Local Image Patterns for Counterfeit Coin Detection and Automatic Coin Grading

Sofia Gakhar

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By: Sofia Gakhar

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Signed by the final examining committee:

______________________________________ Chair
Dr. C. Poullis

______________________________________ Examiner
Dr. C. Poullis

______________________________________ Examiner
Dr. M. Khayyat

______________________________________ Thesis Supervisor
Dr. Ching Y. Suen

Approved by ____

Dr. Leila Kosseim, Graduate Program Director

____

Dr. Lata Narayanan, Dean of Faculty

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Abstract

Local Image Patterns for Counterfeit Coin Detection and Automatic Coin Grading

Sofia Gakhar

Coins are an essential part of our life, and we still use them for everyday transactions. We have always faced the issue of the counterfeiting of the coins, but it has become worse with time due to the innovation in the technology of counterfeiting, making it more difficult for detection. Through this thesis, we propose a counterfeit coin detection method that is robust and applicable to all types of coins, whether they have letters on them or just images or both of these characteristics. We use two different types of feature extraction methods. The first one is SIFT (Scale Invariant Feature transform) features, and the second one is RFR (Rotation and Flipping invariant Regional Binary Patterns) features to make our system complete in all aspects and very generic at the same time. The feature extraction methods used here are scale, rotation, illumination, and flipping invariant. We concatenate both our feature sets and use them to train our classifiers. Our feature sets highly complement each other in a way that SIFT provides us with most discriminative features that are scale and rotation invariant but do not consider the spatial value when we cluster them, and here our second set of features comes into play as it considers the spatial structure of each coin image. We train SVM classifiers with two different sets of features from each image. The method has an accuracy of 99.61% with both high and low-resolution images. We also took pictures of the coins at 90˚ and 45˚ angles using the mobile phone camera, to check the robustness of our proposed method, and we achieved promising results even with these low-resolution pictures.

Also, we work on the problem of Coin Grading, which is another issue in the field of numismatic studies. Our algorithm proposed above is customized according to the coin grading problem and calculates the coin wear and assigns a grade to it. We can use this grade to remove low-quality coins from the system, which are otherwise sold to coin collectors online for a considerable price. Coin grading is currently done by coin experts manually and is a time consuming and expensive process. We use digital images and apply computer vision and machine learning algorithms to calculate the wear on the coin and then assign it a grade based on its quality level. Our method calculates the amount of wear on coins and assign them a label and achieve an accuracy of 98.5%.

Acknowledgment

I want to say the biggest thanks to Professor Dr. Ching Y. Suen. I am thankful to him for showing faith in my abilities and giving me this opportunity to work with him. It has been an enjoyable experience to be able to work with him. He has been supportive, patient, and very motivating. He encouraged me to explore, learn, and gave me beneficial insights which helped me much with my work. He paved the way for me to learn and grow with his great ideas. His positive attitude and confidence in me kept me going to achieve better results. I am grateful for such an enriching experience.

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CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

A Coin is generally a small piece of metal or plastic that is flat and round, mainly used as a medium of transaction or legal tender. Coin collecting is a popular hobby among people because of their aesthetic and historical value. Unfortunately, we have experienced massive economic and social setbacks in the last few years because of the actions of illegal counterfeiting rings that manufacture and sell counterfeit coins. Counterfeiting of coins has become the topic of research in the field for the last few years.

Much work has been done on coin recognition and counterfeit coin detection by many researchers [2, 5, 6, 7, 10, 11, 13] while few have also worked on coin grading systems. In the last few years, MUSCLE CIS- Benchmark has boosted the research on the coin recognition systems by holding the Competition in 2006 and 2007 [18]. The motive for the Competition was to classify European coins from 12 countries before the introduction of Euro coins. The issue of counterfeit coin detection is worked on by scientists, and methods devised by them are to handle superior quality counterfeit coins detection. There is a dire need for systems that can grade the coins automatically and assign them a quality level as per the standards.

This research targets two issues. One is counterfeit coin detection, and the other is automatic coin grading. Detection of counterfeits is a current research path, and many methods have been designed by various researchers to tackle this issue. Many applicable studies take into account the physical characteristics of coins to detect the counterfeits [34].

The main reason for shifting from physical characteristics to machine learning and computer vision techniques to detect counterfeits is that coins across the world may have the same physical characteristics and metal type. For instance, the 2-Euro coins across various European nations have similar physical characters and designs on the obverse side of the coin. The main drawback of systems based on physical characters is that a metal piece with an exact metal type, weight, and size can easily deceive the system. Hence, a focus on design features can eliminate the inaccuracies and provide a more robust system for classification. Automated solutions designed by computers are more methodical, cheaper, and can be applied remotely without human intervention.

Coin recognition is often confused with counterfeit coin detection, but they are different from each other in the way that coin recognition is less taxing than counterfeit coin detection. The reason behind this is that coin recognition needs minimal features to recognize different coins from each other. In contrast, coin attributes differ greatly even for currencies of the same country with different denominations. The quality of counterfeits has advanced so much that there is barely any difference between genuine and fake coin attributes. Consequently, counterfeit detection ought to understand coin images and extract comprehensive features to reduce the error rate. Counterfeit detection differentiates fake and genuine. Nowadays, there are large numbers of counterfeit coins in the market [1]. For instance, the Royal Canadian Mint announced a new device in Aug. 2015, Bullion DNA, to authenticate Gold and Silver Maple Leaf coins [35]. They applied this to coins minted after 2014 for the Gold coins and coins minted after 2015 for the Silver coins. This device uses the added micro-engraved security marks. Several studies suggest the need for robust systems for counterfeit coin detection.

(a)

(b)


MARGRETHE II DANMARKS DRONNING
1991

(c)


MARGRETHE II DANMARKS DRONNING

(d)


MARGRETHE II DANMARKS DRONNING
1996

(e)


MARGRETHE II DANMARKS DRONNING
1996

(f)


MARGRETHE II DANMARKS DRONNING
2008

(g)


MARGRETHE II DANMARKS DRONNING
2008

(h)

(i) (j)

Fig. 1. Samples of Genuine and Fake Danish and Chinese Coins

(a) Genuine Danish Kroner Year 1990, (b) Fake Danish Kroner Year 1990, (c) Genuine Danish Kroner Year 1991, (d) Fake Danish Kroner Year 1991, (e) Genuine Danish Kroner Year 1996, (f) Fake Danish Kroner Year 1996, (g) Genuine Danish Kroner Year 2008, (h) Fake Danish Kroner Year 2008, (i) Genuine Chinese Coin Year, and (j) Fake Chinese Coin Year

1.2 OBJECTIVES

Coins are the oldest medium of trade for ages and an essential part of our daily life. In today's world, with a growing number of coins, there is an increasing demand for robust systems to recognize and detect counterfeit coins accurately. All existing research done focuses on the text on coins, which differentiates the genuine coins from fake ones based on differences in character edges. In these methods, they manually select ROI (Region Of Interest), and features are extracted from the edges of the text which involves a lot of manual work. Therefore we need to automate this due to the manual nature of this method.

In documents and images, the method of segmenting characters works but does not work very well on coins because of the different types of coins and designs across the globe. Therefore, a method that can extract effective features from all types of coins and are not limited to characters is essential for coin detection.

The technique used by counterfeiters to forge the coins is that, they develop the new counterfeit stamps or by simulating the original coin stamps. The reality is that the features of fake coins are very close to the genuine ones but are never identical. The fake coins have a weak point, and that is their strokes. These strokes are always different in high quality forged coins and make them an easy catch. Strokes represent the unique features of a coin that are difficult to locate without the exceptional human intellect. It also takes much time considering the enormous number of coins, different languages, and their tiny sizes, which adds to the difficulty. Also, in different countries, texts are is minted on the coin in different languages and origins. A robust counterfeit coin detection should be able to detect all types of coins irrespective of their design or engraved text.

Local features such as SIFT and texture features such as Regional Binary Patterns have extensive use in different types of systems such as object recognition and classification and have shown tremendous results and differentiates images based on robust keypoint, which are scale, Rotation and flipping invariant. Various methods are put into use to measure crucial local key point differences between images based on various attributes. This new collaboration of local features and texture features helps to overcome all the shortcomings which usually occur when we generally stick to one method of feature extraction and provide excellent results and robust features to classify the genuine coins from counterfeit ones without having to devise different feature extraction methods for each type of coin.

1.3 CHALLENGES

There are serious challenges involved in processing coin images. Some of the challenges are as below:

Dimensions of the Coins - The size of coins pose a real challenge when trying to differentiate genuine coins from fake ones because most coins are tiny in size and look alike. The small size of the coins makes it hard to notice changes in those tiny details which set genuine coins apart from fake ones and that is where knowledge of experts comes into play as they can differentiate the coin by touch and feeling the surface, edges, letters, size, and texture compared to the average person.

The lack of tools to help us find these differences and tell genuine coins apart from the fake ones is another issue we face today.

Inconsistencies in the design of Fake Coins - In general, coins can be made in two ways: by striking and casting. Although it is tough to be precise when manufacturing, it is not at all difficult to acquire the talent to forge the coins. There is a plethora of knowledge on the internet. Coin forging has spread like an epidemic in parts of the world and breeds in coin factories and at home in small workshops set up for this purpose. This process of coin forging leads to a problem as different manufacturers follow different techniques to forge coins, so there is no particular set of features that can be put into place to tell genuine coins apart from fake ones.

Well forged Fake coins - The challenge is not only in different methods of forging coins but also the quality of forged coins and the advancement in forging technologies. The difference between the quality of genuine and fake coins is diminishing day by day, making it even harder to distinguish fake from real coins. On the other hand, the general knowledge possessed by people is not sufficient enough to locate these fake coins. This significant advancement in forging technology and lack of expertise required to detect this issue has led to high economic losses and poses a significant hazard for society. This issue also creates a significant need for more research on counterfeit coin detection.

Insufficient available Data - There are a plethora of genuine and fake coins in the market, but access to labeled fake coins is almost nil. It is forbidden by the government to possess fake coins and poses legal threats for anyone who has them. The government would not release the fake coins or their images for security reasons, but it makes the life of researchers difficult. It is almost impossible to carry out any research without sufficient data and in the case of counterfeit coins where we hardly have any data. We are profoundly grateful to Ultra Electronics Forensic Technologies and Danish authorities for providing us access to their collection of fake coins to carry out this research.

1.4 CONTRIBUTIONS

This thesis presents a robust system designed for counterfeit coin detection and automatic coin grading using a combination of two very effective feature extraction methods, namely SIFT (Scale-Invariant Feature Transform) and RFR (Rotation and Flipping invariant Regional patterns) using gradient magnitudes. It extracted Rotation, scale, and flipping invariant features that are very robust. We concatenate both our feature sets and use them for training our classifiers. Our feature sets highly complement each other in a way that SIFT provides us with most discriminative features that are scale and rotation invariant but do not consider the spatial value when we cluster them, and here our second set of features comes into play as it considers the spatial structure of each coin image. A combination of these features extracted from coins is further applied to train the classifiers and produce significant results. We also considered the scenario of developing our system into a mobile phone application. We took pictures of the coins at different angles using the mobile phone camera as a regular user of the application, to check the robustness of our proposed method, and we achieved promising results even with low-resolution pictures taken at a 90˚ angle and 45˚ angle with a regular mobile phone.

Additional work is done to automatically grade coins using the same feature extraction methods as described above, where we employ a combination of features to grade our coins. SVM (Support Vector Machine) is put into use to train and test those features, which also gave us good results

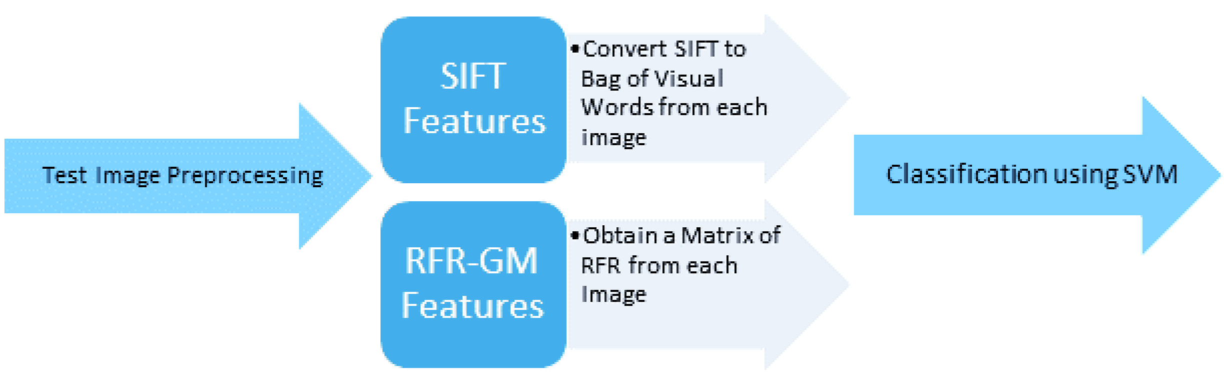

Fig. 2. The Proposed Counterfeit Coin Detection and Automatic Coin Grading Method

1.5 THESIS OUTLINE

The following chapters are as follows:

● Chapter 2: A thorough discussion of computer vision methods to handle different coin problems and existing research on different coin applications, i.e., coin recognition, grading, and counterfeit coin detection, are discussed in this chapter.

● Chapter 3: Discussion about Image acquisition and Image preprocessing methods.

● Chapter 4: Discussion about two feature extraction methods used in this research. The first one is SIFT (Scale-Invariant Feature Transform) that we have discussed thoroughly, and it is a very robust method that is scale and Rotation invariant and is best suited to our research. The second most robust feature extraction method is RFR (Rotation and Flipping invariant Region patterns) based on gradient magnitudes and the classification method used in our experiments.

● Chapter 5: Discussion about our experiments and results.

● Chapter 6: Discussion about the automatic coin grading problem worked on.

● Chapter 7: Discussion about our work and also provided some insight into the future work that is required to be done.

CHAPTER 2

LITERATURE REVIEW

2.1 COUNTERFEIT COIN DETECTION

One of the most significant financial and social challenges faced by governments and the general public is the detection of counterfeit currency. it is generally thought that coin counterfeiting is a wasteful task because of very little financial value of coins used in everyday lives. But when they are compounded, it leads to substantial economic losses. Now, the Government has realized the severe nature of coin counterfeiting and the way it is affecting the economy, loss of historical value of genuine coins, and playing with the sentiments of coin collectors. The Government is taking serious steps towards this issue. As a sincere effort made by the Royal Canadian Mint and the Canadian Government, an introduction of Bullion DNA is used to determine real Gold and Silver Maple Leaf coins. The UK lacked the technology to find counterfeits, and they were left with only one option to remove counterfeits from their system and introduce newly designed coins with added security features to detect and remove counterfeits from their system.

The common difference between Genuine and fake coins irrespective of their country of origin is a significant variation between edges of fake and genuine coins and unusual noise present in the background of fake coins. The counterfeiters can develop near-perfect counterfeits these days mostly by copying the stamp or making a similar stamp, but still, there are loopholes. The counterfeiters miss some finer details which seem negligible to them but, it proved to be a boon for modern technological counterfeits detection systems to detect these coins easily.

Several studies mainly focus on detecting fake coins. The previous studies took into account the physical features of coins such as size, weight, width, thickness, color, and electromagnetic properties. Size and weight are predominant features that are into practice in our current systems, such as vending machines and parking meters. Also, some researchers [2], for instance, employed the frequencies obtained from test coins to distinguish fake coins from genuine ones. The experiment used Euro coins of 50 cents, 1 and 2 Euro. This method has a high success rate, but the only issue is that these frequencies solely rely on the type of metal and if some counterfeiters were to use the same metal type then this system would fail miserably as the counterfeits with the same metal type may pass the test too as their genuine counterparts.

A method devised by Wang *et al*. [3] used a machine learning technique in which the coin under test is rotated in different angles until it matches a reference coin, and it works by matching images. After matching the coin images, a comparison between the test and reference coin is made by taking the relative distance between any two points on the test coin and matching it to similar points on the/a reference coin.

A method proposed by Tresanchez *et al.* [4] takes images of coins to find counterfeits with an optical mouse. The optical mouse captures images of 2-Euro coins partially and compares it to reference coins. The authors argued in favor of the optical mouse due to the compact size, cheap cost, and do not require technical skills. However, the optical mouse considers only one-fourth of the whole coin, which is a limitation that would affect the accuracy rate and also ruin the classification.

A method proposed by Sun *et al.* [5] for counterfeit coin detection combines the contour features and local image features. Contour features used in this research consist of letter attributes such as letter width, height, a stroke of letters, corresponding distances and angles between characters. *Maximally Stable Extremal Region (MSER)* was used to extract local image features to compare the test coin with a set of genuine and fake coins used as a reference. Though the results were promising, the dataset taken for experiments was tiny, and there is very little chance for this method to fit other coins.

A method proposed by Liu *et al.* [6] detects counterfeit coins based on local image features. The authors compare a set of SIFT keypoints extracted from both test and reference images. They represented coins in dissimilarity space, and stored results obtained after comparison of SIFT descriptors (which represents SIFT key points) on a test, and reference coins as a vector. They reduced the number of mismatched keypoints by improving the key points of the selection process. Unfortunately, the key points on some of the high-quality fakes can still fool the system.

A technique based on 3D image features to detect counterfeit coins used by Khazaee *et al.* [7]. The author examined the outer ring of the coin, having characters and numbers. They made use of 3D images to distinguish genuine and fake coins by taking the height and depth information from the coin images. The coin image is transformed into a new rectangular image by this method. After, we train the classifier by using height and depth from each row as features. The results obtained are impressive but require time, money, and expertise to use a 3D scanner.

2.2 LOCAL IMAGE FEATURES

One of the main issues in feature extraction is to maintain rotation, scale, and flipping invariance. The directions in which we align the coins are not fixed and are challenging to maintain while creating samples. Local image features and texture features which scale, flipping, and rotation - invariant features are used in our system to remove such issues.

Local image features have been used in several coin recognition systems [8, 9, 10, 11]. Local image features can define the image regions and specific interest points. In these papers [8, 10, 12, 13] the most widely used coin recognition method is the *Scale-Invariant Feature Transform (SIFT)* proposed in 2004 by David G. Lowe [14]. SIFT is considered the best method for coin recognition because of scale and rotation invariant. The SIFT considers images at different scales and uses the local gradient distribution, while based on the peak histogram of a local gradient, it nominates the orientation [14]. There is a location, scale, and orientation associated with every SIFT feature. In the second step, they extracted local image features by utilizing the peaks in the *Difference of Gaussians (DoG)* scale space and SIFT keypoint. Belongie *et al*. [15] use *Shape Context* as a feature descriptor. It creates the shape of each object as a set of points. The points connect to boundaries around the object by locating the missing points of each edge pixel. Ancient coin recognition has also used the shape context [9].

Anwar *et al*. [11] proposed the coin recognition method using the *Bag of Visual Words (BoVWs).* BoWs take into account the coin's texture and consider the local and statistical attributes. Anwar *et al*. divided the coin image into circular, rectangular, and log-polar areas and applied the

BoVWs method into them. Then, The BoVWs of the three are combined, and final BoVWs are decided to use for classification but spatial relationships are ignored among the image patches, which are very important in image representation. Several local image features were studied by Kampel *et al*. [9]. The authors take ancient coin images and detect several interest points in them and represent those interest points using local descriptors. The different interest points explored in this study include The Harris corner, Hessian-Laplace, Hessian-Affine, fast-Hessian, geometry-based region, intensity-based region, and difference of Gaussian. Al-Frajat [36] used a set of edge-based measures to find the differences in coin stamp's edges between the test coin and a training dataset. He then trained a binary classifier based on the results of those measures.

2.3 TEXTURE FEATURES

Features based on the texture of the coin are also popular alongside edge-based and local features. Xu [16] proposed a system based on *gray level co-occurrence* matrices to extract texture features. To estimate the gray level co-occurrence, it uses a statistical estimation of the spatial arrangement. The second feature extraction method used for coins is a Gabor *feature* [17]. Shen *et al*. [17] argued that the Gabor wavelet feature represents local texture features more efficiently and is very robust against noise. Coin recognition systems [18] have also employed gradient features. Fabrication of a system robust against illumination and change in image contrast Reisert *et al*. [18] used the direction of the gradients without considering the magnitude.

To extract texture features, Shen *et al*. [8] employed the Gabor wavelets and *local binary pattern (LBP)*. In the method, they have taken an image matching the coin, and they rotate it to match a training image. The statistics of Gabor coefficients or LBP values are extracted by dividing the coin into little areas. We use distance measures instead of classifiers to categorize the coins. To calculate the distance between two texture features extracted from the test and training coin image. The Euclidean distance and normalized correlation are used to calculate the distance between the feature vectors.

CHAPTER 3

IMAGE ACQUISITION AND GENERAL IMAGE PREPROCESSING

3.1 IMAGE ACQUISITION

CENPARMI [7] provided a labeled dataset of Danish coins consisting of both genuine and fake coins. This data set consists of coins of four different years that are 1990, 1991, 1996, and 2008 respectively and all four years having both Genuine and Fake coins. These images are taken with a Powerful professional camera, with the "CANON 60MM F2.8 MACRO EF-S" camera lens. We also used images of the Genuine Danish coins of Years 1996, 1991, and 1990 and Chinese coins available at CENPARMI taken by the author of the thesis with an iPhone 6 using the Macro Universal clip lens coupled with 0.67X wide-angle lens. This lens can take clear photos of small objects but had no resolution power as compared to original images taken with powerful cameras. We prepared this dataset using a mobile phone lens to check the robustness of our method for both high and low-resolution images.

3.2 IMAGE PREPROCESSING

The images collected as part of the dataset are not suitable for direct processing because of the different kinds of noise present in them. It becomes mandatory to remove all non-essential details before we can process them so that even the minor details can be detected correctly to improve our method. Preprocessing an image involves various steps such as resizing, noise removal, and enhancing the quality of the image. Different algorithms can be applied for the preprocessing of digital images to improve the feature extraction step.


MARGRETHE II • DANMARKS DRONNING
1991

(a)


MARGRETHE II • DANMARKS DRONNING
1996

(b)


MARGRETHE II • DANMARKS DRONNING
1991

(c)


MARGRETHE II • DANMARKS DRONNING
1991

(d)

(e)

Fig. 3. Danish coin images taken with high and low resolution camera

(a) Danish coin image taken with a powerful professional camera with the “CANON 60MM F2.8 MACRO EF-S” camera lens, (b) Danish coin images taken with a powerful professional camera, (c) Danish coin images taken with a mobile phone using lens taken head-on, (d) Danish coin images taken with a mobile phone using lens taken head-on, (e) Danish coin image taken with a mobile phone using the lens taken at an angle of 45 degree.

3.3 NEED FOR IMAGE PREPROCESSING

The raw data we obtained for our experiments is usually full of noise and come from different sources. It's challenging to write a different algorithm for each image to process it since each image is different. So, the best practice is to preprocess all the images and convert them to a generalized form so that processing them becomes more manageable, and the general algorithm can be applied to all of them to process them.

In this research, we use the following preprocessing techniques to improve the quality of the images.

1. Conversion of the RGB images to grayscale: To reduce the complexity of image processing steps, conversion of the RGB image to a gray-scale as the color is not crucial in coin classification or grading. In this case, converting colored images to grayscale because colored images contain more information than just black and white pixels and add to the complexity of the algorithm and also the color is not required features in many cases, and grayscale can be enough to process the data and provide sufficient information.

Fig. 4. Colored Image and Converted Grayscale Image

2. Segmentation - We segment the image by separating the foreground objects from the background using the Hough transform, and segmentation improves significantly by removing the noise.

Fig. 5. Coin Image with background and coin image segmented from the background

3. Image Restoration - Here in the Figure 6, you can see the degraded image, which was not suitable to be fed into our program, and we had to do some preprocessing to enhance the image. The restored image is the result of a high pass filter using wavelet and Fourier transform. On the right, you can see the filtered image after restoration and we can extract some useful features from the filtered image. This image is a better input for our program and gives us improved results by removing all the unnecessary information after preprocessing.

Fig. 6. Original Degraded Image Danish Kroner and Filtered Image

CHAPTER 4

FEATURE EXTRACTION

We use two feature sets obtained from two different methods. The first is SIFT (Scale Invariant Feature Transform), and the second is RFR (Rotation- Flipping invariant region binary patterns) based on gradient magnitudes to find effective features. Usage of these features to classify coins using very robust classifiers such as SVM and Random Forest produced some of the best results.

4.1 FEATURE EXTRACTION USING SIFT

SIFT image features are free from many complexities found in other methods such as object rotation and scaling, and they are resistant to any kind of noise in the image. The SIFT method converts the whole image into "Group of local feature vectors" [27]. Every feature obtained is a scale and rotation invariant.

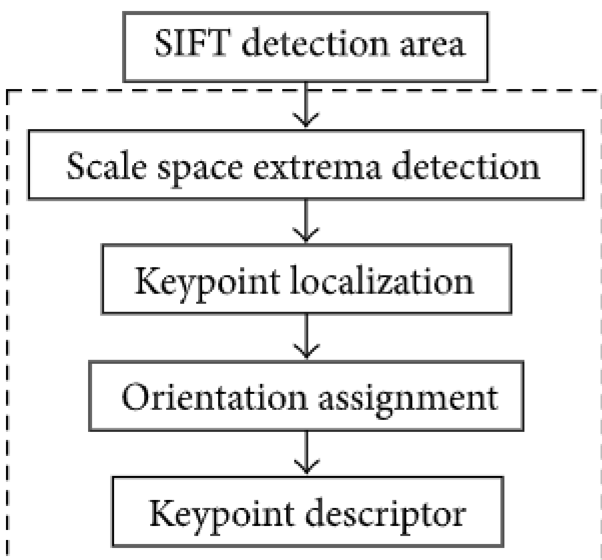

Fig. 7. SIFT Key points extraction Process

4.1.1 SIFT ALGORITHM FOUR-STAGE FILTERING PROCESS:

1. Scale-Space Extrema Detection

In this stage, we obtain the location and scale of the same object with different views by using the "scale-space" function, and as per assumptions, it is based on the Gaussian function. Out of several techniques available to find stable key Points in scale space. The difference of Gaussians is one of the methods to find the scale-space extrema, $D(x, y, \sigma)$ by calculating the difference between the two images, where we have one image with scale k times the other. $D(x, y, \sigma)$ is then given by:

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma)$$

We detect local maxima and minima of $D(x, y, \sigma)$ and compare it with its 8 neighbors that are at the same scale as well as nine neighbors from above and below of one scale. The point is taken as an extremum If this value is the minimum or maximum of all these points.

2. Key point Localization

At this stage, we remove key points that are poorly localized or have low contrast from the list of key points extracted. We find the Laplacian value for every key point in stage 1. We take the location of extremum z, and the point is left out if it's below the threshold value when taking function value at z. In this way, we remove extremes with low contrast from the set of points. We consider a sizable principal curvature across the edge to remove poorly localized points, but there is also a small curvature in the perpendicular direction in the difference of Gaussian function. We reject the key point if the difference is lower than the ratio of the largest to the smallest eigenvector, from the 2x2 Hessian matrix at the location and scale of the key point.

3. Orientation Assignment

This stage takes into account the local image properties, the key points are assigned a consistent orientation, and then a key point can be represented relative to it, making it invariant to rotation. Orientation can be assigned by selecting the Gaussian smoothed image L from above by using the key points scale, compute gradient magnitude m, and compute orientation θ. Gradient orientations of the sample points form an orientation histogram. We find the highest peak in the histogram. This peak and any other peak within 80% height of this peak create a key point with that orientation.

4. Key point Descriptor

The algorithm creates the key point descriptors by local gradient data, used in the above steps. The gradient information is rotated and then weighted by a Gaussian with a variance of 1.5 * key point scale to align with the orientation of the key point. We create a set of histograms over a window centered on the key point. A set of 16 histograms, aligned in a 4x4 grid, each with 8 orientation bins are usually used by keypoint descriptors, one for each of the mid-points of these directions and other for the primary compass directions. We obtain a feature vector with 128 elements. These vectors obtained are called SIFT keys and make use of the nearest-neighbors technique to detect the possible objects in an image. There is a large number of SIFT keys in an image of the object. A 500x500 pixel image gives around 2000 features despite the number of blockages that program experiences while recognizing the image. Points extracted on any image describe the features in an image. We use the features extracted from the training image to recognize and classify the test object. Classification of the features extracted from the training image must be scale, illumination, and noise invariant for accurate and efficient recognition. The essential attributes of these features are their fixed relative positions within the image and do not change in different images. Initially, for the Scale-Space, the extreme is calculated, then the key points are localized, and nearby points interpolate. Then the edge responses and low contrast key points are eliminated. In Figures 8-10 we represent the SIFT descriptors extracted from three different types of images from our dataset. Figure 8 is an image of the coin taken with a powerful camera with the "CANON 60MM F2.8 MACRO EF-S" camera lens. Figure 9 and 10 are the images of the coins taken with an iPhone 6 at 90˚ and 45˚ angle

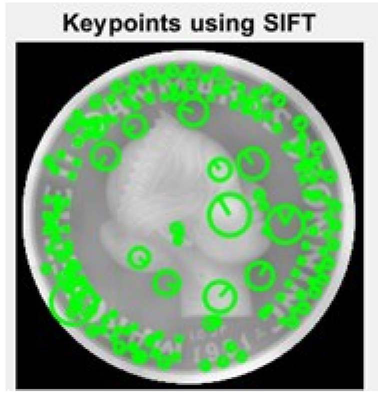

Fig. 8. The coin image with a powerful camera took head-on

Fig. 9. Coin Image with Mobile using a Macro lens taken head-on

Fig. 10. Coin Image with Mobile using a Macro lens taken at 45-degree angle

4.2 BOVW MODEL TO USE EXTRACTED SIFT DESCRIPTORS

After extraction of the robust scale and rotation invariant SIFT keypoint descriptors, Bag of Visual Words (BOVW) is employed to use these extracted key points for counterfeit coin detection. Bag of Visual Words is used as an extension to the NLP algorithm Bag of Words and is useful for image classification. C. Surka et. Al [28] developed the BOV, and the way it works is by creating a vocabulary that represents the image in terms of extrapolated features. We can create Bag of Visual words from key points generated from the SIFT Features.

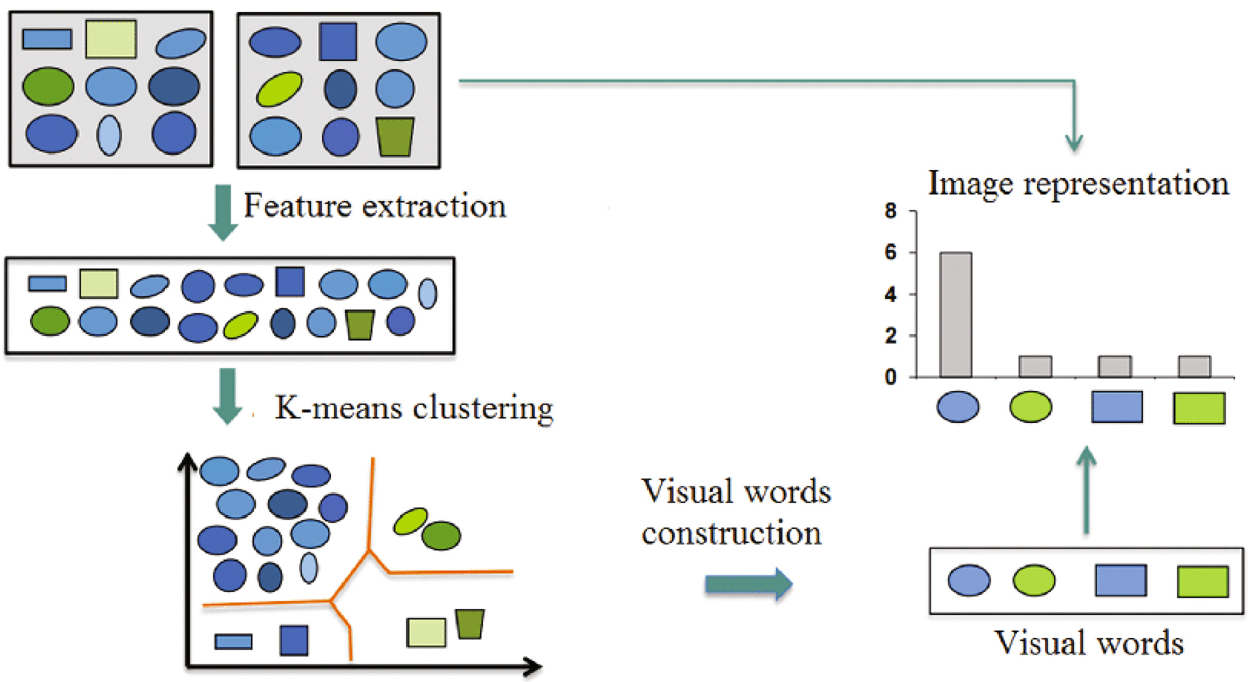

Fig. 11. Construction of Bag of Visual Words from SIFT descriptors [26]

The procedure of vocabulary development is as follows:

- **Clustering:** Clustering can be understood as a process to group a set of objects such that similar objects lie in the same group. The selection of clustering algorithms is problem-specific. In our case, we use KMeans clustering. An initial random solution is defined, and we call it cluster centroid. Cluster centroids are placed randomly within data bounds. Afterward, Assignment step KMeans goes over each key point descriptor to find the closest cluster centroid to it. It assigns the descriptor to its closest cluster centroid. We use The Average & Update Step after the initial clustering. We relocate the cluster centroids based on the sum of all members of that particular cluster. It results in a more tightly aligned distribution, which leads to the computation of new clusters and the process is repeated until the position of new cluster centroid co-aligns with the old cluster centroid.

- **Bag of Visual Words Model:** Every point in the cluster has a minimum distance from its centroid, and a minimum threshold is set to stop the clustering process from running infinitely. BOVW (Bag of visual words) works by partitioning similar features extracted from a training set of images. The frequency and collection of certain features help to determine the class of the image.

- **Training and testing:** It is a supervised learning model. It involves a training set and a testing set. We divide Dataset into training and testing. We use the 70-30 proportions. BOVW is a supervised learning model. Therefore according to the class, it belongs to we assign a label to each image. We have extracted features using SIFT to convert the image into a feature vector. The final step is to generate the vocabulary. We can consider it as a dictionary that stores corresponding relationships between features and their definition in the object. Each feature in the image is a device to help describe the image.

4.3 FEATURE VECTOR USING BOVW

Linking vocabulary and clustering:

Using SIFT, we detect and compute features of each image. SIFT gives us a dimensioned array of m×128m×128, where m is the number of features extracted from the image. We obtain a list of visual words from each image to group similar features together. Similar features help define the image and when training our system on several images. Similar features help describe similar ports of different images, and it forms a broad vocabulary base. These small groups of similar portions represent a word, and all groups combined giving us the complete vocabulary created from training data. We can simply define similar words by their cluster number.

Our histogram describes each image in the form of generated vocabulary; therefore, the size n_images×n_clusters.

4.4 FEATURE EXTRACTION USING RFR

4.4.1 FEATURE EXTRACTION USING RFR BINARY PATTRENS

Histogram information is a basis in many feature extraction methods for image-based coin recognition and Classification. This feature extraction method, on the contrary, considers the spatial structure. To make the system rotation and flipping invariant Rotation-and-Flipping-Robust Region (RFR), binary patterns are taken as the features [19]. It takes the gradient magnitude of the coin image and uses local difference magnitude to extract the RFR. This method stands out for the accuracy, smaller feature dimension, and time.

We calculate the gradient magnitudes from the boundaries of characters and symbols that represent the structure of the coin image. We use the mean gradient magnitudes for inter RFR while the differences of mean gradient magnitudes are for Intra RFR. This modified RFR for coin detection is known as RFR-GM (RFR-gradient magnitude).

This feature extraction brings the following benefits:

1. High discriminating capability: This method surpasses the methods using histogram information for coin recognition as it makes use of the spatial structure.

2. Compact feature size: This method has a minimal feature dimension as it extracts features from rings in a coin and stores features as index numbers.

3. Fast feature extraction: This method is straightforward as it extracts features by comparing the texture of sub-regions, and it takes very little time.

We divide the coin into several rings and each ring into several sub-regions and Regional Binary Pattern (RBP) templates. Then calculate the mean luminance of sub-regions and generate two types of RBP features: Intra RBP and inter RBP. Intra RBP compares mean luminance of sub-regions in a ring, and Inter RBP compares mean luminance from sub-regions between two adjacent rings. Each RBP represents the left-right and top-down spatial structure information. The RBPs generally form circular patterns since they are extracted from rings and can form duplicates when we flip or rotate them. Thus, the conversion of RBP to RFRs removes duplication.

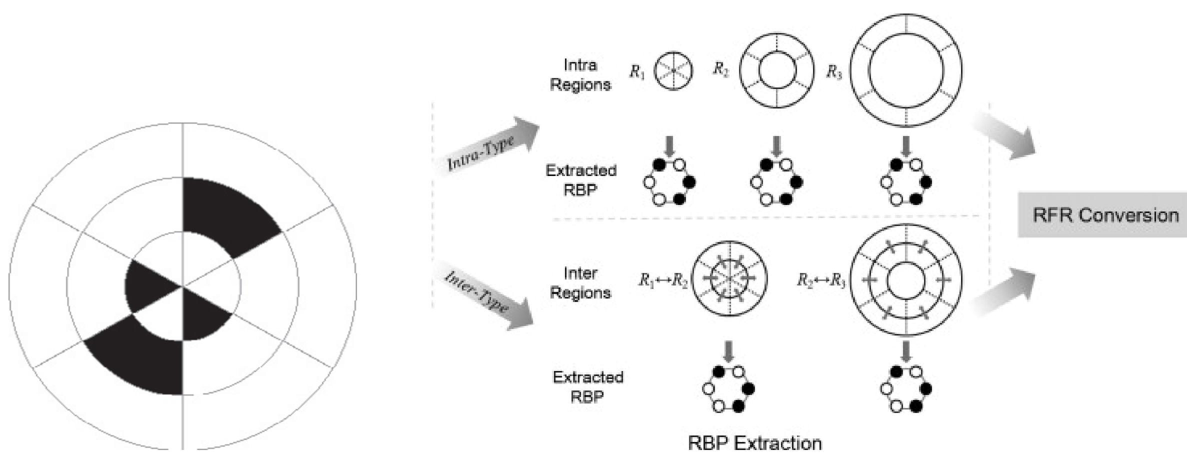

Fig. 12. Generation of the proposed RFR [20]

4.4.2 CONVERTING RBP INTO RFR

We consider RFR and RBP in the above figures with the number of subregions as 6. Following rotation or flipping transformations, RBP can be converted into RFR. For Instance, such as two binary patterns' 010110', and '110100'. When we shift '010110' in a circular way, the transformed pattern can be '001011'. Also, if we flip '110100', the new pattern can be '001011'. These two patterns are precisely the same after we flip or rotate them. The RBP becomes robust to rotation and flipping transformation after we convert them to RFR. RBP is converted to RFR by using the indexes described by RFR. An index table assigns the index numbers (e.g., look-up table), which is defined as IND by the RFR method. For Instance, if an RBP is '010110', then it gets index ten by IND (010110), and if an RBP is '110100', then it too gets index 10 by IND (110100). Thus, these two RBPs ('010110' and '110100') turn out to be the same by the index table IND. RFR computes the minimum Hamming distance between two RFRs to keep the error to the minimum.

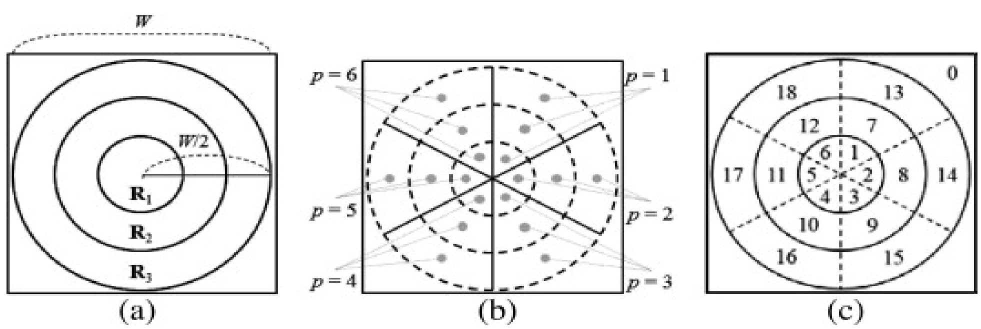

Fig. 13. An example of a template with 3 rings and 6 sub-regions

(a) A template with 3 rings (b) 6 divided sub-regions with gray spots per each ring. (c) The numbers in (c) denote the position numbers of sub-regions. [20]

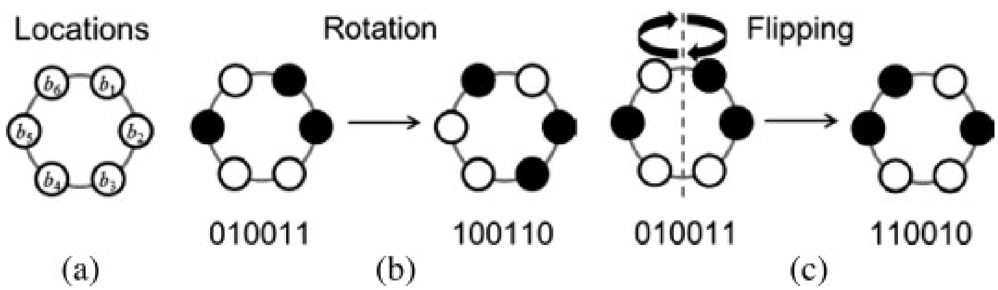

Fig. 14. Illustration of the rotation and flipping of a region binary pattern

(a) Shows locations of each bp, (b) shows a new binary pattern 100110 after rotation of the original pattern 010011, and (c) shows a flipping pattern 110010 [20]

An RBP template having 3 rings and 6 sub-regions per ring is considered for our experiments. Every sub-region is described as p(n, s), where n is taken as an n-th ring in the RBP template, and s is taken as the s-th sub-region in the ring. For Instance, p(3,1) and p(2,3) show the 1st sub-regions in the 3rd ring, and the 3rd sub-regions in the 2nd ring, respectively. In this example, m(3,1) and m(2,3) are 13 and 9 when calculating the mean magnitudes, respectively. Intra RBPs and inter RBPs can be calculated from m. Intra and Inter RBPs after extraction can be converted to RFRs to have robustness against rotation. An Index table IND[19] is used to convert RBPs to RFRs. All RBPs are assigned to one of the RFRs and defined to an index set as X = {x1, x2, ... , x2N1}. Finally, RFRs are extracted from gradient magnitudes, and local difference magnitude transform is applied to Intra RFR. The improved RFR is called RFR-GM.

4.4.3 FEATURE VECTOR USING RFR

Analysis of the proposed feature RFR-GM was done thoroughly to select the best parameters (the number of rings and sub-regions in an RBP template) for image-based coin recognition. We have tried the RFR-GM with different RBP templates that consisted of 6–30 rings with 6 increments and 4–20 sub-regions with 2 increments.

RFR-GM has just 23 feature dimensions, which are the minimum among all similar types of features and performed well compared to existing features [29, 30, 31, 32] for coin classification.

RFR-GM is well-suited for image-based coin detection. The given RFR-GMs performed better than all other features while keeping the smallest feature dimension. RFR-GM achieved the highest accuracy and robustness against rotation because it bases itself on the spatial structure. This method aimed at improving the discrimination and robustness of features in coin detection.

4.4.4 FINAL FEATURE VECTOR USING SIFT AND RFR FEATURE SETS

We extract two feature sets from each image in our dataset. We extract our first set of features, the SIFT Descriptors, and create visual words after using the k - means clustering on all the descriptors. We do this to reduce the dimensionality of our SIFT features since they have a very high dimension. After we create the visual words, we represent each image as a histogram of all the visual words. We then extract our second set of features. The RBP's and convert the RBP's into RFR to make it rotation and flipping invariant, and we create a Feature vector which has 23 dimensions. We concatenate both our feature sets and use them for training our classifiers. Our feature sets highly complement each other in a way that SIFT provides us with most discriminative features that are scale and rotation invariant. When we create the visual words from SIFT descriptors after clustering them, we can reduce the dimension of our feature sets, but we lose on the spatial value, and here our second set of features comes into play as it considers the spatial structure of each coin image. In this way, we can extract the best set of features from each coin image to train our classifiers. Given below in the Figure is the feature extraction framework of our proposed method.

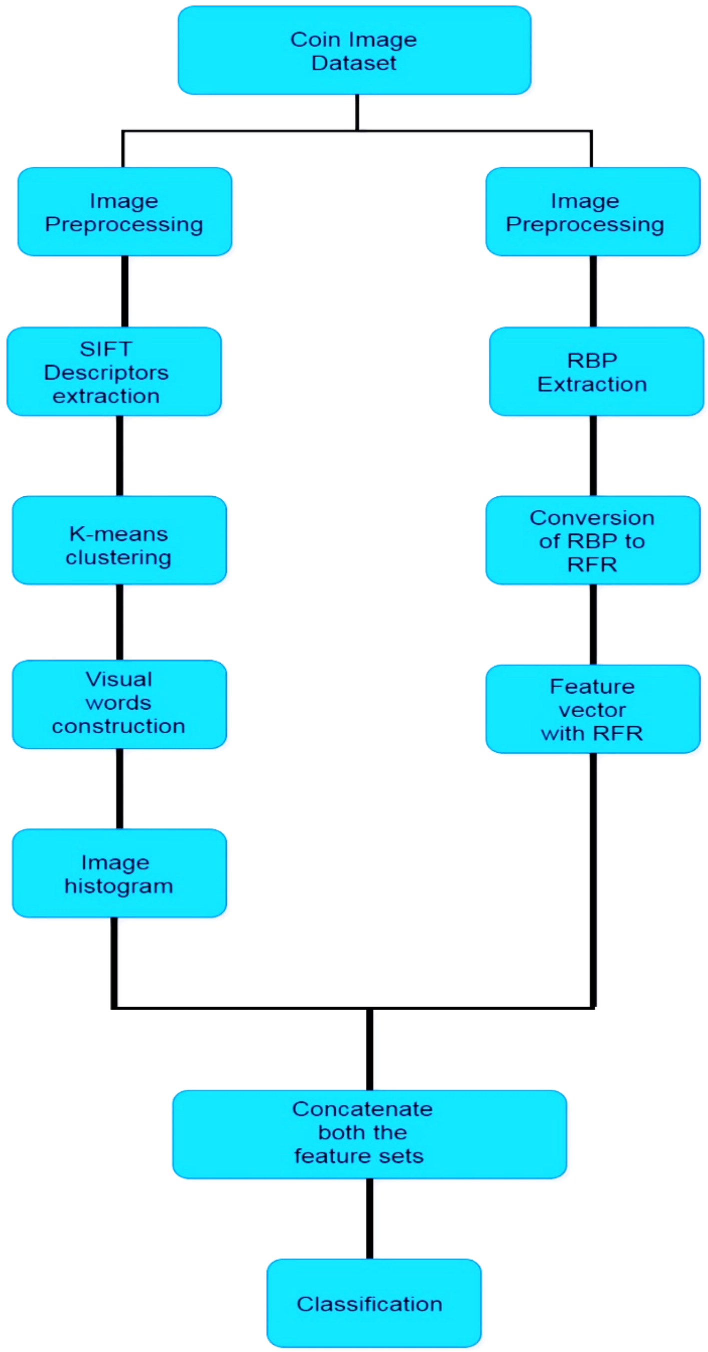

Fig. 15. Feature Extraction framework of our proposed method

4.5 CLASSIFICATION

We have used different types of classifiers to evaluate the performance of our proposed system. We derive two different feature sets from each image in the dataset, and then we concatenate our feature sets and use them for training our classifiers. We tested our system on a total of 5 classifiers to find out the classifier that best suits the needs of our system and gives us the highest results. In the next chapter we will discuss about the performance of each classifier for our dataset for different visual words selected by concatenating that with our second feature set.

CHAPTER 5

EXPERIMENTAL RESULTS AND DISCUSSION

This section describes how the methods used in the detection of counterfeit coins produced results. The results in this section look promising; they identify the validity and reliability of the feature extraction methods (discussed in Chapters 3, 4, and 5) used in carrying out the tests of the counterfeit coins. The results were obtained using Datasets in the experiment. The Ultra Electronics Forensic Technology provided one of the datasets. It contained data of coins from different years: 1990, 1991, 1996, and 2008. The Danish coins in the dataset consisted of both genuine and fake coins. The second dataset used in obtaining the results used in this section consisted of images of the Danish coins taken with a mobile phone. The Danish coins are from 1990, 1991, 1996, and 2008. The images used in training and testing were taken at CENPARMI by the author of the thesis. The Third dataset we used was of Chinese coins of different years provided by CENPARMI.

5.1 SELECTION OF CLASSIFIER

We trained out feature sets using the SVM, Random Forest, K-nn, Stochastic Gradient Descent or SGD (with loss function: Hinge loss (SVM), learning rate: 0.01, epoch: 500, and lambda: 1.0E−4), and MLP (with learning rate: 0.2, momentum: 0.3, number of sigmoid nodes in hidden layer: 20). The tables given below show the performance of each classifier for our dataset for different visual words selected and concatenating that with our second feature set.

Table. 1. Comparing the classification accuracy obtained using various classifiers

Classifiers	Number of Visual words					
	10	15	20	25	30	35
SVM	78.15	82.69	87.75	93.55	99.61	95.69
Random Forest	70.02	75.36	83.25	89.36	97.02	91.36
k-NN	68.26	72.86	81.36	85.95	92.04	88.53
SGD	76.77	80.45	84.69	88.57	97.56	92.45
MLP	77.12	79.56	83.69	89.12	98.21	91.69

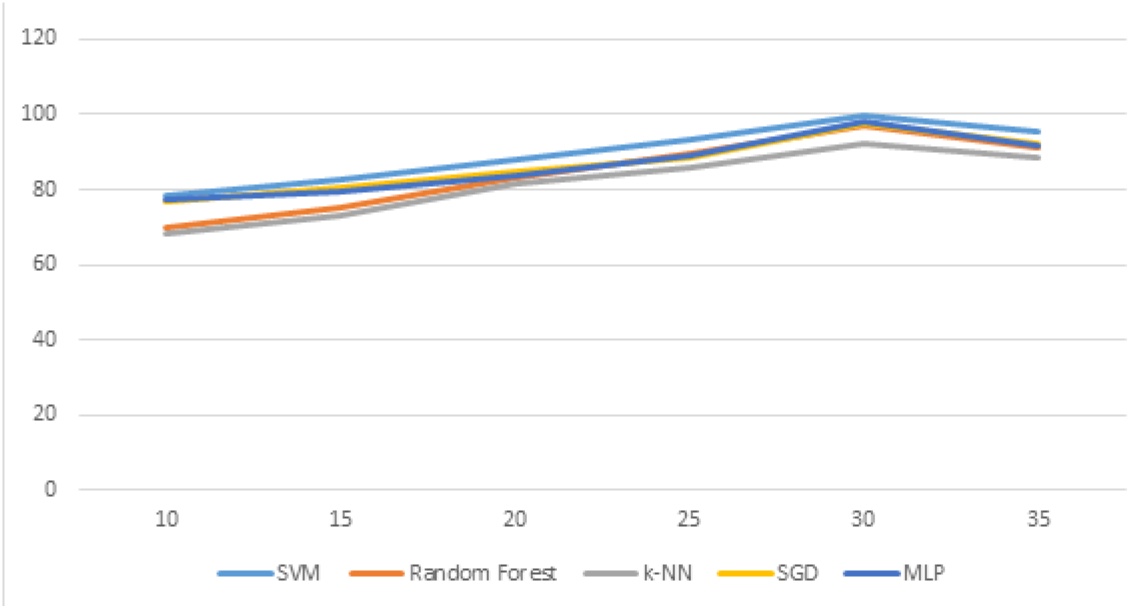

Fig. 16. Accuracy obtained from five classifiers for different visual words selected

After looking at the results of the above-given classifiers, we concluded that k-NN gave the lowest accuracy, whereas the other three classifiers: Random Forest, SGD, and MLP, gave good results. However, SVM performed best, and also it has been proven in various studies [24, 25] that SVM works best with SIFT Features. We decide to use SVM for our experiments taking into account the results obtained from all the five classifiers. We discuss SVM classifiers in the next subsection.

5.2 SUPPORT VECTOR MACHINE (SVM)

A support vector machine classifies data into two categories. It is an algorithm that uses supervised learning. We train it with a set of labeled data sorted into two categories. The SVM Algorithm determines the category of new data points. SVM is a type of non-binary linear classifier. We feed the feature vectors after the reduction of their dimensionality into the Support Vector Machine (SVM) classifier as an input. The SVM was introduced by Vapnik [21], and since then, the SVM showed excellent results in classification systems.

The SVM was initially designed as a linear classifier that placed a hyperplane between two classes to divide them. The goal of the SVM was to maximize the distance from the hyperplane of each class element. To work on the non-linear (multiclass) classifications, SVM was later redesigned. We used the SVM to classify the coins into one of the two categories that are either "Genuine" or "Fake." The support vector machine aims to distinctly classify the data points by finding a hyperplane in N-dimensional space (where N — the number of features). We can choose different hyperplanes that maximize the margin and provide a stronger basis to differentiate between the two classes of data points at that instant and later.

The SVM mainly finds a hyperplane, keeping the margin between the two classes as most significant. Taking as the feature points that are linearly separable and as the labels, the hyperplane can be defined as below. The weight vector, and, the bias, are taken as the parameters of the hyperplane.

$$f(X) = Xprime\beta + b = 0$$

The following optimization problem is solved to obtain the highest margin, :

$$max\ \beta, b, ||\beta|| = 1\ M\ subject\ to\ yi(x0i\beta + b) \geq M, i = 1, \ldots, N$$

That can be summarized by solving the given below Lagrangian optimization problem to find the weight vector β and the bias b:

$$min\ \beta, b\ L(\beta) = 1/2||\beta||2 - X\ N\ i = 1\ \alpha i\ [yi(\beta\ T\ xi + b) - 1]$$

As in any other Lagrangian problem, they solve the above Equation by taking the derivative of the Equation for β and b separately and set it to zero. The obtained amounts for β and b are substituted in the above Equation, and a solution to a more straightforward optimization problem is obtained.

Hyperplanes act as a boundary between different data points. Data points are assigned to different classes on the basis of the side of the category of the hyperplane. The number of features decides the dimension of the hyperplane for the two input features. The hyperplane is a line for two features and a two-dimensional plane for 3 features. SVM algorithm classifies objects into categories and maximizes the distance between them to achieve excellent discrimination power.

The Some Uses of SVM include: Face detection, Text and hypertext categorization, Classification of images, Bioinformatics, Protein fold and remote homology detection, Handwriting recognition. The SVM classifier makes the differentiation between the counterfeit coins and the real coins based on the methodologies used in training. The training consisted of the use of Danish genuine and fake coins of all the four years. The reason why the training was carried out was to enable the SVM classifier to identify the features of the genuine coins and have the capability of identifying defective coins. Based on the training offered to the SVM classifier to detect the characteristics of the coins, the matching keypoints existing between the images are identified efficiently. We used the SVM classifier for the classification of the features of different coins, and the coins were grouped into two groups marked as "Fake" and "Genuine." The table below shows the variation of the samples of coins used in the experiment. We have used coin images taken with Powerful canon camera at 90˚ angle, and coin images were taken with an iPhone 6 at 45˚ angle and 90˚ angle from all four sides of coins by keeping coin at the flat surface such as a table. We tilted our camera lens at respective angles to capture the coin image.

Table. 2. The Dataset of coins used in this research

	Training set		**Testing set**		**Total Images**	
Dataset	**Genuine Coins**	**Fake Coins**	**Genuine Coins**	**Fake Coins**	**Genuine Coins**	**Fake Coins**
Danish 2008	16	81	7	36	23	117
Danish 1996	72	7	31	3	103	10
Danish 1991	75	9	32	5	107	14
Danish 1990	120	17	52	8	172	25
Danish Coin images taken at 90° angle	100	0	44	0	144	0
Danish Coin images taken at 45°angle	100	0	44	0	144	0
Chinese coin images	30	70	10	30	40	100
Total	513	184	220	82	733	266

5.3 EXPERIMENTAL RESULTS

During the experiment, there is selection and extraction of SIFT key points and Regional binary patterns from every image from the training set. There are three tests to come up with an appropriate number of clusters or visual words used in the appropriate distribution of key points of the training set. The number of visual words built was 10, 15, 20, 25, 30, and 35. There was checking how many visual words would provide the highest data accuracy. We initially set our number of visual words to 10 as in literature, there is no fixed number for the visual words, and it is thus obtained experimentally. The accuracy when the number of visual words was 10 was lower and kept increasing as we increased the number of visual words by increments of 5 and was highest at visual words equal to 30 and started decreasing as we increased the number of visual words to 35. The SVM was very useful in testing all the procedures for all different types of Coins including Danish and Chinese coins, and the results that were finally produced are represented in the table below:

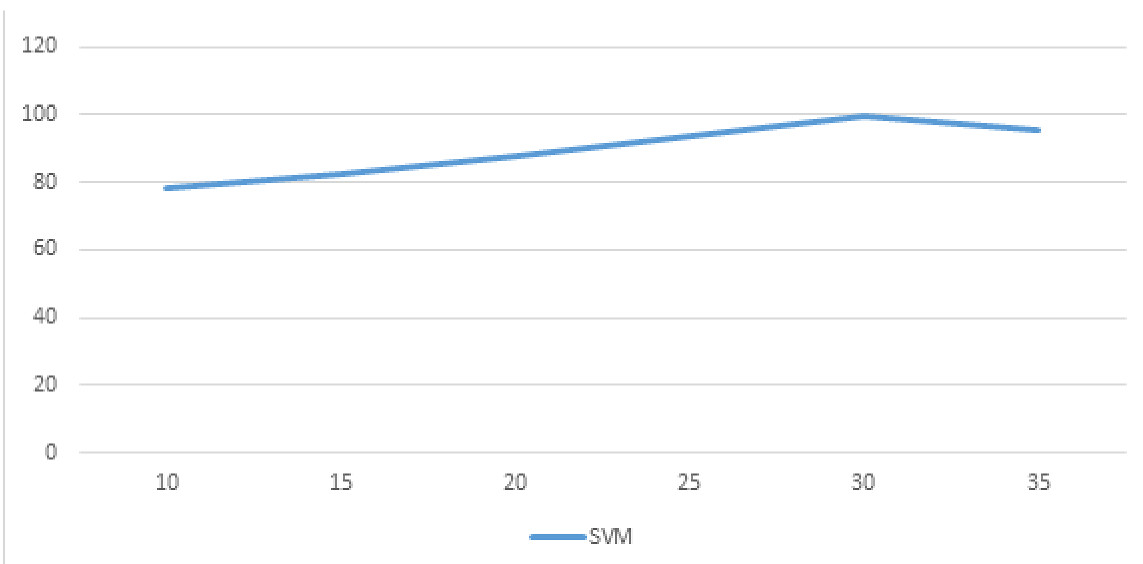

Fig. 17. Accuracy obtained for Danish coins for different visual words from the SVM

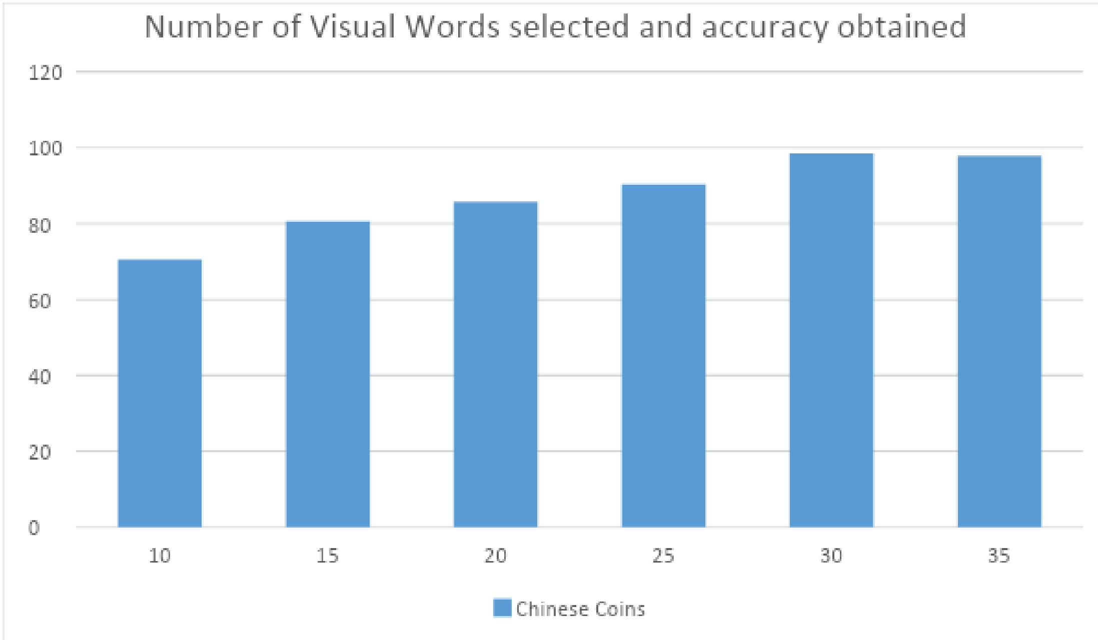

Fig. 18. Accuracy obtained for Chinese coins for different visual words from the SVM

Table. 3. Accuracy obtained for Chinese coins for different visual words from the SVM

Classifiers	**Number of Visual words**					
	10	**15**	**20**	**25**	**30**	**35**
SVM	78.15	82.69	87.75	93.55	99.61	95.69

The results identified in the chart were obtained after testing the dataset 3-times. The reason for testing 3-times is to ensure that there is overcoming a certain level of uncertainty within the final results, which are removed through re-undertaking the tests and finding out the average of the overall results which are obtained from the different results which are obtained. Undertaking or re-doing the results is very important in making the judgment of the final results for every step which is undertaken. The Table 3 illustrates the different results which are obtained when using the SVM.

Images of the different datasets of Danish and Chinese coins obtained using a Powerful Camera taken head-on, using iPhone 6 taken head-on and, using iPhone 6 taken at 45˚ angle are used in our experiments. To take the images of the coins at 45˚ angle, we placed the coins on the table and tilted our camera at 45˚ angle and took a picture of the coin from all four directions to capture the coins from all directions in order not to miss any distinctive features. We then calculated values of precision, recall, as well as f-measure for each coin image taken from all four directions and took an average of all four results for the final value of precision, recall, as well as f-measure for each coin image at 45˚ angle. We also tested our system with the mix of the Danish coins taken by camera and iPhone 6 at 90˚ and 45˚ angle. We also tested our system with the mix of the Chinese coins taken by camera and iPhone 6 at 90˚ and 45˚ angle The different results of precision, recall, as well as f-measure, were obtained during the experiment. They are presented in the Table 4 and Figure 19 and 20 below. The highest f-value was obtained during the segmentation of the Danish and Chinese coin images taken with a powerful camera because the quality of the images obtained using a specialized scanner was high. The Images of Danish and Chinese coins with camera had sharp edges and were very clear.

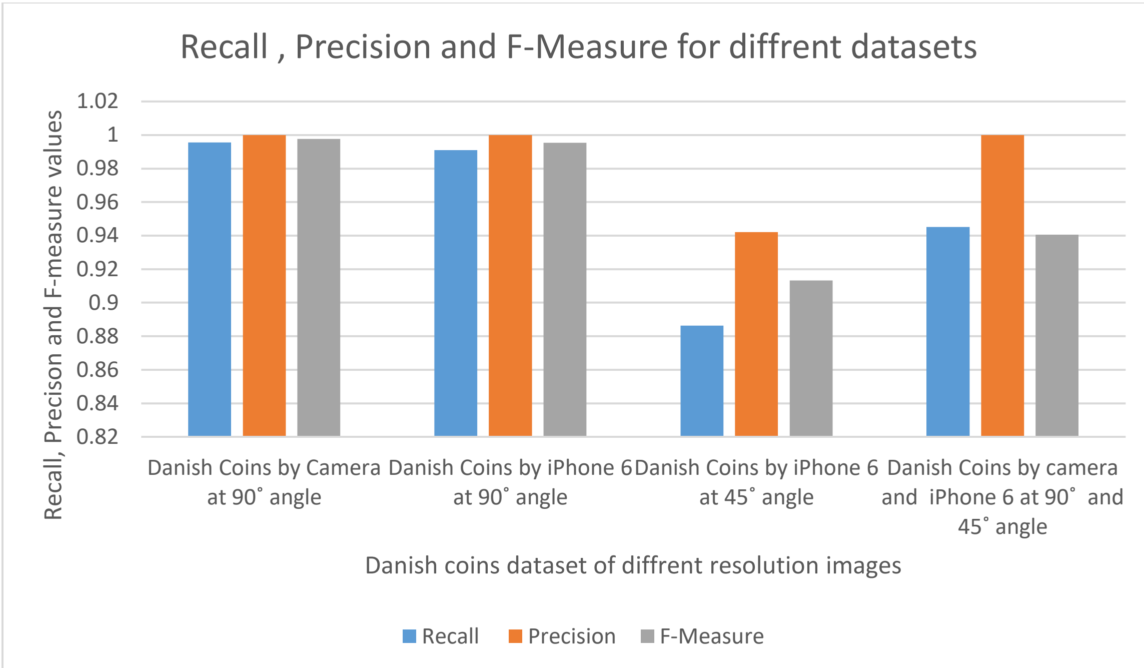

Fig. 19. Recall, Precision and F-measure for Danish Coins of different resolution

Table. 4. Recall, Precision and F-measure for Dataset of different resolution

	Recall	**Precision**	**F-measure**
Danish Coins by Camera at 90˚	0.9955	1	0.9977
Danish Coins by iPhone6 at 90˚	0.9909	1	0.9954
Danish Coins by iPhone 6 at 45˚ angle	0.8864	0.9420	0.9133

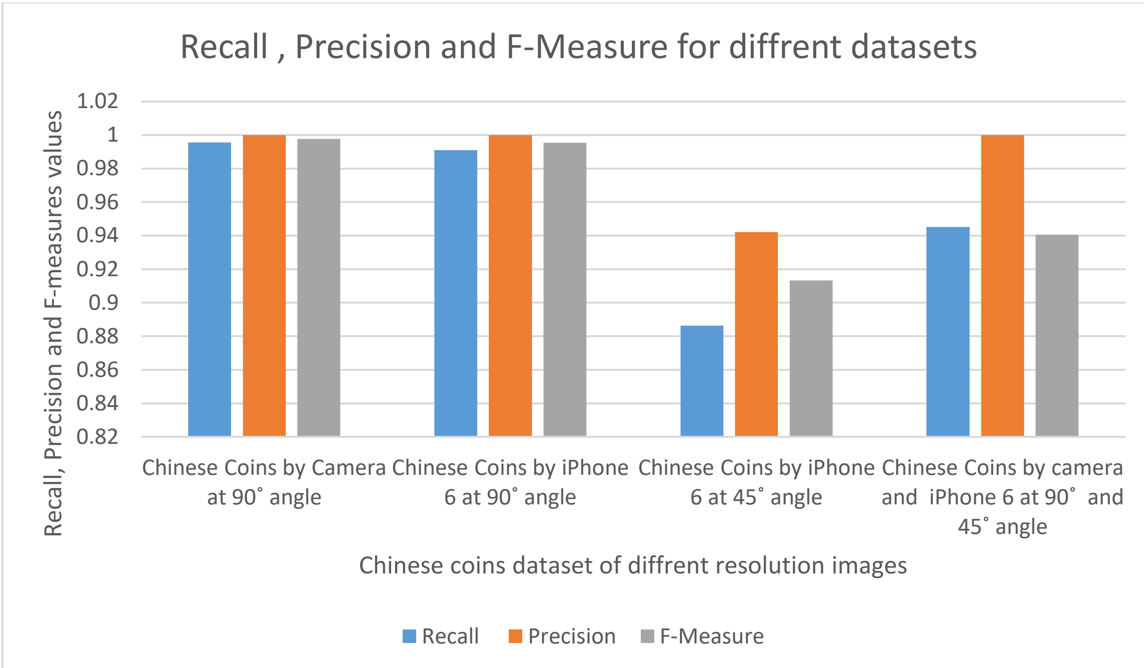

Fig. 20. Recall, Precision and F-measure for Chinese Coins of different resolution

The lowest f-value among the 3 different categories of datasets used originated from the dataset obtained using iPhone 6 by taking images of the coins at 45˚ angle.

The main reasons why there was a low f-value for that specific type of coins are: The quality of dataset obtained using iPhone 6 by taking images of the coins at 45˚ angle was lower when compared with other dataset obtained using the Powerful camera by taking Danish coins images head-on.

Table. 5. F-measure for Dataset of different resolution

	F-measure
Danish and Chinese Coins by Camera at 90°	0.9977
Danish and Chinese Coins by iPhone6 at 90°	0.9954
Danish and Chinese Coins at 45° angle	0.9133

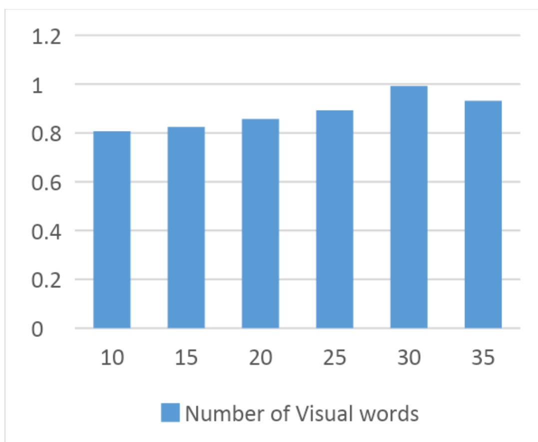

Fig. 21. F-measure values obtained for different datasets of Chinese coins.

CHAPTER 6

AUTOMATIC COIN GRADING

6.1 PRELIMINARY CONCEPTS

Coin grading is a method to find the grade or quality of a coin. The value of the coin is decided mainly by its grade. Coins get a specific grade after a series of experiments on coins to determine its quality per numismatic studies [33]. Usually, to avoid any personal bias, the task is undertaken by three expert numismatists. Some of the parameters can be left out while testing the grade of coins under different parameters by a Numismatist, while some receive extra weight. Therefore, coin grading becomes very subjective. American Numismatic Association Certification Service (ANACS), the Professional Coin Grading Service (PCGS), and Numismatic Guaranty Corporation (NGC) are among the most prominent numismatic institutions. In the coin collecting market, the numismatic institutions act as third-parties and grade the coins. These institutions grade coins without the influence of the buyer and the seller.

Coin grading divided coins under these three broad categories:

Good: The texture of the coin wears out, but the details can be recognized.

Fine: To some extent, you can see the mint luster.

Uncirculated: The luster band can be well recognized, and the features are very sharp.

6.2 PROBLEM DEFINITION AND MOTIVATION FOR COIN GRADING

The coin collecting market consists of significant users of coin grading facilities and applications. However, we realize there is a requirement for a stable coin grading system when we study more in-depth into this field and find its further applications.

Some of the applications of coin grading are as follows:

(1) Banks can reject damaged coins more quickly.

(2) Grading systems can be improved further at numismatic institutions.

(3) Online coin buyers can have access to a quality measurement tool.

Coin counterfeiting is a universal problem, and people in every field of life are affected by it, such as the government, the general public, or coin collectors. Many countries like China and Denmark have faced many issues because of counterfeits in their banking and trading systems.

Since coin grading is heavily dependent on the expertise of the numismatist, an automatic system for coin grading is a boon for conducting further research in this field. The system proposed by us for automatic coin grading uses features extracted from the images of the coins. The grade assigned by this system to the coins can be used as a means of removing the completely damaged coins from circulation. In the Era of E-Commerce, it has become much more comfortable for many counterfeiters and frauds to sell low quality and fake coins instead of high-quality genuine coins and many coin collectors easily fall prey to this trap. In our proposed method, SIFT descriptors, along with RFR-GM pattern features extracted from coin images, are used to assign the grades to the coins by taking into account the amount of wear on the coins.

6.3 DATASET PREPARARTION

The Dataset for this study is made available by CENPARMI and contains Canadian Toonies. The Dataset provided by CENPARMI is entirely suitable to conduct experiments related to coin grading by following the details released by numismatic centers as in [25]. We use a "CANON 60MM F2.8 MACRO EF-S" camera lens to get the desired image resolution. The black background for capturing these coins is selected, and it removes shadow casting on the outer edges of the coins. The camera inner calibration effect is reduced which can lead to degradation in the representation of visual details. All these steps ensure that there is a proper detailed representation of each part and a no underestimation/overestimation of scratches or edges. Afterward, an expert hired by CENPARMI graded all the coins after careful consideration of all the wear and tear on coins.

Given below are various quality levels in our Dataset:

Uncirculated (UC): The field is smooth with visible mint marks and small scratches. Edges are very sharp and shiny (Figure 2.5a).

Choice Extremely Fine (EF+): It is almost uncirculated, but the design edges are a bit more rounded. The field around the legend has some scratches, but otherwise, around the design, it is almost clear (Figure 2.5b).

Very Fine (VF): The design looks complete but is missing minor details of the necklace and hair of the queen. The design edges badly wear out, and bumps and scratches ranging from slightly visible to noticeably visible and deep are visible on the coins. Also, some parts of the legend merge with the field (Figure 2.5c).

(a) An uncirculated sample (b) A choice extremely fine sample (c) A very fine sample

Fig. 22. Samples of different quality degradation levels exist in CENPARMI dataset

6.4 FEATURE EXTRACTION

As discussed in earlier Chapter 4, the SIFT and RFR features extracted from coin images can effectively find the wear on the coins and are best suited for coin trading problems. The SIFT descriptors make use of stable and robust corner areas while the RFR takes into account the spatial structure of the coin for coin grading.

Factors that decide the amount of wear on the coins during detection are as follows:

(1) The overall amount of scratches and bumps on the field of the coin

(2) The sharpness of design and legend edges.

The SIFT and RFR features mainly focus on worn-out edges where stronger key points are hard to detect, which works to our advantage. As the coin ages with time, more bumps and scratches become visible on the surface, and more points of interest are available on the coin surface. Thus, the density of key points reduces the design and legend. Our results justified our claims made above on testing the coins with features extracted. Considering our first feature extraction method to make use of the SIFT keypoint descriptor matrix in a feature vector, we employed Bag of Visual Words (BoVW). A feature vector using the key point descriptors is built using BoVW's.

We extract the SIFT descriptors and then develop BoVW's vocabulary using them are as listed below:

(1) Putting together the SIFT descriptors extracted from all the images in a single big SIFT matrix.

(2) Using the clustering technique that is k-means in our case to create a defined number of clusters by grouping the descriptors.

(3) Assigning each of the descriptors extracted from an image to one of the clusters defined in the last step.

(4) Creating the Histogram of the distribution of the descriptors in the given clusters using the second step.

BoVW helps to reduce the feature vector size where a decision must be made on the number of clusters. For our study, we set the number of clusters to 30.

Our second feature extraction method is rotation-and-flipping-robust region binary patterns (RFR). We generally use Histogram information in many feature extraction methods for image-based coin recognition and classification. This feature extraction method, on the contrary, considers the spatial structure. To make the system rotation and flipping invariant, we adopt rotation-and-flipping-robust region binary patterns (RFR) as the features. It takes the gradient magnitude of the coin image and uses local difference magnitude to extract the RFR. This method stands out for the accuracy, smaller feature dimension, and time.

We calculate the gradient magnitudes from the boundaries of characters and symbols representing the structure of the coin image. We use the differences of mean gradient magnitudes for Intra RFR while we use the mean gradient magnitudes for inter RFR. This modified RFR for coin detection is RFR-GM (RFR-gradient magnitude).

We then create a feature vector using the BoVW's and features extracted from RFR into one feature vector for each image. We feed the matrix consisting of feature vectors from each image into the classifier, which is the next step in our coin grading problem.

6.5 CLASSIFICATION

We have completed the image preparation and feature extraction from all the images. The next step is the classification process with the following purposes:

(1) The authenticity of the selected features is verified and validated for selected study.

(2) We develop an automated system to complete tasks with minimal human assistance.

The selection of the classifier is a crucial step in the development of such a system. A thorough understanding of existing classifiers is needed to select a good classifier about the need for the topic and Dataset. Coin grading is actually about assigning the correct label to the coins, and this is a supervised study. We need to choose from supervised classifiers, and the neural network ranks the highest on that list as it is the most potent supervised classifier but needs a large dataset. Since our Dataset has only 129 coins, we use SVM with our SIFT and RFR features for our study in terms of validity, stability, and accuracy [23][24].

6.6 EXPERIMENTAL RESULTS AND DISCUSSION

The SVM is an accurate method for discovering counterfeit coins as well as automatic Coin grading. The results obtained in the automatic coin grading were beneficial in the justification of the algorithms designed to grade coins. Automatic coin grading classified the coins into two quality classes to have a distinct boundary of making decisions. We use the SVM classifier for the classification. The first class was the "UC" (Uncirculated Class) labeled class. The second class is the "CC" (Circulated Class). The accuracy level achieved for our dataset of Canadian Toonies through using the Methodology was 99.1%. SVM results in the experiment showed accuracy and consistency.

Table. 6. Coin Grading Dataset of Canadian toonies

Type	Number of Uncirculated samples	Number of Circulated samples
Training	64	36
Test	20	9

During the experiment, there is selection and extraction of SIFT key points and Regional binary patterns from every image from the training set. After six tests we came up with an appropriate number of clusters or visual words used in the appropriate distribution of key points of the training set. Altogether 10, 15, 20, 25, 30, and 35 visual words were built. There was checking how many visual words would provide the highest data accuracy. We initially set our number of visual words to 10 as in literature, there is no fixed number for the visual words, and experiments thus obtain it. The accuracy when the number of visual words was 10 was lower and kept increasing as we increased the number of visual words by increments of 5 and was highest at visual words equal to 30 and started decreasing as we increased the number of visual words to 35. The SVM was very useful in testing all the procedures, and the final results are in the table below:

Table. 7. Accuracy obtained for coin grading dataset for different Visual words

Number of Visual words	Accuracy
10	78.15
15	82.69
20	87.75
25	93.55
30	98.5
35	95.69

We obtain the identified results in the chart after testing the dataset 3-times. The reason we test 3-times is to ensure that there is overcoming a certain level of uncertainty within the final results. The uncertainty is removed through re-undertaking the tests and find out the average of the overall results. Undertaking or re-doing the results is very important in making the judgment of the final results for every step. The table illustrated below illustrates the different results obtained when using SVM.

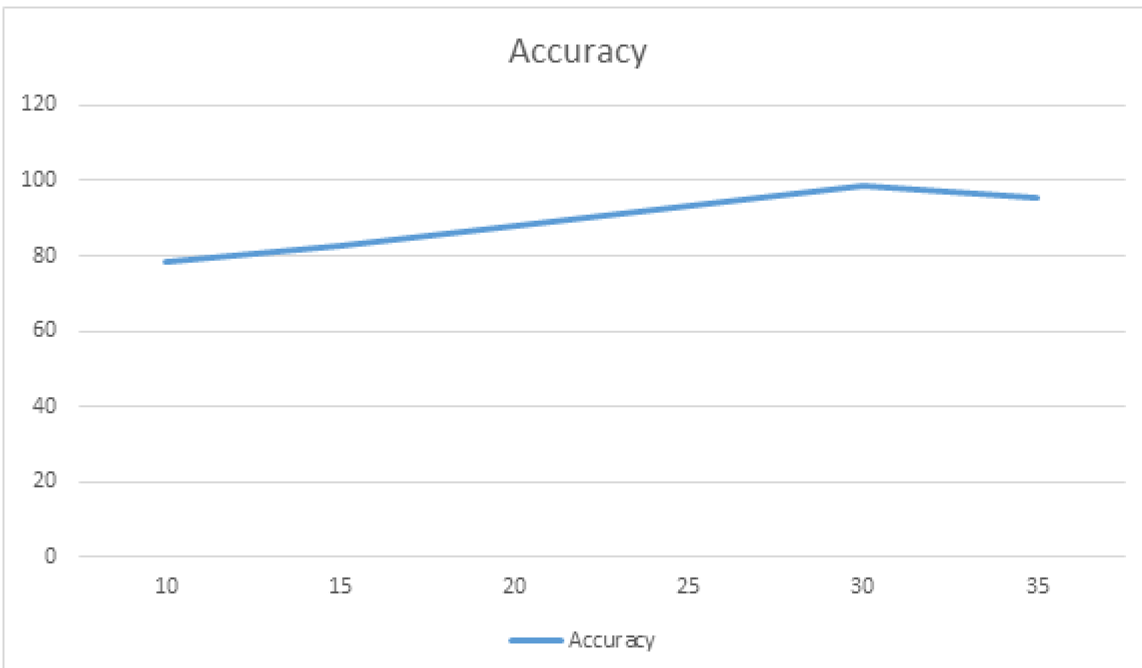

Fig. 23. Accuracy obtained for different values of visual words for the Dataset

The different results of precision, Recall, as well as f-measure, were obtained during the experiment. They are in the table below.

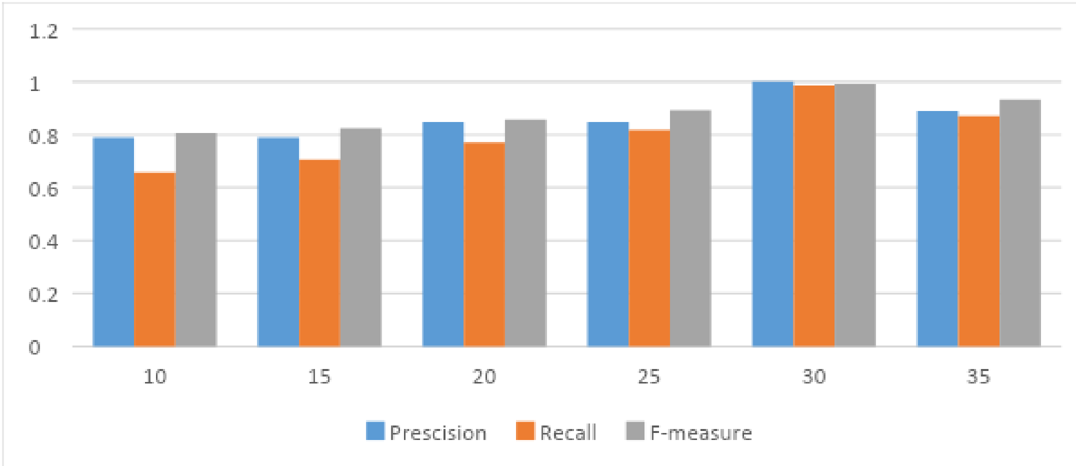

Fig. 24. Precision, Recall and F-measure obtained for Coin grading dataset

The overall f-values of the coins used in the experiment ranged between 0.806 and 0.992. That identifies that there was effectiveness in our feature extraction methods.

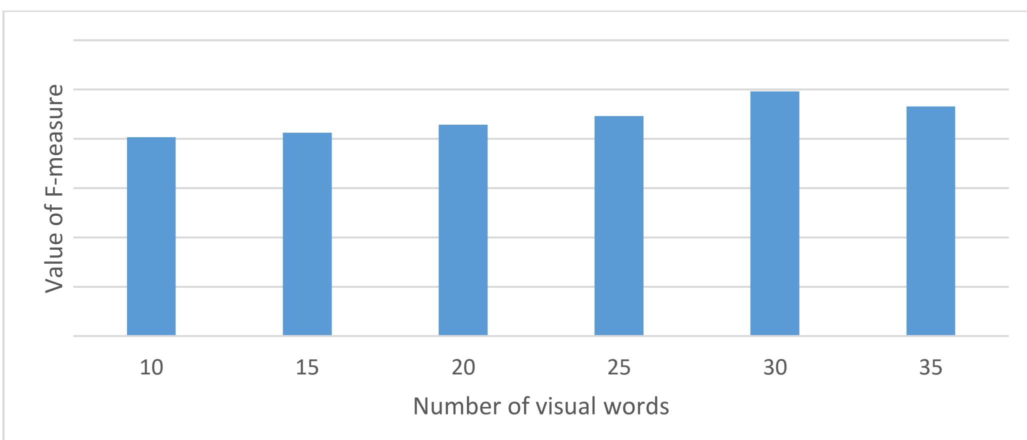

Fig. 25. F-measure values obtained for the Coin grading dataset

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

This thesis focused on solving the counterfeit coin detection and coin grading problems by using a simple yet efficient set of features. The proposed method was able to detect the high-quality counterfeit coins that were almost impossible to be recognized by untrained people. We have considered different attributes of coins and have come up with a set of features that can locate minute differences between coins. This method is very generic and can be applied to any type of coins. In this study, we have tested Danish and Chinese coins and got excellent results for Counterfeit Coin Detection. We have used Canadian coins for Coin grading and achieved promising results. Since counterfeits come from different sources, our proposed method is well suited to all types of coins. Our proposed method can efficiently distinguish genuine coins from fake ones and prove to be a boon for the general public, law enforcement offices, financial institutions, and for coin collectors. Since coins are small in size due to advancement in technology, genuine coins differ from fake ones only in minor details, so this system helps locate those fine details and help distinguish between both types of coins. We also considered the scenario of developing our system into a mobile phone application. We took pictures of the coins at different angles using the mobile phone camera as a regular user of the application to check the robustness of our proposed method, and we achieved promising results even with low-resolution pictures taken at a different angle with a regular mobile phone.

In this thesis, we also designed an automatic coin grading system that grades coins of different qualities using their digital images. Various factors such as scratches, bumps, and the amount of wear help determine the quality of the coins. We aimed at developing a consistent system that could remove all the variance and noise from the factors. We used a pattern recognition approach to determine the quality of the coin using the overtime wear. The approach handled the scale, rotation and illumination and flipping changes.

For both problems, we use SIFT features, which are rotation and scale-invariant, and find the most stable key points. SIFT is accurate, time-efficient, and is easily applicable in real-world applications. Our second feature extraction method RFR exploits the spatial structure of the coin with rotation and flipping invariant feature attributes. RFR feature extraction completes SIFT feature extraction in the sense that SIFT is a suitable feature extraction method for these problems but because we use the Histogram to train our classifier in a particular way that the spatial information is left out and RFR takes care of that by taking into account the spatial information. This collaboration of two complementary features used together makes our system reliable and efficient without any shortcomings and gives us the best results.

7.2 FUTURE WORK

As discussed at the beginning of the thesis with the advancement in technology, the quality of fake coins is also improving, making it more and more difficult to separate genuine coins from fake ones. We have tried to select the best set of features. However, we still need to make improvements to these types of systems. For instance, 3D modeling and reconstruction techniques can provide some interesting insights into these studies. The available datasets for fake coins are very minimal. Thus, the development of systems that can use smaller datasets is a requirement for counterfeit coin detection. For the cases of rare coins, we do not have sufficient data on genuine coins to train the classifiers. We can also make use of the deep learning methods, which is not viable now because of small datasets available. Since fake coins come from different sources of forgery, recognition could be another step for further studies to investigate.

As far as the coin grading problem, and this is a relatively new area of study, we leave some work for future studies. In this study, we consider the factors related to the wear of coin. However, We can consider factors such as color and eye appeal in future studies in addition to the wear factor. For this study, the Dataset was very small and with limited variation in quality. We can use a larger dataset with a more significant variation in quality for better and inclusive results. We can also use Deep learning methods, and a more extensive dataset to expand the scope of this study. Expert numismatics currently use advanced applications such as testing a coin based on a 70-level quality scale system, and we can also develop that by using deep learning methods.

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