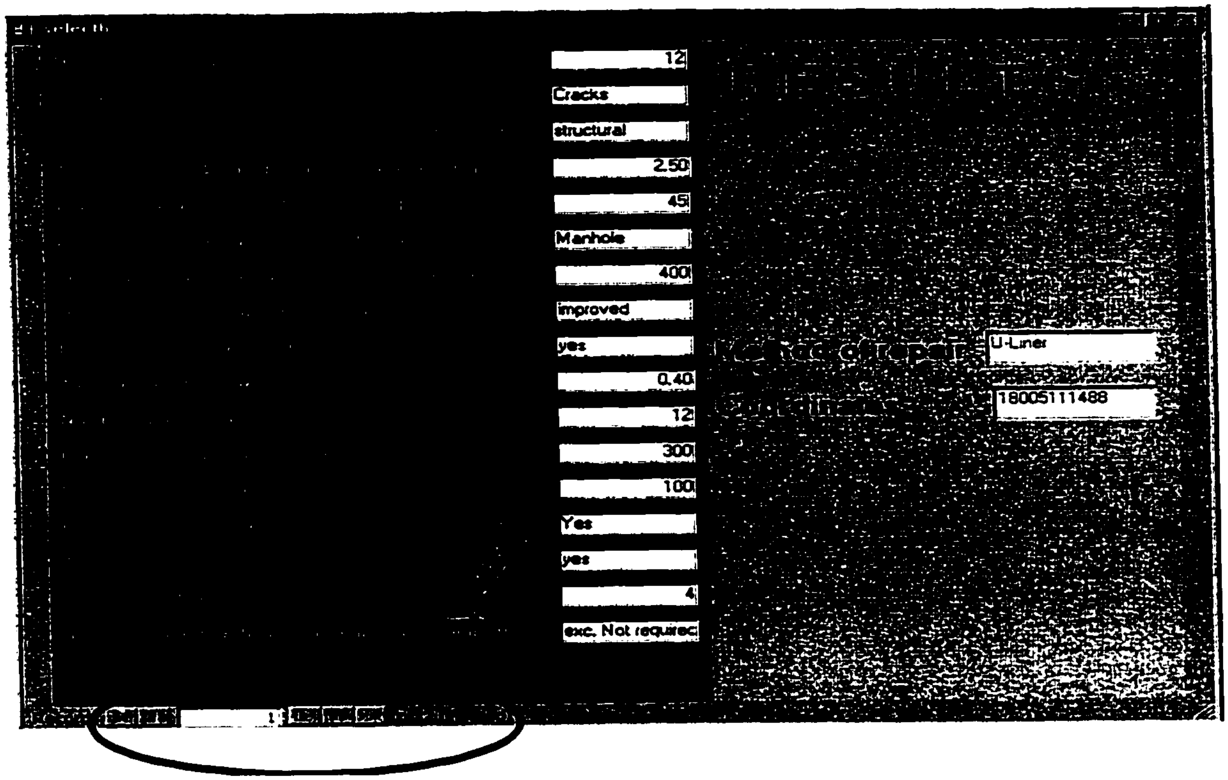


Figure 5-7: Database Output

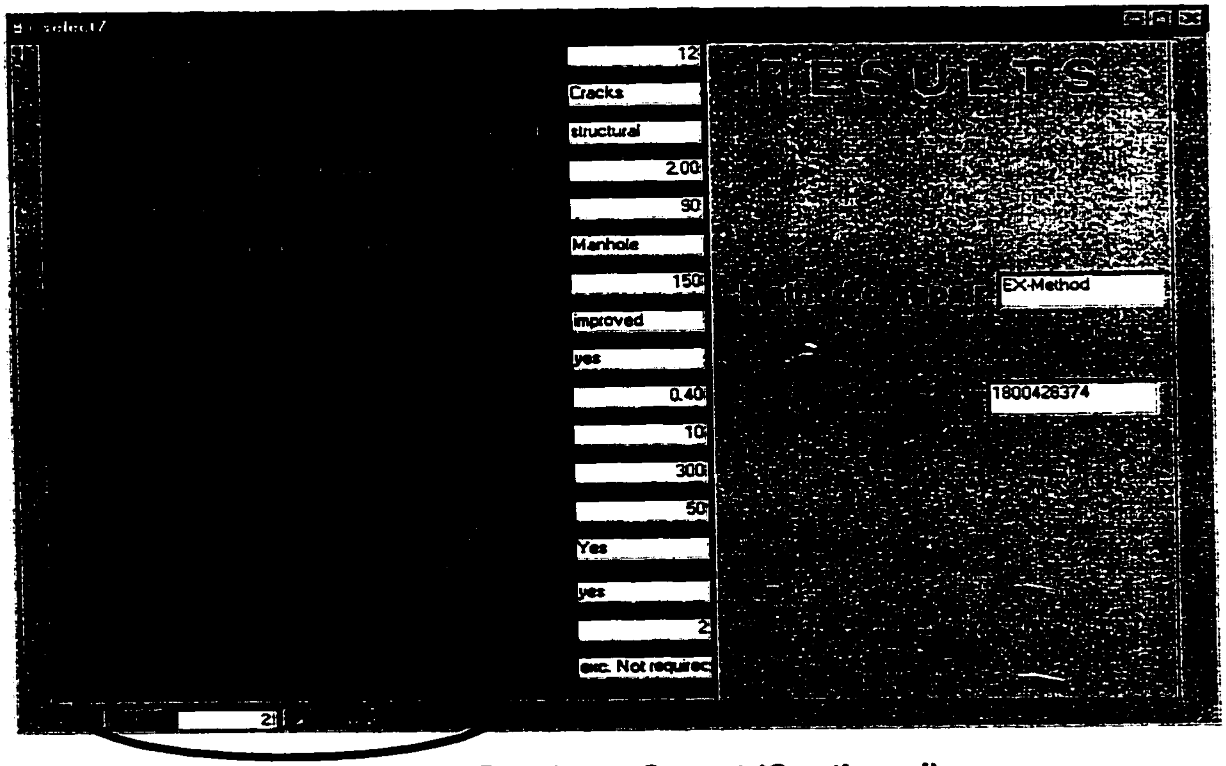


Figure 5-7: Database Output (Continued)

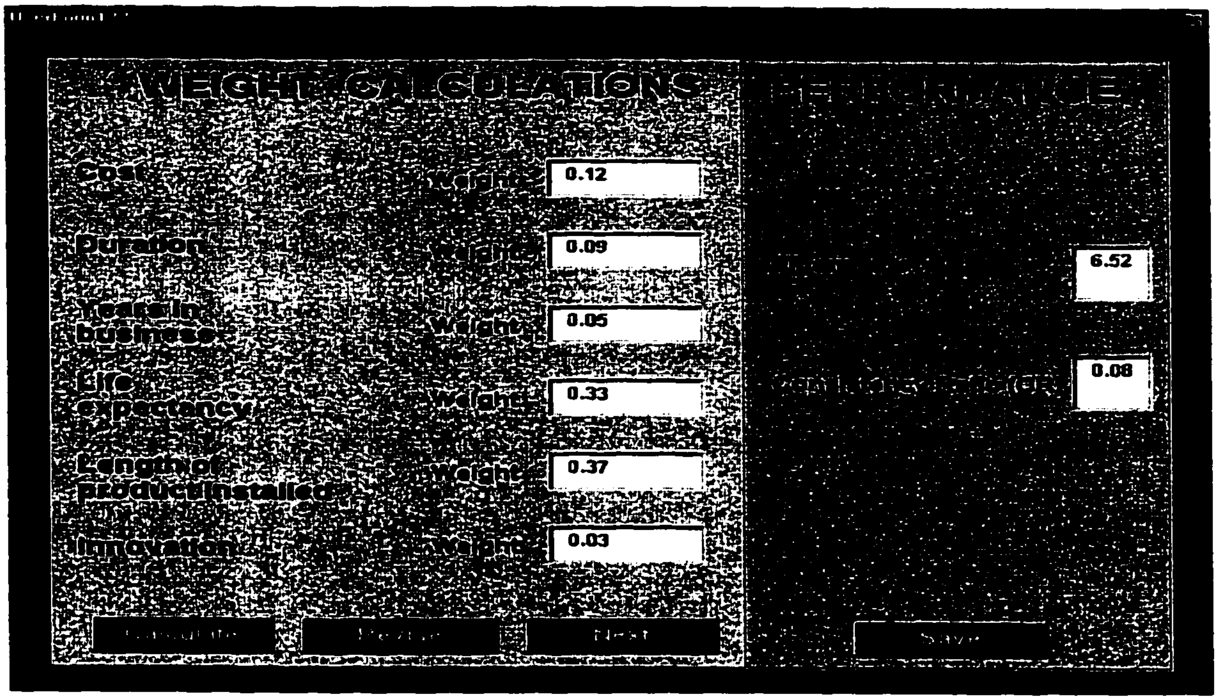


Figure 5-8: Weight Calculations for a Case Example

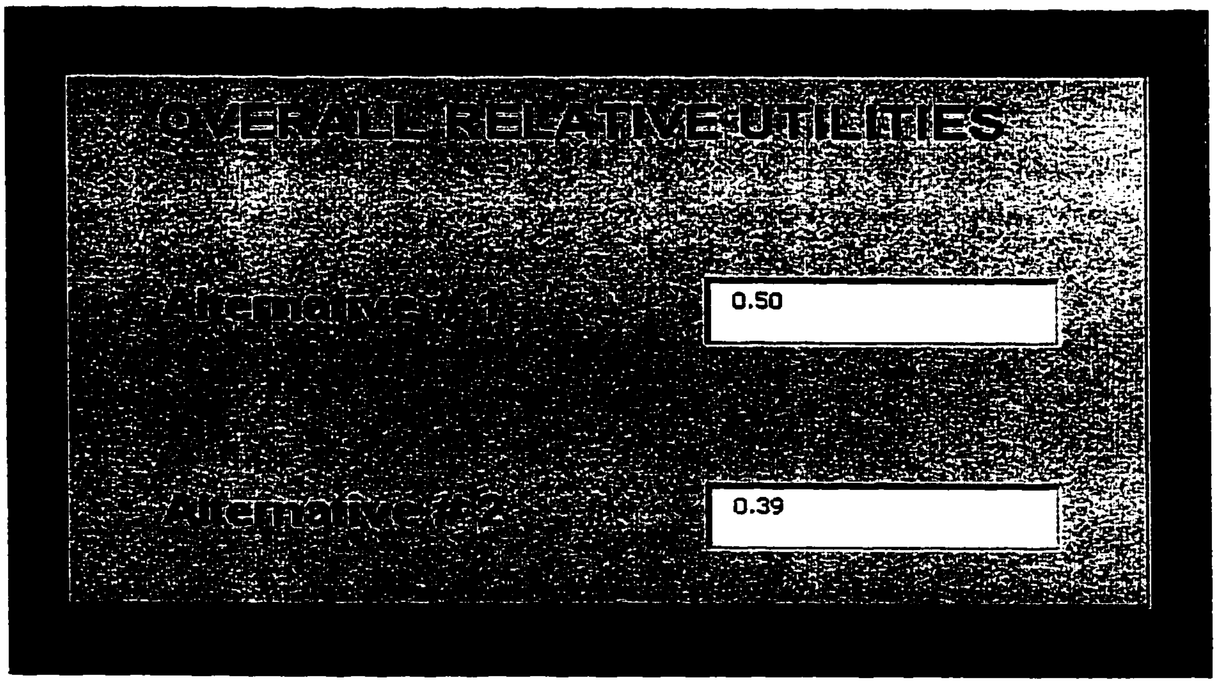


Figure 5-9: Overall Utilities for a Case Example

CHAPTER 6

SUMMARY, LIMITATIONS AND RECOMMENDATIONS

6.1 SUMMARY

A methodology for detection, classification and rehabilitation of defects in sewer pipes has been developed. The developed methodology was implemented in two automated systems: AUTO-DETECT and AUTO-SELECT. AUTO-DETECT detects and classifies defects in sewer pipes automatically. The system utilizes frame grabber, image analysis software and artificial intelligence software for performing its task. The frame grabber captures and digitizes the frames of the acquired images. The image analysis software analyzes those digitized images and processes them in a manner so as to prepare a suitable input to neural networks (i.e. feature vectors). The neural networks are then used to classify the processed image into five categories of defects. These categories are deposits, x-sectional reductions, misalignments, infiltration and cracks. As such, the system is designed to acquire video images, analyze them in a manner that defects are detected and classified automatically. It should be noted that establishing an automated link between the image analysis and the artificial intelligence software packages was not attempted.

To improve the overall performance of the developed automated detection and classification system, it was supplemented by a multiple classifier system that counter checks the results obtained from several neural networks in a similar manner to a team of human experts. The automated inspection system was validated using actual data (recorded on a videotape) of conditions of randomly selected sections of the sewer network at Hamilton municipality. The data used covers about 450 (m) of sewer pipes. The data was processed and a total of 679 patterns were detected. The detected patterns were classified and accuracy ranged from 80% to 100% was reported.

AUTO-SELECT is a multi-attribute decision support system designed to select and rank the most suitable rehabilitation methods for sewer pipes. The system utilizes two modules: 1) DBMS and 2) DSS. The modules were developed utilizing Microsoft Access and Visual Basic. The developed relational database assists in identifying suitable trenchless rehabilitation techniques that satisfy a total of sixteen factors which account for technical, contractual and cost requirements of projects as well as user specified preferences. The factors are type of defect, structural repair, diameter of pipe, degree of bends, ability to improve the hydraulic characteristics of original pipe, distance between access points, duration of project, by-pass requirements, ability to accommodate future settlements, years in business, length of product installed, life expectancy of products, availability of local suppliers, type of access to the original pipe, method of service connections, degree of innovation and cost of product. In case of having more than one suitable rehabilitation method, a DSS, utilizing MAUT, was developed to evaluate and rank them and, accordingly, suggest the most suitable one. A case example has been worked out to demonstrate the use and capabilities of the developed system. It should be noted that AUTO-DETECT and AUTO-SELECT are not automatically linked and function primarily as standalone systems.

6.2 LIMITATIONS OF THE DEVELOPED SYSTEMS

The developed systems are limited to concrete and clay sewer pipes and to the range of parameters used in the developments. Below are a set of specific itemized limitations of AUTO-DETECT and AUTO-SELECT.

I- AUTO-DETECT

- The developed system is limited to inspection of concrete and clay pipes.
- The system is applicable to diameters ranging from 200 (mm) to 1000 (mm).
- The system is limited to detection and classification of cracks, misalignments, deposits, cross-sectional reductions and infiltration.

II- AUTO-SELECT

- The system is limited to rehabilitation of concrete and clay pipes.
- The information stored in the system's database were collected from material suppliers and have not been checked with end users, such as

consultants, contractors and municipal engineers, to ascertain the stated performance.

- The system can be used once a decision has been made to proceed with repair rather than replacement.

6.3 RESEARCH CONTRIBUTIONS

The contributions of this research can be summarized as:

1- The development of an automated inspection system (AUTO-DETECT) for detection and classification of defects in sewer pipes. AUTO-DETECT is expected to save significant time and money in performing the inspection of sewer pipes. The system also provides an incentive for checking sewer pipes more regularly; this will help municipality engineers to plan ahead suitable preventive maintenance programs and avoid unpleasant surprises. A US provisional patent (no. 60/252,484) was granted for the developed system.

2- A multiple classifier system was developed to improve the overall performance of AUTO-DETECT and the user's confidence in its obtained results.

3- The development of an automated rehabilitation system (AUTO-SELECT) for suggesting the most suitable trenchless rehabilitation techniques for sewer pipes. The system assists municipal engineers and contractors in selecting the most suitable trenchless rehabilitation technique. It also facilitates transfer of knowledge and experience to new engineers who are involved in sewer pipes rehabilitation projects.

4- The development of a decision support system to evaluate and rank different alternatives in a multi-attributed decision environment.

6.4 RECOMMENDATIONS FOR FUTURE RESEARCH

1- This research presented a model for automating the process of inspection of sewer pipes. The same proposed methodology could be extended for inspection of other infrastructure facilities such as water pipes. The proposed methodology could be further extended to determine the severity of defects.

2- The proposed methodology utilized in developing AUTO-DETECT can be further expanded to develop an automated system for inspection of manholes. The surface conditions of these manholes can be recorded using the CCTV cameras as it enters the sewer pipes.

3- The output generated by AUTO-DETECT can be utilized, along with other parameters, as an input to another artificial intelligence system (i.e. expert system or neural network) to determine the remaining life of sewer pipes. This artificial intelligence system will help municipalities to plan ahead and prevent sudden failures and unpleasant surprises. This recommended artificial intelligent system will also help municipalities to better plan for budget allocations.

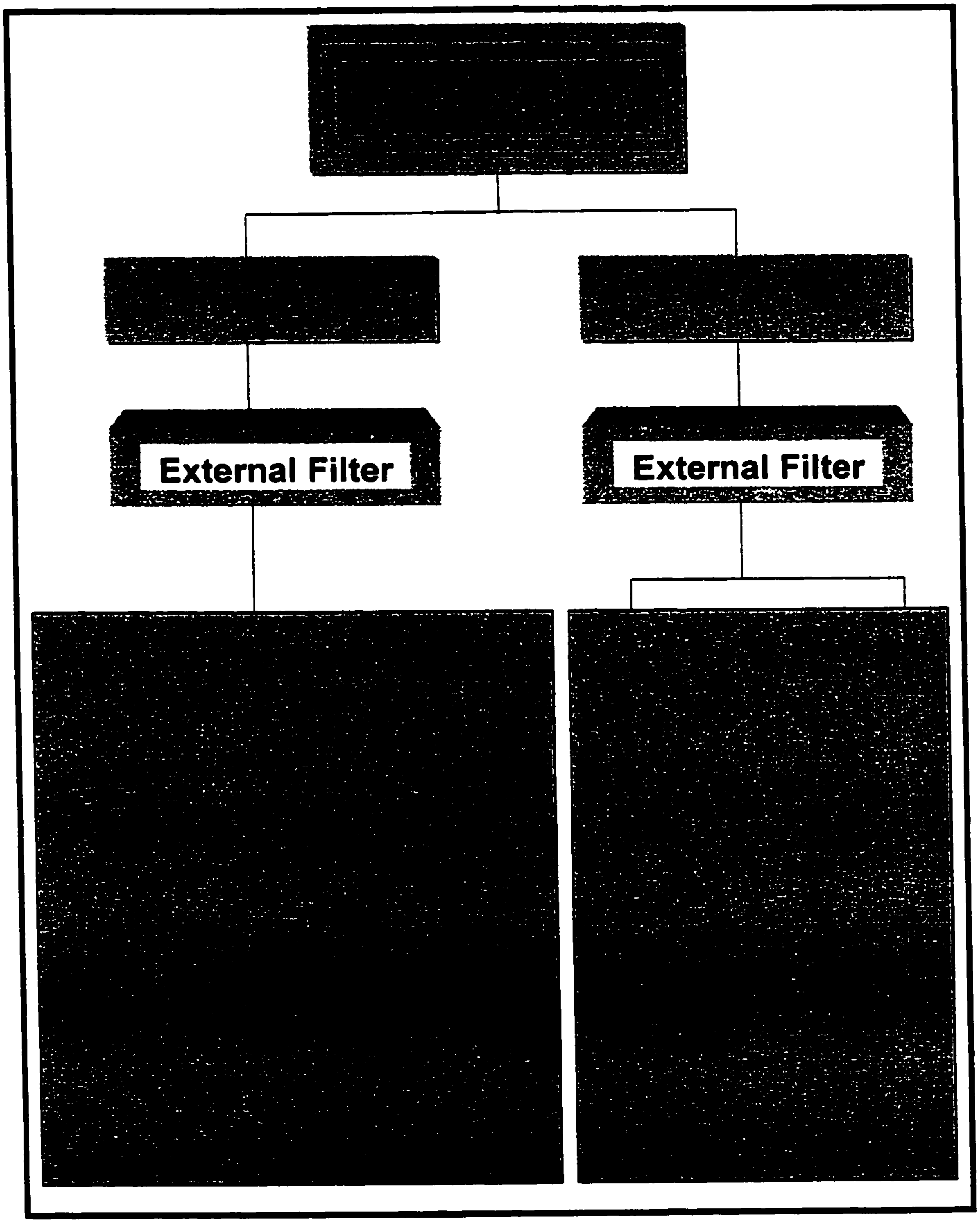
4- The performance of the developed AUTO-DETECT can be further improved by introducing external filters to screen out all common non-defects (see Figure 6.1).

5- Field experiments should be made to recommend proper operating instructions (i.e. light intensity, degree of focus, camera direction.... etc) for CCTV cameras. This is necessary to further improve the results obtained from AUTO-DETECT.

6- The development made in AUTO-SELECT can be extended to calculate the total cost and duration of rehabilitation projects. This can also be useful to contractors and municipal engineers.

7- The benefits realized from this research could be further enhanced by developing an automated link between AUTO-DETECT and AUTO-SELECT.

8- The benefits realized from AUTO-SELECT can be further enhanced by checking the information stored in its DBMS with municipalities, consultants and contractors.



6.1: Recommended Future Research

REFERENCES

Abraham, D., Chae, M. and Gokhale, S.(2000). " Utilizing Neural Networks for Condition Assessment of Sanitary Sewer Infrastructure." **Proceedings of the 17th International Conference on Robotics and Automation in Construction**, Taipei, Taiwan, 423-427.

Adobe PhotoShop 5 reference manual (1999). Adobe systems incorporated, San Jose, California.

Aguiar, L., Scheller, T., Cowgill, J. and Noor, I. (1996)." NO-Dig Gains Ground.", **Civil Engineering**, ASCE, 66(8), 54-57.

Al-Tabtabi, H., Alex, A. and Tantash, M. (1999)." Preliminary Cost Estimation of Highway construction Using Neural Networks." **Cost Engineering**, AACE, 41(3), 19-24.

Anderson, J. (1995). **An Introduction to Neural Networks**, MIT Press, Cambridge.

Aqua Data (2001). Wastewater Collection System Diagnosis and Analysis using the Aqua Zoom Tele-objective Camera. Available online via http://www.aquadata.com.

Ariaratnam, S., Lucke, J. and Allouche, E. (1999)." Utilization of Trenchless Construction Methods by Canadian Municipalities." **Journal of construction Engineering and Management,** ASCE, 125 (2), 76-86.

Batchelor, B. and Whelan, P. (1997). **Intelligent Vision Systems for Industry**, Cambridge University Press, Cambridge, England.

Casey, T. (1989), " Removing Roots from a Sewer System", **Public Works**, Municipal Journal & Engineer, Inc., 119(10), 134-135.

Caudill, M. and Butler, C. (1992), **Understanding Neural Networks**. MIT press, England.

Chae, M., Abraham, D. (2001)." Neuro-Fuzzy Approach for Sanitary Sewer Pipeline Condition assessment." **Journal of Computing in Civil engineering**, ASCE, 15(1), 4-14.

Chen, P. and Chang, L. (2000)," Application of Neuro-Fuzzy Thresholding to Bridge Painting Defect Recognition", **Proceedings of the 17th International**

Conference on Robotics and Automation in Construction, Taipei, Taiwan, 1105-1110.

Cheng, H. and Miyojim, M. (1998)." Novel system for Automatic Pavement distress Detection." **Journal of Computing in Civil engineering**, ASCE, 12(3), 145-152.

Cheng Y. (1999). " Design of High- Performance Concrete Mixture Using Neural Networks and Nonlinear Programming." **Journal of Computing in Civil Engineering**, ASCE, 13 (1), 36-42.

Collins, C. (1998)," Image Classification Using Neural Network Technology", **Proceedings of a Symposium on Applications of Neural Networks**, Kiel, Germany, 201-212.

Cutts, W. (1986)," Infiltration/Inflow Abatement Program Gets Results", **Public works**, Municipal Journal & Engineer, Inc., 117(3), 70-71.

Darwln, D. (1994)," Automated Crack Identification for Cement Paste", **Proceedings of an Engineering Foundation Conference**, University of New Hampshire, Durham, 613.

deMonsabert, S. and Thornton, P. (1997)," A Benders Decomposition Model for Sewer Rehabilitation Planning for Infiltration and Inflow Planning", **Water Environment Research**, Water Environment Foundation, 69(2), 162-167.

Duggan, E. W., and Dohery, D. J. 1995. Practical Selection of Trenchless Technology Methods for Sewerage and Drainage System Rehabilitation/Replacement. **Proceedings of the North American No-DIG' 95**, Chicago, Illinois,SB2: 2- 68.

Elmasri, R. and Navathe, S. (1994). **Fundamentals of Database Systems**, Redwood City, Calif. California.

Everett, J. and Saito, H. (1996)." Construction Automation: Demands and Satisfies in the United States and Japan." **Journal of Construction Engineering and Management**, ASCE, 122(2), 147-151.

Faghri, A., Martinelli, D. and Demetsky, M. (1997). **Neural Networks Application in Transportation Engineering: Fundamentals and Applications**, ASCE, New York.

Faghri, A. and Hua, J. (1995). " Roadway Classification Using Neural Networks." **Journal of Computing in Civil Engineering**, ASCE, 9 (3), 209-215.

Fausett, L. (1994). **Fundamentals of Neural Networks, Architecture, algorithms and Applications**, Prentice- Hall, Inc., New Jersey.

Flood, I. and Kartam, N. (1994 (A))."Neural Networks in Civil engineering. A: Principles and Understanding." **Journal of Computing In Civil Engineering**, ASCE, 8 (2),131-148.

Flood, I. and Kartam, N. (1994 (B))."Neural Networks in Civil engineering. B: Principles and Understanding." **Journal of Computing In Civil Engineering**, ASCE, 8 (2),149-162.

Freeman, C. (1997), **Microsoft access 97 Step by Step**, Microsoft Press, Redmond, Washington.

Gokhale, S., Abraham, D. and Iseley, T. (1998)," Intelligent Systems Evaluation Technologies- An Analysis of Three Promising Options". **Proceedings of the North American No Dig 98**, New Mexico, 254-256.

Gokhale, S., Hastak, M. and Huang, R. (2000), " Automated Assessment Technologies for Renewal of Underground Pipeline Infrastructure", **Proceedings of the 17th International Conference on Robotics and Automation in Construction**, Taipei, Taiwan, 433-438.

Gonzalez, R, and Wintz, P. (1997), **Digital image processing**, 2nd Edition, Addison – Wesley Publishing Company.

Gose, E., Johansonbaugh, R. and Jost, S. (1996). **Pattern recognition and image analysis**, Prentice Hall, Inc, N. J.

Hadipriono, F., Larew, R. and Lee, O. (1987)." Service Life Assessment of Concrete Pipe." **Journal of Transportation Engineering**, ASCE, 114(2), 209-220.

Hason, S. (1994). **Feasibility and Implementation of Automation and Robotics in Canadian Building Construction Operations**. Masters theses, Concordia University. Montreal, Canada.

Hegazy, T. Fazio, P. and Moselhi,O. (1994)."Developing Practical Neural Network Applications Using Back-Propagation." **Microcomputing in Civil Engineering**, ASCE, 9 (2),145- 159.

Hogan, M. (1998)." Problems Caused by Roots in Sewers." **Proceedings of INFRA 98 International Conference, Center for Expertise and Research on Infrastructures in Urban Areas (CERIU)**, Montreal, Canada, 25-30.

ISTT (1998). **Trenchless Technology Guidelines,** ISTT, London, UK.

Johnson, J. 1997. **Database Models, Languages, Design**. Oxford University Press, Inc., New York, N.Y.
Karlalopoulo, S. (1996), **Understanding Neural Networks and Fuzzy Logic**. IEEE press, New York.

Karunanithi, N., Grenney, W., Whitley, D. and Bovee, K. (1994)." Neural Networks for River Flow Prediction." **Journal of Computing in Civil Engineering**, ASCE, 8 (2), 201-220.

Kaseco, M. and Ritchie,S. (1994). "Comparison of traditional and neural classification for pavement – crack detection." **Journal of Transportation. Engineering**, ASCE, 120 (4), 552 – 569.

Keefe, L., and Phillips, M. 1993. Trenchless Sewer Rehabilitation: Case Histories and Rehabilitation Strategy Modeling. **Proceedings of the North American No-DIG' 93**, San Jose, California, M1: 2- M1-34.

Keeney, R., and Raiffa, H. 1976. **Decision with multiple objectives: Preference and value tradeoffs**. John Wiley & sons, New York, N.Y.

Kramer,S., McDonald, W. and Thomson, J. (1992). **An Introduction to Trenchless Technology**, Van Nostrand Reinhold, New York.

Larsen, J., Struve, J. and Murray, P., (1997)," An Inside Look at Common Sense Application of Trenchless Technologies in South Florida", **North American No-Dig 98**, New Mexico, 35-45.

Landis, E., Nagy, E. and Keane, D. (1997)." Microtomographic Measurements of Internal Damage in Portland-Cement-Based Composites." **Journal of aerospace engineering**, 10(1), 2-6.

Lofthouse, P. (1983). **Sewerage Rehabilitation Manual**, UK.

Looney,C. (1997), **Pattern recognition using neural networks**, Oxford University Press, Inc., New York.

Makar, J. (1999). " Diagnostic Techniques for Sewer Systems." **Journal of Infrastructure Systems,** ASCE, 5 (2), 69- 78.

Masad, E., Muhunthan, B. and Harman, T. (1999)." Internal Structure Characterization of Asphalt Concrete Using Image analysis." **Journal of Computing in Civil Engineering**, ASCE, 13(2), 88-95.

Mashford, J. (1995), "A neural network image classification system for automatic inspection", **Proceeding of IEEE International Conference on Neural Networks**, University of Western Australia, Perth, 2, 713 – 717.

McKim, R. (1997). " Selection Methods for Trenchless Technologies." **Journal of infrastructure Systems**, ASCE, 3(3), 119-125.

Miller, P. (1998), " Trenchless Design Moves into Its own", **Trenchless Technology**, ISTT, 7(12), 30-31.

Morici, P. (1997), "Small cameras: diagnosing sewer lateral quickly and easily", **Trenchless Technology**, ISTT, 6 (10), 40 - 45.

Moselhi, O. (1998) (a),"Neural Networks and Their Applications in Civil Engineering. **Proceeding of First international conference on New Information Technology for Decision Making in Civil Engineering Conference**. Montreal, Canada, 17- 27.

Moselhi, O. (Editor) (1998) (b). **Robots and Automated Machines in Construction**, Watford, England, UK.

Moselhi, O., and Deb, B. (1993)."Project Selection Considering Risk." **Construction Management and Economics**, E. & F.N. Spon, 11 (1), 45-52.

Moselhi, O., Fazio, P. and Hason, S. (1992) (a)." Automation Of concrete Slab-on-Grade Construction." **Journal of Construction Engineering and Management**, 118(4), 731-748.

Moselhi, O. Hegazy, T and Fazio, P (1991)." Neural Networks as Tools in construction." **Journal of Construction Engineering and Management**, ASCE, 117 (4), 606-625.

Moselhi, O. Hegazy, T and Fazio, P (1992) (b)." Potential Applications of Neural Networks in Construction." **Canadian journal of Civil Engineering**, CSCE, 19(3), 521-529.

Moselhi, O. Hegazy, T and Fazio, P (1994)." Developing Practical Neural Network Applications Using Back-Propagation." **Microcomputers in Civil Engineering**, Blackwell, 9 (2), 145-159.

Moselhi, O. and Shehab-Eldeen, T. (1999) (a),"Automated Detection of Defects in Underground Sewer and Water Pipes." **Journal of Automation in Construction**, Elsevier Science, 8, 581-588.

Moselhi, O. and Shehab-Eldeen, T. (1999) (b)." An AI-Based System for Detection and Classification of Defects in Sewers." **Proceedings of INFRA 99**

International Conference, Center for Expertise and Research on Infrastructures in Urban Areas (CERIU), Montreal, Canada, 3B: 42-54.

Moselhi, O. and Shehab-Eldeen, T. (2000) (a). " Classification of Defects in Sewer Pipes Using Neural Networks." **Journal of Infrastructure Systems**, ASCE, 6 (3), 97-105.

Moselhi, O. and Shehab-Eldeen, T. (2000) (b). " An Automated System for Rehabilitation of Sewer Pipes." **Canadian Civil Engineer**, CSCE, 17 (3), 6-8.

Moselhi, O. and Shehab-Eldeen, T. (2001)." Multiple Classifiers for Automated Detection of Defects in Sewer Pipes"." **Proceeding of 2001 International Conference on Rehabilitation of Infrastructures**, Waterloo, Canada, 273-278.

Moselhi, O., and Sigurdardottir, V. Y. (1998). Rehab Select : A Decision Support System for Selecting Trenchless Pipeline Rehabilitation Techniques. **Proceedings of the North American No-DIG' 98**, New Mexico, 14-23.

Najafi, M., Virendra, K., and Stutterheim, K. (1997). Feasibility study for Sewer force-Main Rehabilitation. **Proceedings of the North American No-DIG' 97**, Orlando, Florida, 504-513.

Navon, R. Kelly, P. and Johnstone, D. (1992)," Identification of Human Barriers to the Successful Implementation of Construction Automation". **Proceeding of the 9th International Symposium on Automation and robotics in Construction**, Tokyo, Japan, 138- 140.

Nekovei, R. and Sun, Y. (1995)."Back-Propagation Networks its configuration for Blood Vessels Detection in Angiograms." **IEEE Transaction on Neural Networks**, IEEE, 6 (1), 64-72.

NeuroShell-2 reference manual(1996). Ward Systems Group. Inc., Frederick, Md.

Ortiz, J., Ferregat, C. and Osegueda, R. (1997), " Damage detection from Vibration measurements using Neural Network Technology" **Artificial Neural Networks For Civil Engineers: Fundamentals and Applications**, ASCE, New York.

Pla-Rucki, G. and Eberhard, M. (1995). " Imaging of Reinforced Concrete: State-of-The- Art Review." **Journal of Infrastructure Systems**, ASCE, 1 (2), 134-141.

Regional Municipality of Hamilton (1997)."Preliminary Diagnosis Report of the Sewer System". **Aqua Data Inc.**, Hamilton, Canada.

Rens, K. and Greimann, L. (1997). " Ultrasound Approach for Nondestructive Testing of Civil Infrastructure." **Journal of Performance of Constructed Facilities**, ASCE, 11(3), 97-104.

Reyna, S., Vanegas, J. and Khan, A. (1994). "Construction Technology for Sewer Rehabilitation." **Journal of Construction Engineering and Management**, ASCE, 120 (3), 467-487.

Ritchie, S. (1989). "Digital image concepts and application in pavement management." **Journal of Transportation Engineering**, ASCE, 116 (3), 287 – 298.

Ritchie, S., Kaseko, M. and Bavarian, B.(1991), " Development of an intelligent system for automated pavement evaluation" **Transportation Research Record**, National Research Council, 1311, 112 -119.

Russ, J. (1992). **The Image Processing Handbook**, CRC press, Inc. Florida.

Saaty, T. L. 1982. **Decision Making for Leaders**. Life time learning publications, Inc., Belmont,Calik.

Schalkoff, R. (1992). **Pattern recognition: Statistical, Structural and Neural Approaches**, John Wiley & Sons, Inc. New York.

Schrock, J. (1985)." Solutions in the Pipeline.", **Civil Engineering**, ASCE, 55(9), 46-49.

Scion Image for windows reference manual(1998). Scion Corporation, Frederick, Maryland.

Semenak, S. (1999), "$15-Bilion Pipe Dream". **The Gazett**, August 30, A-1 and A-5.

Setiono, R. and Liu, H. (1997)." Neural Network Feature Selector." **IEEE Transaction on Neural Networks**, IEEE, 8(3), 654-661.

Siddiqui, S. and Mirza, S. (1996)" **Report on the State of Municipal Infrastructure in Canada**" the Federation of Canadian Municipalities and Department of Civil Engineering and Applied Mechanics, McGill University.

Simpson, P. (1996). **Foundations of Neural Networks: Neural Networks Theory, Technology, and Applications**, The institute of Electrical and Electronics Engineers, New York.

Sinha, S. (2001). " Development of An Automated Pipeline Inspection system", **Proceeding of the International Symposium on Underground Infrastructure Research**, Waterloo, Canada, 279-286.

Shehab-Eldeen, T. and Moselhi, O. (2000)." A Database System for Rehabilitation Techniques of Sewer Pipes." **Proceedings of the 17th International Conference on Automation and Robotics in Construction**, Taipei, Taiwan, 1085-1090.

Shehab-Eldeen, T. and Moselhi, O., (2001). " A Decision Support System for Rehabilitation of Sewer Pipes." **Canadian Journal of Civil Engineering**, CSCE, 28(3), 394-401.

Siqueira, I. (1999)." Automated Cost Estimating System Using Neural Networks." **Project Management Journal**, Project Management Institute, , 30 (1) 11-18.

Skipworth, P., Tait, S. and Saul, A. (1999)." Erosion of Sediment Beds in Sewers: Model Development." **Journal of Environmental Engineering**, ASCE, 125(6), 566-572.

Smith, G. and Raynar, K. (1993). " Application of Digital Image and Processing for As-Built Construction Drawings.", **Proceedings of the international conference on digital image processing techniques**, ASCE, Kone, Hawaii, 263-269.

Tait, S., Rushforth, P. and Saul, A. (1998). " A Laboratory Study of the Erosion and Transport of Cohesive-Like Sediment Mixtures in Sewers." **Water science and Technology**, Pergamon Press, 37(1), 163-170.

Tamura, S. and Tateishi, M. (1997)."Capabilities of four-Layered Feedforward Neural Networks: Four Layers Versus Three." **IEEE Transaction on Neural Networks**, IEEE, 8 (2), 251-255.

Teh, C, Wong, K, Goh, A. and Jaritngan, S. (1997)." Prediction of Pile Capacity Using Neural Networks." **Journal of Computing in civil Engineering**, ASCE, 11 (2), 129-138.

Thomson, J.C. 1991. Pipeline Rehab: Underground Options. **Civil Engineering**, ASCE, 61(5), 64-66.

Tsao, S., Kehtarnavaz, N., Chan, P. and Lytton, R. (1994)." Image–Based Expert-System Approach to Distress Detection on CRC Pavement." **Journal of Transportation Engineering**, ASCE, 120(1), 52-64.

Udo-Inyang, P. and Chen, C. 1997. Integrated DBMS and KBES Application for Construction. **Proceeding of the fourth Congress Computing in Civil Engineering**, New York, 16-18.

Vernon, D. (1991). **Machine Vision**, Prentice Hall, New York.

Wang, K. (2000). " Designs and Implementations of Automated Systems for Pavement surface Distress Survey." **Journal of Infrastructure systems**, ASCE, 6(1), 24-32.

Wang, K. and Nallamothu, S.(1998)." Classification of Pavement surface Distress With an Embedded Neural Net Chip", **Neural Networks for Civil Engineers Advanced Features and Applications**. ASCE, 131-161.

Weil, G. (1998). " Detecting the Defects", **Civil Engineering**, ASCE, 59(9), 72-77.

Wirahadikusumah, R., Abraham, D., Iseley, T. and Prasanth, R. (1998), " Assessment Technology for sewer Rehabilitation". **Journal of Automation in Construction**, Elsevier Science, 7(4), 259-270.

Yuan, X., Lu, Y. and Sarraf, S. (1994)." A Computer Vision system for Automatic Vehicle Classification." **Journal of Transportation Engineering**, ASCE, 120 (6), 861-876.

Zhao, J., ivan, J. and DeWolf, J. (1998)."Structural Damage Detection Using Artificial Neural Networks." **Journal of infrastructure Systems**, ASCE, 4(3), 93-101.

APPENDIX A: DESIGN PARAMETERS OF THE DEVELOPED CLASSIFIERS

Table A-1: Final Parameters Used in Designing InfiltrationNet 1

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	17
Number of neurons in output layer	2
Number of neurons in hidden layer	35
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	1.2
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

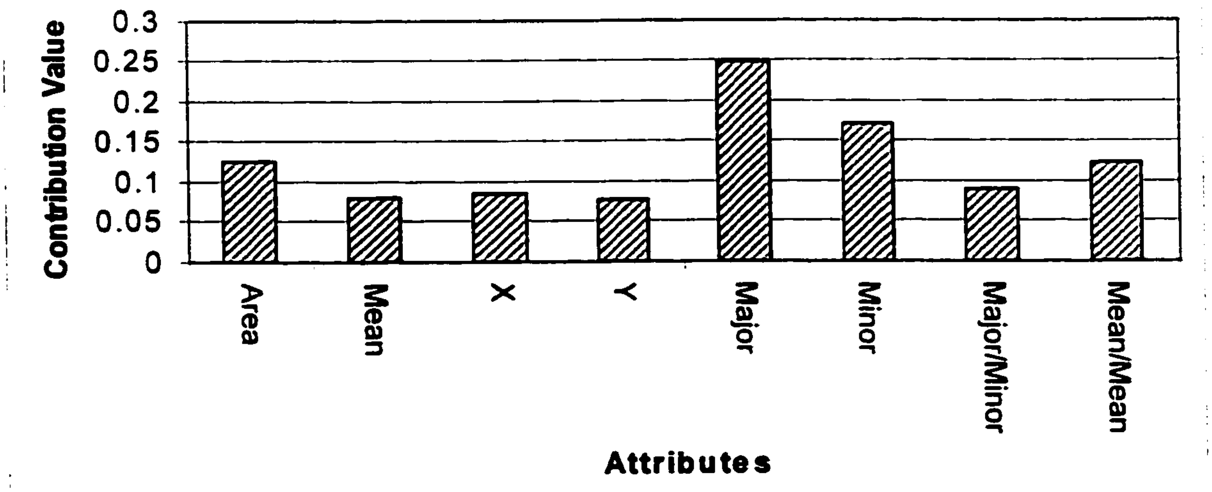


Figure A-1: Contribution Values of Attributes Utilized in Designing InfiltrationNet 2

Table A-2: Final Parameters Used in Designing InfiltrationNet 2

Parameter	Value
Network paradigm	Back-propagation
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.1
Momentum	0.1
Number of neurons in hidden layer	39
Number of neurons in input layer	8
Number of neurons in output layer	2
Calibration interval	50
Saving of network	At the best testing set
Number of hidden layers	1

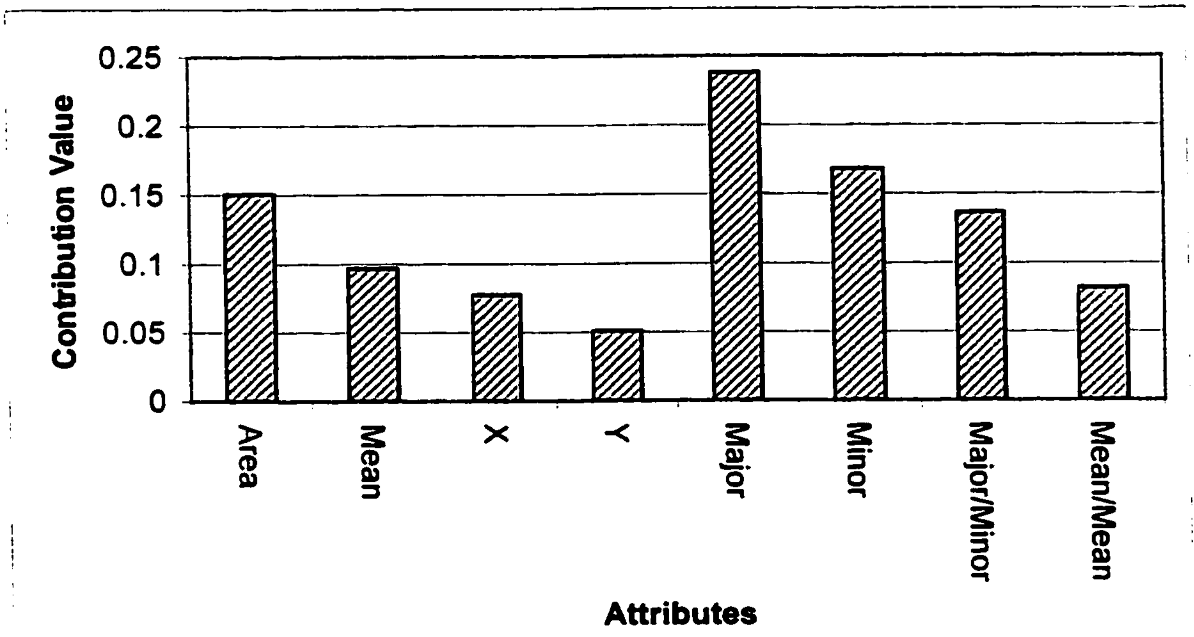


Figure A-2: Contribution Values of Attributes Utilized in Designing InfiltrationNet 3

Table A-3: Final Parameters Used in Designing InfiltrationNet 3

Parameter	Value
Network paradigm	Back-propagation
activation function in hidden layers	Gaussian
Activation function in output layer	Logistic
Initial weight	0.7
Learning rate	0.2
Momentum	0.2
Number of neurons in hidden layer # 1	32
Number of neurons in hidden layer # 2	47
Number of neurons in input layer	8
Number of neurons in output layer	2
Calibration interval	50
Saving of network	At the best testing set
Number of hidden layers	2

Table A-4: Final Parameters used in Designing DepositNet 1

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	17
Number of neurons in output layer	2
Number of neurons in hidden layer	40
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.1
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

Table A-5: Final Parameters Used in Designing DepositNet 2

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	10
Number of neurons in output layer	2
Number of neurons in hidden layer	28
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.1
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

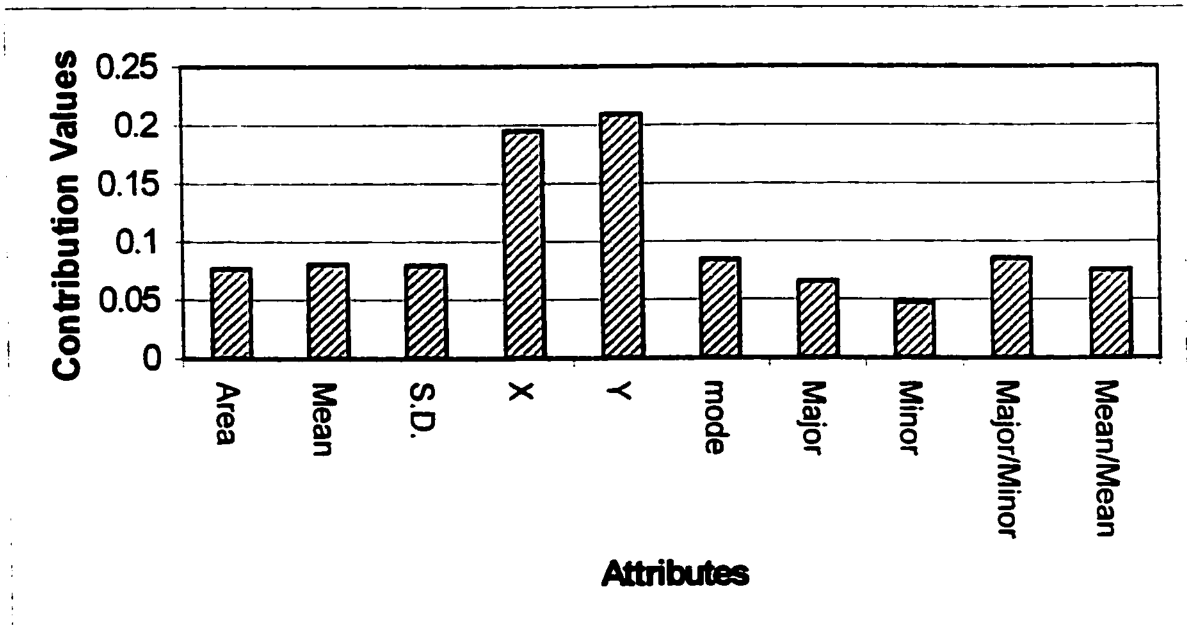


Figure A-3: Contribution Values of Attributes Utilized in Designing DepositNet 2

Table A-6: Final Parameters Used in Designing DepositNet 3

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	10
Number of neurons in output layer	2
Number of neurons in hidden layer	49
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.1
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

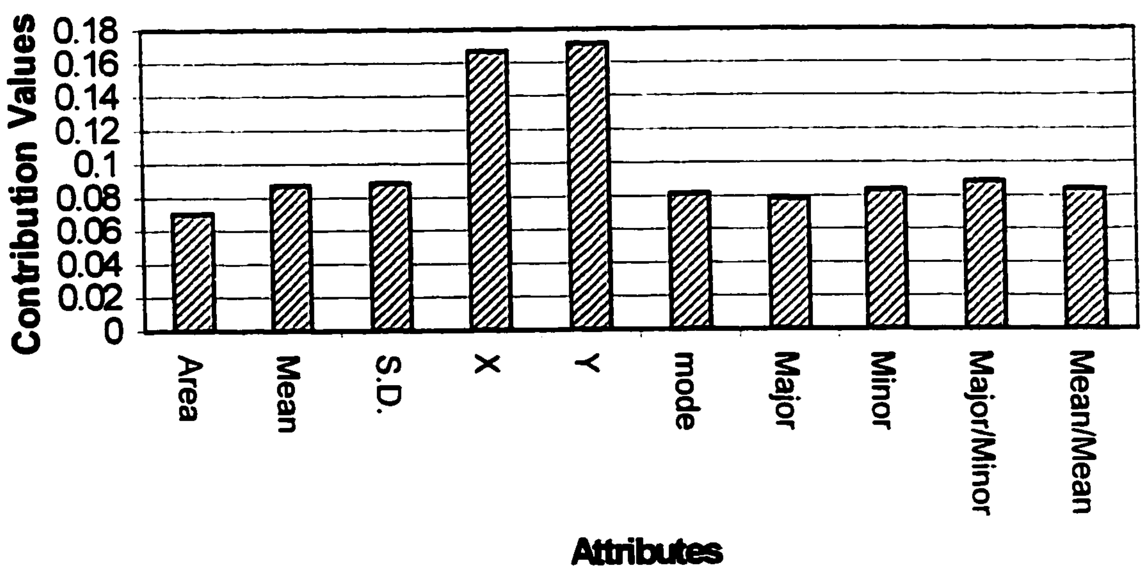


Figure A-4: Contribution Values of Attributes Utilized in Designing DepositNet 3

Table A-7: Initial Parameters Used in Designing a Preliminary Neural Network for Classification of Cross-sectional Reductions

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	17
Number of neurons in output layer	2
Number of neurons in hidden layer	19
Number of hidden layers	1
activation function in hidden layer	Sine
Activation function in output layer	Logistic
Initial weight	0.2
Learning rate	0.5
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

Table A-8: Final Parameters Used in Designing CrossNet 1

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	13
Number of neurons in output layer	2
Number of neurons in hidden layer	39
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

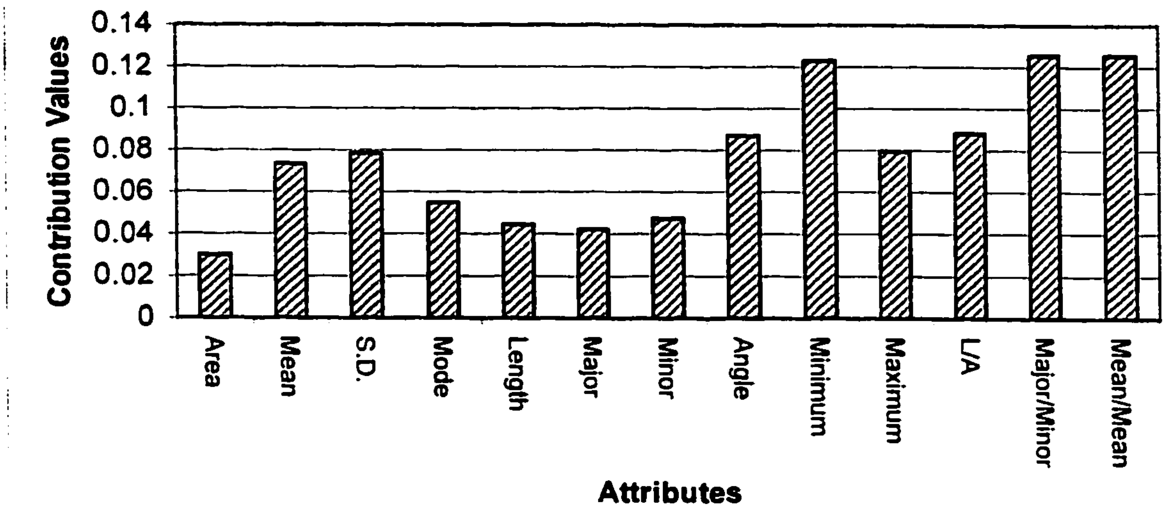


Figure A-5: Contribution Values of Attributes Utilized in Designing CrossNet 1

Table A-9: Final Parameters Used in Designing CrossNet 2

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	13
Number of neurons in output layer	2
Number of neurons in hidden layer	21
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.3
Learning rate	0.1
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

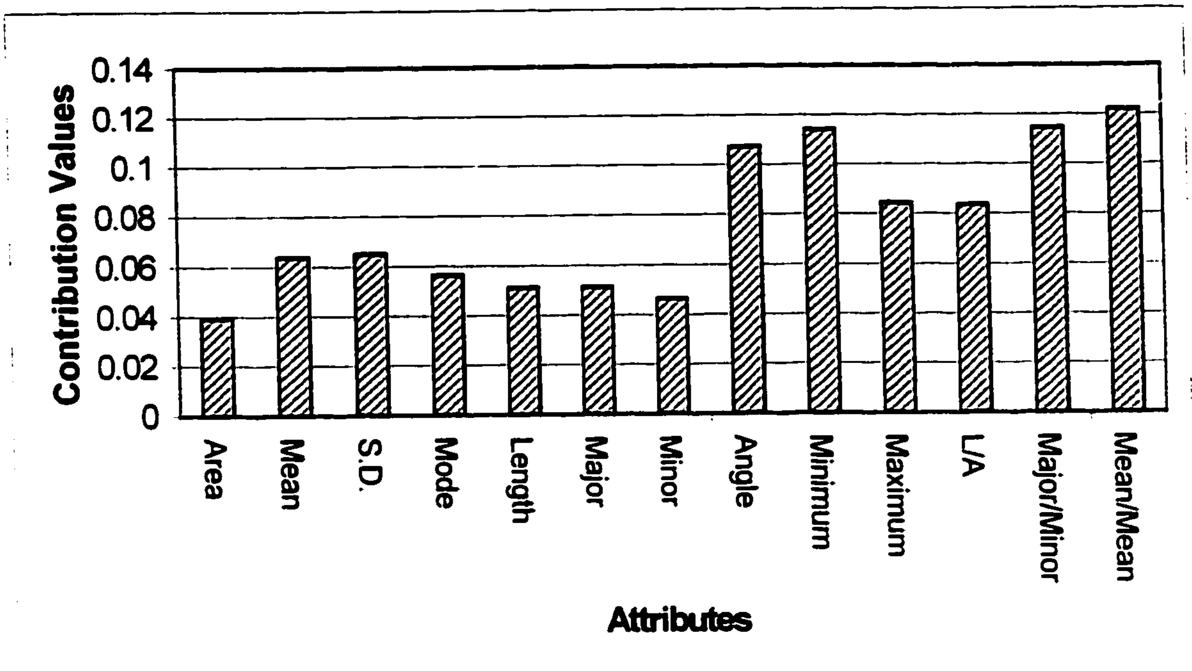


Figure A-6: Contribution Values of Attributes Utilized in Designing CrossNet 2

Table A-10: Final Parameters Used in Designing CrossNet 3

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	13
Number of neurons in output layer	2
Number of neurons in hidden layer	22
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	1.2
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

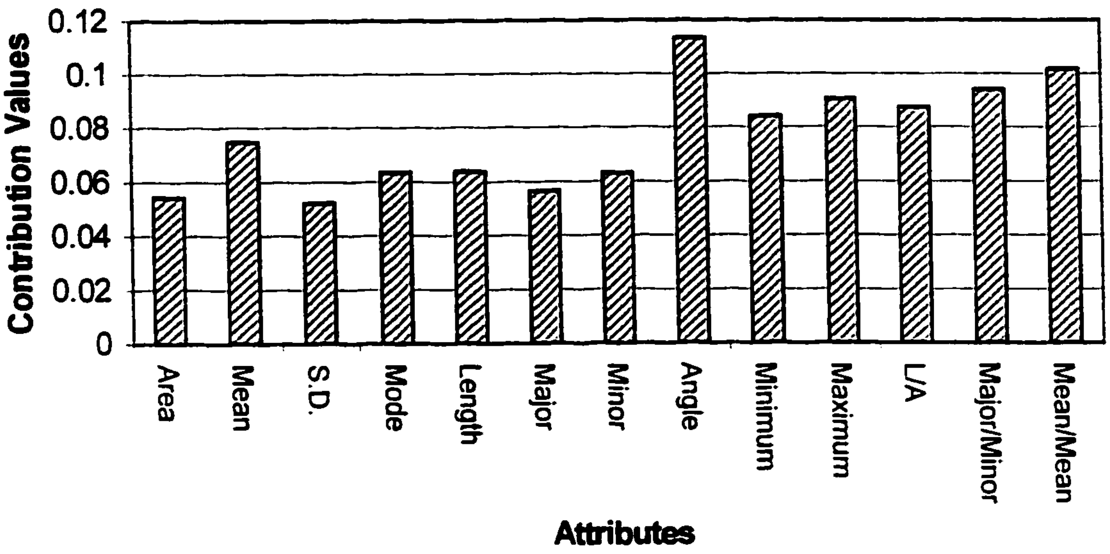


Figure A-7: Contribution Values of Attributes Utilized in Designing CrossNet 2

Table A-11: Initial Parameters Used in Designing a Preliminary Neural Network for Classification of Misalignments

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	17
Number of neurons in output layer	2
Number of neurons in hidden layer	19
Number of hidden layers	1
Activation function in hidden layer	Sine
Activation function in output layer	Logistic
Initial weight	0.2
Learning rate	0.5
Momentum	0.1
Calibration interval	50
Saving of network	At the best testing set

Table A-12: Final Parameters Used in Designing AlignmentNet 1

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	11
Number of neurons in output layer	2
Number of neurons in hidden layer	32
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	1.2
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

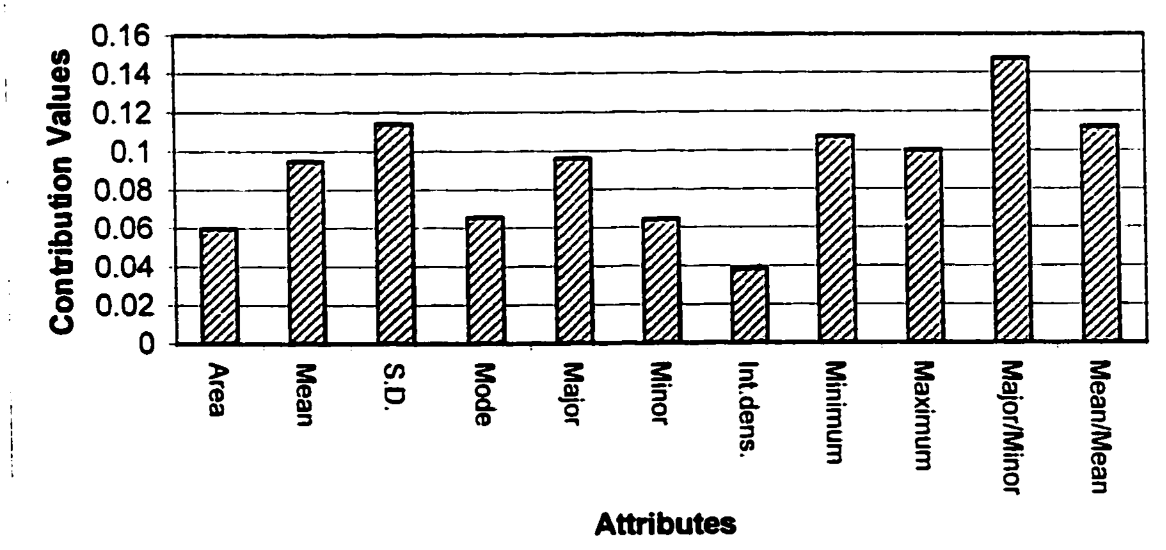


Figure A-8: Contribution Values of Attributes Utilized in Designing AlignmentNet 1

Table A-13: Final Parameters Used in Designing AlignmentNet 2

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	11
Number of neurons in output layer	2
Number of neurons in hidden layer	35
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	1.2
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

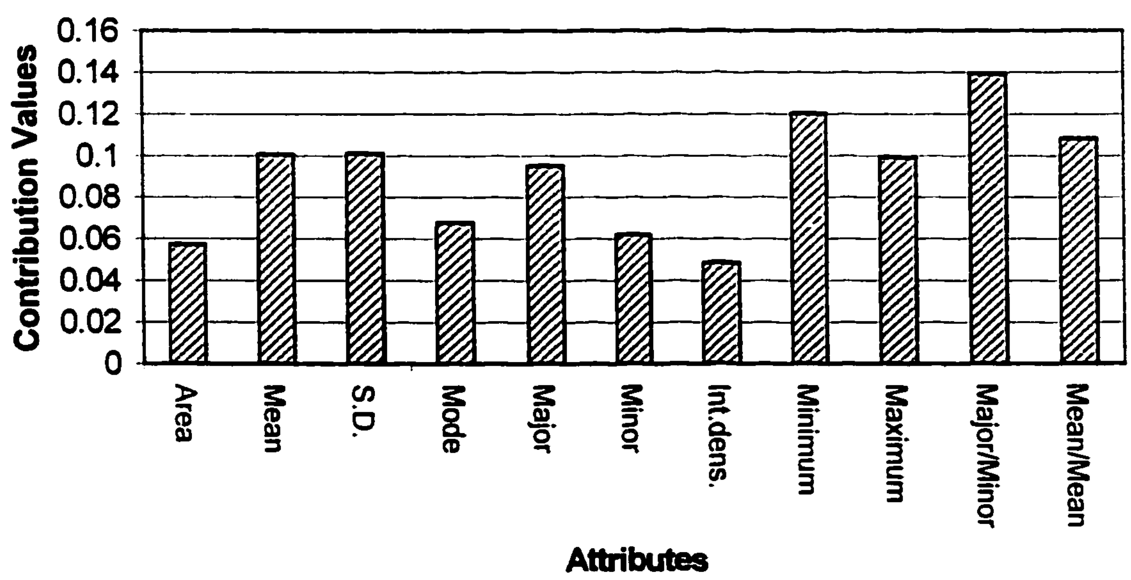


Figure A-9: Contribution Values of Attributes Utilized in Designing AlignmentNet 2

Table A-14: Final Parameters Used in Designing AlignmentNet 3

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	11
Number of neurons in output layer	2
Number of neurons in hidden layer	37
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	1.2
Learning rate	0.2
Momentum	0.2
Calibration interval	50
Saving of network	At the best testing set

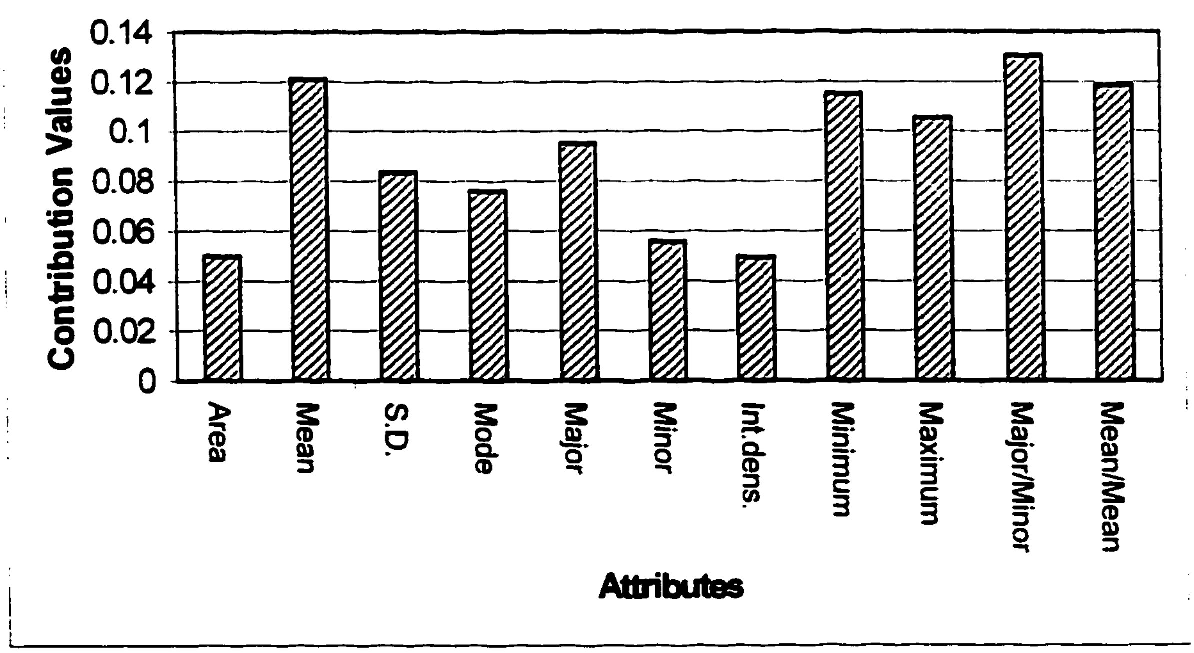


Figure A-10: Contribution Values of Attributes Utilized in Designing AlignmentNet 3

Table A-15: Final Parameters Used in Designing ModCrossNet 1

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	5
Number of neurons in output layer	2
Number of neurons in hidden layer	32
Number of hidden layers	1
activation function in hidden layer	Gaussian
Activation function in output layer	Logistic
Initial weight	0.7
Learning rate	0.1
Momentum	0.3
Calibration interval	50
Saving of network	At the best testing set

Table A-16: Performance Results of ModCrossNet 1

Performance Criteria	X-sectional Red.	Non X-sect. Red.
R^2	0.8429	0.8420
Mean squared error	0.036	0.036
Mean absolute error	0.111	0.109
Min. absolute error	0	0
Max. absolute error	0.608	0.615
Correlation coefficient (r)	0.9239	0.9229
Recognition rate	85.7%	100%

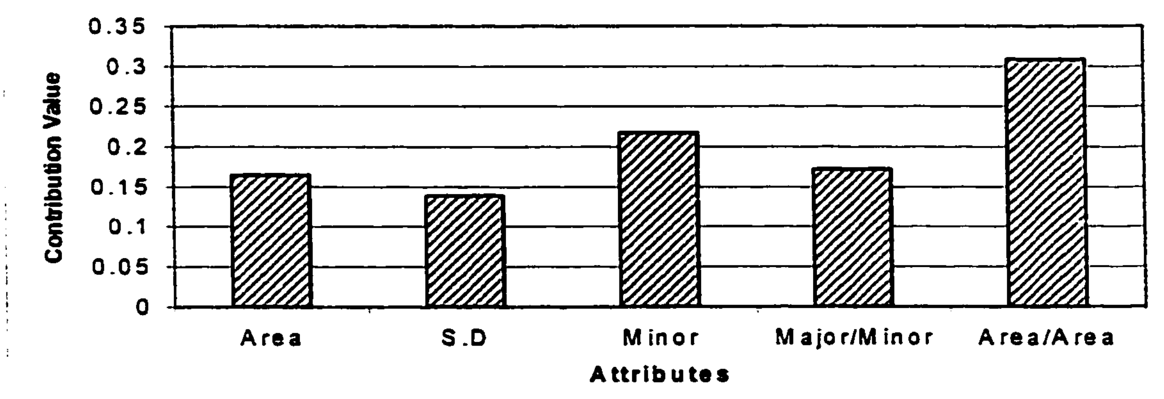


Figure A-11: Contribution Values of Attributes Utilized in Designing ModCrossNet 1

Table A-17: Final Parameters Used in Designing of ModCrossNet 2

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	5
Number of neurons in output layer	2
Number of neurons in hidden layer	39
Number of hidden layers	1
activation function in hidden layer	Gussian
Activation function in output layer	Logistic
Initial weight	0.6
Learning rate	0.2
Momentum	0.4
Calibration interval	50
Saving of network	At the best testing set

Table A-18: Performance Results of ModCrossNet 2

Performance Criteria	X-sectional Red.	Non X-sect. Red.
R^2	0.9061	0.9071
Mean squared error	0.021	0.021
Mean absolute error	0.083	0.083
Min. absolute error	0	0
Max. absolute error	0.279	0.268
Correlation coefficient (r)	0.9573	0.9581
Recognition rate	100%	100%

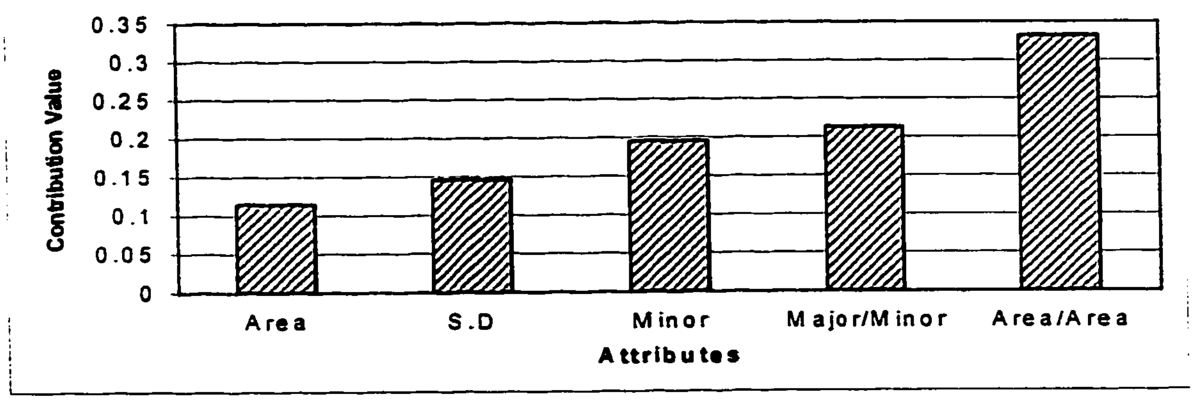


Figure A-12: Contribution Values of Attributes Utilized in Designing ModCrossNet 2

Table A-19: Final Parameters Used in Designing ModCrossNet 3

Parameter	Value
Network paradigm	Back-propagation
Number of neurons in input layer	5
Number of neurons in output layer	2
Number of neurons in hidden layer	36
Number of hidden layers	1
activation function in hidden layer	Gussian
Activation function in output layer	Logistic
Initial weight	0.7
Learning rate	0.2
Momentum	0.3
Calibration interval	50
Saving of network	At the best testing set

Table A-20: Performance Results of ModCrossNet 3

Performance Criteria	X-sectional Red.	Non X-sect. Red.
R^2	0.9880	0.9859
Mean squared error	0.003	0.003
Mean absolute error	0.028	0.031
Min. absolute error	0	0
Max. absolute error	0.112	0.126
Correlation coefficient (r)	0.9965	0.9958
Recognition rate	100%	100%

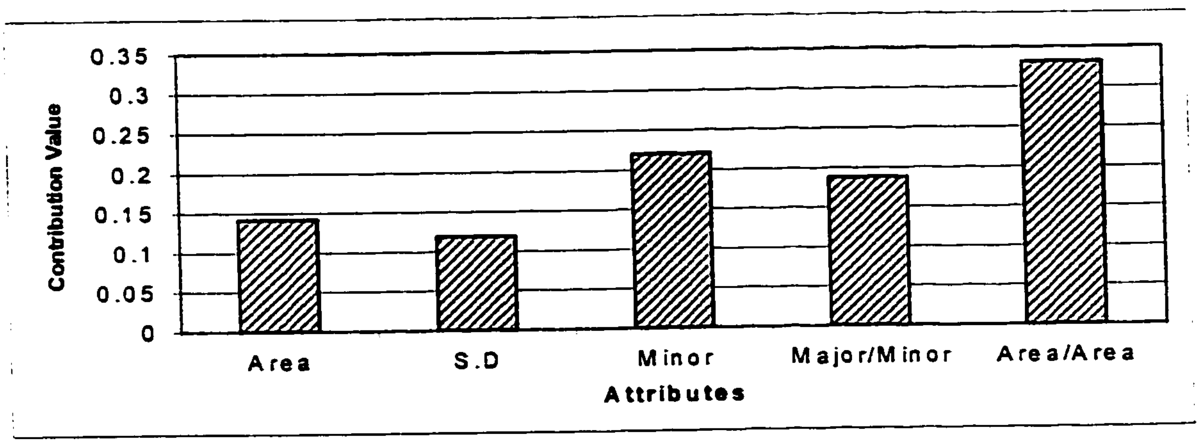


Figure A-13: Contribution Values of Attributes Utilized in Designing ModCrossNet 3

APPENDIX B: QUESTIONNAIRE

Name of company:

Name of product:

Telephone number(s):

1- Indicate the type of repair for which your product is suitable...?

☐ Structural ☐ Non-Structural

2- What is your product's range of diameters...?

3- What is the maximum allowable degree of bend for your product...?

☐ 0° ☐ 45° ☐ 90° ☐ Others (please specify)

4- What kind of impact (i.e. improve or degrade) your product will have on the original hydraulic characteristics of pipes...? . Please give reasons for your answer.

☐ Improve ☐ Degrade

Reasons:

5- How many meters of your product can be installed without intermediate intervention of a human or a machine (i.e. Maximum distance between access points)...?

6- Does your product accommodate differential settlement...?

☐ Yes ☐ No

7- How long does it require, on average, to install 500 (m) of your product...?

☐ One week ☐ Two weeks ☐ Three weeks ☐ Other (please specify)

8- While installing your product, do you need to by-pass the host-pipe...?

☐ Yes ☐ No

9- How many years have you been in business...?

10-How many meters have you installed...?

11-What is the design life of your product...?

12-Do you have any offices in Canada...?

☐ Yes ☐ No

13-What type of access, to the host pipe, is required to install your product...?

☐ Manhole ☐ Excavation pit

14-Do you need to dig in order to reconnect Laterals...?

☐ Yes ☐ No

15-Can you accommodate new client requirements that are not part of your design or production standards...? . If yes, please rank your ability to accommodate on a scale of 1-5 for low and high ability, respectively.

☐ Yes (☐ 1, ☐ 2, ☐ 3, ☐ 4, ☐ 5) ☐ No

16-What is the cost per centimeter of diameter per linear meter of your product...?

17- What materials of host-pipes your product is suitable for...?

☐ Concrete ☐ Clay ☐ Others (please specify)

18- What type of defects can your product repair...?

☐ Roots ☐ Misalignments ☐ Infiltration ☐ Deposits ☐ Cracks

Name of company: KWH

Name of product: Weholite

Telephone number(s): (514) 3523540

1- Indicate the type of repair for which your product is suitable...?

⊕ Structural ⊕ Non-Structural

2- What is your product's range of diameters...?

10" – 120"

3- What is the maximum allowable degree of bend for your product...?

□ 0° ⊕ 45° □ 90° □ Others (please specify)

4- What kind of impact (i.e. improve or degrade) your product will have on the original hydraulic characteristics of pipes...? . Please give reasons for your answer.

⊕ Improve □ Degrade

Reasons: Reduce the manning coefficient

5- How many meters of your product can be installed without intermediate intervention of a human or a machine (i.e. Maximum distance between access points)...?

200 (m)

6- Does your product accommodate differential settlement...?

□ Yes ⊕ No

7- How long does it require, on average, to install 500 (m) of your product...?

⊕ One week □ Two weeks □ Three weeks □ Other (please specify)

8- While installing your product, do you need to by-pass the host-pipe...?

□ Yes ⊕ No

9- How many years have you been in business...? 30 Years

10-How many meters have you installed...? 3000 km

11- What is the design life of your product...? 50 years

12-Do you have any offices in Canada...?

⊕ Yes □ No

13-What type of access, to the host pipe, is required to install your product...?

⊕ Manhole ⊕ Excavation pit

14-Do you need to dig in order to reconnect Laterals...?

□ Yes ⊕ No

15-Can you accommodate new client requirements that are not part of your design or production standards...? . If yes, please rank your ability to accommodate on a scale of 1-5 for low and high ability, respectively.

□ Yes (□ 1, □ 2, □ 3, □ 4, ⊕ 5) □ No

16-What is the cost per centimeter of diameter per linear meter of your product...?

$6

17- What materials of host-pipes your product is suitable for…?

⊕ Concrete ⊕ Clay ☐ Others (please specify)

18- What type of defects can your product repair…?

⊕ Roots ☐ Misalignments ⊕ Infiltration ☐ Deposits ⊕ Cracks

APPENDIX C: CALCULATION OF CONSISTENCY RATIO (CR)

CR = CI/ random consistency

Where

CI = λ_{max} – N/ (N-1)

λ_{max} : Eigenvalue value of the matrix containing weights associated with all attributes

N: number of considered attributes

Random consistency: a random number that is a function of number of attributes, and accordingly the size of matrix (see Table 43)(Saaty 1982).

Table 43: Random Consistency Values

Size of Matrix	Random Value
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

APPENDIX D: OUTPUT RESULTS OF THE DEVELOPED CLASSIFIERS

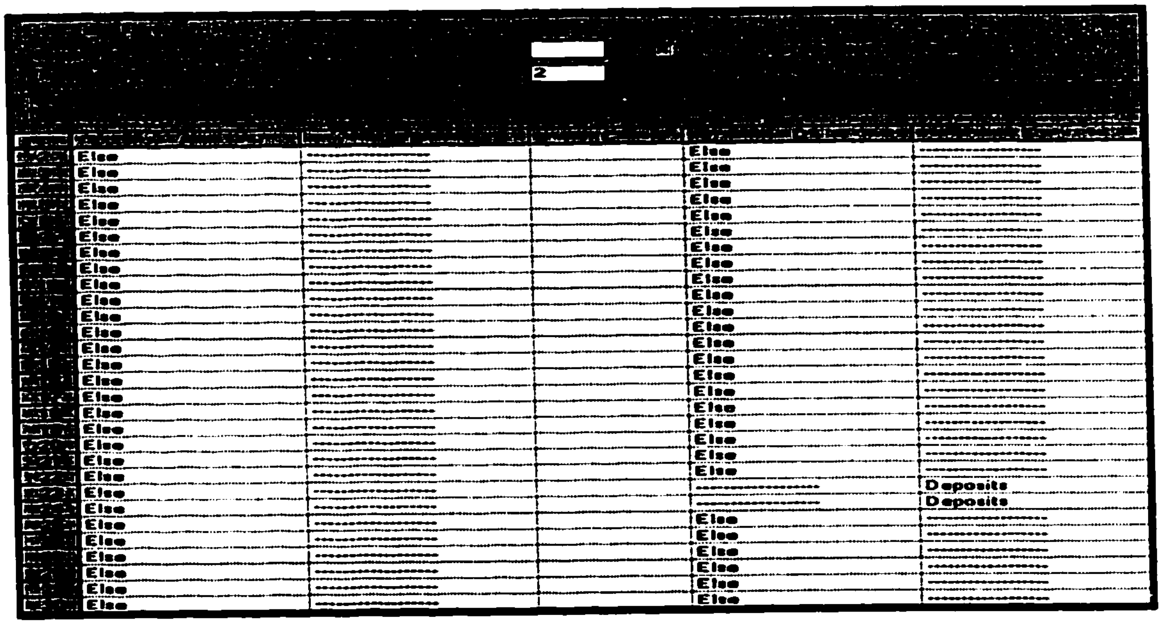


Figure D-1 : Output Results of DepositNet 1

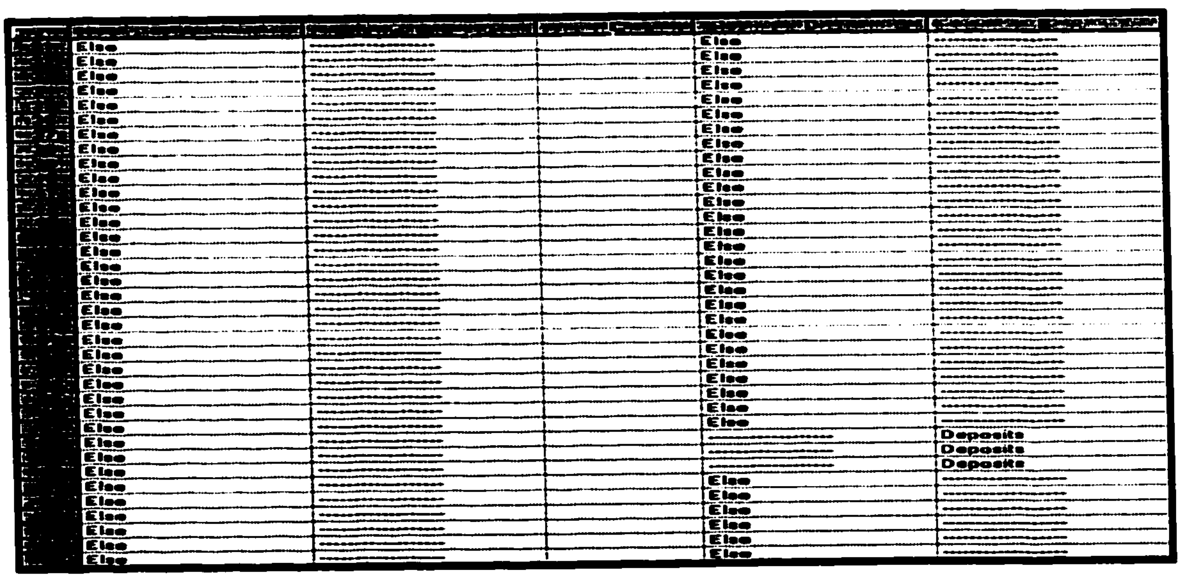


Figure D-1 : Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------

Figure D-1 : Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		----------------	Deposits
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits
Else	----------------		----------------	Deposits
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		Else	----------------
Else	----------------		----------------	Deposits

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	----------------	Deposits		----------------	Deposits
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

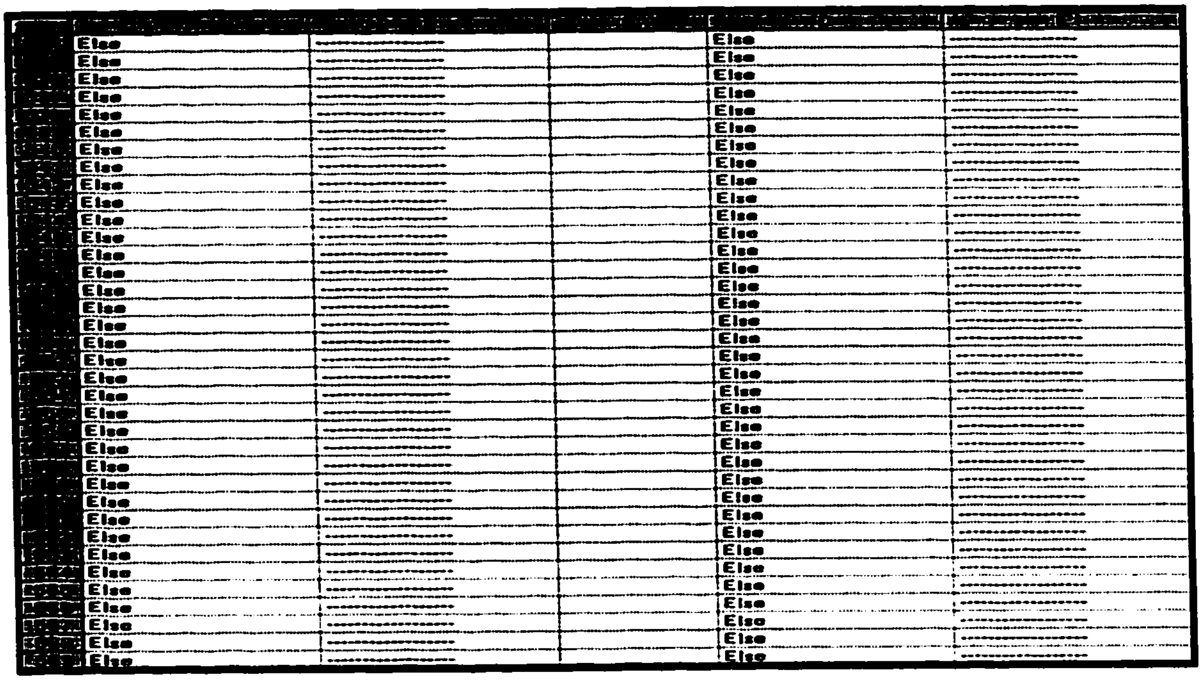
Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

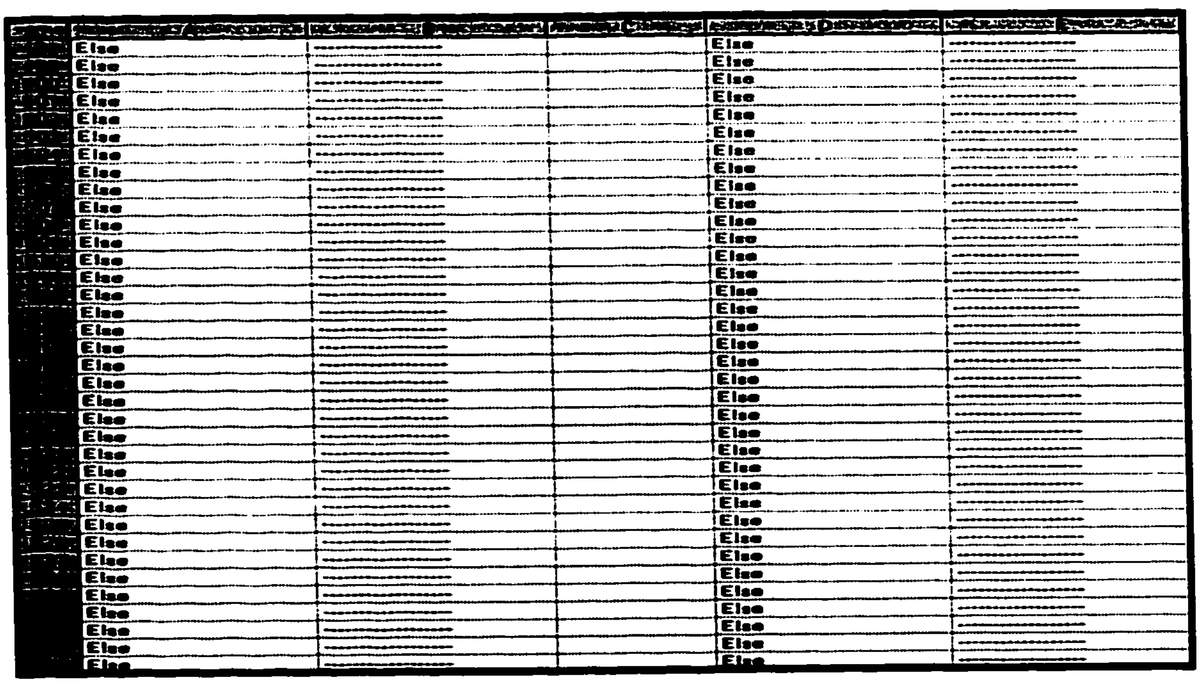
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	----------------	Deposits		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		----------------	Deposits
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)



	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)



	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------
	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	Else	--------------		Else	--------------
[illegible]	--------------	Deposits		--------------	Deposits

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits

Figure D-1: Output Results of DepositNet 1 (Continued)

[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	----------------	Deposits		----------------	Deposits
[illegible]	Else	----------------		Else	----------------

Figure D-1: Output Results of DepositNet 1 (Continued)

2

	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	X-sectional Reduction	--------------------		X-sectional Reductions	--------------------
	X-sectional Reduction	--------------------		X-sectional Reductions	--------------------
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		X-sectional Reductions	--------------------
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		X-sectional Reductions	--------------------
	X-sectional Reduction	--------------------		--------------------	Else

Figure D-2: Output Results of ModCrossNet 1

	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	X-sectional Reduction	--------------------		X-sectional Reductions	--------------------
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	X-sectional Reduction	--------------------		X-sectional Reductions	--------------------
	X-sectional Reduction	--------------------		X-sectional Reductions	--------------------
	--------------------	Else		X-sectional Reductions	--------------------
	--------------------	Else		--------------------	Else
	--------------------	Else		X-sectional Reductions	--------------------
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else
	--------------------	Else		--------------------	Else

Figure D-2: Output Results of ModCrossNet 1 (Continued)

	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		X-sectional Reductions	----------------------
	----------------------	Else		----------------------	Else
	X-sectional Reduction	----------------------		X-sectional Reductions	----------------------
	----------------------	Else		----------------------	Else
	X-sectional Reduction	----------------------		X-sectional Reductions	----------------------
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else
	----------------------	Else		----------------------	Else

Figure D-2: Output Results of ModCrossNet 1 (Continued)

2

	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	Else	----------------------		Else	----------------------
	Else	----------------------		Else	----------------------
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		Else	----------------------
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		Else	----------------------
	----------------------	Misalignment		----------------------	Misalignment
	Else	----------------------		Else	----------------------
	Else	----------------------		Else	----------------------
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment
	----------------------	Misalignment		----------------------	Misalignment

Figure D-3: Output Results of MisalignmentNet 1

[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	Else	----------------------		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	Else	----------------------		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	Else	----------------------		----------------------	Misalignment
[illegible]	Else	----------------------		Else	----------------------
[illegible]	Else	----------------------		Else	----------------------
[illegible]	Else	----------------------		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	Else	----------------------		Else	----------------------
[illegible]	Else	----------------------		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment

Figure D-3: Output Results of MisalignmentNet 1 (Continued)

[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	Else	----------------------		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	Else	----------------------		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	Else	----------------------		Else	----------------------
[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	----------------------	Mislignment		Else	----------------------
[illegible]	----------------------	Mislignment		----------------------	Misalignment
[illegible]	----------------------	Mislignment		----------------------	Misalignment

Figure D-3: Output Results of MisalignmentNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		Infiltration	------------------

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Infiltration	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Infiltration	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Infiltration	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Infiltration	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Infiltration	------------------
	------------------	Else		Infiltration	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Infiltration	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Infiltration	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else

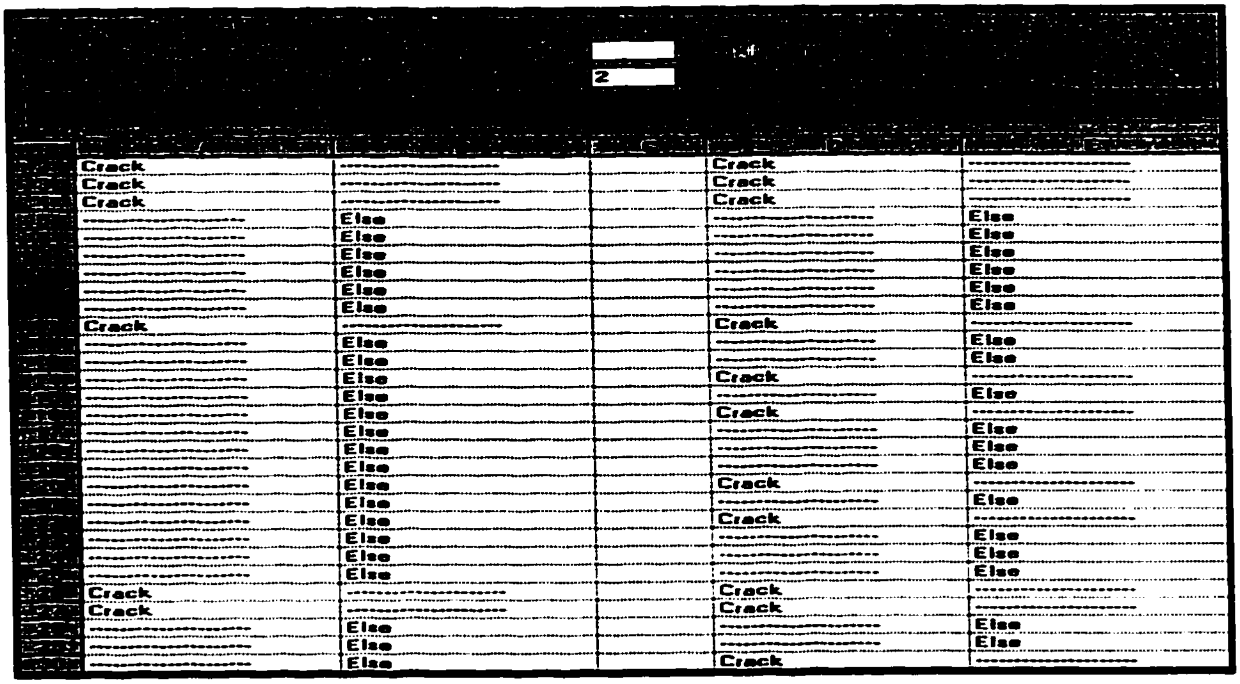
Figure D-4: Output Results of InfiltrationNet 1 (Continued)

	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	Infiltration	-----------------		Infiltration	-----------------
	Infiltration	-----------------		Infiltration	-----------------
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		Infiltration	-----------------
	-----------------	Else		-----------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)

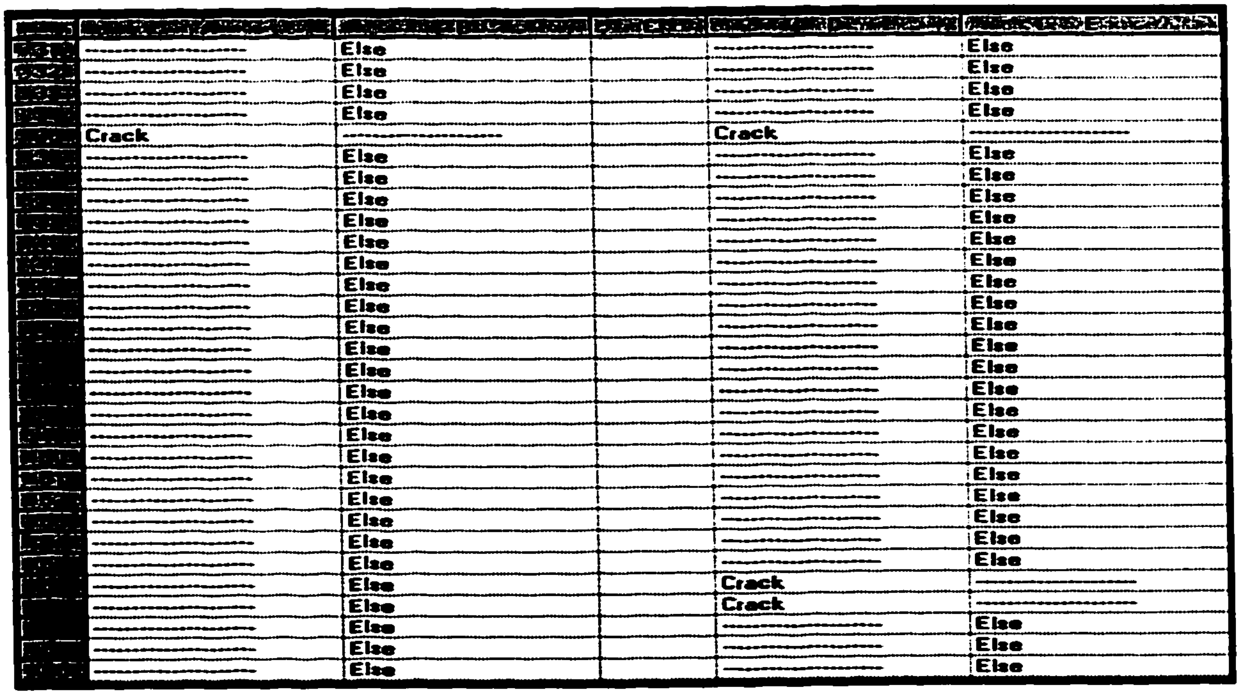
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	Infiltration	-----------------		Infiltration	-----------------
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else
	-----------------	Else		-----------------	Else

Figure D-4: Output Results of InfiltrationNet 1 (Continued)



Crack	----------		Crack	----------
Crack	----------		Crack	----------
Crack	----------		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
Crack	----------		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		Crack	----------
----------	Else		----------	Else
----------	Else		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		Crack	----------
----------	Else		----------	Else
----------	Else		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
Crack	----------		Crack	----------
Crack	----------		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		Crack	----------

Figure D-5: Output Results of CrackNet 1



----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
Crack	----------		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		Crack	----------
----------	Else		Crack	----------
----------	Else		----------	Else
----------	Else		----------	Else
----------	Else		----------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	Crack	-------------------		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	Crack	-------------------		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	Crack	-------------------		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------

Figure D-5: Output Results of CrackNet 1 (Continued)

	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	Crack	-------------------		Crack	-------------------
	Crack	-------------------		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		Crack	-------------------
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	Crack	-------------------		Crack	-------------------
	-------------------	Else		-------------------	Else
	Crack	-------------------		Crack	-------------------
	Crack	-------------------		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else
	-------------------	Else		-------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		Crack	--------
[illegible]	Crack	--------		Crack	--------
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	Crack	--------		Crack	--------
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	Crack	--------		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------
[illegible]	Crack	--------		Crack	--------
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	Crack	--------		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		Crack	--------
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else
[illegible]	--------	Else		--------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	Crack	------------		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	Crack	------------		Crack	------------
[illegible]	Crack	------------		Crack	------------
[illegible]	Crack	------------		Crack	------------
[illegible]	Crack	------------		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		Crack	------------
[illegible]	Crack	------------		------------	Else
[illegible]	------------	Else		------------	Else
[illegible]	------------	Else		------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	Crack	----------------		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	Crack	----------------		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	Crack	----------------		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	Crack	----------------		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	Crack	----------------		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		----------------	Else
[illegible]	----------------	Else		Crack	----------------
[illegible]	----------------	Else		Crack	----------------

Figure D-5: Output Results of CrackNet 1 (Continued)

	Crack	----------		Crack	----------
	Crack	----------		Crack	----------
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	Crack	----------		Crack	----------
	Crack	----------		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	Crack	----------		Crack	----------
	Crack	----------		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	Crack	----------		----------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

	----------	Else		----------	Else
	Crack	----------		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	Crack	----------		Crack	----------
	Crack	----------		Crack	----------
	Crack	----------		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		----------	Else
	Crack	----------		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		----------	Else
	----------	Else		Crack	----------
	----------	Else		----------	Else
	----------	Else		----------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		Crack	------------------

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		------------------	Else
[illegible]	Crack	------------------		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		Crack	------------------
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	Crack	------------------		Crack	------------------
[illegible]	------------------	Else		------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	Crack	------------------		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	Crack	------------------		Crack	------------------
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	Crack	------------------		Crack	------------------
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	------------------		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

	Crack	------------------		Crack	------------------
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	Crack	------------------		Crack	------------------
	------------------	Else		Crack	------------------
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		Crack	------------------
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else
	------------------	Else		------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)

[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else
[illegible]	------------------	Else		------------------	Else

Figure D-5: Output Results of CrackNet 1 (Continued)