SURGICAL SKILLS MODELING IN CARDIAC ABLATION USING DEEP LEARNING

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Abstract

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Seyedfarzad Famouri

Cardiovascular diseases, a leading global cause of death, can be treated using Minimally Invasive Surgery (MIS) for various heart conditions. Cardiac ablation is an example of MIS, treating heart rhythm disorders like atrial fibrillation and the operation outcomes are highly dependent on the surgeon's skills. This procedure utilizes catheters, flexible endovascular devices inserted into the patient's blood vessels through a small incision. Traditionally, novice surgeons' performance is assessed in the Operating Room (OR) through surgical tasks. Unskilled behavior can lead to longer operations and inferior surgical outcomes. However, an alternative approach can be capturing surgeons' maneuvers and using them as input for an AI model to evaluate their skills outside the OR. To this end, two experimental setups were proposed to study the skills modelling for surgical behaviours. The first setup simulates the ablation procedure using a mechanical system with a synthetic heartbeat mechanism that measures contact forces between the catheter's tip and tissue. The second one simulates the cardiac catheterization procedure for the surgeon's practice and records the user's maneuvers at the same time. The first task involved maintaining the force within a safe range while the tip of the catheter is touching the surface. The second task was passing a catheter's tip through curves and level-intersection on a transparent blood vessel phantom. To evaluate attendees' demonstrations, it is crucial to extract maneuver models for both expert and novice surgeons. Data from participants, including novices and experts, performing the task using the experimental setups, is compiled. Deep recurrent neural networks are employed to extract the model of skills by solving a binary classification problem, distinguishing between expert and novice maneuvers. The results demonstrate the proposed networks' ability to accurately distinguish between novice and expert surgical skills, achieving an accuracy of over 92%.

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Nomenclatures

Abbreviation	Definition
MIS	Minimally Invasive Surgery
CVD	Cardiovascular Disease
AF	Atrial Fibrillation
RFA	Radio-Frequency Ablation
CrA	Cryo Ablation
ED	Endovascular Devices
OR	Operating Room
AI	Artificial Intelligence
ML	Machine Learning
RBM	Restricted Boltzmann Machine
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
LSTM	Long Short Term Memory
CF	Contact Force
IMU	Inertial Measurement Unit
ADC	Analog-to-Digital Converte
EAM	Electroanatomical Mapping
FDA	Food and Drug Administration
SVM	Support Vector Machine
ECG	Electrocardiac Graphy
FTD	Frontotemporal Dementia
CN	Cognitive Normal
MCI	Mild Cognitive Impairment
AD	Alzheimer's Disease
ANN	Artificial Neural Networks
AE	Autoencoder
GRU	Gated Recurrent Unit
RMIS	Robot-assisted Minimally Invasive Surgery

Chapter 1

Introduction

1.1 Cardiovascular Disease

Cardiovascular Diseases (CVDs), which refer to a set of ailments that affect the heart and blood vessels, constitute one of the leading causes of death in the entire world (Organization et al., 2009). Atrial Fibrillation (AF) or (AFib) is one of the most prevalent kinds of heart disease that cause cardiac arrhythmia and needs hospitalization in most cases (Shoei, Huang, & Wood, 2010) (An arrhythmia is a situation when the heart beats slower or faster than usual or in an irregular way.) Defective electrical signal distribution in the heart tissue is known to be the principal cause of AF (Virani et al., 2021). The cardiac cycle is regulated via electric pulses produced in heart tissues. Figure1.1 illustrates and compares normal beating and AF pathways.

In other words, the sinoatrial node on the right heart atrium generates chemical-electrical signals to be transferred to the normal electrical pathway in the normal beating. In addition, the atrioventricular node (AV node) is in charge to ensure the heart muscle's contractions beat normally by slowing down the transferring process (Bittihn, 2014). AF happens when the normal electrical pathway in the heart is interrupted by a mass of cells on the left side of the heart. As a result, the electricity would rapidly be quenched and causes the top chamber to quiver. In consequence, the bottom chambers of the heart beat irregularly, and sometimes, faster than normal (Vanderschuren, Sieverink, & Wilders, 2013).

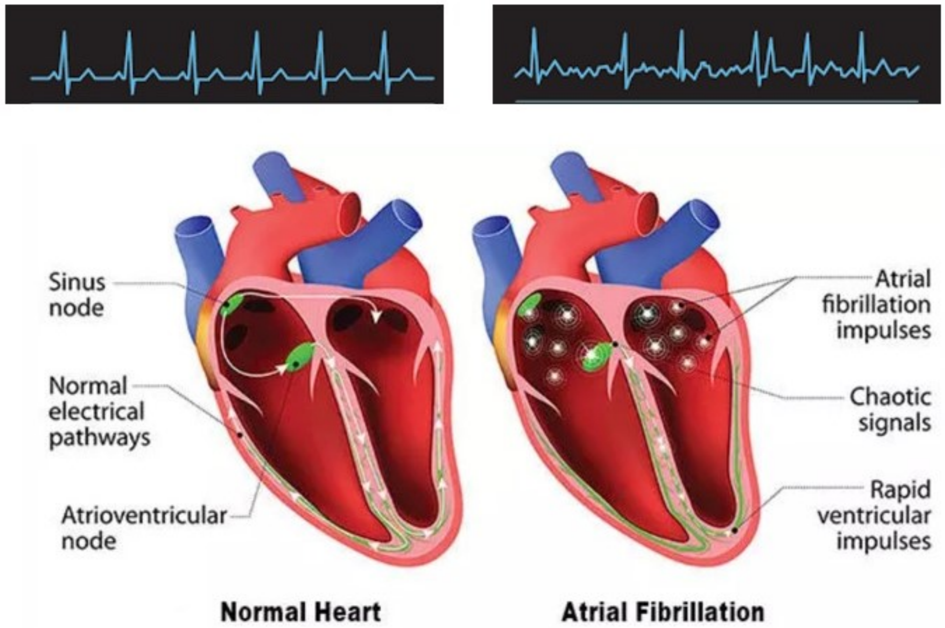

Figure 1.1: The Normal and AF electrical pathway. The electrical signal travels through special pathways to the right and left atria. The arrhythmogenic spots in heart tissue cause erratic impulses. (Froedtert and Medical College-Wi, Milwaukee, USA (Maiman, 2001))

1.1.1 AF Treatment

AF treatments can be categorized into two general groups, Pharmacological and Non-pharmacological therapy (from another view, therapies can also be grouped into stroke prevention, sinus rhythm control, and heart rate control during AF (Prystowsky, Padanilam, & Fogel, 2015).) Although rate-control and anti-arrhythmic medicines are common in pharmacological therapy, catheter ablation therapy is considered the standard non-pharmacological treatment (Prystowsky et al., 2015; Wood, Miller, Chen, & Petrellis, 2010). Inactivating the over-active cardiac cells can be done through either a burning process such as Radio-Frequency Ablation (RFA), or Freezing, Cryo-ablation. In study (Wazni et al., 2005), 70 patients suffering from AF were studied and results showed that ablation therapy was about five times more effective than drug therapy and only 13 percent of Case's illness had recurrences after surgery in comparison with 63 percent of patients had recurrences after pharmacological-based treatment. An RFA catheterization inside the left atrium is shown schematically in Figure1.2.

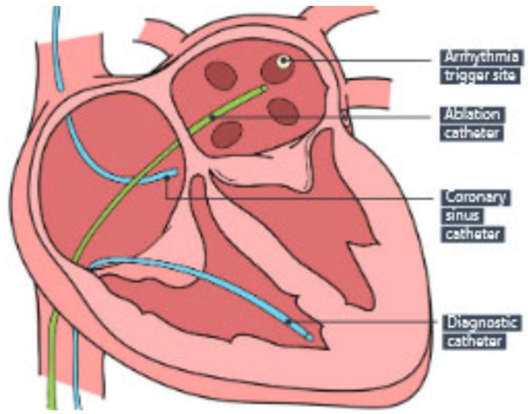

Figure 1.2: The overall schematic of the steerable ablation catheters inside the right atrium during ablation interventions. (British Heart Foundation, London, UK,(Collins & Julian, 1991))

The RFA involves the surgical insertion of a flexible catheter into the patient's femoral vein, which is then progressed toward the right or left atrium. The surgeon performs the ablation to burn the excessively active cells once the tip of the catheter is within the atrium and in touch with the appropriate region on the atrial wall. In the following, the cardiac ablation treatment is explained as minimally invasive surgery.

1.2 Minimally Invasive Surgery

Since the advances (Awtar, Trutna, Nielsen, Abani, & Geiger, 2010) in biomedical engineering from 1990, surgeons have benefited from cutting-edge and liable surgical instruments and robotic systems to accomplish highly effective surgeries through a few small incisions (Frank, Hanna, & Cuschieri, 1997). Surgical operations with minor incisions are known as Minimally Invasive Surgery (MIS). Because of the shorter hospital stays, lower blood loss during surgery, and quicker patient recoveries compared to open surgery, this type of surgical technique can result in considerable cost savings (Figure1.3 is shown as an example of MIS.) In consequence, MIS procedures have evolved massively in a wide range of surgeries including endocrine, urological, abdominal, gynecological, general, orthopedics, and especially in cardio-thoracic (Awtar et al., 2010).

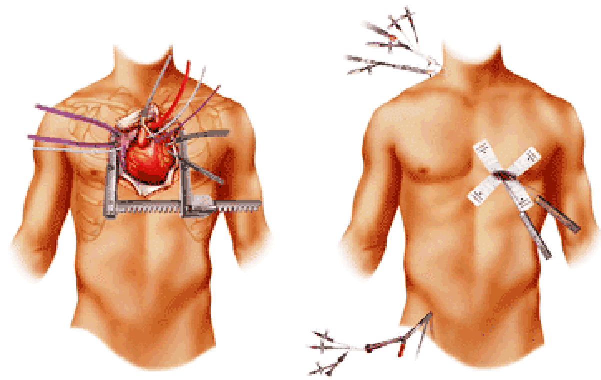

Figure 1.3: Traditional surgery versus Minimally invasive surgery. (Tavakoli et al., 2003)

1.2.1 Cardiac Ablation Treatment

Ablation treatment is an MIS procedure that involves destroying (ablating) the target areas of the heart muscle that cause electrical abnormalities. It entails inserting a flexible tube into the blood vessel via a minor skin incision in order to reach the sites of the arrhythmia within the heart (Ndrepepa & Estner, 2006). The procedure is shown in Figure1.4. This tube/ soft robot is called an ablation catheter and has the responsibility for transferring energy to the area of interest for ablation (Haemmerich, 2010).

In recent years, many advances in cardiac ablation treatments have enhanced the procedure's safety and efficacy. The most important ones are listed below:

- Use of 3D mapping systems: Using 3D mapping technologies enables for more precise identification of the tissue producing the arrhythmia. These technologies provide a thorough, real-time picture of the heart, allowing doctors to precisely target the afflicted tissue (Pappone et al., 1999).
- Contact force sensing technology: This technology enables the physician to monitor the amount of pressure given to the heart tissue by the catheter tip. This can assist to guarantee that the tissue is eliminated without causing harm to the healthy tissue around it (Mansour

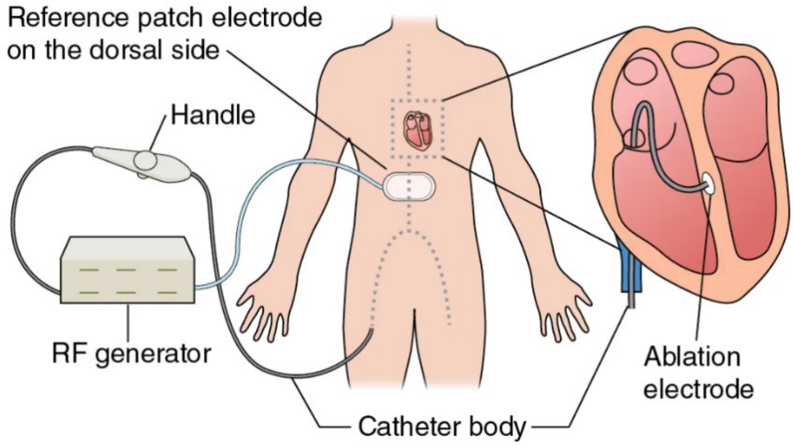

Figure 1.4: The schematics of cardiac radiofrequency (RF) ablation surgery. To access the target areas inside the heart chamber, an ablation catheter is inserted into the body system through the femoral vein in the patient's leg. (Panescu et al., 1995)

et al., 2020).

- Cryoablation: It is a recent method that employs intense cold rather than heat to remove the tissue that is generating the arrhythmia (Figure1.5) This approach may be especially beneficial for treating arrhythmias in certain parts of the heart, such as around the pulmonary veins (Andrade et al., 2021).

- Hybrid procedures: A hybrid technique that combines surgical and catheter-based methods may be performed in some circumstances. This might entail a minimally invasive surgical treatment followed by catheter-based ablation to address any residual arrhythmias (Khalil, Siontis, Bagameri, & Killu, 2020).

- Improved patient selection: Advances in diagnostic testing and patient selection criteria have made it possible to better identify individuals who are likely to benefit from cardiac ablation. This has resulted in improved results and lower risks for people receiving the surgery (Johner, Namdar, & Shah, 2019).

In the following, the cardiac ablation catheter device is described in detail.

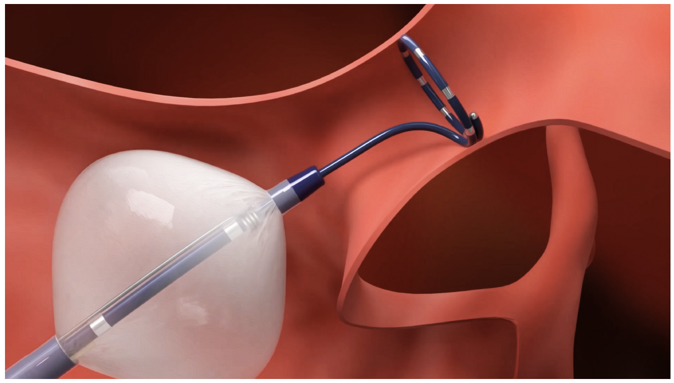

Figure 1.5: The Cryoablation cardiac ablation treatment. (Boston Scientific, USA, (Tedrow & Stevenson, 2009))

1.2.2 Ablation Catheter

Endovascular devices (EDs), such as guide-wires and catheters, are long, flexible medical devices that are placed into the patient's vasculature through a tiny skin incision, or vascular port, to provide minimally invasive access to the veins and heart. Tendon-driven catheters having a tiny diameter, 3-6 mm, are suitable for use in endovascular procedures during minimally invasive procedures. Such catheters also provide the surgeon with a lot of room to operate because the position of their tip may be adjusted by pulling the tendons. Soft catheters are an advantageous option because they provide more flexibility and more dexterity that leads to more robust and dexterous manipulation of the catheters (Runciman, Darzi, & Mylonas, 2019).

A steerable catheter has a non-steerable body (80–150 cm), a control handle (handle), and a controlled tip part (distal part) (4–10 cm). The tendons that are internally linked to the tip at the distal part are directed normally by twisting the knob on the handle (Jelínek, Arkenbout, Henselmans, Pessers, & Breedveld, 2015). The embedded sensors in these catheters may also be useful for measuring precisely the contact force at the tip (Bandari, Dargahi, & Packirisamy, 2019a, 2019b). The drawback of employing embedded sensors is that it makes catheters more expensive, less manoeuvrable, and more difficult to design and build. These technological restrictions have prevented the widespread clinical use of sensorized catheters. The pros and cons details of different behavioural sensing in ablation treatment are discussed in the next chapter 2. Figure1.6 illustrates different parts of the ablation catheter.

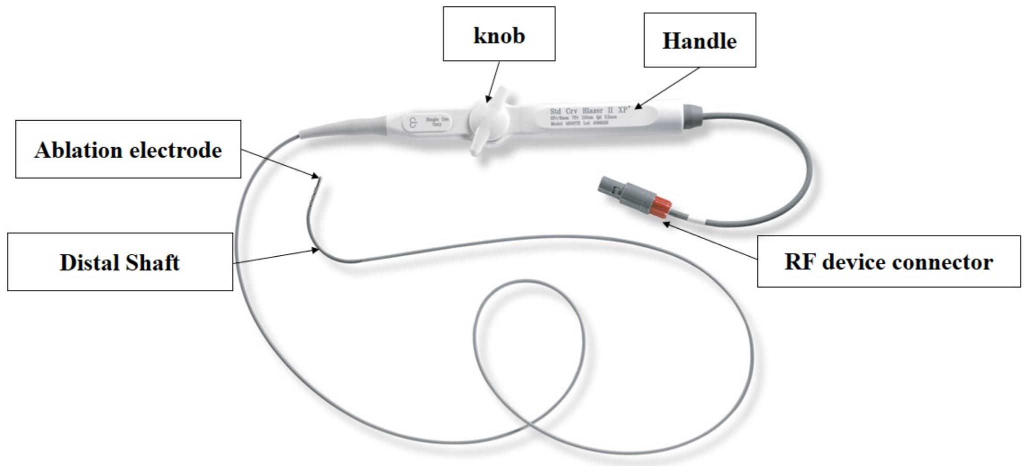

Figure 1.6: Ablation Catheter parts, including handle, knob, distal shaft, ablation electrode and RF device connector. (Boston Scientific, USA, (Tedrow & Stevenson, 2009))

Usually, continuous X-ray fluoroscopy is required to visualize the guide-wires and catheters inside the body during minimally invasive procedures. Unfortunately, the long-term effects of X-ray fluoroscopy exposure on patients, surgeons and surgeon assistants' health might be irreversible and cause fatal diseases such as cancer (Hasan & Bonatti, 2015). Consequently, surgery time and people's health in the operating room (OR) are interrelated with each other and operation duration time should be shortened as could as possible.

1.3 Artificial Intelligence

Artificial Intelligence (AI) encompasses the creation of machines that can carry out tasks typically associated with human intelligence. These machines are programmed to imitate human intelligence and can be classified into two categories (Winston, 1984): narrow or weak AI, designed for specific tasks, and general or strong AI, capable of performing any intellectual task that a human can.

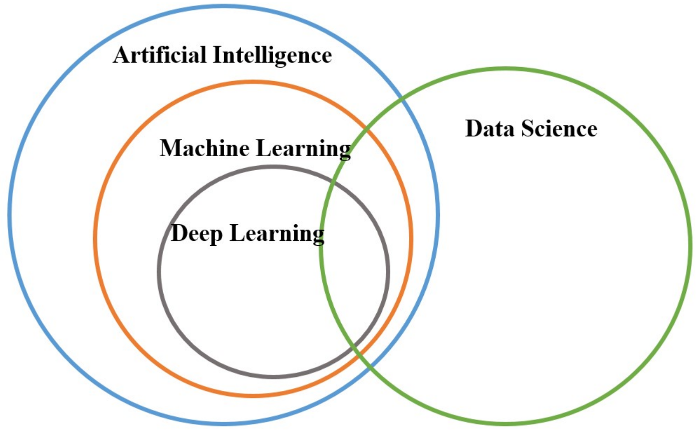

Figure 1.7: Artificial Intelligence subsets and its overlap with Data Science.

Various applications of AI include speech recognition, image recognition, natural language processing, and decision-making. AI encompasses different branches, with Machine Learning (ML) being recognized as a prominent one, as depicted in Figure 1.7. ML is a field within computer science and AI that aims to mimic human learning through the utilization of datasets and statistical algorithms (Kaplan & Haenlein, 2019). In essence, machine learning focuses on analyzing and correlating data within datasets of varying sizes to identify common patterns. Its origins can be traced back to the 1940s and are credited to the work of Gregory Powell and Mike Donavan. As illustrated in Figure 1.7, deep learning is also a subset of ML and AI, all of which contribute to the field of data science.

1.3.1 Machine Learning

Machine learning is the process of learning to make decisions from given data without being explicitly programmed (Mitchell et al., 2007). In other words, the ability to generate predictive models without the need for strong assumptions about key mechanisms that are often unknown or inadequately articulated will be the main appeal. Based on the learning principles, machine learning is classified into three categories of parameters: supervised, unsupervised, and reinforced (Bishop & Nasrabadi, 2006; Müller, Michoux, Bandon, & Geissbuhler, 2004; Murphy, 2012).
Figure1.8 provides an overview of different machine learning methods and techniques (Sarker, 2021). One of these approaches is supervised learning, which involves training the algorithm using

labelled data. In supervised learning, the dataset is typically split into two portions: the training data and the testing data. The algorithm undergoes training using the training data and subsequently undergoes testing using the testing data to evaluate its ability to generalize to new and unseen data. Supervised learning is specifically employed for tasks involving classification, regression, and prediction. Numerous applications make use of supervised learning, including image recognition, speech recognition, and natural language processing (Singh, Thakur, & Sharma, 2016).
Unsupervised learning is a machine learning approach that involves training an algorithm on unlabeled data. Unlike supervised learning, where prior knowledge about the data is available, unsupervised learning requires the algorithm to discover patterns and structure in the data autonomously. One common technique used in unsupervised learning is clustering, which groups similar data points together based on their shared characteristics. Other examples of unsupervised learning methods include dimensionality reduction and anomaly detection. Unsupervised learning has various applications, including customer segmentation, recommender systems, and anomaly detection tasks (Alloghani, Al-Jumeily, Mustafina, Hussain, & Aljaaf, 2020).

Reinforcement learning, on the other hand, is a type of machine learning that relies on trial and error. In reinforcement learning, the algorithm interacts with an environment and receives feedback in the form of rewards or punishments based on its actions. The goal of the algorithm is to learn how to maximize its cumulative reward over time. Reinforcement learning finds applications in areas such as game playing, robotics, and autonomous driving. An example of successful reinforcement learning is AlphaGo, a program developed by Google that achieved victory over a world champion in the game of Go (Mahesh, 2020).

Semi-supervised learning is a type of machine learning that utilizes a combination of labelled and unlabeled data during the training process (Hady & Schwenker, 2013). This approach is particularly valuable when labelled data is limited or expensive to acquire, while a substantial amount of unlabeled data is readily available. By learning from the labelled data to make predictions and leveraging the unlabeled data to uncover additional patterns and relationships, semi-supervised learning improves the algorithm's performance. Its applications span across various fields, including speech recognition, natural language processing, and image classification. The primary objective of semi-supervised learning is to enhance accuracy and efficiency by harnessing the untapped potential of

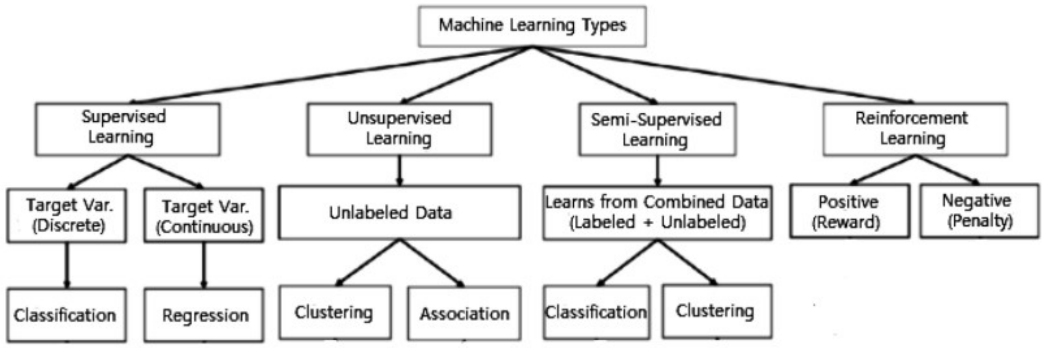

Figure 1.8: There are several sorts of machine learning techniques, which are discussed at (Sarker, 2021).

unlabeled data.

1.3.2 Deep Learning

Deep learning is a specialized branch of machine learning that leverages multi-layer artificial neural networks to learn intricate representations of data. It aims to extract high-level features directly from raw data, such as time series, images, audio, or text, without relying on manually engineered features. The field of deep learning has achieved remarkable breakthroughs across various domains, including computer vision, speech recognition, natural language processing, and robotics. Deep learning models are trained on large datasets and refined using techniques such as backpropagation and stochastic gradient descent. The ultimate goal of deep learning is to develop models capable of effectively generalizing to unseen data and tackling tasks that were previously considered challenging or even infeasible for machines (LeCun, Bengio, & Hinton, 2015).

Within the realm of deep learning, there are specialized branches that cater to specific data types and tasks. Computer vision focuses on tasks such as image and video processing, object detection, and recognition. Natural language processing deals with language understanding, sentiment analysis, and machine translation. Voice recognition is concerned with speech interactions and transcription. Reinforcement learning, on the other hand, focuses on training agents to make decisions in dynamic environments, such as gaming and robotics. Additionally, there is a subset of deep learning known as generative models, which is dedicated to generating new data samples that resemble the original data, such as images or text. These fields are continuously evolving and adapting to new applications and domains, driven by advancements in hardware, algorithms, and software (Bengio, Goodfellow, & Courville, 2017; Goodfellow, Bengio, & Courville, 2016; Learning, 2020).

1.3.3 Recurrent Neural Networks

One more time, Deep Learning can be classified as a subset of ML and AI and it can be divided into Restricted Boltzmann Machine (RBM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Auto-Encoders, and hybrid methods. However, traditional neural networks are not able to remember events, in other words, they do not have persistent memory over time and it is considered a major shortcoming (Sutskever, 2013).

RNN is designed to handle sequential data in contrast to traditional feedforward neural networks that handle data linearly. RNNs possess an internal state, which they use to process sequences of inputs, including natural language text and time-series data. A key feature of RNNs is the feedback loop that enables the transfer of information between each step of the sequence. This allows the network to maintain an internal state that contextualizes the current input and facilitates the generation of predictions based on previous inputs. RNNs are commonly employed in natural languages processing applications such as text generation, language modeling, and machine translation, as well as in other fields such as image captioning, speech recognition, and video analysis (Karita et al., 2019).

In order to tackle the challenge of persistent memory, RNNs incorporate loops within their structure, enabling the retention of information over time. These loops enable the passage of information from one step of the network to the subsequent step, thereby facilitating the preservation of important data.

Figure1.9 illustrates a depiction of a single unit within the described neural network. To construct a complete recurrent neural network, multiple instances of the same network are interconnected, with each unit passing its data to the next unit in line, as demonstrated in Figure1.10.

Besides RNNs mentioned successes, the use of Long Short Term Memory, known as “LSTM”, a

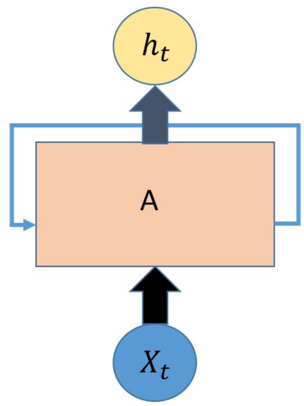

Figure 1.9: Recurrent Neural Networks have loops.

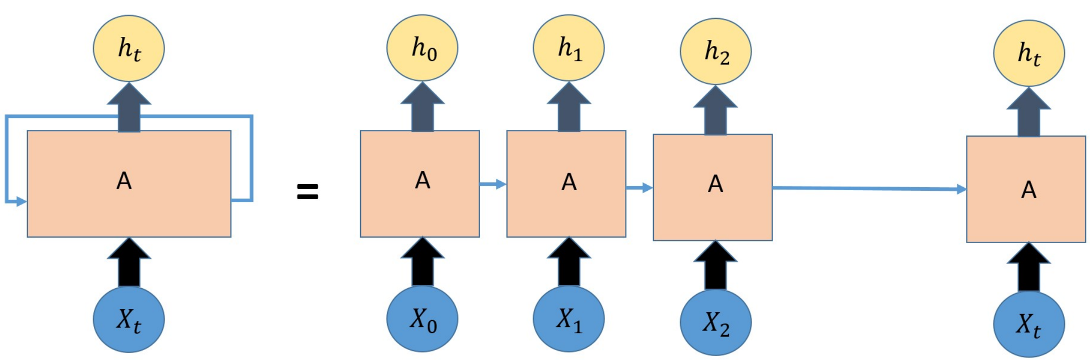

Figure 1.10: A recurrent neural network that has been unrolled.

very special kind of recurrent neural network has been increased because it works, for many tasks, better than the standard version (RNNs). According to the (Hochreiter, 1991) study, the regular recurrent neural network does not have enough capability of long-term memory due to the vanishing gradient problem.

Hochreiter and Schmidhuber initially introduced LSTMs, which were further developed and gained widespread popularity. LSTMs were specifically designed to overcome the challenge of long-term dependencies in sequential data and excel at retaining information over extended periods. Therefore, they are well-suited for effectively modeling time-series problems (Hochreiter & Schmidhuber, 1997).

All recurrent neural networks take the form of a chain of repeating neural network modules. This repeating module in ordinary RNNs will have a relatively basic structure, including a single activation function such as tanh in the layer, as depicted in Figure 1.9. LSTMs also have this chain similar to mentioned structure, but the repeating module has a different architecture. Instead of having a single tanh activation function, there are four ones, interacting in a very special way shown in Figure1.11.

The diagram illustrates the flow of data as vectors moving between the output and input nodes. Within this process, mathematical operations, such as vector addition, are applied pointwise, while activation functions such as tanh and sigma play a crucial role. At the core of the LSTM architecture is the horizontal line positioned at the top of the diagram, representing the cell state. This cell state can be modified by adding or removing information, a process tightly regulated by specialized structures called gates. The detailed formulation of these gates will be discussed in subsequent chapters 3.

There are some other variants of LSTM with some minor differences in their architectures. The (Gers, Schmidhuber, & Cummins, 2000) introduced a popular LSTM variation that includes ”peephole connections.” This signifies allows the gate layers to examine the cell state. The Gated Recurrent Unit, or GRU, created by (Cho et al., 2014) is the more dramatic version of the LSTM. They forget and input gates are combined into a single ”update gate.” It also integrates the cell state with the hidden state, among other things. The resultant model is simpler than normal LSTM models and has grown in popularity. In (Yao, Cohn, Vylomova, Duh, & Dyer, 2015), an extension of LSTM was

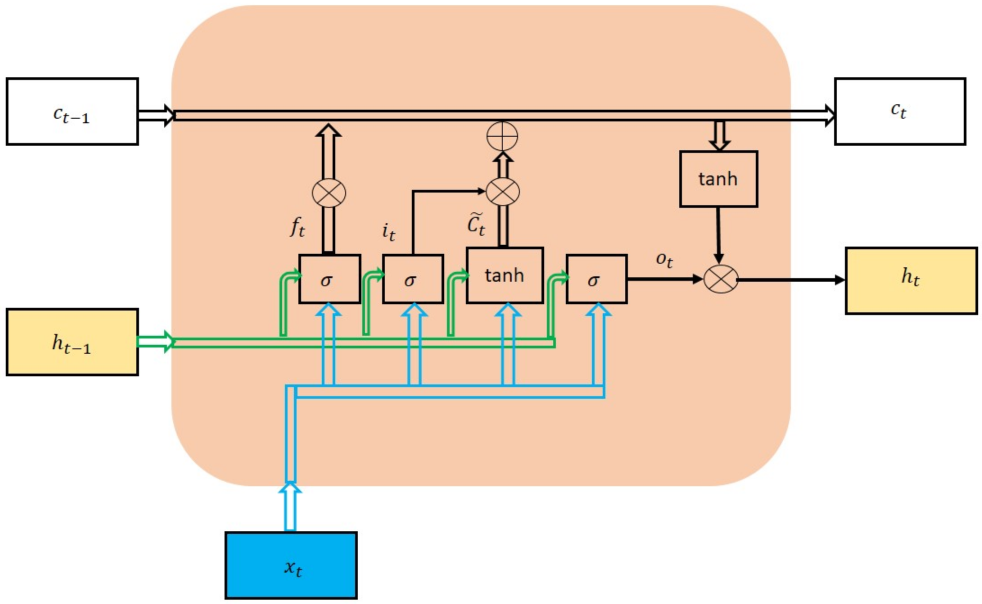

Figure 1.11: The LSTM unit contains gates and cell state.

presented, in order to use a depth gate to connect memory cells of adjacent layers. Furthermore, Clockwork RNNs by (Koutnik, Greff, Gomez, & Schmidhuber, 2014) is a whole new technique for dealing with long-term dependency. In general, (Greff, Srivastava, Koutník, Steunebrink, & Schmidhuber, 2016) compare common versions and discover that they are all roughly the same. (Jozefowicz, Zaremba, & Sutskever, 2015) evaluated over ten thousand RNN designs, discovering several that performed better than LSTMs on specific tasks.

1.4 Objectives

The principal aim of this thesis is to build a robotic experimental setup to simulate ablation surgery outside the operation room for the practice of expert and novice surgeons and model a deep learning method to assess their dexterity. The approach of this research can be divided into:

- To design and build an experimental setup equipped with synthetic heart beating for practicing control of the catheter's tip force during ablation surgery via adjusting the knob on the catheter's handle manually.

- Collecting the force data and developing a deep learning-based model to asses the kinesthetic sense of the surgeon while controlling the force.
- To design and build an experimental frame to simulate the insertion and passing catheter inside a plastic blood vessel phantom during an ablation surgery.
- Collecting the surgeon's behaviour and hand gesture information during the insertion and passing catheter inside the plastic phantom and later, developing a deep learning-based model to asses the kinetics of the surgeon's hand movement.

1.5 Publications

The following manuscripts were accomplished and written during the author's research as a master of applied science program:

- **Seyedfarzad Famouri**, Pedram Fekri, Majid Roshanfar and Javad Dargahi. "Towards Surgical Skill Modeling in Cardiac Ablation Using Deep Learning." Accepted for the 2023 Conference on Methods and Models in Automation and Robotics Conference (MMAR):
- **Seyedfarzad Famouri**, Pedram Fekri, and Javad Dargahi. "Kinematics Skill Modeling of Cardiac Catheterization via Deep Learning Method." Submitted.

1.6 Thesis Layout and Contribution

The thesis manuscript is written and organized based on the thesis style introduced by the School of Graduate Studies of Concordia University (Thesis Preparation and Thesis Examination Regulations for Manuscript-based Thesis).

Chapter 2: Includes review of the previous related study and research such as robotic-assisted surgeries, surgeon's behavioural sensing, and deep-learning-based applications.

Chapter 3: Presents a kinesthetic-based method of modelling expert and novice behaviour. In this study, an experimental setup was built to simulate the ablation procedure in AF treatment outside the operation room. Besides, the mechanical frame was equipped with artificial heart beating to induce real surgery conditions. The forces were being recorded while users working with the setup to be fed as the input feature for the deep-learning-based neural networks. The expert and novice behaviours were robustly modelled by LSTM architecture with 95% accuracy. The model can be used to assess the surgeon's skill and correct the surgeon's hand gestures and manoeuvring in real-time. This chapter is based on a manuscript accepted for the 2023 Conference on Methods and Models in Automation and Robotics Conference (MMAR):

- Seyedfarzad Famouri, Pedram Fekri, Majid Roshanfar and Javad Dargahi. "Towards Surgical Skill Modeling in Cardiac Ablation Using Deep Learning." accepted for the 2023 Conference on Methods and Models in Automation and Robotics Conference (MMAR).

The second author of this paper mentored and contributed to the main idea of the study, modelling and evaluation. The third author contributed to the data acquisition. The fourth author is the academic supervisor.

Chapter 4: Explains a kinematic-based system, of modelling and assessing surgeon's expert and novice gesture and maneuvering. An experimental framework simulates the catheterization procedure in AF treatment outside the operation room. The catheter's knob angles and the surgeon's hand positions were assumed to be the deep-learning method's input. The expert and novice kinematic behaviours were modelled by RNN and LSTM networks with more than 92% accuracy. The model can be used to assess the surgeon's skill and correct the surgeon's hand gestures and manoeuvring in real-time as in the study in chapter 3. This chapter is based on a manuscript submitted.

- Seyedfarzad Famouri, Pedram Fekri, and Javad Dargahi. "Kinematics Skill Modeling of Cardiac Catheterization via Deep Learning Method." Submitted.

The second author of this paper mentored and contributed to the main idea of the study, modelling and evaluation. The third author is the academic supervisor.

Chapter 5: The thesis's conclusion of findings serves as a concise representation of the primary results and significant discoveries that have been attained during the diligent research journey. Through this comprehensive overview, readers are provided with a holistic understanding of the research's contributions, accentuating the fresh perspectives and consequential implications that have surfaced as a result of the study. Moreover, the exploration of potential future research endeavours offers a well-defined pathway for continued investigation, pinpointing specific areas or subjects that possess the potential to amplify the existing findings. This thoughtful consideration of potential avenues not only unveils exciting prospects for forthcoming scholars but also lays the groundwork for expanding upon the solid groundwork established within this master's research, propelling the advancement of the field to new frontiers.

Chapter 2

Literature Review

2.1 Surgical Skills

2.1.1 Skill Transferring

Skill transferring in surgery refers to the ability to transfer a surgeon's skills and knowledge from one expert surgeon to another inexperienced surgeon. This is a crucial aspect of surgical training and practice as it allows surgeons to expand their repertoire of procedures, increase their efficiency and improve patient outcomes. Surgical training has advanced substantially in the previous two decades (Stefanidis, Scott, & Korndorffer Jr, 2009). Traditional time-based training methods, following the Halstedian approach, have transitioned towards competency-based training, as highlighted by Nataraja (Nataraja, Webb, & Lopez, 2018). Given the highly specialized nature of the surgical field, it demands comprehensive training and substantial experience. Surgeons need to acquire proficiency in a diverse array of procedures and techniques, each necessitating specific skills and knowledge. Additionally, the concept of skill transferring in surgery encompasses the capacity of surgeons to effectively apply the expertise and insights gained from performing one procedure to the execution of another.

2.1.2 Advantages and Challenges

Although there are several technical and non-technical aspects that impact a surgical result (such as situational awareness, collaboration, and communication), a surgeon's particular surgical talents have a significant effect (Aggarwal & Darzi, 2006). One of the benefits of skill transferring in surgery is increased efficiency. Surgeons who are able to transfer their skills to others can help novice surgeons to work more quickly and effectively, reducing the time required to perform a procedure and improving patient outcomes (Aggarwal & Darzi, 2006). Moreover, surgeons possessing a diverse repertoire of skills exhibit enhanced responsiveness when confronted with unforeseen circumstances during surgical procedures. This heightened adaptability contributes to their overall capability in managing intricate cases. Additionally, skill transferring in surgery yields favorable patient outcomes. Surgeons adept at skill transfer excel in identifying and addressing potential complications, mitigating the chances of surgical errors, and ultimately elevating patient outcomes. This aspect holds particular significance within the realm of surgery, as the quality of the procedure substantially influences the health and well-being of the patient.

Nevertheless, skill transfer in surgery presents its own set of challenges. One of the most formidable hurdles is discerning the transferability of skills. While surgeons may possess a wide array of talents, not all of them are applicable to every surgical procedure. To tackle this obstacle, surgical training programs must implement a systematic approach to identify and assess the transferability of surgical skills. Moreover, a continuous evaluation of a surgical trainee is required as part of competency-based training, allowing feedback and focused skill improvement within training programs (for Graduate Medical Education et al., 2014). Another barrier to surgical skill transfer is a lack of uniformity in surgical training. Because surgical training is not standardized, it is difficult for surgeons to transfer their talents from one surgery to another, as each procedure may need distinct skills and knowledge.

It is crucial to guarantee that the skills being transferred are of high quality to ensure their safety and effectiveness. If the skills being transferred are not properly assessed, there is a risk that they may not meet this standard. The assessment of surgical skills involves an objective evaluation of a surgeon or trainee's proficiency in performing a specific surgical task. This assessment highlights areas where improvement is needed. In contrast, surgical skill transferring involves the teaching and transfer of a proficient surgeon's skills to another surgeon or trainee. While this is an essential aspect of surgical training, it is important that the skills being transferred are of high quality and have been assessed beforehand to ensure their safety and effectiveness. Therefore, surgical skill assessment may take priority over surgical skill transferring to guarantee that the recipient surgeon or trainee can safely and effectively perform the skills being transferred.

2.1.3 Surgical Skill Assessment

Surgical skill assessment involves the evaluation of a surgeon's technical ability and performance during surgical procedures. This evaluation can be carried out using diverse techniques such as direct observation, video recordings, simulations, and objective measurements of surgical outcomes. The aim of surgical skill assessment is to guarantee that the surgeon is sufficiently skilled to perform surgical procedures safely and effectively and to highlight any areas where further training or improvement may be required. Precise and dependable surgical skill assessment is essential for upholding high levels of patient care and advancing continuous improvement in surgical practice (Liu et al., 2021).

Minimally invasive surgical abilities are essentially made up of fine motor skills that include an interaction between the surgeon, the surgical tools (laparoscopic or open operative method), and the pathology (Vaporciyan, 2016). While conventional evaluation systems can objectively assess academic knowledge, assessing practical surgical abilities remains difficult. Existing practical surgical skills evaluation techniques, including work-based assessments, are frequently inconsistent and subjective since they rely on the judgement of an individual assessor (Genovese et al., 2016; Reiley, Lin, Yuh, & Hager, 2011). This assessment, in particular, is dependent on an expert surgeon actually monitoring the surgical trainee and offering constructive input to facilitate surgical skill improvement (Vaporciyan, 2016; R. G. Williams & Klamen, 2006).

For the aforementioned reasons, this study can be a starting point to meet the discussed needs and introduce a standard setup for practising outside the OR and assessing different surgeons' skills without supervision. In other words, a junior trainee can have self-directed practice whilst still receiving expert feedback based on models built on experts' behaviour info extracted from installed sensors on setups. Previous research has found a relationship between a surgeon's hand gesture (Kinematic and kinesthetic information) and their level of surgical expertise(Ahmad, Yaser, Kourosh, & Sanju, 2017; Uemura et al., 2014). There is a substantial variation in hand motion across various degrees of experience in open surgery, laparoscopic surgery, and especially, Robot-assisted Minimally Invasive Surgery (RMIS) (Liang et al., 2018; Mason, Ansell, Warren, & Torkington, 2013). It has been shown that an expert moves their hand more efficiently than a novice. This could be made up of the length of the journey, the time it takes, the trajectory, and the smoothness of the motions (Grober, Roberts, Shin, Mahdi, & Bacal, 2010). Hence, skills evaluation through analyzing motion analysis (kinematics and kinesthetic) is feasible with the help of effective motion collection technology such as sensors being discussed in the following sections.

2.2 Behavioral Sensing in Ablation Treatment

The behaviors can be classified into two categories: kinesthetic demonstrations and kinematic demonstrations. Kinematic demonstrations involve extracting the positional body movements of the expert during the operation. Several studies, including those by (Abbott, Marayong, & Okamura, 2007; Zahedi, Dargahi, Kia, & Zadeh, 2017), have emphasized the significance of learning kinematic demonstrations. On the other hand, kinesthetic information can be acquired through physical interaction between robots and users. This approach involves direct collaboration between the surgeon and the robot to accomplish a specific task. (Kronander & Billard, 2013; Rozo, Jiménez, & Torras, 2013) have explored the use of this method in obtaining kinesthetic information.

The main goal of this research is to meet the needs of a standard assessment method outside of the OR to evaluate the different skills of surgeons during ablation surgery. The importance of sensors' existence in the setup to acquire hand movement and behaviour information of surgeons from kinesthetic and kinematic views to extract expertise by AI-based methods are discussed in the following.

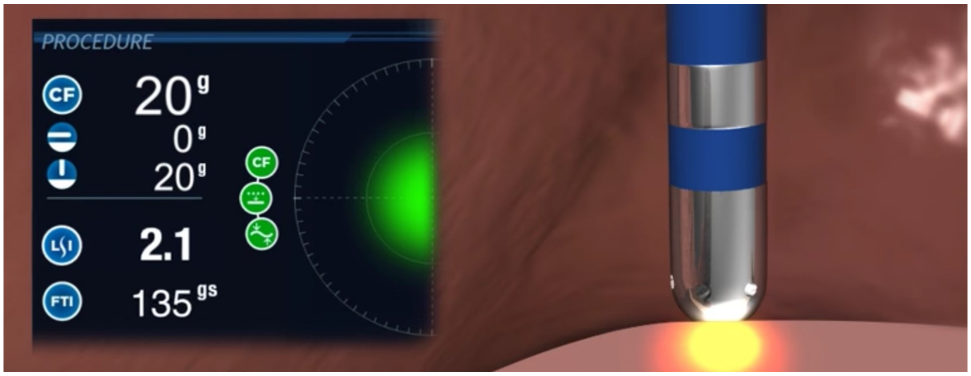

Figure 2.1: Reading real-time contact force of ablation catheter on the monitor.(TactiCath, Radcliffe Group, UK)

2.2.1 Applying Contact Force

The force between the catheter tip and heart tissue is known as Contact Force (CF) and is applied via adjusting the knob by the surgeon to bend the distal part of the catheter interacting with the heart wall tissue. Thus, the CF can be considered a kinesthetic feature to describe a surgeon's feelings of tangibility during the operation. The CF has a key impact on the outcome of ablation treatment(Chapter 1) and could be useful information for surgeons to apply adequate force while ablating. By way of explanation, the CF can represent kinesthetic information from behaviour while using the catheter. Surgeons can read the contact force in real-time from the monitor in front of them like Figure2.1. In the following, the importance of CF at the catheter's tip during the ablation surgery is discussed.

Importance of Contact Force in Ablation Surgery

As it was explained in 1, the catheter's tip (electrode) produces thermal energy to burn the determined area of heart tissue during the radiofrequency ablation surgery. After surgeons insert the catheter inside the body and guide it through the heart, they make sure contact between the catheter's tip and heart tissue is secure before starting ablating the intended tissue for a specific time. For improving the outcome, several methods can be considered. The (Ariyarathna, Kumar, Thomas, Stevenson, & Michaud, 2018) stated that enlarging the electrode's size and increasing the temperature of the catheter's tip can expand the burning area and volume size. The larger electrode needs a stronger power source and a higher set temperature. For electrodes with smaller diameters, surgeons need to increase the tip's temperature to ablate larger volumes as well(tissue's thickness and structure besides blood flow change the (Tsai et al., 1999).) Increasing the temperature has a limitation which expresses that if the tip's electrode hits 100 degrees Celsius, intramyocardial steam is generated, resulting in heart perforation (Nakagawa et al., 1995).

In addition to the previous factors, adjusting the catheter-tissue CF can control the ablating rate at the contact area (Shurrab et al., 2015). Clinical investigations show that CF is a determinant aspect of lesion formation at contact points and its precise regulation ensures the treatment's endurance and effectiveness. The adequate force causes the tip to keep fixed on the desired spot and helps electrical current to travel easier into the tissue to burn the tissue (Shah & Namdar, 2015; Thiagalingam et al., 2010). Lack of force might result in irreparable damage in patients suffering from arrhythmia; In other words, insufficient force at the catheter tip will cause incomplete treatment. Moreover, excessive force can lead to perforating heart tissue as well. Hence, the appropriate amount of value is required (Khoshnam, Yurkewich, & Patel, 2013). For monitoring the CF, different methods have been introduced and can be categorized as sensor-based and sensor-free in general (French, Tanase, & Goosen, 2003; Xu & Simaan, 2008).

Sensor-based Methods

Sensor-based method refers to the catheters having embedded a miniature sensor at their tip to measure forces. However, sensor-free methods are defined on the analysis of the catheter's distal shaft bending shape. Each of the strategies has advantages and disadvantages. On one hand, sensors give reliable measurements, but using them in the unstructured environment of the heart chamber is difficult (Zou, Ge, Wang, Cretu, & Li, 2017). On the other hand, the challenge of the method without a sensor can be the mathematical complexities in some cases (Xu & Simaan, 2008).

Microsystem technologies have been developed in recent years in an effort to enhance RFA treatment and the primary purpose of this technique in AF therapy is to provide haptic input to the surgeon using this type of sensor. Clinical investigations have indicated that utilizing catheters with

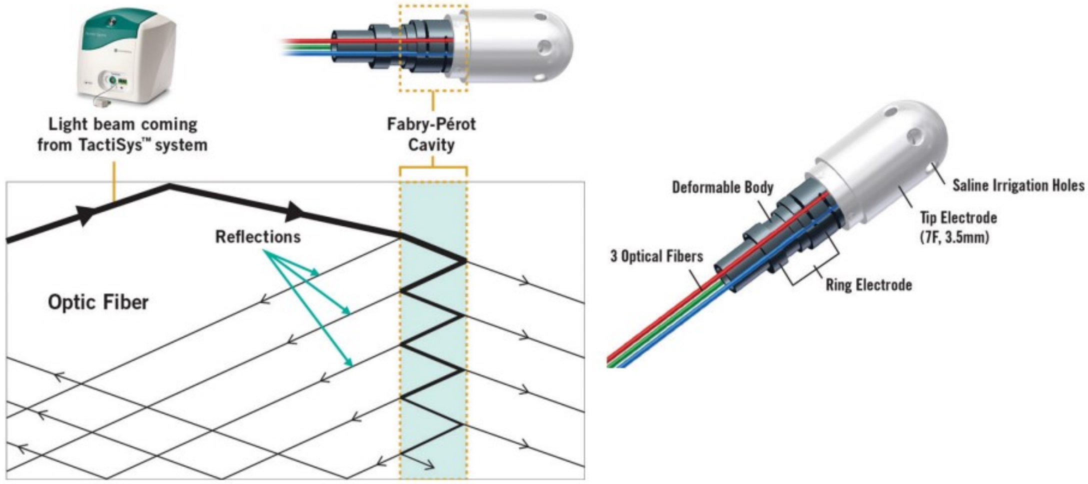

Figure 2.2: Commercially available sensing technologies of ablation catheters- $TactiCath^{TM}$ technology contact force ablation catheter. (Abbott Laboratories, Abbott Park, Illinois, USA)

a sensor is related to greater safety and a better success rate besides faster surgery and less X-ray exposure (Lee et al., 2016; Reddy et al., 2015). St Jude Medical introduced the catheter $TactiCath^{TM}$ in 2014 Figure2.2, which uses fibre-optic technology to provide touch detection. The applied force is determined by analyzing the reflected light from the catheter's optical fibres. The wavelength of light in fibres is modified by the deformation of the optical package when it comes into touch with tissue, and it coincides with the angle and magnitude of CF (Yokoyama et al., 2008). As a result, the surgeon not only checks the orientation of the CF but also detects the strength of the applied force in real-time, for instance, work of (Lin, Ouyang, Kuck, & Tilz, 2014) can illustrate the application.

Another commercially marketed catheter with CF sensing capabilities is the Biosense Webster $ThermocoolSmarttouch^{TM}$ catheter shown in Figure2.3. Three location sensors use a magnetic transmitter coil to calculate distance. The lateral and axial forces of the tip are estimated using the sensor's spring deflection. The CF readings are shown on the mapping system.

The two previous catheters described do not demonstrate the quality of the ablation or the tissue's characteristics. To that aim, Boston Scientific has launched, Figure $Directsense^{TM}$, which uses the

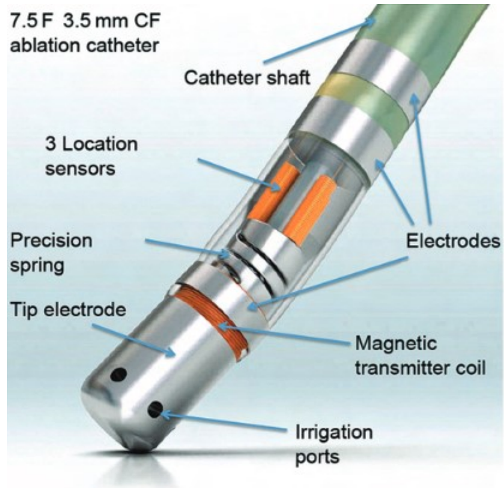

Figure 2.3: Commercially available sensing technologies of ablation catheters- $Thermocool^{TM}$ catheter. (Biosense Webster Inc., California, USA)

electric field around the catheter's tip to present electrophysiologic information to the clinician. A comparable electric field is created surrounding the catheter's electrodes in the Directsense, and the mapping system estimates the local impedance, which is an indicator of catheter-tissue contact and the quality of the ablation technique (Martin et al., 2018). Haptic feedback could give a sense of touch (helps the kinesthetic behaviour) and improve the AF treatment. so, Directsense catheterization can be a supplement for the CF sensing catheters.

Catheters with implanted sensors give vital information that improves AF treatment outcomes, although they have certain drawbacks, for example, sensor-based catheters are expensive due to the technology, and the fact that they are disposable compounds the problem. This system also faces calibration and data-gathering challenges in an unstructured environment.

Sensor-free Methods

Besides reading Contact Force by sensors, they can be predicted and estimated through different mechanical and AI methods without using embedded sensors. In recent years, the model-based technique has been innovated and used for estimating the Contact Force of conventional catheters. This approach is based on the shape deflection of commonly accessible catheters and the advantage of using physical modelling theories. This solution necessitates the use of machine vision algorithms, model algorithms, and optimizations. The extracted model should be precise, resilient, and quick enough to estimate CF in real-time (Guo et al., 2016). An image processing algorithm should be used in this manner to extract the catheter from the input picture. The input picture might be an X-ray or a camera image from an experimental setup. Continuum mechanics, multi-body dynamics, differential geometry, and particle-based models have all been used to simulate a catheter for CF estimation (Hooshiar, Najarian, & Dargahi, 2019).

For example, Khoshnam et al. designed a model for force-position control and modelled the catheter based on a large deflection beam theory. The model was able of estimating the shape independent of the internal structure of the catheter, but it was developed for 2-dimensional mapping of applied CF at the tip and was not generalized (Khoshnam, Azizian, & Patel, 2012; Khoshnam & Patel, 2014; Khoshnam et al., 2013). In another recent work (Hooshiar, Sayadi, Jolaei, & Dargahi, 2021), the Cosserat rod model was implemented and the model accurately estimated the Contact Force but the out-of-plane deflection can directly affect the accuracy of the estimation.

Mechanical models are complicated owing to the numerous parameters that must be identified. The best parameter identification is critical for producing an accurate model. Furthermore, the speed of Contact Force estimation is a significant aspect, and in certain models, the computation speed is not fast enough to give the force rapidly. In recent years, the machine learning technique has been adopted for cardiac intervention to overcome the constraints of model-based CF estimating. The (Khodashenas, Fekri, Zadeh, & Dargahi, 2021) introduced a sensor-free method able to estimate the force directly from image data. The different feed-forward neural network was designed and implemented to make a regression over the image data to predict the CF. Furthermore, (Fekri et al., 2022) implemented a deep convolutional neural network to predict the applied forces to the tip of the catheter (Contact Force) in 3D main directions directly from the images.

2.2.2 Surgeon's Maneuver

However, while the Contact Force information can be helpful in presenting the kinesthetic maneuver of a surgeon during cardiac ablation surgery, the physician's hand movements and gestures

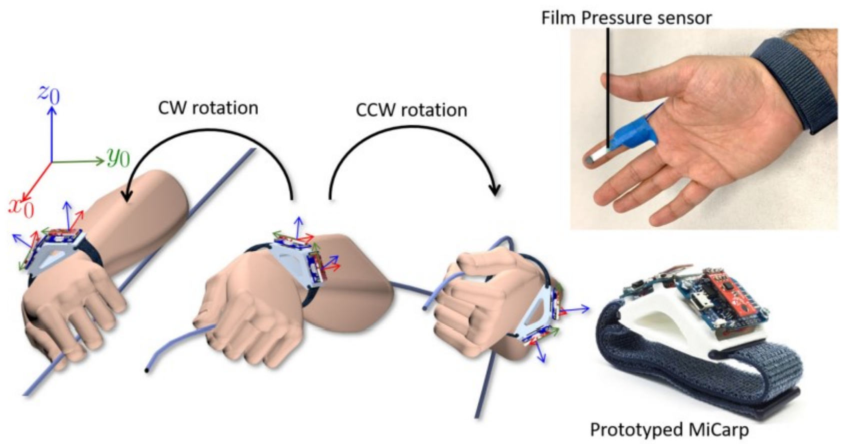

Figure 2.4: Wearable gadget for measuring surgeon's hand rotation. (Hooshiar, Sayadi, Dargahi, & Najarian, 2021)

could also serve as kinematic information. They not only represent the surgeon's skill but can also have a significant impact on the outcome of the surgery. Additionally, maneuvering information could include the adjustment of the knob to change the angle and position of the catheter's handle during the procedure.

An Inertial Measurement Unit (IMU) is a device that measures acceleration, angular velocity, and sometimes magnetic field strength in three dimensions. Typically, an IMU is deployed to monitor the surgeon's spatial hand movements by tracking changes in roll, pitch, and yaw angles. In other words, an IMU can be attached to the catheter to track its position and orientation in real-time. However, it's important to note that the computed orientation may not be precise enough due to measurement noise in the IMU sensor and the cumulative impact of integration over time. To address this issue, Hooshiar et al. proposed a learning-based strategy for estimating spatial orientation without the need for integration. For this purpose, a three-layer feedforward ANN was trained using roll and pitch angles to calculate the equivalent yaw angle for orientation estimation. They developed a wearable device, as shown in Figure 2.4, with two IMU sensors to be used in catheter steering systems. However, it should be noted that the suggested system requires further improvement in terms of sensor data fault detection (Hooshiar, Sayadi, Dargahi, & Najarian, 2021).

The measurement of knob angles can be accomplished using a potentiometer, which utilizes a variable resistor to create a voltage divider circuit. When the potentiometer's wiper moves, it changes the resistance between the wiper and one end of the resistive element, resulting in a corresponding adjustment in the output voltage. To measure an angle using a potentiometer, the potentiometer can be attached to the rotating catheter knob. As the system rotates, it moves the potentiometer's wiper along the resistive element, causing the output voltage to vary accordingly. The output voltage can be measured using a voltmeter or an Analog-to-Digital Converter (ADC). By applying a simple calculation based on the potentiometer's characteristics, such as the total resistance and the angle range of the catheter's knob, the voltage can be converted into an angle value. This method allows for the accurate determination of knob angles during the catheter procedure (Silva et al., 2013).

2.3 Robotic-assisted Surgery

The ablation surgery is carried out using X-ray imaging equipment. The fluoroscopy imaging equipment collects images from the patient in real-time, allowing the surgeon to follow the catheter' tip path. Furthermore, as illustrated in Figure 2.5, an Electroanatomical Mapping system (EAM) depicts cardiac arrhythmia areas in a coloured frame form utilizing 3D reconstruction techniques (Hirao, 2018; Nedios, Sommer, Bollmann, & Hindricks, 2016).

Although fluoroscopy equipment is useful in catheterization operations, x-ray exposure can pose health concerns to both patients and physicians (Hofstetter, Slomczykowski, Sati, & Nolte, 1999). Ablation surgery takes roughly four hours from catheter insertion to the end of ablation therapy, with an hourly risk for cancer and genetic abnormalities for all patients exposed (Calkins et al., 1991). Robotic-assisted surgery has been introduced to mitigate these health concerns for both the surgeon and the patient (Hooshiar et al., 2019). Because of the significant benefits of robotic systems in surgery, these systems have been employed in a number of surgeries in recent years, including minimally invasive cardiac, gynecological, orthopedic, and laparoscopy (Lanfranco, Castellanos, Desai, & Meyers, 2004; y Baena & Davies, 2010). In comparison with open surgery, minimally invasive robotic surgeries offer some remarkable benefits consisting of a low risk of infection and blood loss

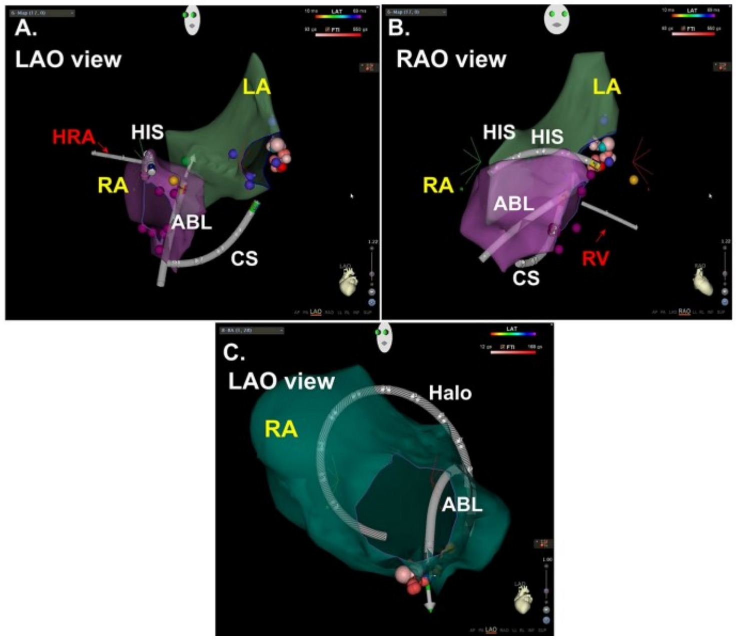

Figure 2.5: Mapping system showing the catheter inside the heart (Catheters visualization.) (Matsubara et al., 2020)

due to small incision size, faster patient recovery resulting in shorter hospitalization, greater vision for the surgeon because of enhanced visualization systems, enhanced precision of the surgical procedure, the possibility of performing live broadcasting of surgery with more expert surgeons and telerobotic surgery capabilities. (Mullins et al., 2012) Four well-known robotic systems for different kinds of surgery are explained in the following.

First on is Intuitive Surgical Inc.'s Da Vinci robotic system Figure2.6 a). It is the most well-known robotic system in medical applications. The FDA (Food and Drug Administration) authorized this system, which includes a surgeon's console and robotic arms, in 2000. To execute the operation, the surgeon can use haptic joysticks in the console to operate the robotic arms. The console has a screen to provide the surgeon with a good view from the robot's camera. Additionally, depending on the technique, a range of surgical equipment, such as scissors, scalpels, and graspers, might be mounted to the end effector of robotic arms and employed by the surgeon. The system is capable of replicating surgical operations in an attempt to teach surgeons (Tewari et al., 2002).

The second one is MAKO by Stryker Inc. Figure2.6 d), which is a robotic platform that can aid surgeons during knee and hip orthopedic surgery. Using CT pictures of the patient, this method can preplan the surgery so that the implants are precisely positioned. Before beginning the operation, the surgeon can check the method for any changes, and lastly, the robotic arm only enables the physician to do the surgery inside the desired boundaries. As a consequence of the navigation and help provided by the robotic arm in this system, the outcome improved significantly, and this technology is now recognized as a helpful platform for surgeons (Roche, 2021).

In addition, another notable system is the ROSA Knee System developed by Zimmer Biomet Co. (Figure 2.6 c). This innovative system provides objective feedback on soft tissue and accurate predictions of bone resections, aiming to restore a patient's knee to its natural state. By capturing and analyzing surgical measurements, ROSA Knee assists surgeons in making informed decisions, enabling them to prioritize achieving optimal outcomes for each individual patient based on data-driven insights (Batailler, Hannouche, Benazzo, & Parratte, 2021).

The last one that has recently authorized technology that allows surgeons to do minimally invasive lung biopsy surgery is Ion by Intuitive Surgical Inc. Figure2.6 b). This device includes an actuatable ultra-thin catheter that enters the airways and travels to the target location inside the lung. The flexible catheter enables surgeons to reach difficult-to-reach areas of the lung during catheterization Reisenauer et al. (2022).

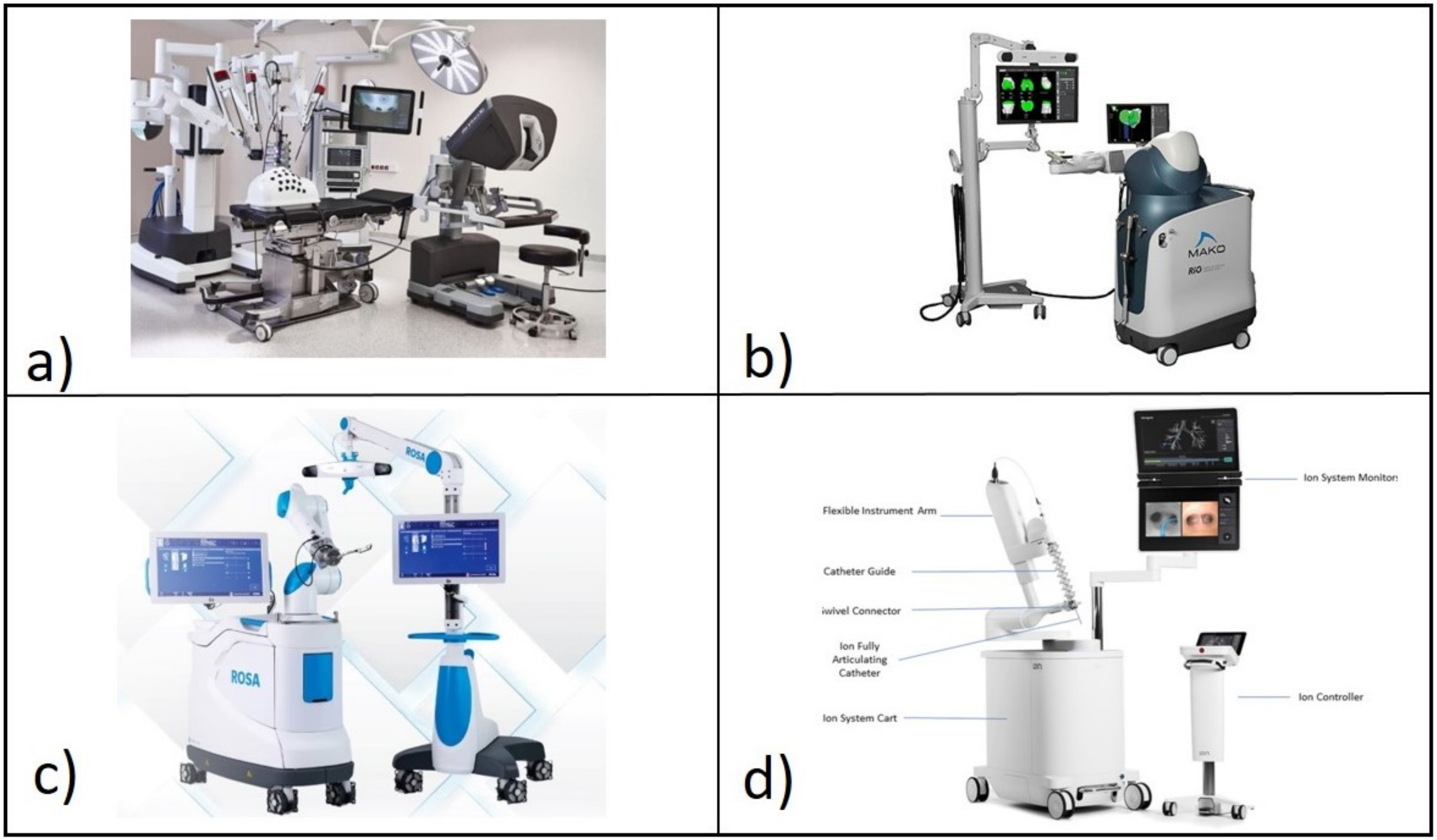

Figure 2.6: Robotic assisted surgeries: a)Da Vinci robotic system(Intuitive Inc., California, USA), b) Ion platform(Intuitive Inc., California, USA), c) Robotic Knee Replacement (Zimmer Biomet Inc.Indiana, USA) and d) Mako robotic arm system (Stryker Inc., Michigan, USA)

2.4 Cardiac Ablation Surgery with Robotic Systems

Ablation surgery is the most favourable and accepted method of treating AF. This surgery is often performed under X-ray exposure and the use of equipment such as catheters, guide wires, and sheaths. The surgeon's ability to manoeuvre the catheter to reach the areas of interest, as well as haptic input, are critical components in this surgery (Bai et al., 2012). The master-slave robotic systems have been created to improve safety and operation in some circumstances, as well as to mitigate radiation risks (Aagaard, Natale, & Di Biase, 2015; Bonatti, Vetrovec, Riga, Wazni, & Stadler, 2014). Biase et al.(Di Biase et al., 2009) compared traditional ablation treatment with conventional catheters to robotic-based catheterization devices in a clinical investigation including 390 patients. The final results indicate that the robotic navigation system has a somewhat greater success rate than manual ablation. Besides, the fluoroscopy duration was significantly shorter in robotic-based operations. Because of the encouraging outcomes of the aforementioned platforms, the FDA has authorized ablation control systems as a safe and effective approach for the treatment of the AF.

Most robotic-assisted approaches available for AF treatment are master/slave robots. On the master side of the robotic platforms, the surgeon controls the mechanical mechanism on the slave side using hand joysticks or foot pedals. The console's monitors provide several perspectives of the patient's anatomy as well as certain critical data, such as the RF generator's characteristics. In terms of navigation technology, robotics-based AF surgery is divided into two types of platforms. First, magnetic field vectors are used to regulate the location of the catheter within the patient's body. External magnets drive the custom-designed catheter in this technology. The second platform, on the other hand, uses electromechanical devices to operate routinely accessible catheters. In this device, a mechanism guides a catheter in the same way as a surgeon's hand would. Some examples of explained methods are gathered in the next paragraph

The Figure2.7 b) Niobe system (Tolga, Bozyel, Golcuk, Yalin, & Guler, 2015) is a magnetically guided frame in which two external magnets on opposite sides of the body guide a custom-designed catheter. Moving and twisting the huge external magnets to adjust the magnetic field vectors allows the catheter with integrated magnets to be navigated. The Niobe catheter is soft and less likely to perforate than regular catheters, although it takes longer to ablate. Moreover, the Figure2.7 a)

Sensei robotic system (Shurrab, Schilling, Gang, Khan, & Crystal, 2014) is a master-slave platform that includes a catheter-control mechanism positioned on the operating table as well as a 3-DOF hand-operated joystick on the console side. The electromechanical device inserts a conventional catheter for the procedure such as ablation after guiding a dedicated guide sheath into the cardiac system to reach the point of interest. This technique ensures catheter stability during the surgery, but mechanical complications are a significant danger due to the hardness of the guide sheath. The next one is the Figure2.7 c) Amigo (Shaikh, Eilenberg, & Cohen, 2017), which is a remotely controlled device that consists of a mechanical component positioned on the patient's table as well as a handle that looks like a typical catheter handle. The user may execute the procedure in a radiation-free environment while holding the remote controller like a typical catheter handle. If fitted with sensor-embedded catheters, this handling system can offer force feedback information on the catheter's tip contact force. Furthermore, the Figure2.7 d) CorPath robotic device (Legeza, Britz, Loh, & Lumsden, 2020) for cardiac intervention allows the physician to sit in a protected chamber and use joysticks to operate a catheter within the patient's body. Furthermore, the catheter or guide wire (a solid flexible wire for insertion guidance) can only be manoeuvred using a customized mechanism that is not compatible with other types of cardiac catheters.

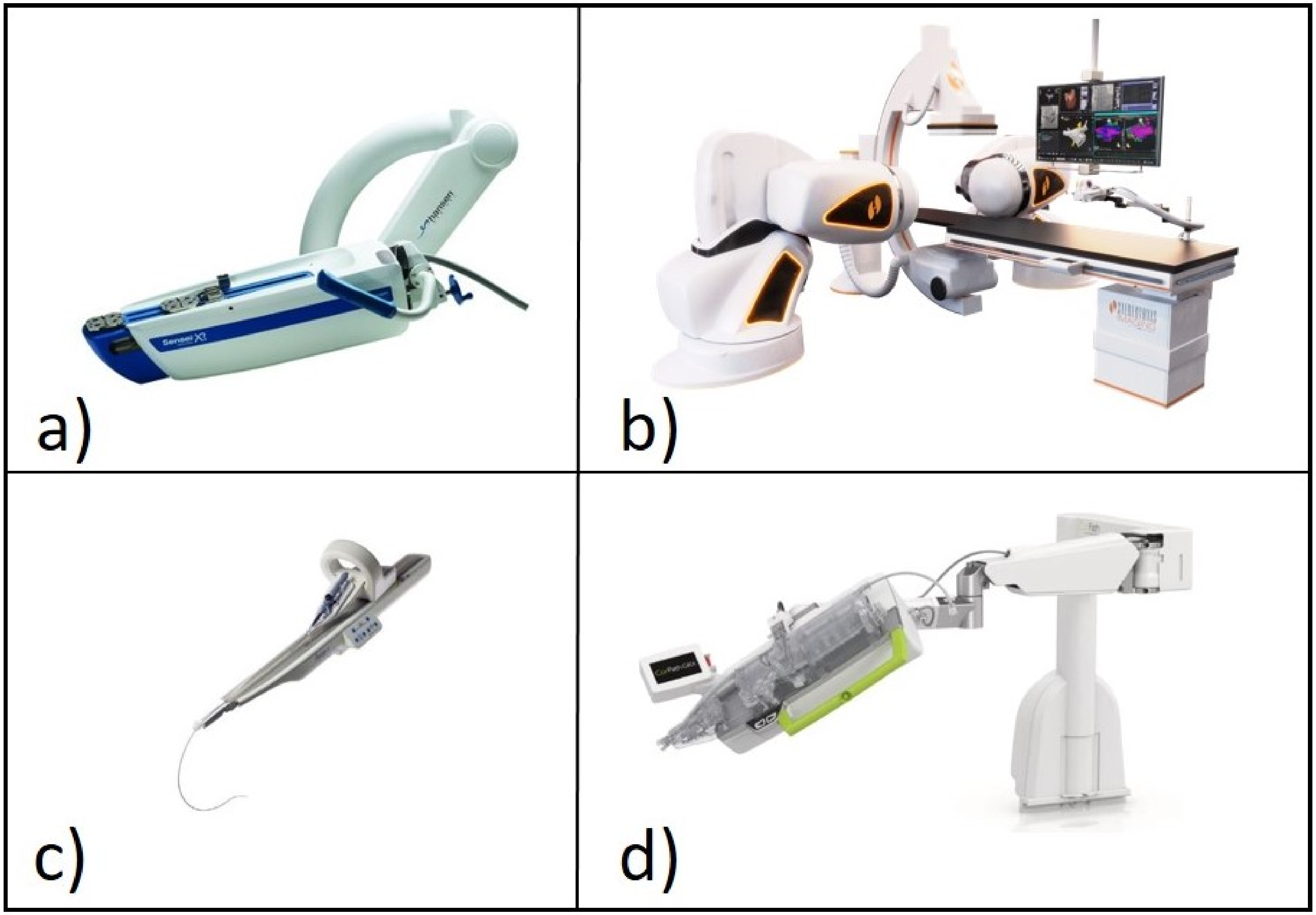

Figure 2.7: Robotic systems for cardiac ablation surgery a) Sensei Hansen Medical, Inc.(USA), b) Niobe Stereotaxis Inc. (USA), c) Amigo Catheter Precision Inc. (USA) and d) CorPath Corindus Inc.(USA).

2.5 AI Biomedical Applications

AI is being used to enhance patient outcomes, diagnosis, and treatment in a variety of medical applications. AI has the potential to transform healthcare by providing more personalized and effective treatment, improving disease management, and reducing healthcare costs.

2.5.1 Machine Learning Applications

Machine learning-based approaches are widely used in medical applications. Abdar and colleagues, for example, proposed a computer-aided diagnostic technique that uses a supervised model to predict liver disease in its early stages with an accuracy of 93.75% (Abdar, Zomorodi-Moghadam, Das, & Ting, 2017). Moreover, Abdar et al. developed a machine learning system, which included a Support Vector Machine (SVM), to detect Parkinson's disease with an average accuracy of 99.18% (Abdar & Zomorodi-Moghadam, 2018). In addition, to detect Wart, a skin ailment, ML approaches such as linear SVM and random forest algorithms were used with a 91.116.67% accuracy (Alizadehsani et al., 2019). Or Bagherian et al. (2022) utilized the A-star algorithm to optimize a statistical descriptor called quality of connection which was later used by (Famouri et al., 2022, 2020; Shahmohammadi et al., 2022) to predict osteoporosis procedure through reconstruction methods. Moreover, a categorization of cardiac diseases was proposed in another work utilizing electrocardiography (ECG) data analysis and an SVM classifier. This study used ECG signal fragments from the MIT-BIH arrhythmia database from 29 individuals. This investigation yielded a model accuracy of 98.99% (Pławiak, 2018). E.Bron et al. also introduced a computer-aided SVM classification model with a 90 % accuracy for Frontotemporal Dementia (FTD), which includes Cognitive Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD), which underlying dementia using MRI neuroimages (Bron et al., 2017).

2.5.2 Deep Learning Applications

Deep learning networks have recently been effectively employed in a variety of fields, including economics, robotics, and healthcare. Deep learning varies from traditional machine learning in how representations are learned from raw data. In actuality, deep learning allows computer models composed of several neural network-based processing layers to learn complicated and abstract characteristics (LeCun et al., 2015). The primary distinctions between deep learning and conventional Artificial Neural Networks (ANNs) are the number of hidden layers, their interactions, and the ability to learn significant properties of the inputs.

Moreover, conventional ANNs are often limited to three layers and equipped to provide supervised interpretations that are exclusively adapted for the specific job and cannot be generalized (Rumelhart, Hinton, & Williams, 1986). Deep learning technology has aided in illness diagnosis in the medical profession. To recognize feature amounts of texts, photos, and so on, this approach employs multi-layer non-linear data processing. The main advantage of deep learning is that a very exact model may be learnt from huge amounts of data without having to grasp the entire fundamental structure (Ahmad et al., 2017).

Convolutional Neural Networks (CNNs) (LeCun, Bottou, Bengio, & Haffner, 1998), RBMs (Smolensky, 1986), Autoencoders (AEs) (Hinton & Salakhutdinov, 2006), and RNNs (R. J. Williams & Zipser, 1989) are the focus of the majority of the profound architectures suitable to the medical areas. These methodologies are used in a variety of medical applications, including tumour or lesion classification, nodule classification, fetal and neonatal classification, and cardiac classification.

A CNN is a type of Deep Neural Network extensively utilized for deep learning-based visual image analysis. CNNs are specifically designed to process images by employing a series of essential components. These components typically include a convolutional layer that applies filters to extract relevant features from the input images, followed by a pooling layer that reduces the spatial dimensions of the extracted features. Additionally, an activation function is applied to introduce non-linearity and enhance the network's ability to capture complex patterns. In order to address emerging challenges and enhance performance, several alternative CNN architectures have been proposed. Notable examples include VGG (Simonyan & Zisserman, 2014), LeNet (LeCun et al., 1998), AlexNet, and ResNet (He, Zhang, Ren, & Sun, 2016). These variations in architecture have significantly contributed to the field of image recognition and have played a crucial role in advancing deep learning techniques for visual data analysis.

LSTM Applications

Many sophisticated algorithms have been suggested, and some have even been shown to outperform humans in task performance evaluation. With the capacity to learn high-level features incrementally and solve the end-to-end challenge (LeCun et al., 2015). There are now various types of deep neural networks for processing time series data. LSTM is a powerful tool for processing sequential data with long-term dependencies and has demonstrated its potential in several biomedical applications such as prediction, segmentation, and classification. Disease diagnosis, assessment and prediction is one area where LSTM has been used. For instance, (Li & Fan, 2019) used an LSTM-based model to predict the progression of Alzheimer's disease using MRI data and achieved high accuracy. (Bhati, Velazquez, Villalba, & Dehak, 2019) used LSTM to predict the onset of Parkinson's disease using speech features and achieved an accuracy of over 90%. Murad et al. developed a deep recurrent neural network based on LSTM to identify human activities (Forestier, Weber, Idoumghar, Muller, et al., 2019; Murad & Pyun, 2017). Kim et al. found great accuracy while classifying time series data from dog source events using the CNN-LSTM model (Kim, Sa, Chung, Park, & Lee, 2018). A new automated system that uses a hybrid deep CNN-LSTM neural network for analyzing surgical motion (kinematic) was developed by (Nguyen, Ljuhar, Pacilli, Nataraja, & Chauhan, 2019), to assess surgical skills in suturing, needle-passing and knot-tying. In consequence, LSTM has demonstrated its potential in various biomedical tasks such as disease diagnosis, skill assessment, surgery outcome and related predictions. It could be a valuable tool for processing sequential data with long-term dependencies and has the ability to learn from the past to make accurate predictions.

2.6 Addressing the Potential Need

Throughout time, cardiac ablation surgery has gained significant popularity as an effective approach for addressing specific cardiac conditions. This minimally invasive technique entails the insertion of a catheter into the heart through a small incision in either the groin or neck. By applying radiofrequency energy, the targeted region of the heart, responsible for the irregular heart rhythm, is ablated, offering a therapeutic solution. However, despite its many benefits, this procedure is not without risks. Complications can occur, including bleeding, infection, and damage to surrounding tissues. To mitigate these risks and ensure optimal patient outcomes, it is important for surgeons to have access to comprehensive training programs that enable them to acquire and develop the necessary surgical skills. To this end, robotics setups that simulate various aspects of cardiac ablation surgery have been proposed. Such setups enable trainees to practice and evaluate their surgical skills in a controlled environment that mimics the real operating room.

However, to fully leverage the benefits of these setups, it is important to equip them with various types of sensors that can measure behavioural information during surgical tasks. For example, a force-torque sensor can be used to measure the forces and torques applied by the surgeon during the surgical task, providing insight into their proficiency in performing the task. Similarly, an IMU device can be used to measure the surgeon's maneuvering and orientation of the catheter tip during the procedure, providing information on the surgeon's dexterity and accuracy. Surgeons' hand gesture data is characterized as dynamic and sequential information that evolves over time. To address the skill evaluation problem of distinguishing between experts and novices, we construct two models: one based on a vanilla recurrent neural network (RNN) and the other based on LSTM. These models aim to capture and extract the temporal patterns inherent in the time series data, specifically the gestures made by experts and novices. By utilizing robotics setups equipped with these types of sensors, surgeons and trainees can receive valuable feedback on their surgical skills, enabling them to identify areas where improvement is needed and develop their skills more effectively. In turn, this can lead to shorter, safer, and more accurate surgical procedures, ultimately benefiting patients and improving overall healthcare outcomes.

Chapter 3

Towards Surgical Skill Modeling in Cardiac Ablation Using Deep Learning

The most widely practised method for treating cardiovascular problems is minimally invasive surgery (MIS). The rising interest in surgical robots and simulations has led to a greater demand for more objective methods of skill evaluation. Traditionally, the performance of novices is evaluated using surgeons' skills through a specific and streamlined ablation task. To this end, an experimental setup was proposed to provide a simulated ablation procedure through a mechanical system. It is equipped with the synthetic heartbeat mechanism of the heart with the capability of measuring the contact forces between a catheter's tip and a force sensor. Using a commercially available catheter for ablation, the task was to maintain the force within a safe range while the tip of the catheter is touching the surface of the sensor. Accomplishing multiple experiments by novices and experts, a deep recurrent neural network was considered to extract the model of skills by solving a binary classification problem. The results of the trained model showed that the proposed pipeline was able to properly distinguish the novices' from experts' maneuvers with 95% accuracy.

3.1 Introduction

Cardiovascular diseases are one of the most significant causes of death worldwide. Atrial Fibrillation (AF) is an illness of this kind that generates irregular heartbeat (e.g., arrhythmia) leading to blood clots, stroke, and possibly heart failure. As an effective treatment, an ablation procedure can enable surgeons to destroy the defective spots in the heart and help it to retrieve the normal heartbeat pattern. To perform such a procedure, the surgeon inserts a long catheter into the vascular system and navigates it toward the heart to reach the arrhythmatic spots. By squeezing the tip of the catheter on these spots, the surgeon can ablate them using the energy generated by the catheter (Fuster et al., 2006; Kléber & Rudy, 2004; Motloch & Akar, 2015). The catheter itself is a long flexible tube equipped with a handle to manually control the translation and rotation maneuvers by the surgeon. In addition, there is a knob installed on the handle through which the surgeon can deflect the distal shaft of the catheter (the last 10 cm of a catheter which is deflectible) by twisting it to the right or left (Ganji & Janabi-Sharifi, 2007).

Despite the efficacy of ablation catheters in treating AF, it is likely to develop fatal complications (e.g., puncturing the blood vessel or a failure in ablation) while the surgeon is steering the catheter and squeezing the tip on the lumens (Fekri et al., 2022; Jolaei, Hooshiar, Dargahi, & Packirisamy, 2021). However, this study specifically concentrates on the complications related to the ablation process (e.g., squeezing the tip on the target point, regardless of the steering process). For instance, excessive forces applied by the surgeon during the ablation may damage the cardiac tissues, while an insufficient amount of force can result in the failure of the entire procedure (Ariyarathna et al., 2018; Back et al., 2015; Xin, Zelek, & Carnahan, 2006). The outcome of such a procedure is highly associated with the surgeons' dexterity in controlling the catheter, especially the knob, when it comes to exerting the appropriate amount of force (Hooshiar et al., 2019; Hu, Chen, Luo, Zhang, & Zhang, 2018). The bottleneck of acquiring such hands-on skills is that the ablation procedure is intangible to the surgeon. In other words, the surgeon is not provided with an embedded touch/force sensor in a regular catheter so that the applied forces can be monitored and maintained within a safe range. Hence, it is inevitable for surgeons to rely on their kinesthetic senses by repeatedly performing the task to elevate their skill.

Normally, novice surgeons attend the real operation room (OR) to practice surgical tasks as part of the training process. This might be challenging and adversely affect patients during the surgery. The novices might find it tough to practice in authentic ORs due inaccessibility of such procedures for training purposes. Considering the above-mentioned limitations, there is a vital need to replicate a practical training environment for the ablation treatment out of the real OR. The proposed setup should resemble a real OR through which a novice surgeon can perform the task intraoperatively. In addition, a supervisor is required as a substitute for an expert surgeon to monitor the gestures and maneuvers of the novice throughout the training and reflect on the feedback. Given the supervisory signals, the novice has the chance to correct the maneuver while performing the surgical task. The aforementioned supervisor should be able to distinguish between correct and incorrect motions and gestures.

In (Wang & Wu, 2021), Wang and Wu designed a virtual reality-based interventional simulator for catheter ablation that provides surgeons with a training environment. Rafii-Tari et al. introduced a training platform for catheterization through which tactile feedback helps novices to correct their motions (kinematic) while performing a task (Chi et al., 2017). In addition, Fekri et al. proposed a training setup for the orthopedic surgical drilling procedure. They developed a mechanical drilling platform that interacts with a virtual environment to simulate the drilling task. Using this experimental setup, the novice is able to practice a drilling task while a deep learning model tracks the gestural behaviors. In the other work, the authors benefited from the aforementioned setup to train a deep recurrent neural network that is able to classify the drilling maneuvers into the expert and novice category over time (Fekri, Dargahi, & Zadeh, 2021). This system was utilized to secure a tele-surgical drilling task.

The aim of this study is to develop a training experimental setup for the ablation treatment. The setup will enable the surgeon to perform an ablation task using a regular ablation catheter. In order to replicate the real operation situation, the setup is equipped with a mechanism that generates a synthetic heart-beating motion. Upon such an experimental platform, a simplified ablation task is defined (e.g., squeezing the tip of the catheter on the defective spot) so that a surgeon, either a novice or expert, can practice extraoperatively. This helps the operators not only enhance their hands-on skills in real catheterization but also repeatedly practice the task without attending a real OR. Since the entire procedure is intangible to surgeons, the surface of the heart lumens is replaced with a force sensor to visually provide the surgeons with the applied forces. Using this feature, the surgeon can regulate the kinesthic demonstrations while monitoring the forces during the training process. As the supervisor of the training setup, it strives to model the skill level of surgeons during the intended ablation task using a deep recurrent neural network based on the Long Short-Term Memory (LSTM) method. The networks extract the model of skills related to the experts and novices using the measured forces by the sensor. Deploying such a model on the training setup, the demonstrations of surgeons can be evaluated in real-time. This will help novice surgeons to track their progress over time and enhance their demonstration based on the expert demonstration model through trial and error.

To the best of the authors' knowledge, this work is of the first studies that address skill modeling problems in the ablation procedure by providing a physical training setup. In contrast to the simulation-based skill modeling platform, this study strives to provide a realistic sense of ablation through a mechanical setup equipped with a regular catheter. By measuring and reporting the generated forces between the tip of the catheter and the force sensor, surgeons are able to regulate their kinesthetic sense during practice. As an expert supervisor, the setup is equipped with an RNN model to evaluate the demonstration (applied forces) through a time series binary classification upon which the novice surgeons can compare the motions with experts' ones.

3.2 Deep Ablation Skills Classification

As discussed, the goal of the current work is to design a training cardiac catheterization setup for a simplified ablation task. Upon this platform, a surgeon is able to practice the procedure of squeezing the tip of a regular catheter on the abnormal spots out of a real OR. Given that the applied forces smaller than $0.1\ N$ and greater than $0.3\ N$ may lead to a failure in the surgery, the surgeon will be able to regulate the demonstrations using the reported forces. Using the setup, the surgeon is required to maintain the forces on the desired amount by manipulating the knob on the catheter.

This threshold should be set prior to the training operation (within 0.1 N to 0.3 N). Since the synthetic beating mechanism in the setup changes the catheter deflection causing forces disturbance, the goal for the trainee is to control the deflection accordingly by monitoring the generated forces. To evaluate the demonstrations of the attendees, it is essential to extract the model of maneuvers for both expert and novice surgeons. The input to such a model is the measured forces by the sensor while performing the training task. Hence, the requisite data is compiled from the novice and expert participants while carrying out the task using the experimental setup. Since the surgical skill in controlling the knob can be assessed over time, the kinesthetic gestures are deemed as dynamic and sequential data. For this reason, an LSTM graph is proposed in order to extract temporal dependencies from the data samples. The models are considered to solve a binary classification problem to distinguish between experts' and novices' gestures. This can help the trainees to keep track of their performance compared with a reference model of skills obtained from experts and novices. The following sections explain the experimental setup, surgical task, and data compilation.

3.2.1 Experimental Setup

The intended setup enables the trainees to hold a catheter and maintain the forces on a predefined threshold by controlling the distal shaft deflection using the knob. To this end, the setup (Figure3.1) is equipped with a bidirectional catheter, Blazer II XP from Boston Scientific, with a tip diameter of 8Fr (2.67 mm) and a length of 110 cm. The catheter is passed through a sheath which is held by three printed bridges so as to fix the body of the catheter in place. The distal shaft is out of the aforementioned sheath, and the tip of the catheter is in contact with the artificial heart. This synthetic heart tissue is attached to the surface of a 6-DoF force sensor (ATI Mini40). The knob on the steering handle is manually adjusted by the trainee to achieve the desired bending at the distal shaft and generate the necessary forces at the catheter's tip.

In practice, motions caused by the heartbeat destabilize the workspace for surgeons during the ablation. In fact, the surgeon should tackle such movements in the heart by controlling the deflection while squeezing the tip of the catheter on the defective spot. To this end, a heart simulator was

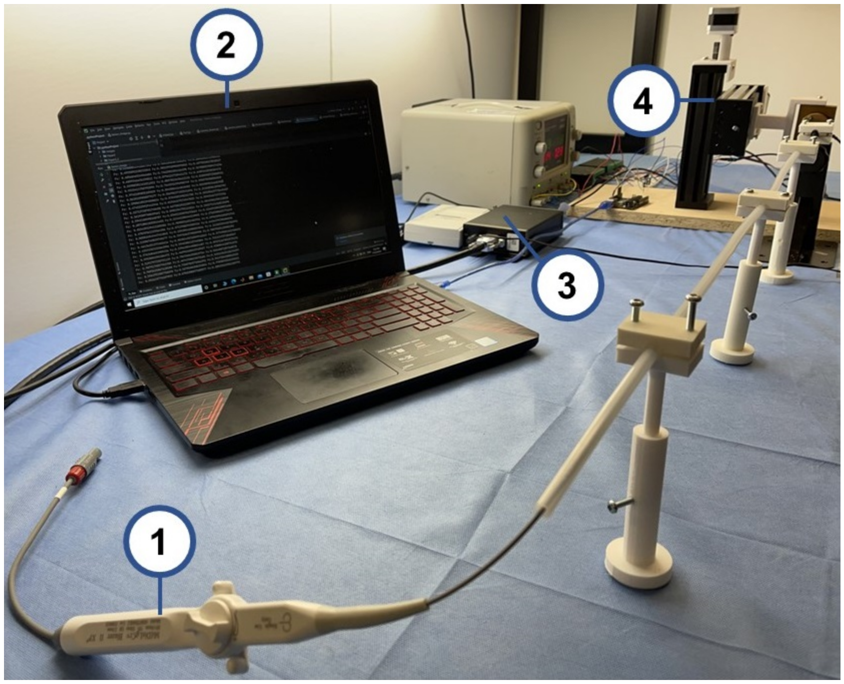

Figure 3.1: Overall view of the experimental setup: (1) catheter, (2) data acquisition user interface, (3) data acquisition system, (4) heart beating simulator.

implemented in order to imitate the heartbeat during the ablation. Two linear actuators were motorized by 2 two-phase stepper motors so as to replicate the beating motion. The force sensor and the artificial heart tissue placed on the linear actuators make the entire beating mechanism. The side view of setup in Figure3.2 illustrates the aforesaid setup parts.

As shown in Figure3.3, the catheter shaft is in the z-direction, and bending would occur in the YZ plane. The target point between the heart wall and the fixed part is displayed by the black line as well.

3.2.2 Surgical Task and Data Compilation

The sinusoidal 0.5 Hz heartbeat frequency is produced via an Arduino program, and the command is transferred to the stepper motors installed on linear actuators through the microcontroller (the driver is set to 500 pulses per revelation for each back and forth). Since the participates for data compilation were non-expert, the heartbeats are assumed to be slower than the normal rate so as to

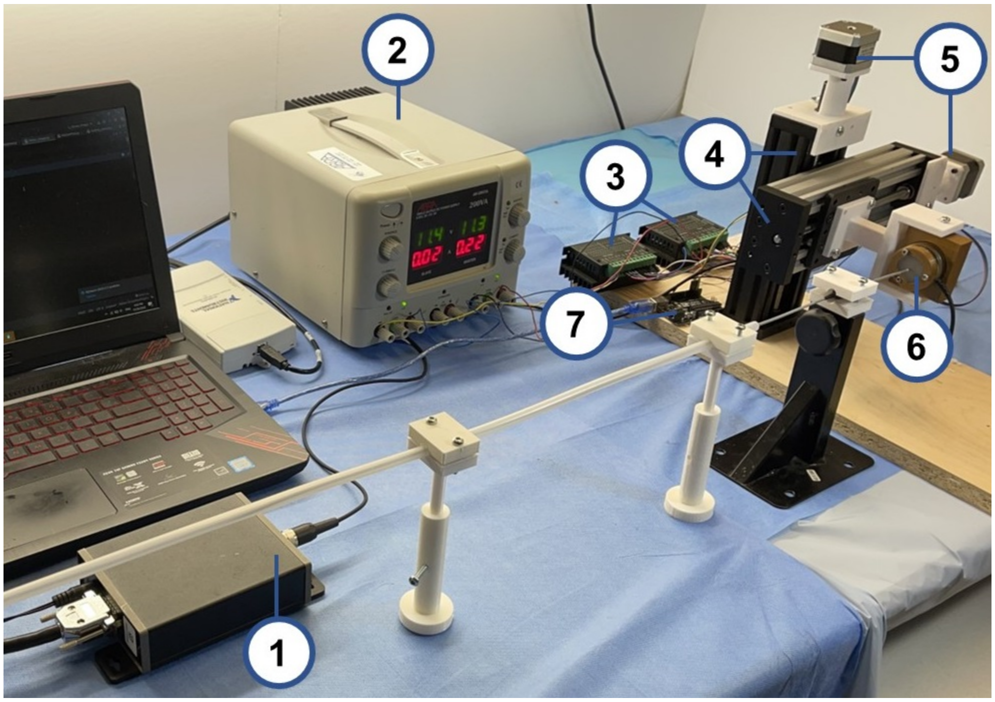

Figure 3.2: Side view (1) force sensor Data acquisition (DAQ), (2) power supply, (3) micro-stepping drivers, (4) linear actuators, (5) stepper motors (17HS4401-S), (6) force sensor, (7) micro-controller board (Arduino Uno).

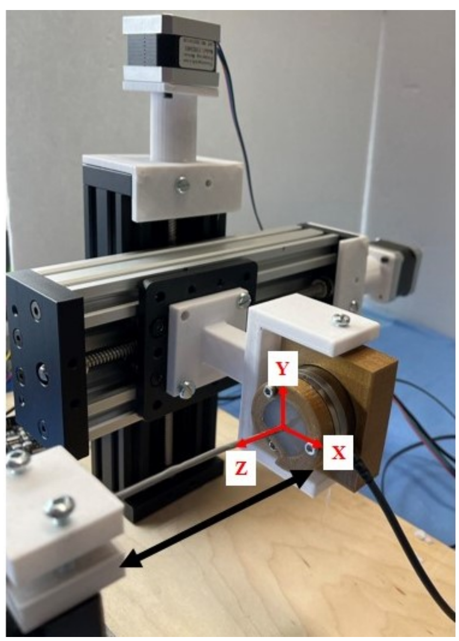

Figure 3.3: Force axes and sweet point distance are displayed concerning the distal part of the catheter.

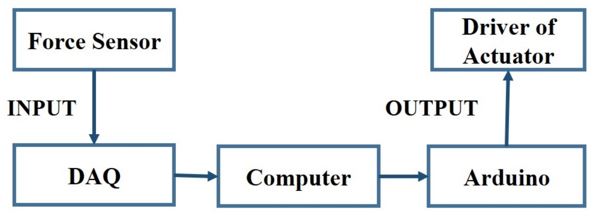

Figure 3.4: Summary of the setup interface between the computer and the driver.

streamline the task. The force sensor was connected to a data acquisition system that transferred the forces and torque data in the voltage unit to the computer via a USB cable. Then, the voltage was converted to Newton's unit by calibration matrix. Moreover, force data was read continuously at 62.5 Hz speed. Figure3.4 summarizes the information discussed.

Since the catheter was fixed at the end of its distal shaft, the insertion skill was not assessed during the study. Users were only able to manipulate the knob to bend the distal part. The effectiveness of our study was tested by collecting a dataset from a group of five experts and five novices. Participants were asked to keep the forces within a safe range by manipulating the knob while the synthetic heart was beating. Furthermore, the instant forces were displayed on the monitor so the users can track the applied forces. All participants were non-expert, however, the group that played the role of expert users was provided with sufficient guidance and amount of time to practice as many times as they needed in order to get familiar with the setup and task properly. Afterward, they were asked to carry out the real task of data compilation. In contrast, the novice group was given a brief introduction and completed the task without prior practice. The proficiency displayed by expert trainees who have attained expertise through practice bears similarities to the conduct of expert surgeons. Consequently, it is justifiable to anticipate a commensurate level of precision when employing the identical model in conjunction with seasoned surgeons in real-world scenarios.
As for the intended task, all volunteers were asked to maintain the applied force along the Z direction in the range of 0.6 to 0.8 N for 85 seconds by manipulating the knob of the catheter while the heartbeat simulation was destabilizing the applied forces. The catheter tip was in touch with the artificial heart tissue during the experiments. It was necessary for the users to harmonize the knob to the rhythm of the heartbeat to reduce the force magnitude to the desired amount. The data

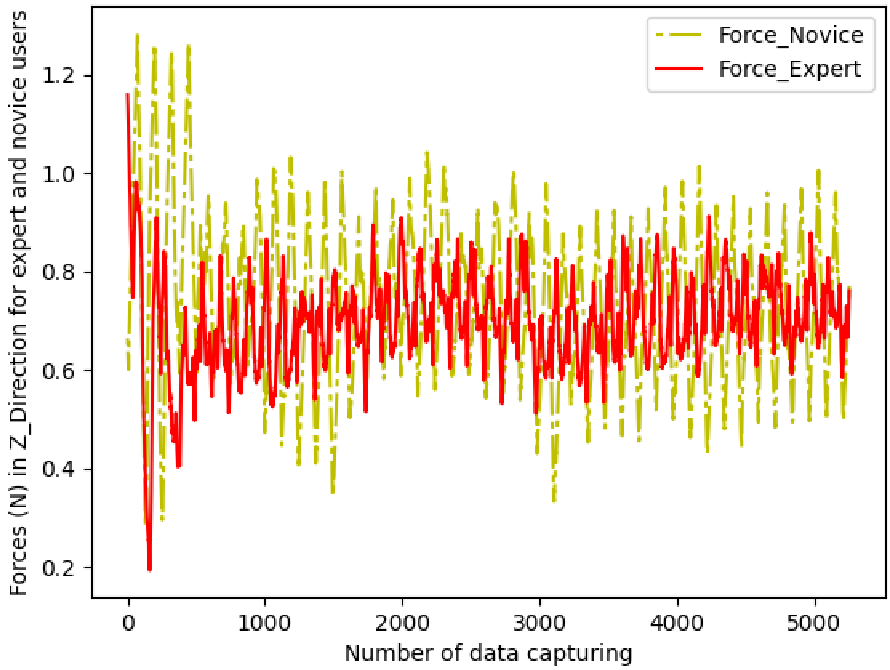

Figure 3.5: The comparison between applied forces on the sensor by expert and novice users via adjusting knob position. A total of 5250 force data in the Z-direction were recorded over a period of 85 seconds.

acquisition frequency was 62.5 Hz and resulted in 5250 records in each data set and 52500 in total. Figure3.5 presents the forces recorded in the Z-direction for a single experiment with a duration of 85 seconds. The red line and green dashed line illustrate the data related to the expert and novice tests, respectively.

3.2.3 Methodology

Having the datasets comprising the completed tasks, the goal is to develop a model so as to identify the skill level of surgeons. The model should classify the records of datasets as novice or expert. The intended model should be fed by the forces recorded during the experiments. In fact, as a feature, the generated forces are supposed to represent the skill level of surgeons in maintaining a safe and effective range of applied pressure while ablating the arithmetic spot in the heart. However, evaluating the performance of maneuvers and discerning the skill level is in need of investigating the feature over time. In other words, it is not conceivable to make a decision on a single record

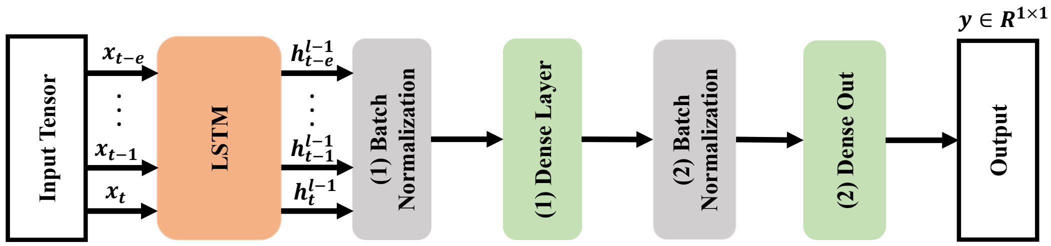

Figure 3.6: An overview of the proposed LSTM architecture. Based on input tensors acquired from defined tasks, surgeons are classified as novices or experts.

of the dataset and distinguish the class of skills. To this end, it is warranted to process temporal characteristics of the data through RNN.

In contrast to the feed-forward networks, the RNN injects the impact of time by engaging the output of the network at time $t-1$ in the input at time instant t. RNNs based on the LSTM architecture have already shown successful performance in modeling the surgical skill by exerting forces (Hochreiter & Schmidhuber, 1997). These kinds of deep neural networks were employed as classifier to categorize the skill into the level of proficiency (Fekri, Setoodeh, Khosravian, Safavi, & Zadeh, 2018). They have been also deployed as a regressor to forecast the applied force one step ahead with the aim to transfer the surgical skill from experts to novices (Fekri, Dargahi, & Zadeh, 2021). Inspired by these systems, in this study an LSTM-based RNN is considered to receive a sequence of data s with length d where each of them $s \in R^{1\times1}$. The regular LSTM encompasses three gates in order to update the cell state (memory) C_t as follows:

$$f^t = \sigma(W_f h^{t-1} + U_f x^t + b_f) \tag{1}$$

$$i^t = \sigma(W_i h^{t-1} + U_i x^t + b_i) \tag{2}$$

$$o^t = \sigma(W_o h^{t-1} + U_o x^t + b_o) \tag{3}$$

Considering C_t as the memory of the network at time t, forget gate f^t removes information from memory, input gate i_t adds new information while output gate o^i contributes to the output of the network. Also, h_{t-1} is the hidden state/output of the network at time instant $t-1$. The size of this vector indicates the size of the memory as well as the corresponding weight matrices W, U and biases vectors b. σ is a sigmoid activation function. Given the updates from the forget and input gates, the memory (cell state C^t) can be updated as follows:

$$C^t = C^{t-1} * f^t + \tilde{C^t} * i^t \tag{4}$$

where $\tilde{C^t}$ is calculated as follows:

$$\tilde{C^t} = tanh(W_{\tilde{C^t}} x^t + U_{\tilde{C^t}} h^{t-1} + b_{\tilde{C^t}}) \tag{5}$$

the activation function is a hyperbolic tangent and the weights and biases are in the same dimension as the other layers. The LSTM layer spits out the output as follows:

$$h^t = o^t * tanh(C^t) \tag{6}$$

where o^t is the output gate (3). The output of the unrolled LSTM from the last time step feeds a batch normalization layer Ioffe and Szegedy (2015):

$$y^l = \gamma \hat{h} + \beta \tag{7}$$

Where $\hat{h}$ is the scaled output of the previous layer (h^t from the LSTM) using mean (μ) and standard deviation ($\sqrt{\sigma^2}$) of the samples in the batch:

$$\hat{h} = \frac{h^t - \mu}{\sqrt{\sigma^2}} \tag{8}$$

In fact, the batch normalization layer scales the output of the previous layer in order to prevent vanishing/exploding gradient and accelerate the training phase by choosing a larger learning rate. It also helps the problem of this study to reach a convergence point in the optimization. However, the scaled output has two trainable parameters (γ and β) so as to obtain exclusive shift and scale. The

LSTM and batch normalization are followed by a stack of dense layers:

$$y^l = w^l y^{l-1} + b^l \tag{9}$$

where l is the layer. It is worth noting that all hidden dense layers' output enters into the batch normalization layer (except the output layer). Moreover, ReLU is the activation function of the hidden dense layers while the output layer with a single neuron calculates the probability through a sigmoid activation function. Since the problem is a binary classification, a binary cross entropy loss function calculates the error of the model for N samples as follows:

$$Loss(y, T) = -\frac{1}{N} \sum_{i}^{N} T_i log(\sigma(y_i)) + (1 - T_i) log(1 - \sigma(y_i)) \tag{10}$$

where T denotes the actual class of the input sequence (novice or expert). The loss function above is optimized in order to tune the network's parameter with Back Propagation Through Time (BPTT) using ADAM optimizer (Kingma & Ba, 2014).

3.3 Result and Discussion

In this section, the data preparation process will be explained to train and validate the model. Furthermore, the model with different configurations will be designed in order to benchmark the performance through eclectic metrics. Subsection A will explain the process of converting the dataset to the sequences compatible with the model. Next, the requisite information about the graph of the model will be provided. The obtained results will be compared in subsection B.

3.3.1 Dataset and Model Configuration

Given the data acquired from the experiments, a dataset comprising ten separate experiments was compiled in order to train, validate and test the model. The dataset is balanced as the number of experiments accomplished by novices, and experts were selected evenly. Thus, it contained 52500 records of data related to the force along the Z-direction. It is imperative to acknowledge that the dataset employed for the study was meticulously curated to uphold principles of generalizability, devoid of noise, and endowed with adequate length to enable the development of a meticulous prediction model. Since the model was unrolled to extract the temporal dependency of the data, it was required to convert the dataset to sequences of data so as to feed the model. Hence, the order of data w.r.t the time was preserved in the main dataset. Upon this dataset, four datasets with time step $t = 20, 100, 200$, and 300 were generated. For example, a single record of the dataset with $t = 300$ is a sequence of 300 force along the Z-direction which is ordered by time. As the intended LSTM network (Figure3.6) is stateless, the dataset of sequences was shuffled and 70% of data was dedicated to the training set while the rest was allocated for the validation and test set equally. Multiple LSTM-based classifiers were implemented to distinguish the skill levels in the datasets with different time steps and window sizes. The goal was to create a benchmark to investigate the impact of the time steps and the network computational complexity. The configuration of the network was customized based on the number of dense/LSTM layers and the hidden state/neurons.

3.3.2 Evaluation and Results

As a benchmark, multiple graphs based on the LSTM architecture were implemented to solve the binary classification problem of ablation skills. Each model was trained on the training set with 64 samples in each batch of data. The models were trained through 200 epochs with a learning rate of 1e-10. The performance of the models was evaluated on the validation set in each epoch in order to perform early stopping and prevent over-fitting. Table 1 reports the designed graphs and their corresponding outputs. The performance of the models was evaluated on the test dataset as the unseen data using the following metrics: precision, recall, f1-score, and accuracy. The first configuration is a layer of the LSTM with 32 hidden state/ memory sizes followed by two dense layers with 16 and 8 neurons respectively. The network is fed by the training dataset in which each sequence comprises 200 samples and classifies the skill level with 91% accuracy. The second configuration has an identical graph but is trained on the data with 300-time steps. It revealed that increasing the length of sequences resulted in a better performance as the model hit 95% accuracy. Configurations 3 to 6 investigated the impact of adding another hidden dense layer with 32 neurons as well as the length of the sequences on the performance of the models.

As can be seen, the performance of the model on the 20-time steps was considerably dropped. However, the model improved the accuracy where the given dataset contained a longer time window. For example, the output of configuration 4 for time step 100 reached 89% accuracy while configuration 5 with time step 300 improved the accuracy by 3%. This indicates that the model requires a longer sequence of surgical tasks in order to extract the temporal dependency and distinguish the novice from the expert maneuvers. Given configuration 7, it is evident that increasing the complexity of the model (e.g., the memory size and hidden layers' parameters) has not significantly affected the performance of the model. Also, the value of the precision, recall and f1-score for all configurations denotes that the dataset was balanced without bias to either of the classes. It indicates that the model is making an equal number of true positive predictions and false positive predictions, resulting in an equal number of true positive predictions and false negative predictions.

In fact, the model prediction of the classes was predominantly correct and the number of correctly classified samples in a specific class was significantly high. The best accuracy was achieved by the unrolled models trained on the sequences with 300 lengths. Compared to the LSTM-based graph proposed by Fekri et al., the proposed LSTM-based architectures in this study were able to improve the accuracy of the skill classification (Fekri, Dargahi, & Zadeh, 2021; Fekri et al., 2018). Using batch normalization layers and stacked dense layers besides a longer time window caused better performance from the LSTM architecture. The models were implemented in Python using Tensorflow 2.0 framework on an Ubuntu 20.04 machine with 24GB RAM equipped with an NVIDIA GeForce 2080 GPU.

3.4 Conclusion

In this study, the surgeons' maneuvering skill during a pre-defined catheterization task was modeled based on the deep learning approach to evaluate the surgical skill of the operators (expert and novice) ablating through the provided mechanical setup. In order to provide users with a realistic experience of surgery, the framework was equipped with the simulated cardiac mechanism. Not only the model could be valuable in skill transfer methodologies, but also it could be the supervisor assessment method in real surgery to evaluate the catheterization procedure based on the recorded expert skill model. The proposed model was developed based on the recurrent neural network with long short-term memory architecture. The presented skill assessment technique predicts surgeons' skills based on the force data acquired over time from the task of controlling applied force on the surface of the sensor in the specific range for a determined time by adjusting the knob while the heart was beating. In conclusion, the results indicated that the model was able to precisely predict the surgeons' skill with an accuracy of 95%. In future work, we aim to work on the method to transfer catheterization skills from experts to novices based on the explained method.

Table 3.1: Performance comparison of multiple modeling methods with different configurations.

No.	LSTM	Hidden Dense	Time steps	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
1	[32]	[16, 8]	200	91.0	91.0	91.0	91.0
2	[32]	[16, 8]	300	95.0	95.0	95.0	95.0
3	[32]	[32, 16, 8]	20	**73.0**	**72.0**	**72.0**	**72.0**
4	[32]	[32, 16, 8]	100	89.0	89.0	89.0	89.0
5	[32]	[32, 16, 8]	200	92.0	92.0	92.0	92.0
6	[32]	[32, 16, 8]	300	94.0	93.0	93.0	94.0
7	[128]	[32, 16]	300	**95.0**	**95.0**	**95.0**	**95.0**

Chapter 4

Kinematics Skill Modeling of Cardiac Catheterization via Deep Learning Method

According to advances in robotic surgery, the importance of data-driven techniques that incorporate deep learning methods is expanding quickly, with a focus on objective surgical skill evaluation. Unlike traditional evaluation where surgeons' skills are evaluated in the real surgery room, capturing users' motion kinematics can be used as input for an AI model to assess their skills. For this study, a simulated mechanical setup has been provided for the trainees, focusing on cardiac catheterization procedures. This setup allows users to engage in hands-on practice while simultaneously capturing their hand movements for further evaluation. Trainees have the opportunity to engage in extensive practice on a mechanical setup as a pre-operation procedure, enabling them to develop a deeper familiarity and understanding. The task is to pass the tip of a commercial catheter through curves and level intersections on a plastic transparent blood vessel phantom. The objective is to guide the catheter's tip from the vessel entry point to the designated ablation target. By conducting various experiments involving both novices and experts, a deep recurrent neural network was employed to extract a skill model by solving a binary classification task. The trained model demonstrated a remarkable 92.3 % accuracy in effectively discerning between the maneuvers performed by novices and experts, indicating the successful implementation of the proposed methodology.

4.1 Introduction

Cardiovascular diseases (CVDs) are widely recognized as a leading cause of mortality worldwide, and minimally invasive surgery (MIS) serves as a viable approach for the treatment of various heart conditions. The steerable catheters and guidewires, known as Endovascular Devices (EDs), are long and flexible medical devices inserted into the patient's blood vessels through a tiny incision. They are often used to access challenging anatomy. They can be manipulated by a mechanism which may be driven by operators or actuators. Thus, they are not fully automated devices and are frequently steered manually (Cheng et al., 2013). For instance, in non-automated surgeries such as Atrial Fibrillation (AF) treatment, the surgeon inserts a long catheter into the vascular system and guides it inside the vein toward the heart to access the arrhythmic spots (Fekri et al., 2022; Fekri, Nourani, et al., 2021; Khodashenas et al., 2021; Roshanfar, Fekri, & Dargahi, 2023). The catheter's rotation and insertion are made manually (Couture & Szewczyk, 2018), and the catheter tip at the distal part (the last deflectable 10 cm of a catheter) is bent via the knob located on the handle by adjusting to the right or left (Ganji & Janabi-Sharifi, 2007).

In catheterization, as a part of MIS, the guide-wire and catheter are steered by the surgeon under the exposure of live X-ray imaging such as fluoroscopy or angiography to improve the access of the aim points in the different organs (Sinaga et al., 2015). The surgeon's lack of experience results in longer hours of operation and surgeons, surgical staff and patients are exposed to serious health risks due to the significant dosage of radiation (Capranzano et al., 2016; Chieffo et al., 2010; Klein et al., 2009, 2015). Furthermore, the lack of expertise would limit a surgeon's geometric perception of the interaction between catheter and blood vessel (Dugas & Schussler, 2016; Rafii-Tari et al., 2017; Rafii-Tari, Payne, & Yang, 2014; Rafii-Tari et al., 2016; Song et al., 2018). For instance, non-expert physicians might apply excessive force on the vascular wall or make wrong insertions in a non-desired direction and cause embolization, perforation, thrombosis and dissection (Guo et al., 2016; Hausegger, Schedlbauer, Deutschmann, & Tiesenhausen, 2001). Therefore, surgeons are required to obtain a high level of hands-on proficiency before any real operation.

In the traditional training process, novice surgeons typically participate in surgical tasks within the real operation room (OR). However, this approach can present challenges and potential risks to patients during surgeries (Arora et al., 2010). Novices often struggle to access ORs for training purposes. Recognizing this limitation and considering the objectives of minimizing radiation exposure from X-rays during the catheterization process, as well as enhancing the surgeon's proficiency in manipulating the catheter handle, there is a critical need to establish a simulated training environment for ablation treatment outside of the OR. The proposed setup aims to replicate the OR experience, enabling novice surgeons to practice the task in a simulated condition. To ensure effective training, a supervisor is required as a substitute for an expert surgeon, overseeing the novices' gestures and maneuvers and providing feedback. This supervision allows novices to correct their maneuvers and improve their surgical skills during the training process.

Surgical skills training could be implemented in various methods. For example, Wang and Wu (Wang & Wu, 2021) integrated the catheter ablation process with virtual reality-based interventional simulation for training surgical skills through the framework of the position-based dynamic or Ikeda et al. (Ikeda et al., 2006) and Thakur et al. (Thakur, Holdsworth, & Drangova, 2009) examined surgical skills by analyzing stresses with sensors and photoelastic images to study catheter motions. Rafii Tari et all. (Rafii-Tari et al., 2017) developed an objective quantitative measurement of surgery skills by analyzing the catheter tip-heart tissue interaction and later (Chi et al., 2017), they transferred skills from experienced trainees to lower-experienced ones through tactile feedback by using online metrics from learned motion patterns to correct operators' catheterization. Fekri et al. built a mechanical drilling platform based on a virtual environment to simulate the drilling task. Their recurrent neural network-based model was trained on the user's gestural maneuvers to categorize the drilling skills into the expert and novice (Fekri, Dargahi, & Zadeh, 2021). In the previous study, a mechanical setup was built to simulate the process of ablation, which involved a synthetic heartbeat mechanism and the ability to measure contact forces between a catheter's tip and heart tissue. The goal was to evaluate the surgeon's skill based on applying the force within a safe range. A deep recurrent neural network based on long short-term memory (LSTM) architecture was used to extract the model of skills. The skill assessment was made on the force control only and steering maneuvers were not considered.

The main objective of this study is to design and build a training catheterization setup considering steering maneuvers for the ablation treatment. The framework will provide a realistic navigation practice outside the OR, which could record gestures and nonlinear user maneuvers. Trainees can practice the insertion and steering of the catheter inside the blood vessel to reach the target abnormal tissue. Therefore, the catheter handle is equipped with sensors for measuring the kinematics information while users navigate the catheter inside a defined blood vessel phantom. So, the trainee's skills are intended to be assessed by completing the defined surgical task by working with the designed setup. The trainee is required to insert the catheter inside the vein and pass the catheter tip through several curves to reach the target points only by rotating the catheter around its axis or by bending the distal part by adjusting the knob at the handle. The hand gesture data of both expert and novice surgeons represents dynamic and sequential data over time. The deep recurrent neural networks based on vanilla recurrent neural networks (RNN) or long short-term memory (LSTM) methods are built to extract the temporal dependencies from the time series data. The model is trained to distinguish between experts' and novices' skills (inspired by the LSTM-based deep learning model developed by Fekri et al. Fekri, Dargahi, and Zadeh (2021); Fekri et al. (2018) for training skill modelling problem.) Simple RNN-based models were incorporated alongside LSTM models to benchmark their performance, with a focus on achieving lightweight and real-time functionality. While LSTM represents a more advanced approach compared to vanilla RNN, the primary objective remains the identification of the simplest and most suitable solution that aligns with the specific requirements at hand. The method can recognize the surgeon's skill level and evaluate each surgeon's manoeuvres in real-time. As a result, surgery time and human errors would decrease in actual operation. Novice surgeons also benefit from the model and setup to track their progress over time and practise to improve their skills based on the expert model through trial and error. The proposed method can be extended to various catheterization surgeries.

4.2 Ablations Skills Classification

As an update on our previous work, which aimed to design a training cardiac catheterization setup for a simplified ablation task of practicing the procedure of applying pressure on abnormal spots using a regular catheter, the primary objective of this study is to build a mechanical framework that allows for the practice of catheterization tasks outside of the operating room. Surgeons can practise navigating the catheter inside the phantom blood vessel, a transparent plastic simulated blood vein for training, via inserting and rotating the handle and twisting the knob on the catheter handle. Using the provided setup, the surgeon is tasked with maneuvering the catheter tip through various curves and level intersections, while simultaneously monitoring the catheter tip from outside the transparent phantom. Insufficient skill may lead to a longer operation time or failure in the surgery. The surgeon will be able to assess their abilities from provided real-time feedback to improve their maneuvers. In order to assess the performances of the participants, it is crucial to derive the maneuver models for both experienced and inexperienced surgeons. The input to the model consists of the catheter knob and the surgeon's hand positions while performing the task. Since the skill can be assessed over time, the dataset is considered as time series, obtained from the experiments accomplished by expert and novice participants. The skill level of surgeons during the intended ablation task is evaluated using a deep recurrent neural network based on the vanilla RNN or LSTM methods to extract temporal dependencies from the data samples. The models are utilized to address a binary classification problem, which involves differentiating between the skills of experts and novices. This can assist trainees in monitoring their progress as they compare it to a reference model of skills acquired from experts and novices. The experimental design, surgical procedure, and data collection are covered in the following sections.

4.2.1 Experimental Setup

The designed setup enables a surgeon to practice insertion and navigation of the catheter through a blood vessel during AF surgery outside of an actual operating room. At the same time, the setup can record the hand gestures and knob position. The overall view of the experiment is shown in

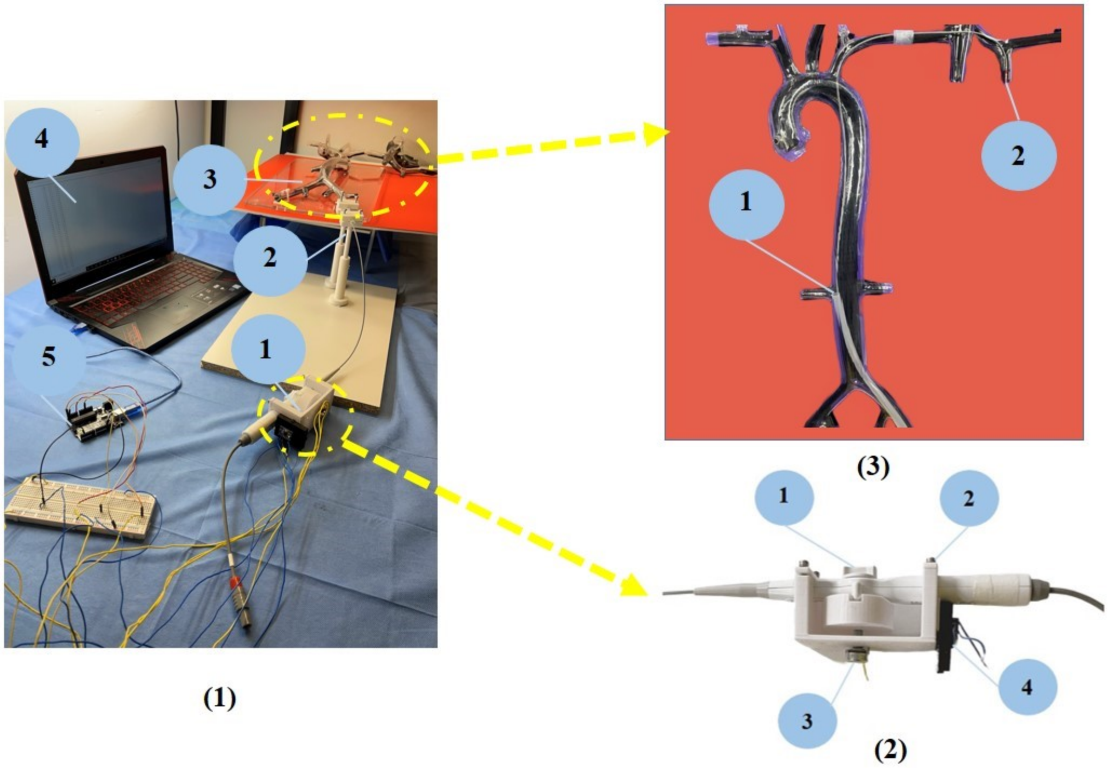

Figure 4.1: (1)The overall view of the experimental setup includes 1. a catheter and catheter handle equipped with IMU and potentiometer modules,2. printed holders and a plastic sheath, 3. a transparent plastic phantom 4. a computer and 5. a microcontroller. (2)The steering handle includes 1. a catheter, 2. a 3D printed holder, 3. an IMU device, and 4. a potentiometer. (3) the overall view of the arc phantom and the defined task path for the user practice. Point 1. shows the beginning and point 2. represents the target point.

Figure4.1 (1).

This setup is an updated version of our previous work, which enabled trainees to hold a catheter and maintain forces below a pre-defined threshold by controlling the deflection of the distal shaft using the knob during ablation treatment. It consisted of a commercial catheter, holders, a steering handle and a transparent plastic phantom. For the experiments, a bi-directional catheter, Blazer II XP from Boston Scientific, USA, with a tip diameter of 8Fr (2.67mm) and a length of 110 cm was utilized. Participants inserted the catheter through the plastic sheath, which was fixed by holders at the entry of the phantom. The printed handle was equipped with an IMU device (SENS-25 6 DOF

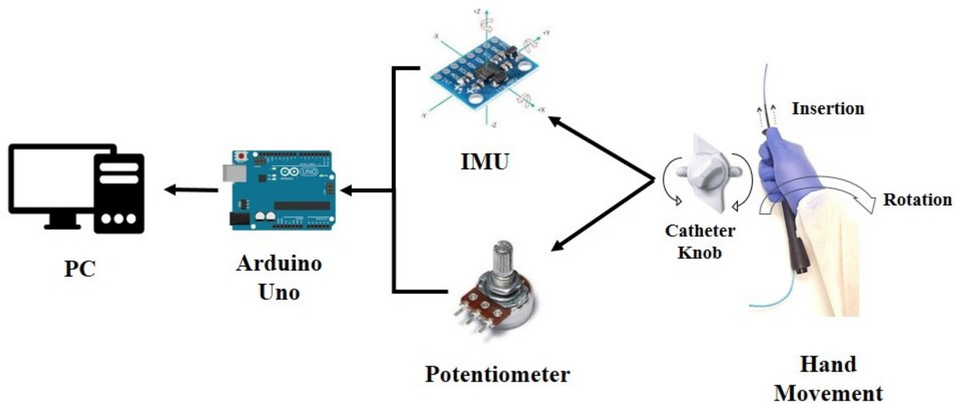

Figure 4.2: Summary of the setup interface between the computer and the driver.

MPU-6050 3-axis Gyro with 3-axis Accelerometer) to record the hand's maneuver and a potentiometer module (P500 500 Ohms 1/2 Watt Linear Taper Potentiometer) to measure knob's angle. The user's maneuvering and knob adjustment information was recorded at the exact same time using a microcontroller (Arduino Uno) connected to the computer. Figure4.1 (2). illustrates the steering handle and the position of the electronic modules. The microcontroller was programmed using code developed in the Arduino application to simultaneously read data from IMU and the potentiometer Figure4.2. Data capture was performed at the sampling rate of 64.5 Hz and the time duration ranged from 30 to 50 seconds, resulting in a total of 35,535 data.

The catheter was inserted into the phantom blood vessel manually through a plastic guide tube. The desired curved path started from point (1) and ended at the target point (2) shown in Figure4.1 (3). The extension path was added to the aortic arch phantom with the purpose of making the route more challenging for the trainees. Participants needed to pass the catheter's tip through sequential curves by adjusting the knob angles or rotating the catheter's handle. Due to the level difference at the intersection between the main vessel and the subsidiary one, the participants need to bend the handle to pass the catheter tip as well. In other words, roll, pitch and yaw angles were changing continuously during the insertion, representing the surgeon's hand maneuver along with the knob angle information. The indicated path is shown in Figure4.1 (3).

4.2.2 Surgical Task and Data Capturing

A group of seven experts and seven novices were invited to participate in the experiment, and the dataset was compiled based on their attempts. They were asked to insert the catheter into the guide tube and pass the catheter's tip through curves and intersections by adjusting the knob or rotating the designed handle. The duration of the experiment varied for each participant depending on their skills, but in general, it was shorter for the experts. There was not a chance to invite experts and novices for conducting the experiment. To this end, we provide the experts to practice as many times as needed to achieve mastery before the final recording. On the other hand, the novice group received a brief introduction and had a few practice sessions.

Figure4.3 visualizes each feature in the dataset separately. The dataset consisted of a combination of the 14 experiments, with each experiment labelled as either expert (1) or novice (0). The participants' kinematic information while adjusting the knob angle or rotating the handle is clearly depicted in the diagrams of Figure4.3.

4.3 Methodology

The objective of this study is to develop a model that can determine the skill level of surgeons using datasets containing completed tasks. The model's task is to classify the dataset records as either novice or expert. The input features of the designated model includes the catheter's knob angle position and the surgeon's hand maneuvering information during the surgical task aimed at reaching the target point. It is important to consider that distinguishing the surgeon's level of expertise is a time-dependent process and cannot be determined based on individual data records. Due to the recurrent nature of RNN, which considers the impact of time by employing the output of the network at time t - 1 in the input at time t. The RNN-based model trained on the time series dataset effectively addresses the aforementioned temporal issue.To capture the temporal dependencies in the data samples, vanilla RNN and LSTM-based models are proposed. Vanilla RNN architectures, known for their simpler mathematical complexity compared to LSTM networks, are often chosen as an alternative solution alongside LSTM architectures.

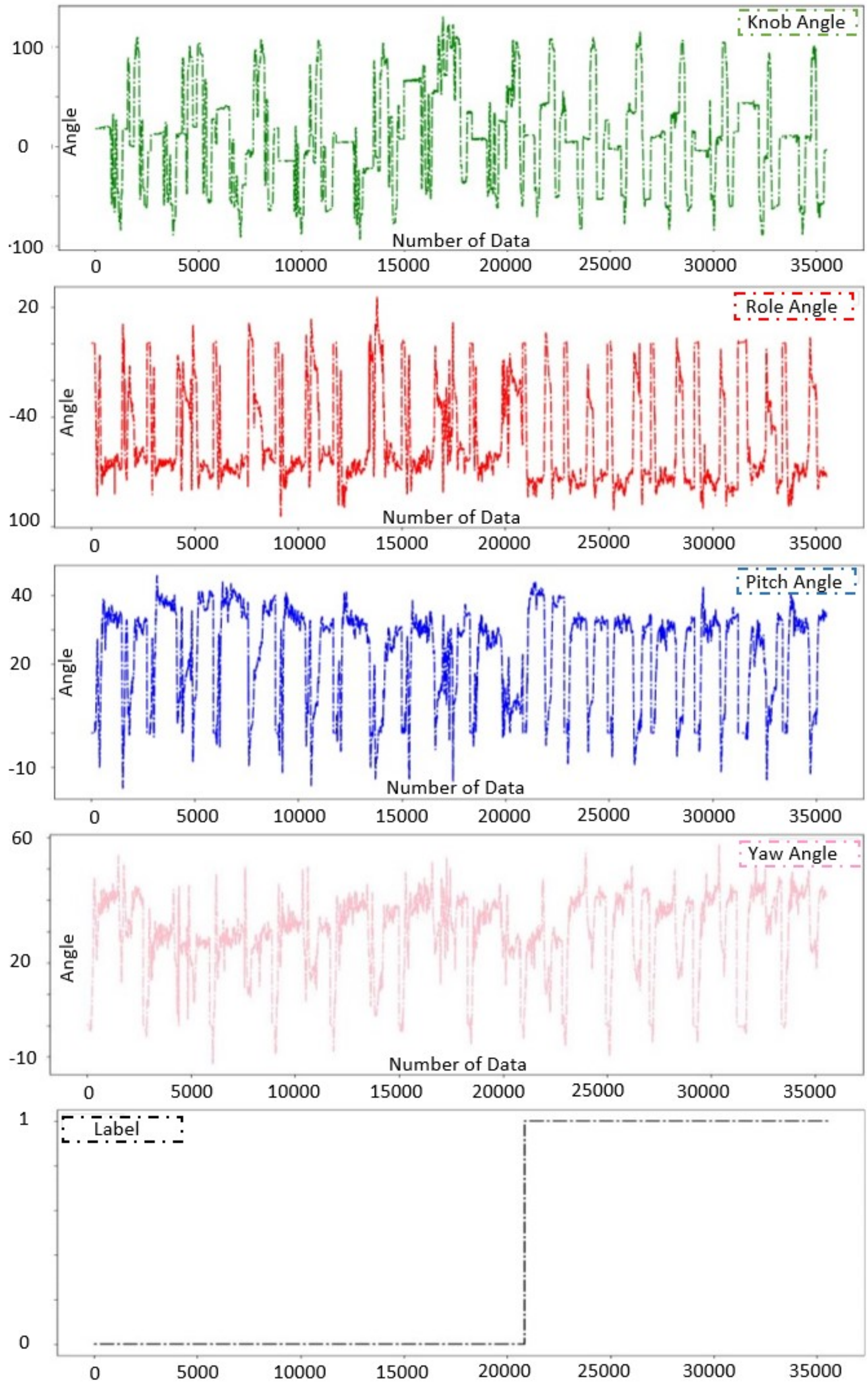

Figure 4.3: The dataset for the group of seven experts and seven novices read from the IMU and the potentiometer modules, including knob, roll, pitch and yaw angles. Data are concatenated and labelled by an expert(1) and novice(0).

Unlike Vanilla RNN, LSTM effectively handles long-term dependencies by incorporating a memory cell and gating mechanisms. These gates regulate information flow, enabling LSTM to retain or forget information over multiple time steps. Additionally, LSTM can handle sequences with varying time gaps, adapt to irregular intervals, and mitigate gradient explosion. However, Vanilla RNN is simpler and computationally less expensive compared to LSTM. In cases where the sequence modelling task doesn't involve long-term dependencies or complex patterns, Vanilla RNN is sufficient and more efficient. Implementing both LSTM and Vanilla RNN provides the flexibility to choose the appropriate model based on the specific requirements of the task. It allows for experimentation and comparing the performance of different architectures to determine the best fit for the problem at hand.

4.3.1 RNN

In the Vanilla RNN method, the inclusion of a feedback loop connecting the previous hidden state (h^{t-1}) of the network to the current input allows for the consideration of time-dependent information (Stérin, Farrugia, & Gripon, 2017). The given feature vector $x \in R^{n \times 1}$ as the input of the network is defined as follows:

$$h^t = tanh(Wh^{t-1} + Ux^t + b) \tag{11}$$

In the above equation, the b is the bias and W and U are the weight matrices. The activation function of $tanh$ is defined below:

$$tanh(h) = \frac{e^h - e^{-h}}{e^h + e^{-h}} \tag{12}$$

The output can be defined as below when the hidden state is h^t:

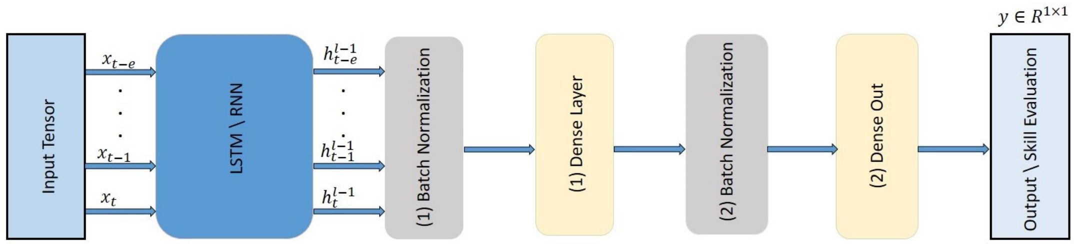

Figure 4.4: The architecture comparison between the proposed LSTM and the Vanilla RNN methods. Based on input tensors acquired from defined tasks, surgeons are classified as novices or experts in skill evaluations.

$$o^t(h^t) = Vh^t + b_o \tag{13}$$

The matrix v indicates the weights and b_o denotes the bias of the layer. As the problem in this study is a binary classification, a softmax function is used to calculate the probability of each class and is defined by the following equation:

$$y^t(o_i^t) = \frac{e^{o_i^t}}{\sum_j^c e^{o_j^t}} \tag{14}$$

4.3.2 LSTM

As it was explained in Chapter 3, the LSTM architectures had a high performance in surgical skill modelling based on time series features captured during the surgical operation such as CF and were used to categorize the level of expertise in Chapter 3. In this study, the series of data s with length d where each $s \in R^{4\times1}$ are fed to the LSTM-based model. The formulations of LSTM neurons are as same as Chapter 3 and skipped here for preventing repetition. To summarize, both Vanilla RNN and LSTM architectures are displayed in Figure4.4.

4.4 Result and Discussion

The data preparation, training and validating process of the deep learning-based models will be discussed in the following section. It is worth mentioning that the performance of different models with different configurations and designs is evaluated and compared through eclectic metrics. In the first step, the dataset preparation procedure will be explained in detail as well as all necessary information about the networks. Later, the results will be presented and compared with each other.

4.4.1 Model Design and Data-set Preparation

A dataset of 35,535 records was collected from 14 separate experiments, as explained in the previous section. The number of experiments performed by experts and novices was equal, and the duration of each experiment and the number of records varied due to the users' expertise in completing the defined task. The present study records four features, namely, the catheter knob angle and the information regarding the surgeon's maneuver in space, including pitch, yaw, and roll angles. These features are saved in each record. To enable the extraction of temporal dependencies and facilitate the use of the dataset in deep learning models, the dataset was transformed into sequences of data. The order of data was preserved in the main dataset. The time steps were chosen as t = 10, 50, and 100. Three datasets were built based on the main dataset. Each individual record of t = 100 consists of a time series sequence of 100 records, including four features: knob angle and surgeon's maneuver information. Each of the three datasets was shuffled and 70% of it was allocated to the training set, 15% to the validation and 15% to the test set. To establish a benchmark and examine the impact of the time steps and the network computational complexity for different designs, different Vanilla RNN and LSTM-based classifiers were implemented to discern the skill levels in the datasets with different time steps. Thus, the network configuration was adjusted depending on the number of dense and hidden layers and the hidden state/neurons.

4.4.2 Results

Several configurations based on the Vanilla RNN and LSTM architectures were constructed as benchmarks for addressing the binary classification problem of assessing ablation skills. Each model was trained on the training set, which consisted of 64 samples for each batch of data. Using a learning rate of 9e-5, the models were trained across 60 epochs. The models' performance on the validation set was evaluated at each epoch to implement early stopping and prevent overfitting. The models' performance was assessed on the test dataset as unseen data using the following metrics: precision, recall, F1-score, and accuracy. Table 1 presents the generated graphs and their corresponding results.

The LSTM 1 configuration consists of an LSTM block with 16 hidden state/memory sizes, followed by one dense layer with 8 neurons. The network is fed with a training dataset with 10 samples per sequence and can classify the skill level at 88.5 % accuracy. LSTM 4 and LSTM 7 have the same design with 50 and 100 time steps, respectively. It shows that increasing the length of sequences does not result in a better performance for this design. In other designs such as LSTM 2, 5 and 8 or LSTM 3, 6 and 9 the accuracy is improved by longer time windows for 1 and 2 %, respectively. This suggests that a longer sequence of surgical tasks helps the LSTM model to capture the time dependency and distinguish between novice and expert skills.

The impact of adding hidden dense layers with 16 and 32 neurons as well as the length of the sequences, on the performance of the LSTM models, was studied. In comparison with the LSTM 1 setup, the LSTM 3 has a more complex graph and was trained with 10 time steps on the data. It is evident from LSTM 3 that an increase in the complexity of the model by adding the memory size and hidden layers' parameters has increased the performance by 2 %. The LSTM model achieved 92.1 % accuracy with a time sequence of 100 and hidden dense layers of 32, 16 and 8 neurons.

Regarding the RNN models, increasing time steps from 10 to 50 and 100 did not have any tangible improvement for each specific design with similar hidden layers. This is evident when comparing the accuracy of similar configurations, such as RNN 1, 4 and 7 RNN 4 or RNN 2, 5 and 8 or RNN 3, 6 and 9. However, like the LSTM models, adding hidden layers makes the models more accurate. Among models RNN 1, 2 and 3, the third model, which is more complex, achieves an accuracy that

is 5 % higher than the first model. Model RNN 9 has the highest accuracy with 92.3 %.
In summary, increasing the time steps primarily improves the accuracy of LSTM-based models with similar configurations, while its impact on the accuracy of RNN models is limited. However, for both models, complexity has a direct relation with accuracy. It was demonstrated that RNN is capable of performing well for the defined tasks with a simpler and more straightforward architecture, in more complex scenarios, LSTM outperforms RNN due to its cell state. In practice, the model predictions of the classes were mostly true, with a considerable proportion of correctly classified samples in each class. Utilizing batch normalization layers and stacked dense layers, as well as a larger time window, results in improved performance.
The models were built in Python with the Tensorflow 2.0 framework on an Ubuntu 20.04 computer with 24GB RAM and an NVIDIA GeForce 2080 GPU.

4.5 Conclusion

In this study, the surgeons' steering skills throughout the time of inserting and passing a catheter tip inside a blood phantom to reach the goal point were modelled by Vanilla RNN and LSTM-based methods. These methods were used to evaluate the kinematic skill of the participants. The proposed network categorized surgeons' skills based on the steering and knob position information over time of a defined task. Trainees practiced the insertion and steering sections of the catheterization procedure via the provided setup outside the OR. Meanwhile, maneuvering information was recorded. The trained model built on the expert dataset can be utilized in the real surgery room to evaluate surgeons' skills and correct maneuvering in real-time. In conclusion, the results showed the capability of the model to precisely predict the surgeons' skills with an accuracy of 92.3 %. In future work, we aim to work on adding a vision feature besides kinematic ones to assess catheterization skills based on the explained method and transfer the surgical skill from expert to novice surgeon as well.

Table 4.1: (1) Performance comparison of multiple RNN and LSTM-based deep learning methods with particular configurations.

No.	LSTM/RNN	Hidden Dense	Time steps	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
LSTM 1	[16]	[8]	10	88.0	89.0	88.0	88.5
LSTM 2	[32]	[16, 8]	10	88.0	89.0	88.0	88.1
LSTM 3	[64, 32]	[32, 16, 8]	10	90.0	91.0	90.0	90.5
LSTM 4	[16]	[8]	50	87.0	88.0	87.0	87.2
LSTM 5	[32]	[16, 8]	50	89.0	90.0	89.0	89.1
LSTM 6	[64, 32]	[32, 16, 8]	50	91.0	92.0	92.0	91.8
LSTM 7	[16]	[8]	100	87.0	88.0	87.0	87.3
LSTM 8	[32]	[16, 8]	100	89.0	90.0	89.0	89.1
LSTM 9	[64, 32]	[32, 16, 8]	100	**93.0**	**94.0**	**93.0**	**92.1**

Table 4.2: (2) Performance comparison of multiple RNN and LSTM-based deep learning methods with particular configurations.

No.	LSTM/RNN	Hidden Dense	Time steps	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
RNN 1	[16]	[8]	10	87.0	88.0	87.0	86.9
RNN 2	[32]	[16, 8]	10	89.0	90.0	89.0	89.4
RNN 3	[64, 32]	[32, 16, 8]	10	91.0	93.0	92.0	91.7
RNN 4	[16]	[8]	50	86.0	87.0	87.0	86.7
RNN 5	[32]	[16, 8]	50	89.0	90.0	89.0	89.2
RNN 6	[64, 32]	[32, 16, 8]	50	91.0	92.0	92.0	91.7
RNN 7	[16]	[8]	100	87.0	88.0	88.0	87.9
RNN 8	[32]	[16, 8]	100	89.0	90.0	90.0	89.8
RNN 9	[64, 32]	[32, 16, 8]	100	**92.0**	**93.0**	**92.0**	**92.3**

Chapter 5

Conclusion and Future Works

5.1 Conclusions

Catheter ablation is the preferred curative therapy for atrial fibrillation heart condition and the surgical outcomes are highly dependent on the physician's skills. Novice surgeons usually gain appropriate surgical experience while doing operations on actual patients under the supervision of experts in the OR. The unskilled behaviour could cause longer operations and poorer surgical results as a consequence. Therefore, experimental setup outsides the OR for their practice and the evaluation of dexterity can have a significant impact on the real surgical quality and the operation duration time. Surgeons' maneuvering information can be categorized into kinematic and kinesthetic approaches. The Kinematics information represents the surgeon's hand or the tool's movements like the surgeon's maneuvering information. On the other hand, the kinesthetic approach describes the interaction between the surgeon and the tools as the CF applied by the catheter tip on the heart tissue. So, the experimental frameworks simulating the cardiac ablation surgery outside the OR and being able to collect the kinematic and kinesthetic data for skill evaluation are required.

In the first setup, chapter3, the ablating task was simulated while the mechanical heart was beating. The users were instructed to maintain the Z-direction force in a desired force range at a specific time by adjusting the angle of the knob on the catheter handle while monitoring the force value on the screen. In the second framework, chapter4, inserting and advancing the catheter's tip inside blood vessels were simulated and replicated. The trainers were asked to pass the catheter's tip through several curves and level intersections only by inserting and rotating the catheter and adjusting the knob angles positioned on top of the designed handle to tend the distal shaft of the catheter. The starting point was at the phantom entry and the endpoint was a target ablating point. Moreover, the completion time varied among users due to their pace and expertise. The experimental setups outside the OR help novice surgeons to practice as often as necessary to develop their skills.

To evaluate the surgeon's skill level, a binary classification problem (Novice/Expert) was developed on the time series maneuvering information captured by the sensors installed within the setups. Furthermore, the solution was assumed to be deep learning models based on the RNN or LSTM architectures to build the model to extract surgeons' skills. The results from the first study in chapter3, and the second study in chapter4 showed the capability of the model built on kinesthetic (CF) and kinematic (movement) information to precisely predict the surgeons' skills with an accuracy of 95 and 92.1 %, respectively. The developed skill classifying model or similar designs can assess users' behaviour in real-time. This work will assist novice surgeons in tracking their skill development over time and improving their expertise through trial and error based on the expert demonstration model.

5.2 Future Works

In future studies, the constraints of this research might be addressed in order to enhance the proposed systems. To address potential improvements in future research:

- The input feature of the deep learning method explained in chapter3, was the desired force applied in the Z-direction by the catheter tip. To make the model more complex, additional features can be controlled during the task. For example, design a framework where users be able to control three forces independently through insertion or rotation.
- In chapter4, the deep learning models were built on the data captured by sensors. To make the model more advanced, the vision-based methodology can be added to the model where a hybrid model combining CNN and RNN can be beneficial.
- The accurate models generated from the kinesthetic and kinematic models can be used to

transfer skills and correct the surgeon's hand movements using haptic devices during the operation to improve surgical outcomes and reduce potential injuries. In the long-term perspective, the approach could be a window to replace the surgeon with a fully automated robot to minimize novice mistakes in the OR.

- In chapter3 and chapter4, the kinesthetic and kinematic behaviours were collected separately in two different mechanical setups. Building a unit setup including both insertion and ablation steps and being able to record both types of behaviour information simultaneously would contribute to a comprehensive study of ablation surgery.

- The mechanical frameworks and AI approaches discussed in both chapters3 and 4 are not merely limited to cardiac ablation surgery and can be generalized to various other types of surgeries that require surgical skills, such as urinary catheterization, balloon angioplasty (with or without stenting), and more.

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