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TÍTULO: Using Deep Learning for Arrhythmia Detection from Electrocardiographic Signals

Trabajo de integración curricular presentado como requisito para la obtención del título de Ingeniero Biomédico

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Dedication

"This work is dedicated to my parents, Luis Cepeda and Soraya Muñoz, my brothers Adrian and Henry, and Francis Tatiana, my emotional supporter.
They are the foundation and driving force of my life. They are the pillar and fundamental engine in my life. They always encouraged me to follow my dreams and continue with my studies."

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Eduardo Luis Cepeda Muñoz

Resumen

Desde principios de la década actual, las enfermedades cardiovasculares (ECV) se han convertido en la principal causa de morbilidad humana a escala mundial. Debido a la gran cantidad de datos de ECG, se cree que el análisis manual requiere mucho tiempo, es caro y es susceptible de errores humanos. Como alternativa, los sistemas informáticos basados en el procesamiento de señales biomédicas y en enfoques de inteligencia artificial son útiles para apoyar los procedimientos de diagnóstico de arritmias y resolver varios de estos problemas. Estos sistemas suelen constar de cinco etapas: adquisición, procesamiento, segmentación, caracterización y clasificación. Sin embargo, siguen sin resolverse varias dificultades básicas, como la sensibilidad de la señal, la precisión, el coste de computación, la generalizabilidad y la interpretabilidad. En este sentido, la presente tesis presenta un estudio de categorización de señales de ECG utilizando dos redes neuronales artificiales híbridas entrenadas mediante aprendizaje profundo. Las redes neuronales se construyeron utilizando una canalización de aprendizaje profundo que busca un compromiso entre la resiliencia, la variabilidad y la precisión de la señal. El método sugerido logra una precisión general de hasta el 99 por ciento para cada registro, manteniendo un bajo coste computacional. En esta investigación de tesis de grado, exploramos el procesamiento de señales digitales y los enfoques de aprendizaje profundo para describir y categorizar los datos de ECG para la arritmia. Nuestro enfoque es encontrar un conjunto adecuado de algoritmos de procesamiento para mejorar el rendimiento, la precisión de la estimación y la comprensión de este fenómeno fisiológico.

Palabras Clave: Aprendizaje Profundo, Electrocardiograma, Redes Neuronales Híbridas, Redes Neuronales Convolucionales, Redes Neuronales Recurrentes.

Abstract

Since the beginning of the current decade, cardiovascular disease (CVD) has become the main cause of human morbidity on a global scale. Due to the vast quantity of ECG data, manual analysis is believed to be time-consuming, expensive, and susceptible to human mistake. Alternatively, computer systems based on biomedical signal processing and artificial intelligence approaches is useful for supporting arrhythmia diagnosis procedures while resolving a number of these issues. These systems typically consist of five stages: acquisition, processing, segmentation, characterisation, and classification. However, several basic difficulties, such as signal sensitivity, accuracy, computing cost, generalizability, and interpretability, remain unsolved. In this respect, the current thesis presents an study of ECG signal categorization utilizing two hybrid artificial neural networks trained using deep learning. The neural networks were constructed using a deep learning pipeline that seeks to strike a compromise between resilience, variability, and signal precision. The suggested method achieves an overall accuracy of up to 99 percent for each record while keeping a low computational cost. In this degree's thesis research, we explore digital signal processing and deep learning approaches to describe and categorize ECG data for arrhythmia. Our approach is to find an appropriate set of processing algorithms to improve the performance, estimate precision, and understanding of this physiological phenomena.

Keywords: Deep Learning, Electrocardiogram, Hybrid Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

The electrocardiogram (ECG) is a graphical depiction of the electrical activity of the heart as a function of time, thus it records the heart's motions visually. Using a continuous electrocardiograph, it signal is acquired from the chest surface of the body. The electrocardiograph is a crucial medical instrument because it monitors and shows the electrical activity of the heart in order to diagnose cardiac abnormalities. This device, when paired with specialized algorithms, can analyze a vast quantity of biometric data, delivering a plethora of information on the heart. Due to the fact that a person with heart illness may have a normal ECG, this test is unable to determine if the individual will have a heart problem. Consequently, ambulatory electrocardiograms are utilized, and significant changes over time, such as many hours or days, are identified [1].

ECG is widely used as a noninvasive screening tool as part of the data gathering process for people with particular symptoms of interest. The conventional 12-lead tracing, which is conducted while the patient is at rest and applied for a brief length of time, is the most exhaustive external electrocardiographic examination. Although computerized techniques allow for more accurate measurements of ECG signals to be collected in order to improve diagnostic accuracy, these ECG recordings or signals are still analyzed by a professional who makes a determination about the patient's cardiac health based on knowledge and experience [2]. Holter recordings are those taken during an outpatient examination, named after Norman Jefferis Holter, the inventor of the first portable ECG recorder.

1.1 Motivation and problem statement

In the recent decade, the incidence of cardiovascular disease (CVD) has grown dramatically, becoming the main cause of human morbidity globally [3]. It is expected to account for 30 percent of global fatalities [4]. Cardiac arrhythmia is a specific cardiovascular disease characterized by an abnormal heartbeat. Although the majority of arrhythmias are minor, some may be deadly [5]. For instance, atrial fibrillation may result in stroke and cardiac arrest [6], which is very serious and requires rapid treatment. In addition, the cost of cardiovascular disease treatments, including medications, is relatively high [7].

Electrocardiogram (ECG) is the most common measuring method for diagnosing cardiovascular disease (CVD) and the primary tool for diagnosing CVD both inside and outside hospitals. A series of periodic heartbeats indicating the electrical activity of the heart over time constitutes an ECG signal [8]. Currently, manual examination of ECG data by physical therapists is time-consuming, expensive, and prone to human error [9] because to the vast quantity of ECG data. Moreover, ECG signals are often composed of several frequency components and even noise, making it difficult to manually extract discriminative characteristics; hence, it is advised to use an artificial intelligence-based approach.

Wavelet transforms (WT) or short-time Fourier transforms are used for this purpose; in general, WT yields more precise time-frequency analysis findings than the Fourier transform. Therefore, computer systems incorporating biomedical signal processing and machine learning methods are well-suited for this work in support of arrhythmia diagnosis procedures [10]. These systems support machine learning in five stages: acquisition, preprocessing, beat segmentation, characterisation, and classification. There are various approaches for classifying ECG signal beats for various reasons, including artificial neural networks, support vector machines, multi-view based learning, and linear discriminants, are employed for this [11]. Despite the increased performance of these methods, key issues such as signal sensitivity, precision, computing cost, generalizability, and interpretability remain unsolved. With the rapid advancement of artificial neural networks in recent years, techniques based on deep learning have gained popularity.

In this context, this thesis offers an application using deep learning techniques for ECG signal processing. For this purpose, a hybrid neural network (HNN) approach capable of recognizing and classifying beats related to cardiac arrhythmias in a framework that optimizes signal robustness, variability and accuracy is conceived and developed. An automated method for classifying ECG signals based on recurrent neural network (RNN) and convolutional neural network (CNN) techniques is developed. Neural networks is an artificial intelligence approach that successfully simulates the human visual system for image categorization and video recognition [12, 13, 14, 15]. The ECG beat signal is converted to the time-frequency domain using the continuous wavelet transform (CWT) [16, 17], and features are recovered from the 2D scalogram created by the previously decomposed time-frequency components using HNN. To take advantage of all available data for ECG signal categorization, we extract and integrate the RR interval features into our HNN. This is achieved using the MIT-BIH arrhythmia database [18]. The constructed approach is compared with the techniques proposed by the literature demonstrating that the use of deep learning techniques in ECG signal processing allows the ideal balance between robustness, signal variability and accuracy, compared to conventional artificial intelligence methods, the HNN used is a promising approach.

1.2 Objectives

1.2.1 General Objective

Develop a hybrid neural network that use deep learning to detect cardiac arrhythmias in long-term ambulatory electrocardiographic recordings to achieve an optimal balance between performance and computational cost in the diagnosis of cardiac arrhythmias.

1.2.2 Specific Objectives

- Considering the separability among ECG data, provide a collection of meaningful beat features that enable successful diagnosis in the study of cardiac arrhythmias.
- To identify cardiac arrhythmias in ambulatory ECG data, develop a deep learning system with the best detection accuracy and lowest computational cost.
- To demonstrate the use of deep learning concepts using artificial intelligence to analyze the behavior of biomedical signals.

1.3 Justification

Extracting relevant ECG features to detect cardiac arrhythmias is a difficult task because some common ECG features vary greatly depending on the morphology and genetics of each individual, making each individual unique in providing the necessary information and distinguishing cardiac arrhythmias from ECG signals [19]. However, some features determined from ECG data based on waveform and signal morphology are accurate in identifying cardiac arrhythmias [20]. ECG signal clustering is crucial in biomedical and biological signal processing disciplines in today's world [21]. Patients with cardiac abnormalities and physicians treating this disease benefit greatly from the information provided by studies on the subject, as the specialist physician can avoid the arduous task of reviewing the large number and morphology of heartbeats, which can lead to serious confusions, such as assuming that a sick patient is healthy[22].

This paper contributes to the scientific and academic community in the field of biological signal processing, particularly in the analysis of ECG signals. Existing computer algorithms for identifying arrhythmias may have problems with morphological variation, minority classes, and unbalanced classes [23]. Therefore, it is vital to undertake research using artificial intelligence methods like as deep learning in order to achieve the most accurate findings and apply them to the construction of a computer system to identify arrhythmias. This system is free and readily available, and it is also supported by the SDAS research group.

1.4 Contribution

Existing computational techniques for identifying arrhythmias may be susceptible to several issues, including the recognition of minority classes or the detection of one aberrant beat amid a large number of normal beats. This may lead to the misclassification of an ill patient as healthy, preventing the patient from obtaining the appropriate therapy for the illness. The method outlined in this thesis is segment clustering, which assists in the identification of minority classes and reduces processing costs via the use of deep learning. The proposed hybrid neural network technique yields the best results since the clustering strategy may get problematic due to the unbalanced minority groups in the data. In addition, feature selection is utilized to eliminate duplicate or unneeded characteristics that may hinder data grouping. This thesis provides a deep learning-based method for identifying cardiac arrhythmias utilizing MIT-BIH database superclasses. This thesis provides a substantial contribution to the development of novel biological signal research techniques employing artificial intelligence.

1.5 Manuscript organization

The structure of this research thesis is as follows. Chapter 2 examines the theoretical background, the presently available methodologies, the recommended classification strategy for ECG data, and the deep learning technique for this purpose. Chapter 3 describes the relevant research, whereas Chapter 4 describes the methods used. Chapter 5 describes the experimental setup, and Chapter 6 includes the results and discussion. This thesis concludes with Chapter 7, which includes future prospects.

Chapter 2

Theoretical Framework

The heart is a voltage conductor with a specific pattern. Consequently, the ECG and analysis of these bio-electrical events constitute a crucial source of information for diagnosing cardiac illnesses such as arrhythmia, which are responsible for a significant number of deaths worldwide each year [4]. Due to the problem that experts have in analyzing the information visually, automatic identification of arrhythmia is necessary. This necessitates a classification of beats that consists of detecting comparable patterns among them so that they may be grouped according to their similarities [21]. Given that beat labels are seldom available, it is advisable to undertake unsupervised beat clustering analysis [24]. Acquisition, preprocessing, segmentation, characterisation, classification, and presentation of results are all aspects of conventional clustering methods.

2.1 Cardiac Arrhythmia

Since cardiovascular disease is the leading cause of death worldwide, it is a vital area of research [3]. Arrhythmias occur when the electrical impulse is disturbed; the normal range for heart rate is between 60 and 100 beats per minute (BPM), and any variation from this range is referred to as an arrhythmia [25]. Due to a lack of continuing patient monitoring, cardiovascular diseases continue to be the leading cause of death worldwide [4]. Due to their increasing incidence and prevalence, cardiovascular diseases have garnered a great deal of global attention [3]. Unlike the 12-lead ECG, ambulatory electrocardiography permits long-term monitoring of a patient's heartbeat without interfering with daily activities.

In ambulatory electrocardiography, the Holter monitor is a device that continuously measures the heartbeat and is worn for a period of time, often 24 to 48 hours. It was named in honor of Norman Jefferis Holter [26, 27]. Electrodes are placed on the patient's chest and connected to the monitor, which is often worn around the neck or waist, as shown in Figure 2.1.

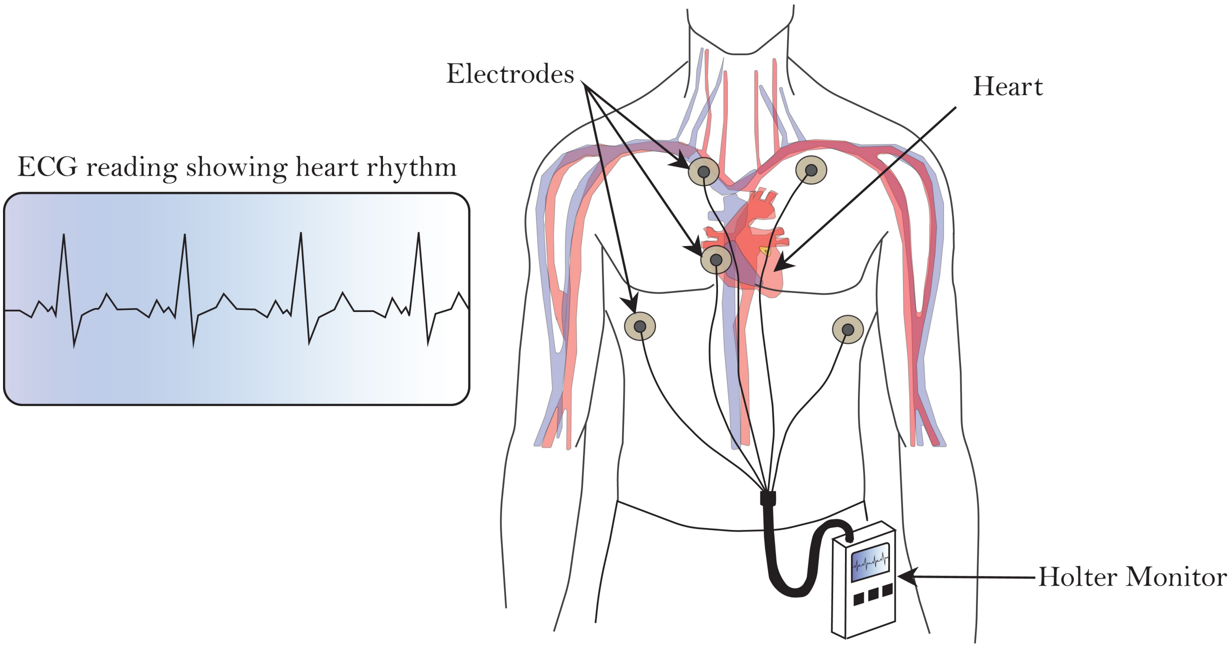

Figure 2.1: A visual illustration of how to operate the Holter monitor. The monitor helps capture the patient's heart activity. This study is the source.

The Holter monitor recordings should be reviewed by a cardiology specialist, who will diagnose the patient's cardiac condition based on the morphology and length of the heartbeats. Visual inspection is expensive due to the large number of beats generated by each Holter recording; thus, it is important to aggregate beats with similar characteristics to facilitate this procedure. As a consequence, computer systems that organize beats based on the extraction of certain beat characteristics have been developed [28].

2.2 Machine learning

In general, each machine learning process follows the same technique, which consists of preparing the data for use with a machine learning algorithm, then the algorithm provides results that can be understood. Because of the nature of the investigation and the data used (raw ECG signals), we can define it as a data mining process: Data mining technology is used to find patterns and trends in large data sets; data science is the investigation, construction and interpretation of the model that has been built, while machine learning is the production of that model [29].

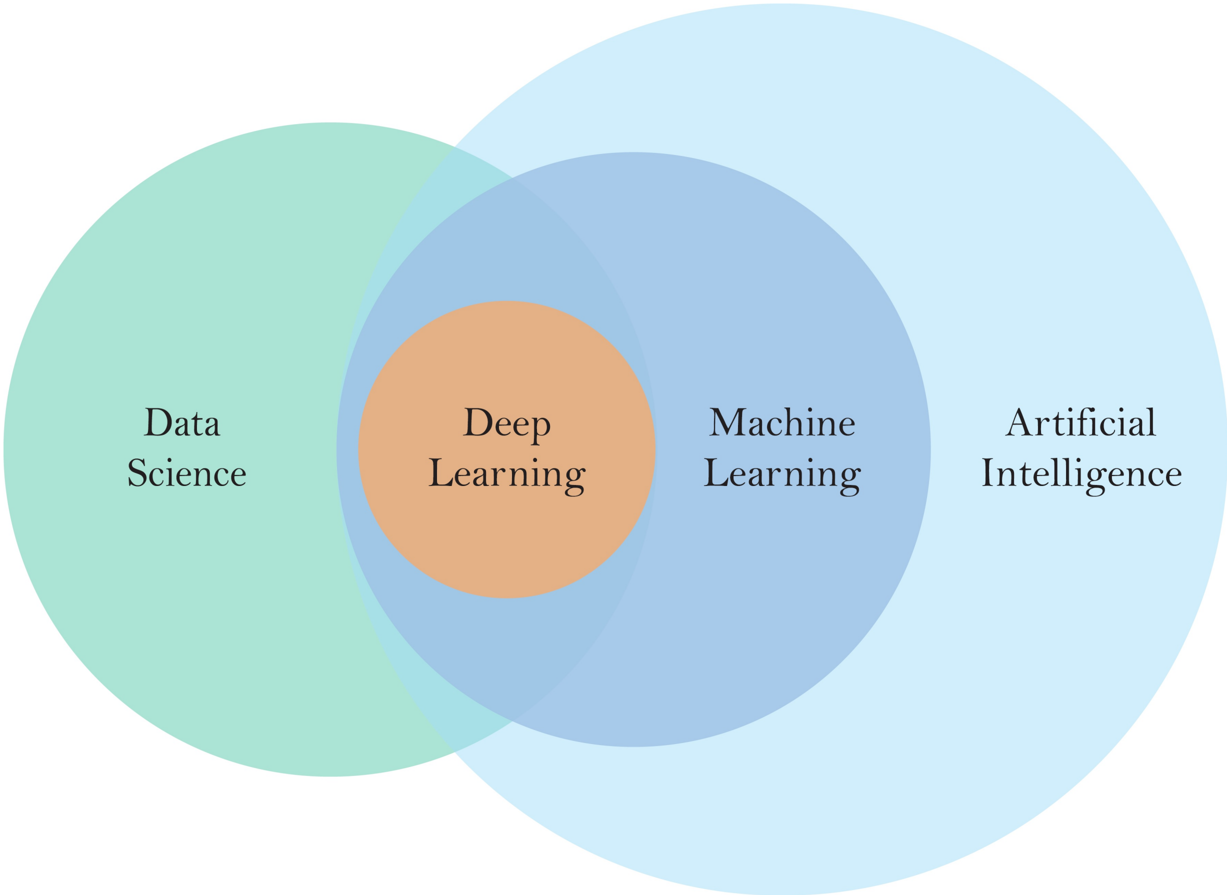

Figure 2.2: A visual illustration of the overlap between various disciplines used for this purpose.

This description clearly indicates, as shown in the Figure 2.2, that there is a substantial overlap between this topic and other fields such as: artificial intelligence, machine learning, deep learning, and data science. Despite some overlap, each of these fields has its unique methodology. It is evident that the three sections overlap, but to distinguish them, let's examine their respective ends: data science is the practice of using data to provide value to an organization, machine learning is the process of optimizing inferences and predictions through the use of data, and artificial intelligence is the use of data to provide machines with human-like decision-making capabilities.

Data science is distinguished from these other professions by the vastness of the data sets, which are often of poor quality, and the complexity of the structures sought. Data science may be separated into two major categories: model construction and pattern recognition, which is the topic of this work, because deep learning incorporates both data science and machine learning techniques. Pattern recognition is the extraction of abnormal or, more precisely, common characteristics from data for study [30].

2.2.1 Data acquisition

The primary step in any machine learning project is to acquire and assess useful data. In this case, the data include ECG signals from patients with cardiac arrhythmias as well as healthy volunteers. ECG signals are commonly acquired by an electrocardiogram, as detailed in Chapter 2, although ECG data may also be accessed for research purposes through publically accessible online sites. The data for this research were collected from the MIH repository [18]. However, ECG signals and other forms of physiological data may be discovered in a number of different areas.

2.2.2 Data processing

Raw ECG signals are inefficient because they include noise caused by artifacts intrinsic to their nature and by situations that may occur during the collection of these data. These signals must be examined to obtain relevant conclusions or results. Lastre et al [31] identified cardiac abnormalities after performing FIR smoothing on the data, therefore, an initial step to ”clean” the ECG signals is necessary.

2.2.3 Data characterization

The objective of completing a beat characterization at this stage is to obtain the most crucial information about the cardiac signal that enables distinguishing between distinct kinds of beats. Certain patterns or characteristics, such as the form of the ECG signal, differ considerably across individuals. As a consequence, various capabilities are more straightforward to employ. Certain characteristics, such as the computation of heart rate variability, the R-R interval, and the post-RR interval, yield very accurate results, such as those found in [32, 33, 34]. Patterns recovered using the Wavelet Transform, as seen in [35, 36, 37], are among those that may be recognized in the cardiac beats.

The use of the wavelet transform is justified because the Fourier transform facilitates signal breakdown in terms of their sinusoidal components, i.e. it changes the signal from a time basis to a frequency basis and vice versa. Due to the risk of information loss during this operation, the signal must be represented in terms of time and frequency. In addition, the Fourier transform has difficulty giving global information since its basis functions are sine and cosine. The solution to the issue is the short time Fourier transform, which involves analyzing a small portion of the signal via a window of a predetermined length. Nevertheless, the constant size of the time window is followed by a fixed window in the Fourier domain, and it is crucial to have a long window to assess the large scale components and a narrow window to identify the small scale features, which the wavelet transform provides [35]. This transformation is more suited for analyzing data such as electrocardiograms.

The transformed wavelet of a function $f(t)$ is the decomposition of $f(t)$ into a set of functions $\varphi_{s,\tau}(t)$ that form a basis and are known as wavelets. Wavelets are created by translating and changing the scale of a mother function called ”wavelet mother” [36]. Furthermore, orthogonal Hermite functions play a crucial role in signal characterization.

Because Hermite bases are orthonormal, each coefficient transmits independent information about the signal's characteristics, meaning that a limited number of coefficients may be used to characterize the signal. [35]. According to [37], a feature selection should be made largely for three reasons following characterization.

- **Existence of irrelevant characteristics:** The existence of qualities that give no information to the clustering system.
- **Existence of redundant attributes:** The possibility that some characteristics fulfill the same function as others.
- **Curse of dimensionality:** The curse of dimensionality is that the quantity of required data rises exponentially with the number of dimensions, and an excess of characteristics might result in overlearning since it increases the model's complexity relative to the available data.

Data science techniques that extract models from instances have a tendency to develop more complex models as the data volume of the set to which they are applied grows. In addition to increased model response time, noise sensitivity, and the risk of overfitting the models in the training set, the large size of the data sets has additional disadvantages. The outcome of extracting large models is unfathomable to the human mind. Therefore, preparatory preprocessing is necessary to reduce the volume of the stored collection. In accordance with the prior work of Eduardo Jose et al. [38], the annotations utilized in this study are those from the original MIT-BIH database, which have been suitably classified by superclasses.

The collection of characteristics may be evaluated using the information provided by the whole subset regarding the foundational feature, or the subset of attributes can be evaluated using the individual predictive capacities of each feature and the degree of redundancy between them. Depending on whether a subset of attributes or each attribute is evaluated independently, there are many methods for identifying the information provided by a subset or a feature. Individual evaluation results in an information gain, which is the decrease of data entropy produced by the knowledge of an attribute's value. On the other hand, subset evaluation employs classification error when the selection relies on the size of the data set [39].

2.2.4 Data classification

The acquired properties are used by the categorization system to assign items to the relevant class. On the basis of the gathered properties, classifiers assign objects to classes. In supervised learning, classifiers consist of knowledge of each pattern as well as criteria or metrics to classify across classes of patterns. To categorize additional data, a collection of labeled data is required to determine if there are significant differences between groups and to guarantee that the observed differences are not artifacts caused by other variables in the training data [40]. In Chapter 3, examples of classifiers are provided pertinent to the thesis's purpose.

2.2.5 Pattern recognition

Pattern identification requires identifying, recognizing, discriminating, and describing processes of objects or occurrences. A pattern's intuitive nature is observable, recognizable, and certain patterns are comparable. Pattern recognition is an essential aspect of science and artificial intelligence that is performed by computers. It has been valued and implemented in numerous fields, such as science, astronomy, economics, medicine, psychology, industrial automation, security, robotics, bio-metrics, medical diagnostics, lifestyle analysis, image processing, process control, aerial photo interpretation, weather forecasting, remote planet life detection, behavioral analysis, and voice recognition, among others [41].

2.3 Deep Learning

Deep learning refers to neural network-based algorithms that are capable of emulating the operations of the human brain, thus the title Artificial Intelligence. Deep learning in particular distinguishes itself from other disciplines of artificial intelligence by being able to evaluate vast volumes of data with relative ease, as a result of the deployment of a several neural network created specifically for ECG cardiac pattern recognition. As can be seen in Figure 2.3 machine Learning algorithms will process quantitative and structured data, while Deep Learning algorithms will process unstructured data [42]. Therefore, the difference is feature extraction.

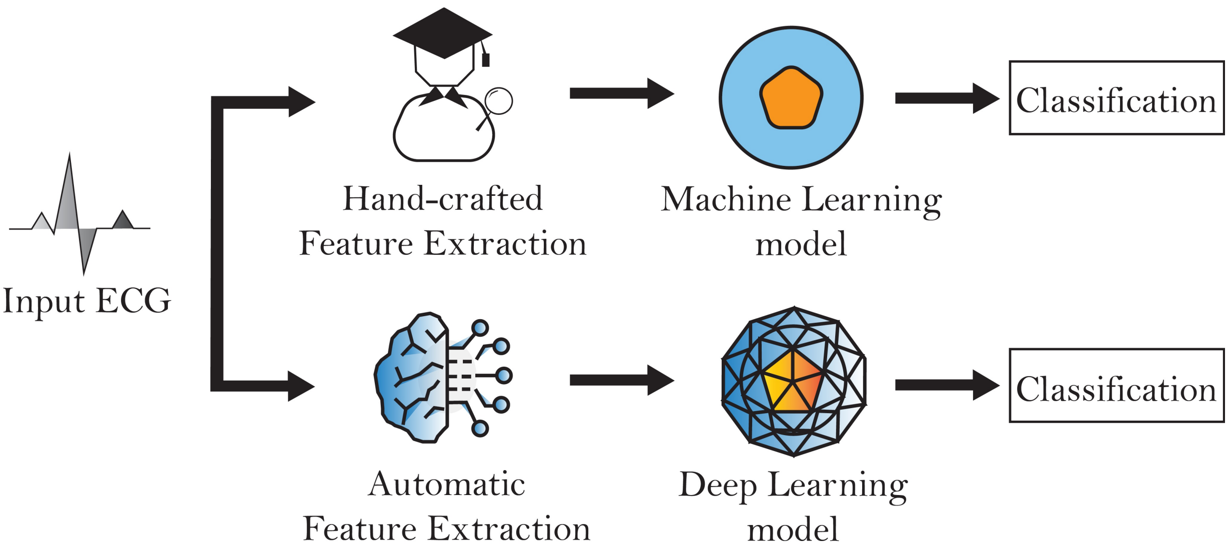

Figure 2.3: A graphic representation of how deep learning differs from machine intelligence. This study is the source.

For this degree project thesis a deep learning with a hybrid neural network was employed; unlike machine learning, deep learning gives a neural network with more layers that also conducts pattern recognition. Although Deep Learning is a subset of Machine Learning, as can be seen in Figure 2.2. Also as seen in the Figure 2.4, the primary contrast between deep learning and machine learning is the number of layers necessary to accomplish the same objective.

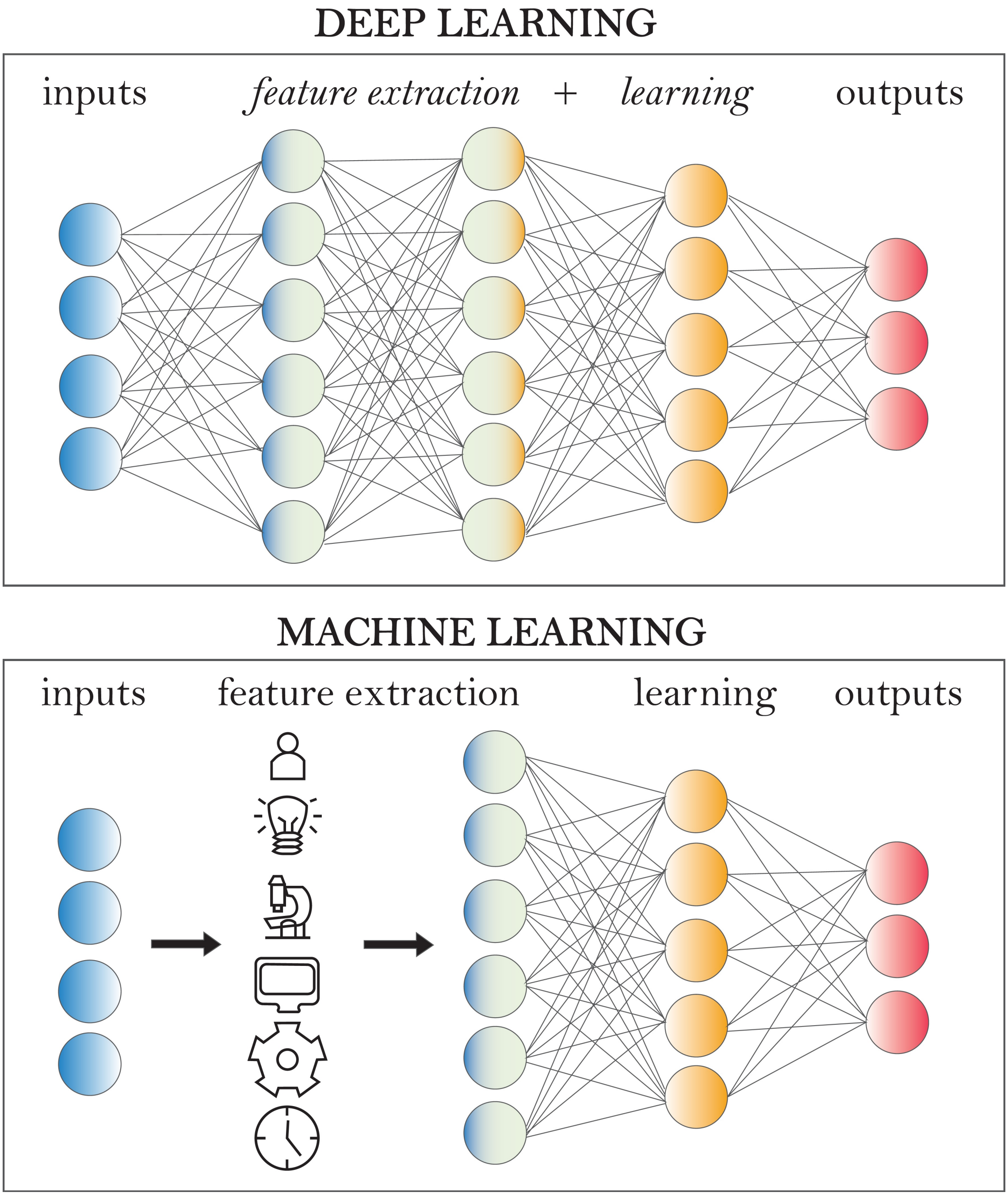

Figure 2.4: A graphic representation of how deep learning differs from machine intelligence. This study is the source.

This was a brief overview to demonstrate a frame of reference research about the distinctions between machine learning, deep learning, and data science. These terms that are now trendy, sometimes misunderstood. As was discussed in the chapter, Artificial Intelligence, Data Science, Machine Learning and Deep Learning all overlap one another, but they are not the same and each has its own methodology.

2.4 Related Works

This section will analyze the publications that are most pertinent to our research, as well as how each of them has approached the issue by using different classification methodologies and discussing their methodology and results. The most prevalent classification techniques include linear classifiers, neural networks, parzen classifier, Gaussian process classifier, support vector machine, k-nearest neighbor, random forest, multi layer perceptron, and fog computing-based. By running deep learning algorithms with Python software aid, the suggested method decreases power consumption, achieves high accuracy, and is simple to comprehend, making these findings notable.

Table 2.1: The most popular methods for achieving the thesis's objective.

Author	Year	Method	Reference
Gorzelany J. et al.	2022	Linear classifiers	[43]
Sheta A. et al.	2021	Neural networks	[44]
Kiranyaz S. et al.	2019	Neural networks	[45]
Chahar R. et al.	2022	Parzen classifier	[46]
Bansal M. et al.	2022	Support Vector Machine	[47]
Rizwan M. et al.	2022	Gaussian process classifier	[48]
Zahi X. et al.	2018	K nearest neighborhood	[49]
Swapna M. et al.	2022	Random forest	[50]
Saravi B. et al.	2022	Multilayer perceptron	[51]
Sutagundar A. et al.	2021	Fog computing based	[52]

2.4.1 Linear classifiers

Linear regression involves fitting a linear model with coefficients that minimize the residual sum of squares between the observed targets in the data set and the anticipated targets by the linear approximation. A linear model calculates sparse coefficients. It is advantageous in some circumstances owing to its inclination to favor solutions with fewer nonzero coefficients, hence minimizing the number of characteristics upon which the supplied solution relies [43]. The exact set of non-zero coefficients can be obtained under certain circumstances.

2.4.2 Neural networks

Serkan K. et al. [44] present a summary of the most prevalent signal processing applications that use CNNs. Using a systematic technique, CNNs may achieve a performance of up to 97% with little computational complexity, according to the study. Using a double beat ECG coupling matrix, Xiaolong Z. et al. [45] offer a CNN-based framework for heartbeat classification. This two-dimensional encoded dual beat ECG coupling matrix accurately depicts the heartbeat's shape and rhythm. The proposed method was verified against the MIT-BIH database and achieved an accuracy of over 90%.

2.4.3 Parzen classifier

Based on stored training samples, Parzen's classifier predicts the probability density of each class using a nonparametric method. When calculating the outcome of a new observation, the contribution of each training example is included. A kernel function models the contribution, which is affected by the smoothing value. By default, sdparzen trains a Parzen classifier using the Laplace kernel function, which is less computationally intensive than the often used Gaussian kernel [46]. A cross-validated log-likelihood optimization approach is used to optimize the smoothing parameter.

2.4.4 Support Vector Machine (SVM)

Naturally, an SVM is a model that represents the sample points in space by splitting the classes into two spaces as broad as feasible using a separation hyperplane defined as the vector between the two points of the two classes, which is closest to the vector known as the support vector. When fresh samples are placed in accordance with the aforementioned model, based on the spaces to which they belong, they may be categorized into one of many classes. Formally speaking, an SVM builds a hyperplane or group of hyperplanes in a very high-dimensional, or perhaps infinite, space that may be utilized to solve classification or regression issues [47]. Correct categorization will be possible if there is sufficient separation between the classes.

2.4.5 Gaussian process classifier

The Gaussian process classifier is a machine learning classification technique. As a generalization of the Gaussian probability distribution, Gaussian processes may serve as the foundation for advanced non-parametric machine learning algorithms for classification and regression. They are a form of kernel model, similar to support vector machines (SVMs), but, unlike SVMs, are capable of forecasting highly calibrated class membership probabilities, despite the fact that the selection and configuration of the kernel employed in the approach may be dynamic [48].

2.4.6 K nearest neighborhood

The concept behind k-NN is rather straightforward: the algorithm classifies each new item of data into the appropriate group based on whether it has k closest neighbors in the same group or in a different group. In other words, it computes the distance between the new element and each of the existing elements then sorts these distances from shortest to biggest to determine which group it belongs to. Therefore, this group will have the greatest frequency across the shortest distances. The k-NN is a supervised learning algorithm, meaning that it determines its goal of accurately categorizing all new instances based on the baseline data [47].

The standard data set for this sort of method has many descriptive features and a single target attribute, sometimes known as a class. Vedavathi G et al. [49] Propose a technique for classifying cardiac arrhythmias using the K-Nearest Neighbor (KNN) classifier; the steps of this technique include data preparation, module extraction, and feature classification. This technique is used to the MIT-BIH database of ECG signals, which are then classified using the KNN method. The dataset gets a 98.4 percent classification accuracy, demonstrating the accuracy of K-NN classifiers.

2.4.7 Random forest

The Random Forest method is a classification technique that is supervised. In this process, a forest is split at random. There is a clear correlation between the quantity of trees in the forest and the accuracy of the findings: the more trees there are, the more precise the results. However, it is important to remember that generating the forest is distinct from constructing a choice based on information gain or rate of return. The decision tree is a decision-making instrument. Employ a tree diagram to illustrate the potential outcomes. If you enter a training dataset including objectives and characteristics into the decision tree, rules will be generated [50]. These guidelines may be used for forecasting.

2.4.8 Multilayer perceptron

The multilayer perceptron is an evolution of the basic perceptron that contains hidden neuron layers to enable representations of nonlinear functions. A multilayer perceptron consists of an input layer, an output layer, and numerous hidden layers in between, as shown in Figure 2.5. It has distinct but linked outputs, so that the output of one neuron is the input of the next. The multilayer perceptron may discriminate between two phases: The propagation in which the network's output is determined from the input values forward and backward. Using the error gradient function, backpropagation is used to alter the weights of the connections such that the estimated value of the network approaches the actual value [51].

- **Input layer:** connects the network to the outside world, and each neuron corresponds to one of the network's input variables.
- **Hidden layers:** are a collection of layers in which each activation of an output is derived from the weighted sum of the activation of the previous connected layer, plus their respective thresholds (biases).
- **Output layer:** links hidden layers to the output of the network, which gives the results.

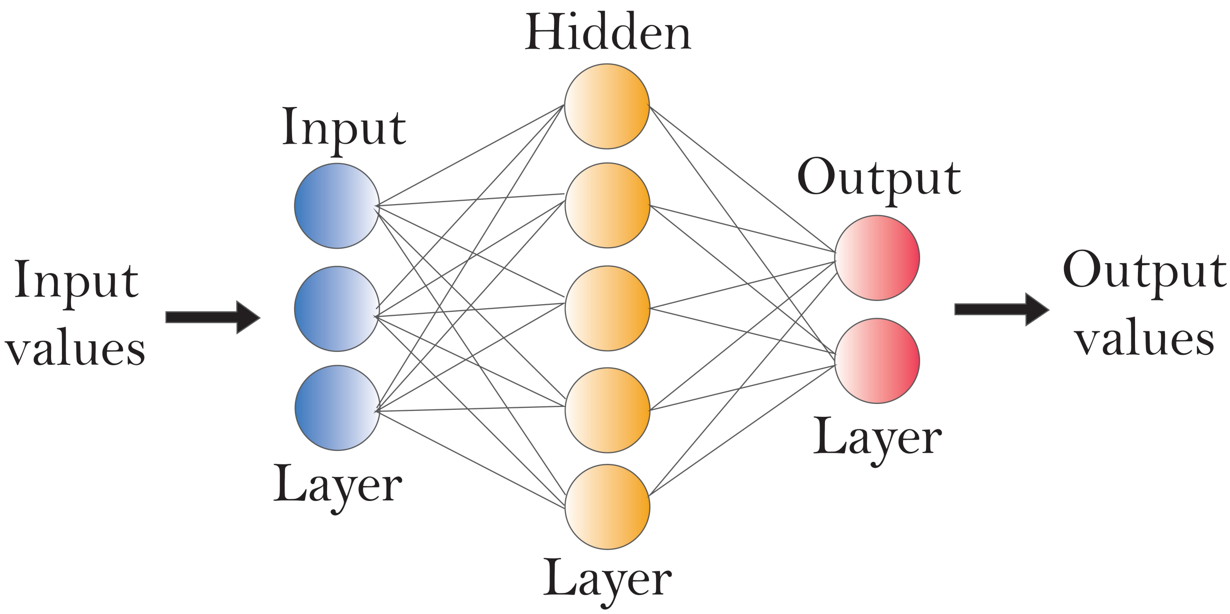

Figure 2.5: A graphic representation of how multilayer perceptron works.

2.4.9 Fog computing based (FCB)

Fog computing analyzes and categorizes data prior to storing it in the sensor cloud. The activation of agents to optimize energy consumption for network longevity. Random forest and genetic algorithm are used to categorize low-variance information. Optimized data with high precision is stored in sensor cloud[52]. The ability of the end-to-end approach to distinguish beats and classify them into four groups was evaluated by Alessandro S. et al.[53]. Normal beats, supraventricular ectopic beats (VEBs), and ventricular ectopic beats were identified using this method. Not classified as N, S, V, or F by the MIT-BIH arrhythmia database. Classifying arrhythmias is accomplished with an accuracy of 89.1 percent using the resulting approach.

Chapter 3

Methodology

Figure 3.1 is a summary of the proposed method for classifying cardiac arrhythmias using deep learning, which consists of the following steps: ECG data collection, preprocessing, segmentation, characterisation, deep learning classification, and performance and precission measurements.

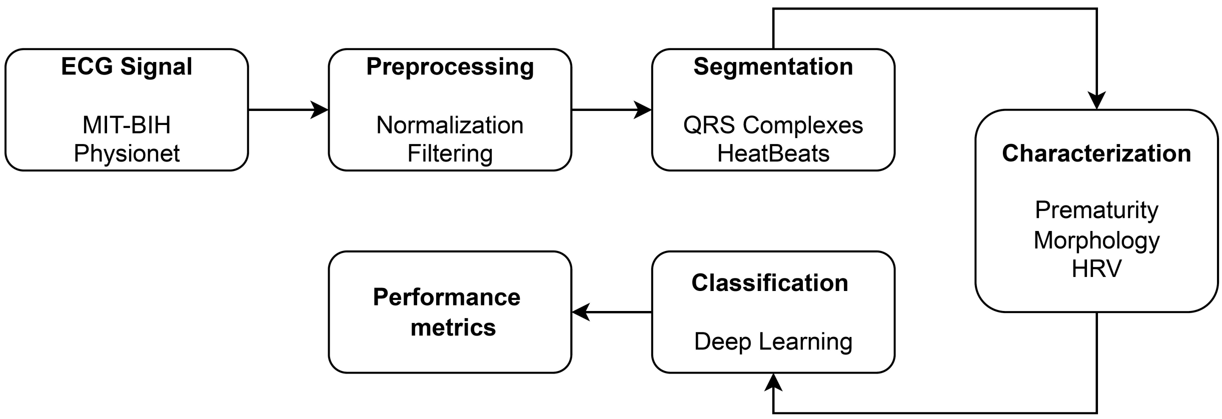

Figure 3.1: Diagram depicting the steps for detecting cardiac arrhythmia. This identifies beats associated with cardiac arrhythmia through acquisition, preprocessing, segmentation, characterization, and deep learning classification techniques.

3.1 Data Acquisition

Using the MIT-BIH arrhythmia database as a reference dataset, this study's program is written in Python and use deep learning classification to identify cardiac arrhythmias.The MIT-BIH arrhythmia database is accessible online; the signals were collected from the database, which consists of 48 recordings lasting around 30 minutes each; the analysis of the following arrhythmias is essential infrastructure plays an important role, as described in Chapter 1 and Chapter 2.

Normal (N), supraventricular (S), ventricular (V), beat fusion (F), and unknown (Q) heartbeats are distinguished by the symbols N, S, V, F, and Q, respectively [18]. The recordings were obtained from ambulatory ECG recordings and reveal arrhythmias that are uncommon yet clinically important. Each recording has two leads, a sampling rate of 360 samples per second, a resolution of 11 bits, and an ECG signal range of 10 mV. The initial lead is modified lead II (ML II), followed by lead VI, VII, V2, V4, or V5. We will apply ML II to classify ECGs in this study due to its prevalence in the recordings. Two or more cardiologists independently name and classify each recording into one of fifteen arrhythmia kinds. According to a previous publication by Eduardo Jose et al. [54], the annotations used in this work are those from the original MIT-BIH database, which have been suitably classified by superclasses.

Table 3.1: Principal beat categories contained in the MIT-BIH database. Where the divide between the superclasses N, SVEB, VEB, F, and Q can be seen respectively.

Group	Annotation	Description
N	N	Normal beat
Any heartbeat not categorized	L	Left bundle branch block beat
as SVEB, VEB, F or Q	R	Right bundle branch block beat
	e	Atrial escape beat
	j	Nodal (junctional) escape beat
SVEB	A	Atrial premature beat
Supraventricular ectopic beat	a	Aberrated atrial premature beat
	S	Supraventricular premature beat
	J	Nodal (junctional) premature beat
VEB	V	Premature ventricular contraction
Ventricular ectopic beat	E	Ventricular escape beat
	!	Ventricular flutter wave
F - Fusion beat	F	Fusion of ventricular and normal beat
Q	Q	Unclassifiable beat
Unknown beat	/	paced beat
	f	Fusion of paced and normal beat

3.2 ECG Signal Preprocessing

Clinically collected ECG signals are frequently corrupted by a number of noise sources, such as baseline drift, electromyography disturbances, and power line interference, making it hard to extract useful information from the ECG signal without processing. Therefore, prior to further processing, normalization and filtering are necessary. The signals in question [38] were normalized using geometric normalization, as indicated in Equation (3.1). This standardization decreases the signal-to-noise ratio. The term $E\{s\}$ signifies the expectation operator; in this instance, the arithmetic mean is analyzed, taking into account the influence of a zero-mean transformation.

$$s \leftarrow \frac{s - E\{s\}}{\max |s|} \tag{3.1}$$

Due to the fact that excessive filtering would result in the loss of crucial information, we remove just the noise: the baseline deviation, which has a substantial impact on the classification of ECG signals. The patient's breathing or movement produces base-line drift. In agreement with previous research [55], a simple 1s window with overlap filter is utilized to reduce signal disturbances and artifacts. Figure 3.2 depicts the impact of noise on the ECG signal. The basic 1s window with overlap filter successfully eliminates outliers without generating phase distortion [56] compared to other filtering methods.

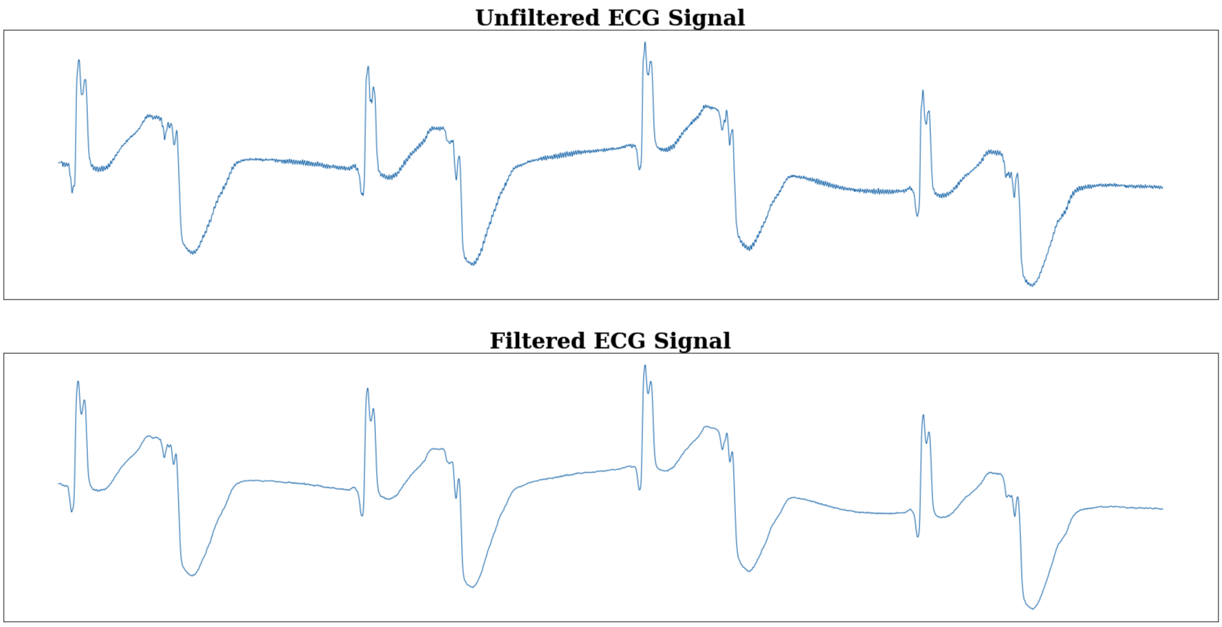

Figure 3.2: Electrocardiographic signal impact retrieved from the MIH database using the suggested filtering strategy. For our purposes, it can be observed that important information is maintained while noise is eliminated.

3.3 Hearbeat and QRS Segmentation

To appropriately segment individual beats from the ECG data, it is necessary to identify the QRS waves and beat reference points [57]. Numerous investigations in the scientific literature suggest that the success rate of this treatment exceeds 99 percent [58]. In this experiment, the R peak serves as a reference point, and the ECG signal is split according to equations (3.2) and (3.3).

$$b_i = y(p_i - 0.3RR_i : p_i + 0.6RR_i) \tag{3.2}$$

and

$$c_i = y(p_i - \alpha\ F_s : p_i + \beta\ F_s), \tag{3.3}$$

Where p_i represents the position of the R peak of the i-th beat (b_i), c_i represents the QRS complex of the b_i, RR is the vector storing the distance between the R_i peaks, and Fs is the frequency of the vector v between locations a and b ($b > a$). Due to the fact that the times are obtained from a dynamic variable, each extracted time has a unique duration. The complexes were extracted using a 200ms window width and the R peak was used as a centering point, it means $\alpha = \beta = 0.1s$. These places correlate to the most prominent beat waves, as seen in Figure 3.3.

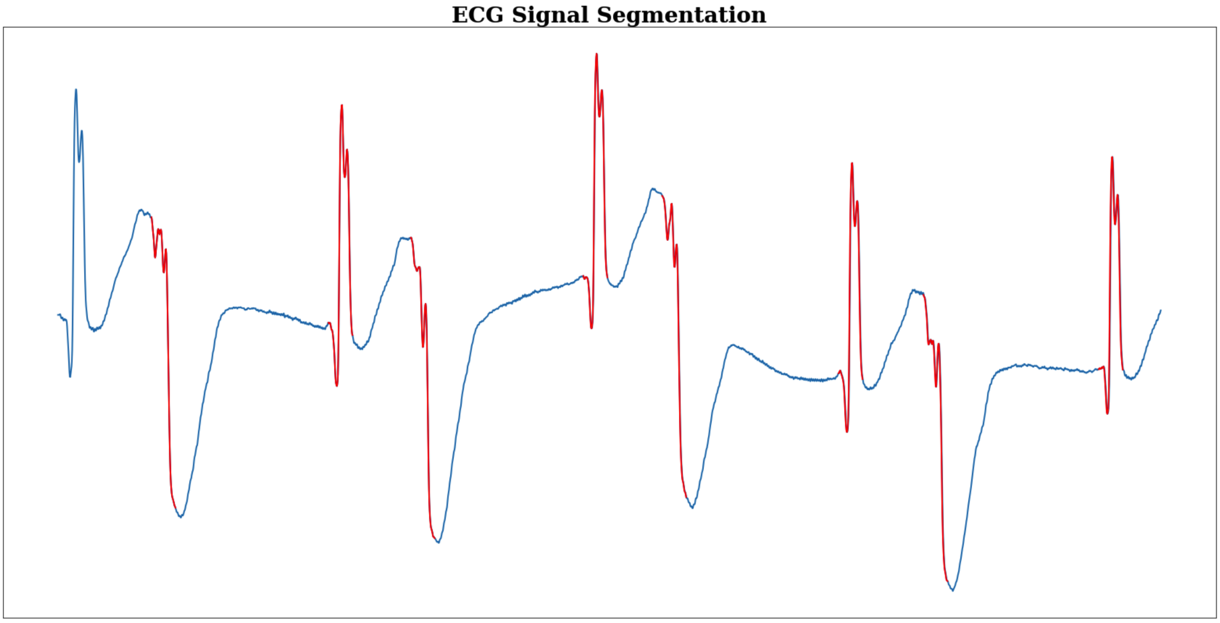

Figure 3.3: Employing segmentation of the heart's QRS complexes, depicted in red in contrast to the blue signal, the electrocardiographic signal is segmented.

Could not only arrhythmia often affect the shape of the pulse, but also the surrounding RR intervals, also known as peak R intervals. Thus, we include RR interval data into our hybrid neural network for ECG classification. Three commonly exploited RR interval features are retrieved. The anterior RR interval is the period between the present and subsequent heartbeats. The RR ratio is the difference between two successive RRs. The local RR is determined as the average of the last 10-RR intervals for the current beat. The anterior RR, posterior RR, and local RR were removed from the mean RR interval to eliminate interpatient variation.

3.4 Characterization

The data set is consistent with traits gleaned from earlier investigations that have shown promising results in the morphology, variability, and representation of the signal [12]. The collection of attributes is detailed in Table 3.2, along with a description and a potential calculation method.

Table 3.2: A characteristics cluster used for arrhythmia analysis

#	Type	Description
1		RR intervals ($f1$)
2	**HRV**	pre-RR intervals ($f2$)
3		post-RR intervals ($f3$)
4		Difference between RR and pre-RR intervals, $f4 = f1 - f2$
5	**Prematurity**	Difference between post-RR and RR intervals, $f5 = f3 - f1$
6		Beats A continuous
		$f6 = (\frac{f3}{f1})^2 + (\frac{f2}{f1})^2 - (f4 + \beta \times \frac{1}{3}\sum_{i=1}^{3} f_i^2 \times log(fi)^2)$
7		DTW between current P wave and average P wave
8	**Morphology**	Polarity of the QRS complex
		Let b be the samples of a beat, then, $f8 = \lvert\frac{max(b)}{min(b)}\rvert$

3.5 ECG Signals Classification using Deep Learning

For the classification methodology a Rectified Learning Unit (ReLU) activation function was used for the performance of a hybrid neural network, which combines three CNNs and eight RNNs, majority of the layers in both instances because it reduces the model's computing complexity, improves its statistical efficiency, and attains nonlinear capabilities. Adam often expedites the network training process in compared to other optimizers. In the following Table 3.3, each model architecture is described in detail.

Table 3.3: RNN and CNN architectures, such that the input consist of eight variables, eight hidden layers, three control layers, and the output has size $(k, 1)$ where $k =$ the ammount of classes for each supergroup.

Layer Type	Hyperparameter	RNN	CNN
Input	Size	(8,1)	(8,1)
Hidden	Neurons or Units	-	10
	Activation	-	ReLU
Hidden	Neurons or Units	-	20
	Activation	-	ReLU
Hidden	Neurons or Units	-	10
	Activation	-	ReLU
MaxPoolingid1D	Neurons or Units	-	-
Dropout	Neurons or Units	-	-
Hidden	Neurons or Units	9	-
	Activation	Softmax	-
Hidden	Neurons or Units	9	-
	Activation	Softmax	-
Flatten	Neurons or Units	-	-
Hidden	Neurons or Units	10	-
	Activation	ReLU	-
Hidden	Neurons or Units	20	-
	Activation	ReLU	-
Hidden	Neurons or Units	10	-
	Activation	ReLU	-
Output	Size	$(k, 1)$	$(k, 1)$

3.6 Performance Metrics

In this thesis degree work, the MIT-BIH database was used to assess the effectiveness of the algorithm that identifies cardiac arrhythmias from ECG signals using the methods provided. All of this occurs in the context of the ECG signal analysis techniques provided in a previous paper [62], which are pertinent to the parameters Recall, Accuracy, Precision, and F-Score, as indicated in equations (3.4), (3.5), (3.6), and (3.7), respectively.

$$Recall(\%) = \frac{TP}{TP + FN} \tag{3.4}$$

$$Accuracy(\%) = \frac{TN + TP}{TN + FP + FN + TP} \tag{3.5}$$

$$Precision(\%) = \frac{TP}{TP + FP} \tag{3.6}$$

$$F1(F - Score)(\%) = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3.7}$$

In accordance with the following convention:

- **TP:** is a true positive, a heartbeat of the class of interest (CI) is correctly classified.
- **TN:** is a true negative, a beat different from the class of interest (NCI) is correctly classified.
- **FP:** is a false positive, an NCI beat is classified as CI.
- **FN:** is a false negative, an NCI beat is classified as NCI.

Precision and Recall quantify, respectively, the fraction of properly detected NCI beats and CI beats. These measurements apply to all classes contained in the recording and help to evaluate the system's performance, but have no bearing on the clustering process's parameter settings. Since a relatively high number of clusters is not advantageous, a other parameter is added to the aforementioned metrics so that a proper clustering conducted with a relatively large number of clusters does not record an incorrect performance. Accuracy and F-Score are employed as measurement parameters for this purpose, as they were for a similar reason in a previous article [62].

3.7 Scientific Contribution

Real-time monitoring of vital signs, particularly heart rate, is essential in today's medical practice and research, allowing the physician to monitor the patient's health status to provide immediate action on possible cardiovascular disease. In previous research, a possible alternative to traditional heart rate signal monitoring systems was presented, a heart pulse system that uses low-cost piezoelectric signal identification.

Despite being an investigation focused on hardware, a signal conditioning stage was carried out to reduce sensor noise when acquiring the data and make it suitable for real-time BPM visualization, which allows us to ensure that a signal conditioning stage the signal at the hardware level prior to obtaining the data could be efficient to further improve the results obtained. [65]

In other previously published research, a study was presented that offers a comparative analysis of ECG signal classification using two artificial neural networks created by different machine learning frameworks. The neural networks were integrated into a pipeline that aims to strike the right balance between signal robustness, variability, and accuracy. The proposed approach achieved up to 99% of the overall accuracy for each record while maintaining a low computational cost. In this thesis, a hybrid neural network was used, obtaining results equal to or better than our previous research, the significant difference between the two processes is the use of more convolution layers. [66]

3.7.1 Exploratory study

Artificial learning has become the most widely used AI technique in recent years, AI approaches have proven their ability to significantly reduce time and physical labor. To facilitate the management of cardiovascular health, most of these approaches use artificial neural networks in ECG diagnosis [44, 45]. The machine learning process used in an exploratory study [66], identifies beats associated with cardiac arrhythmias through various preprocessing, segmentation and characterization techniques, these resulting data were then sent to neural networks and compared to obtain a better performance.

To address the goal, two ANNs were created to automatically extract possible relationships between various arrhythmias and regular heartbeats. The first ANN was built using the [58], MLPClassifier function. All hyperparameters were set to default except the following: alpha $= 1 \times 10^{-5}$, hidden layer sizes $= (10, 20, 10)$, max iteration $= 500$. The second ANN was created using [67] Sequential Dense Layer . All hyperparameters were set to default except for the following: epochs $= 500$, batch size $= 100$, loss $=$ categorical cross-entropy, optimizer $=$ adam, metrics $=$ precision. In both cases, since the rectified learning unit (ReLU) activation function minimizes the computational complexity of the model, increases its statistical efficiency, and achieves nonlinear capabilities, it was chosen for most layers. Compared to other optimizers, Adam tends to speed up the network formation process.

Chapter 4

Experimental Setup

This chapter provides a detailed overview of the most significant studies; four experiments are discussed below. The MIT-BIH database was used to alter a total of three recordings, and the results of these experiments are given in figures and tables for visual comprehension. In each of the conducted experiments, the training layers of the hybrid neural network are described in depth.

Convolutional Layers, MaxPoolingid1D Layers, Dropout Layers, LSTM Layers, Flatten Layers, and Dense Layers are among these layers. This resulted in the construction of a hybrid neural network, which is representative of deep learning and highlights the thesis work. In order to facilitate a better understanding of the design of the methodology based on deep learning, Figure 4.1 illustrates how the input signal passes through the various processes to obtain the output values, thereby identifying the various supergroups of cardiac arrhythmias discussed in Chapter 4.

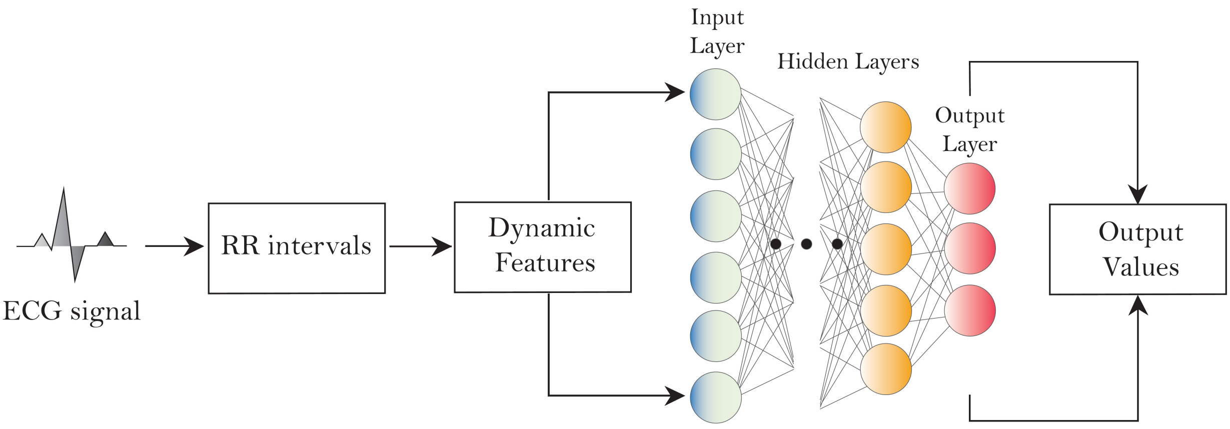

Figure 4.1: Deep Learning using Hybrid Neural Network classification. Where is appreciated ECG signal, RR intervals, Dynamic Features and Deep Learning Classification using a HNN with their input, hidden and output layers respectively.

To achieve the goal, the open-source artificial intelligence framework PyCaret [59] was used, and a hybrid neural network was created to automatically find potential links between various arrhythmias and regular beats. The first CNNN was developed using [60], which explains the deep learning effectiveness of CNNNs. The second CNN network was trained using [61] for each thick layer that followed. With the exception of a few hyperparameters, the majority of hyperparameters were set to their default values, and a few of them were tweaked to determine the optimal design and, therefore, to acquire the most accurate findings while minimizing computational cost.

4.1 Experiment 1

For the first experiment, a hybrid neural network was constructed by initially using an RNN with the majority of hyperparameters set to their default settings with the exception of `alpha` $= 1 \cdot 10^{-5}$, `hidden layer sizes` = (32, 64, 128), `kernel size` = (3, 3, 5), and `activation` = relu, a `MaxPool1D` = (3), and a `Dropout` = (0,1). The majority of the hyperparameters for the second RNN are set to their default values, with the exception of the following: `LSTM` = (64, 64), `dropout` = 0.2, with a Flatten layer, two dense layers with relu activation, and an additional dense layer with softmax activation using accuracy as the measurement metric. Figure 4.2 depicts the train and test Loss Model for the three recordings used in Experiment 1.

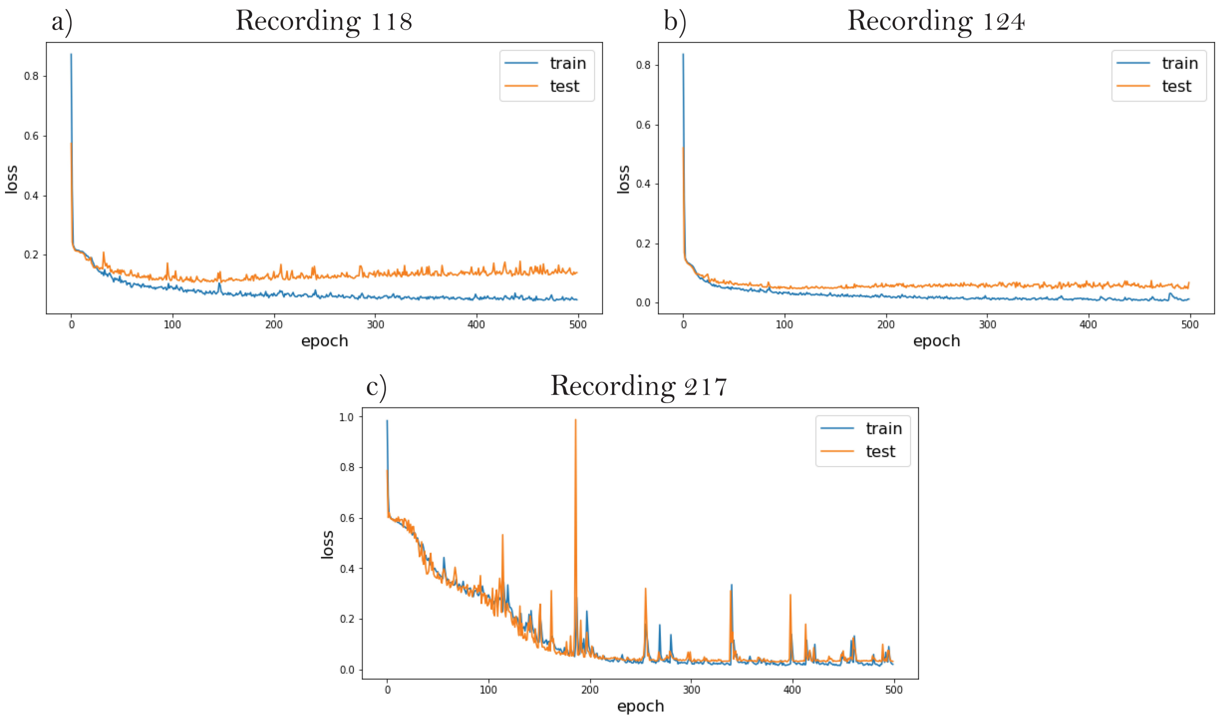

Figure 4.2: Loss model of experiment 1 displaying the train and test outcomes for the three utilized recordings: a) recording 118, b) recording 124, and c) recording 217.

Experiment 1 provides an accuracy rate of up to 98% for record 118, and up to 99% for recordings 124 and 217, employing deep learning using a CNN-RNN hybrid neural network. The following tables 4.1 and 4.2 detail the several layers that make up the hybrid neural network, as well as the number of parameters for each layer, as well as the standard measurement metrics acquired in this experiment, respectively.

Table 4.1: The hybrid neural network broken down into its component layers, each with their own unique output form and appropriate amount of parameters.

Layer	Output Shape	Parameters Number
Conv1D	(None, 8, 32)	128
Conv1D	(None, 8, 64)	6200
Conv1D	(None, 8, 128)	41088
MaxPoolingid1D	(None, 4, 128)	0
Dropout	(None, 4, 128)	0
LSTM	(None, 8, 64)	49488
LSTM	(None, 64)	33024
Flatten	(None, 64)	0
Dense	(None, 512)	33280
Dense	(None, 1024)	525312
Dense	(None, 3)	3075

Table 4.2: Experiment 1 standard metrics.

Register:	118	124	217
Precision:	97.37319767712	98.96637650393	98.78265813559
Recall:	97.51098096632	99.11727616645	98.79154078549
f1 score:	97.31636579840	99.01582884533	98.78629986855
Error:	0.027818448023	0.016393442622	0.019637462235

4.2 Experiment 2

For the second experiment, a hybrid neural network was constructed by initially using an RNN with the majority of hyperparameters set to their default settings with the exception of `alpha` $= 1 \cdot 10^{-5}$, `hidden layer sizes` = (16, 32, 64), `kernel size` = (3, 3, 5), and `activation` = relu, a `MaxPool1D` = (3), and a `Dropout` = (0,1). The majority of the hyperparameters for the second RNN are set to their default values, with the exception of the following: `LSTM` = (64, 64), `dropout` = 0.2, with a Flatten layer, two dense layers with relu activation, and an additional dense layer with softmax activation using accuracy as the measurement metric. Figure 4.3 depicts the train and test Loss Model for the three recordings used in Experiment 2.

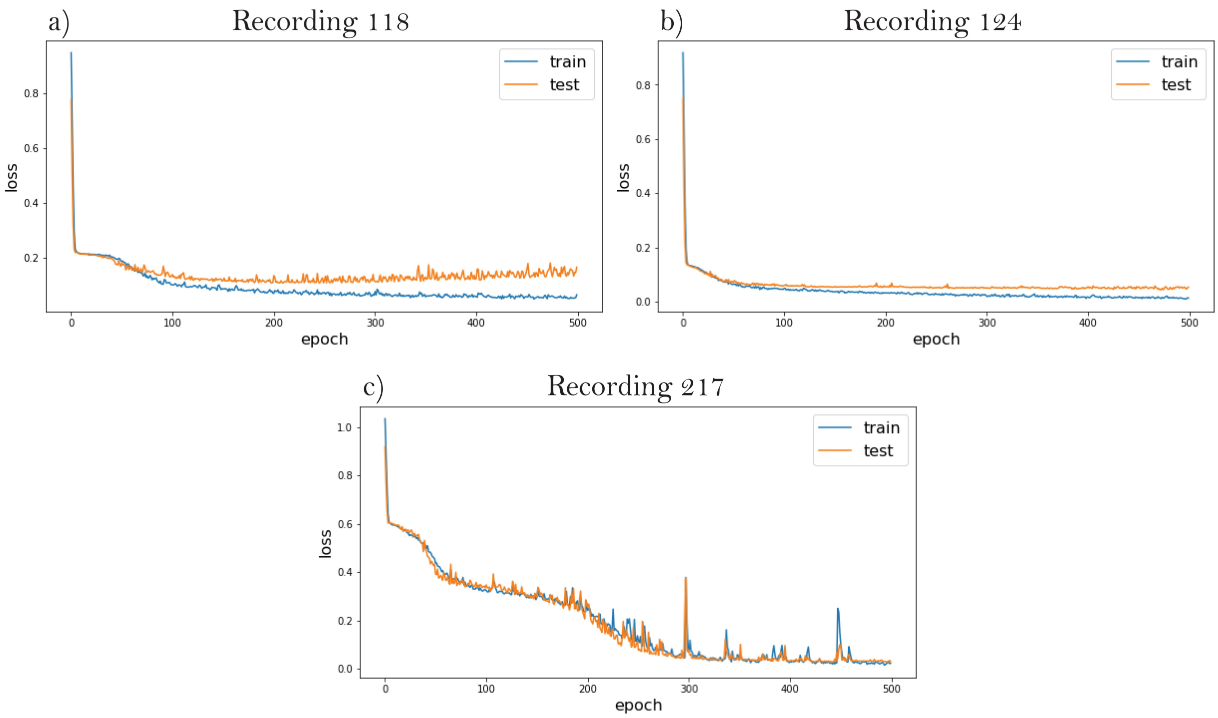

Figure 4.3: Loss model of experiment 2 displaying the train and test outcomes for the three utilized recordings: a) recording 118, b) recording 124, and c) recording 217.

Experiment 2 provides an accuracy rate of up to 97% for record 118, and up to 99% for recordings 124 and 217, employing deep learning using a CNN-RNN hybrid neural network. The following tables 4.3 and 4.4 detail the several layers that make up the hybrid neural network, as well as the number of parameters for each layer, as well as the standard measurement metrics acquired in this experiment, respectively.

Table 4.3: The hybrid neural network broken down into its component layers, each with their own unique output form and appropriate amount of parameters.

Layer	Output Shape	Parameters Number
Conv1D	(None, 8, 16)	64
Conv1D	(None, 8, 32)	1568
Conv1D	(None, 8, 64)	10304
MaxPoolingid1D	(None, 4, 64)	0
Dropout	(None, 4, 64)	0
LSTM	(None, 8, 64)	33024
LSTM	(None, 64)	33024
Flatten	(None, 64)	0
Dense	(None, 128)	8320
Dense	(None, 256)	33024
Dense	(None, 3)	771

Table 4.4: Experiment 2 standard metrics.

Register:	118	124	217
Precision:	97.02416911787	98.68531082692	98.80224068479
Recall:	97.21815519765	98.86506935687	98.79154078549
f1 score:	96.76380642865	98.75075556717	98.79418552685
Error:	0.03074670571	0.021437578814	0.022658610271

4.3 Experiment 3

For the third experiment, a hybrid neural network was constructed by initially using an RNN with the majority of hyperparameters set to their default settings with the exception of `alpha` $= 1 \cdot 10^{-5}$, `hidden layer sizes` = (16), `kernel size` = (3), and `activation` = relu, and a `MaxPool1D` = (3). The majority of the hyperparameters for the second RNN are set to their default values, with the exception of the following: `LSTM` = (16), with a one dense layers with relu activation, and an additional dense layer with softmax activation using accuracy as the measurement metric. Figure 4.4 depicts the train and test Loss Model for the three recordings used in Experiment 3.

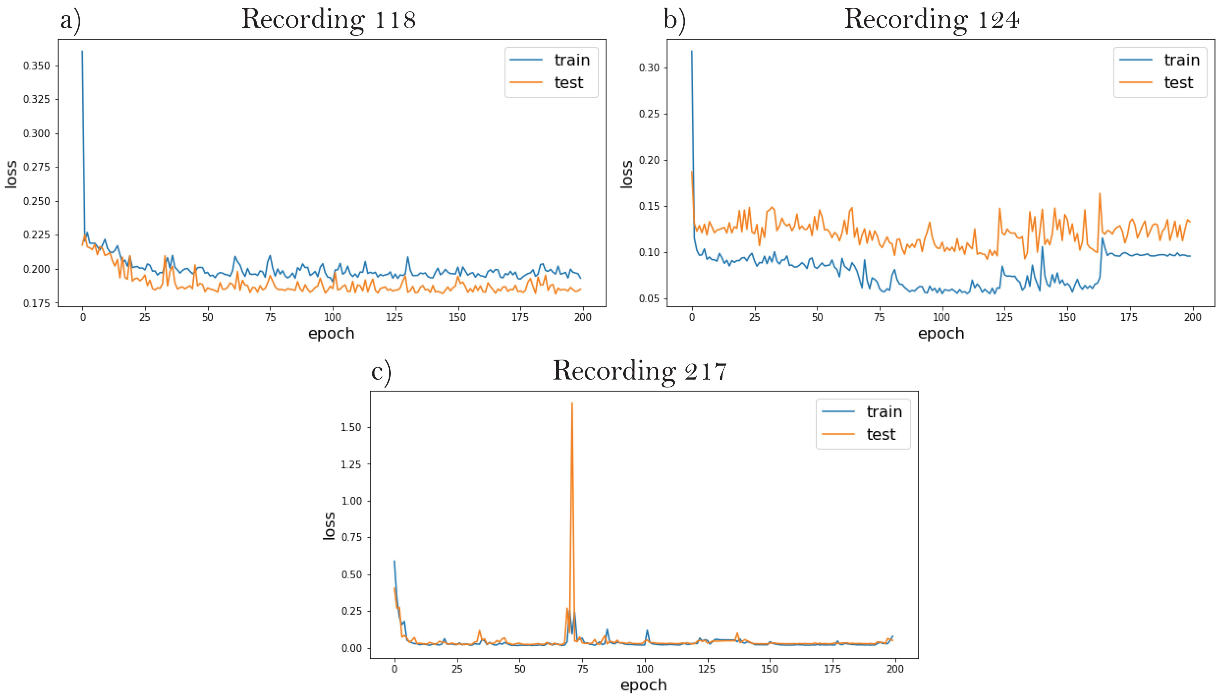

Figure 4.4: Loss model of experiment 3 displaying the train and test outcomes for the three utilized recordings: a) recording 118, b) recording 124, and c) recording 217.

Experiment 3 provides an accuracy rate of up to 90% for record 118, 94% for recording 124, and up to 99% for recording 217, employing deep learning using a CNN-RNN hybrid neural network. The following tables 4.5 and 4.6 detail the several layers that make up the hybrid neural network, as well as the number of parameters for each layer, as well as the standard measurement metrics acquired in this experiment, respectively.

Table 4.5: The hybrid neural network broken down into its component layers, each with their own unique output form and appropriate amount of parameters.

Layer	Output Shape	Parameters Number
Conv1D	(None, 8, 16)	64
MaxPoolingid1D	(None, 4, 16)	0
LSTM	(None, 8, 16)	2112
Flatten	(None, 64)	0
Dense	(None, 8)	520
Dense	(None, 3)	27

Table 4.6: Experiment 3 standard metrics.

Register:	118	124	217
Precision:	90.57019565305	94.5284162016	99.03512084592
Recall:	95.16837481698	97.22572509457	98.94259818731
f1 score:	92.81236853869	95.8580998055	98.9462034485
Error:	0.055636896046	0.05422446406	0.018126888217

4.4 Experiment 4

For the fourth experiment, a hybrid neural network was constructed by initially using an RNN with the majority of hyperparameters set to their default settings with the exception of `alpha` $= 1 \cdot 10^{-5}$, `hidden layer sizes` = (8, 16, 32), `kernel size` = (3, 3, 5), and `activation` = relu, a `MaxPool1D` = (3), and a `Dropout` = (0,1). The majority of the hyperparameters for the second RNN are set to their default values, with the exception of the following: `LSTM` = (32, 64), `dropout` = 0.2, with a Flatten layer, two dense layers with relu activation, and an additional dense layer with softmax activation using accuracy as the measurement metric. Figure 4.5 depicts the train and test Loss Model for the three recordings used in Experiment 4.

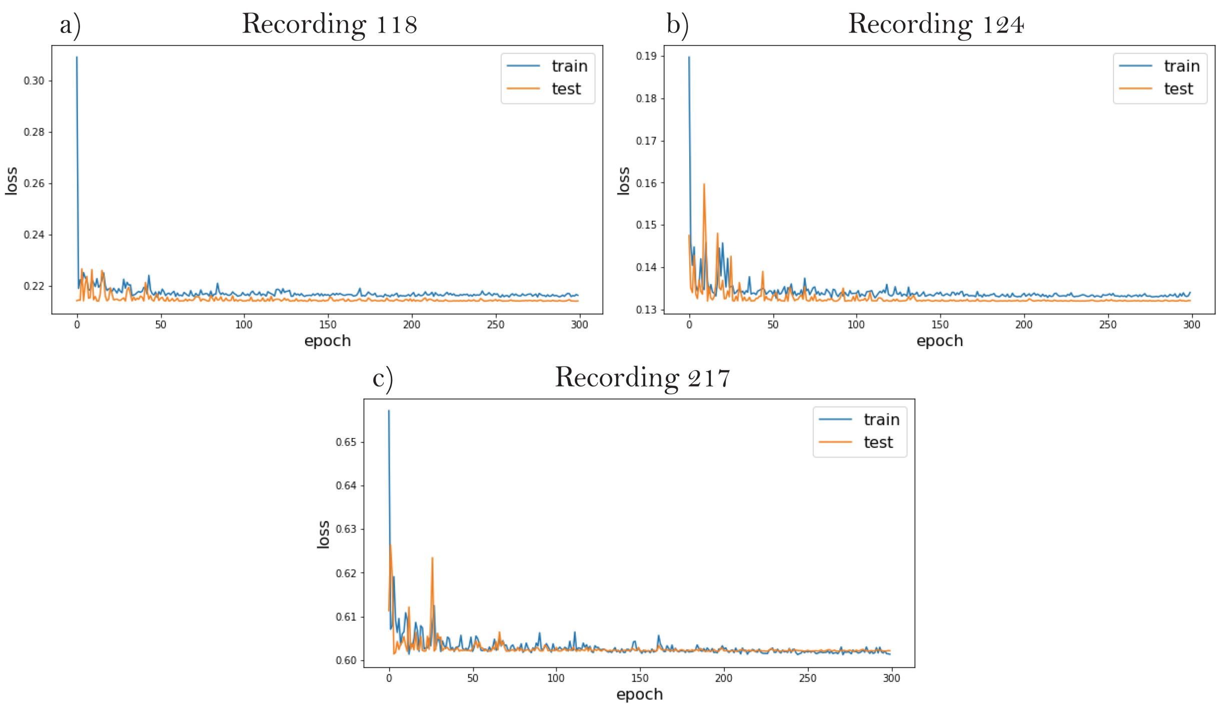

Figure 4.5: Loss model of experiment 4 displaying the train and test outcomes for the three utilized recordings: a) recording 118, b) recording 124, and c) recording 217.

Experiment 4 provides an accuracy rate of up to 90% for record 118, 94% for recording 124, and up to 66% for recording 217, employing deep learning using a CNN-RNN hybrid neural network. The following tables 4.7 and 4.8 detail the several layers that make up the hybrid neural network, as well as the number of parameters for each layer, as well as the standard measurement metrics acquired in this experiment, respectively.

Table 4.7: The hybrid neural network broken down into its component layers, each with their own unique output form and appropriate amount of parameters.

Layer	Output Shape	Parameters Number
Conv1D	(None, 8, 8)	32
Conv1D	(None, 8, 16)	400
Conv1D	(None, 8, 32)	2592
MaxPoolingid1D	(None, 4, 32)	0
Dropout	(None, 4, 32)	0
LSTM	(None, 8, 32)	8320
LSTM	(None, 64)	24832
Flatten	(None, 64)	0
Dense	(None, 128)	8320
Dense	(None, 64)	8256
Dense	(None, 3)	195

Table 4.8: Experiment 4 standard metrics.

Register:	118	124	217
Precision:	90.57019565305	94.52841620166	66.53827548123
Recall:	95.16837481698	97.22572509457	81.57099697885
f1 score:	92.81236853869	95.85809980552	73.29174437367
Error:	0.055636896046	0.054224464060	0.184290030211

Chapter 5

Results and Discussion

5.1 Results of the exploratory study

The exploratory study [66], successfully classified different forms of cardiac arrhythmias using ANN-based deep learning features. The approach takes advantage of ANN's ability to feature representation, which is a nonlinear dimensionality reduction technique frequently used in machine learning. The ANN-based technique can automatically extract discriminant features from the data as a representation learning method. This requires QRS segmentation of the signal, with the R peak serving as the reference point. To validate this ability, accuracy scoring was used, thus comparing it with the multilayer perceptron machine learning approach and establishing that the suggested method is better.

This exploratory study proposed the construction of a machine learning technique capable of identifying cardiac arrhythmias, the way in which this study was carried out allows comparison between multilayer perceptron classification techniques and the suggested approach, which produces results. promising with an accuracy comparable to conventional methods.

5.2 Analysis of the conducted experiments using HNN

To accomplish the objective, the open-source artificial intelligence framework PyCaret [59] was used, and a hybrid neural network was created to automatically find potential links between various arrhythmias and regular beats. The original RNN was developed using [60], which explains the RNN's effectiveness in deep learning.

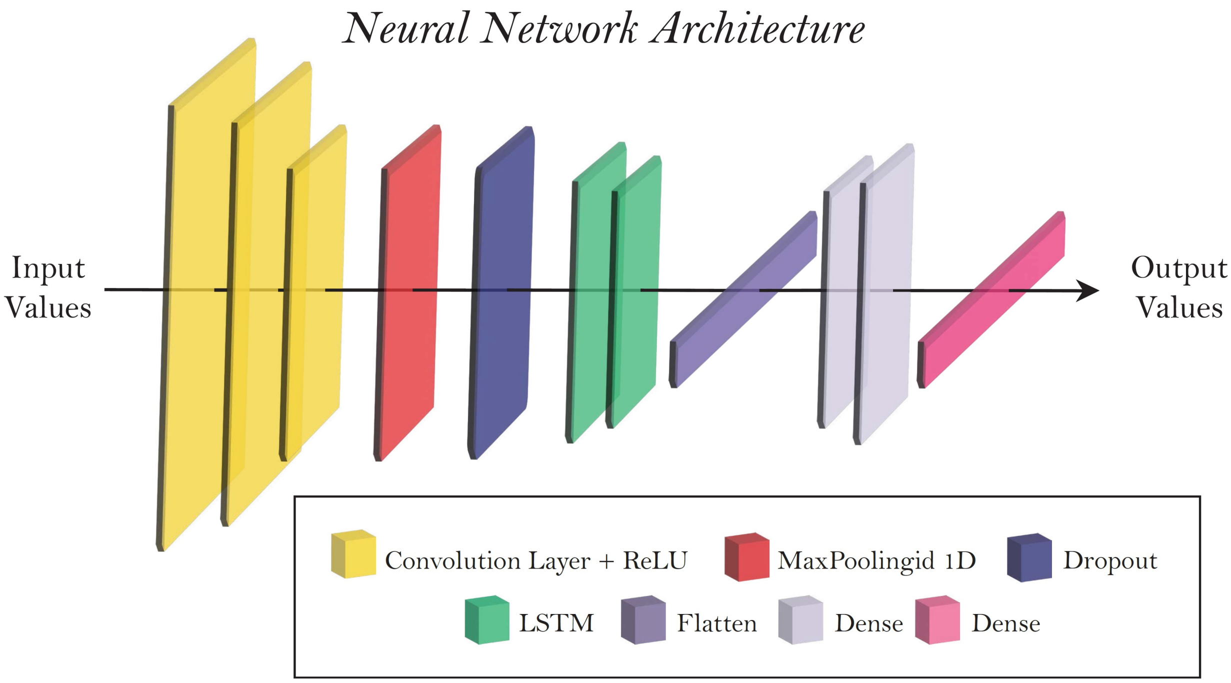

Figure 5.1: Proposed architecture using a hybrid classification neural network. Where we can see the convolution layers + ReLU activation, MaxPooling1D layer, Dropout layer, LSTM layers, Flatten layer, dense layers and their output values, respectively.

Except for `alpha` $= 1 \cdot 10^{-5}$, `hidden layer sizes` = (32, 64, 128), `kernel size` = (3, 3, 5), and `activation` = relu, a `MaxPool1D` = (3), and a `Dropout` = (0,1). The majority of the hyperparameters for the second RNN are set to their default values, with the exception of the following: `LSTM` = (64, 64), `dropout` = 0.2, with a Flatten layer, two dense layers with relu activation, and an additional dense layer with softmax activation using accuracy as the measurement metric, our suggested approach and the best experiment set all hyperparameters to their default levels.

Figure 5.1 illustrates, for a better understanding of the design of the optimal neural network architecture used in the formation of the HNN, as well as how the activities of each of the layers stated in the experiments are carried out. In addition, Figure 5.2 shows a comparative analysis of the accuracy of each recording.

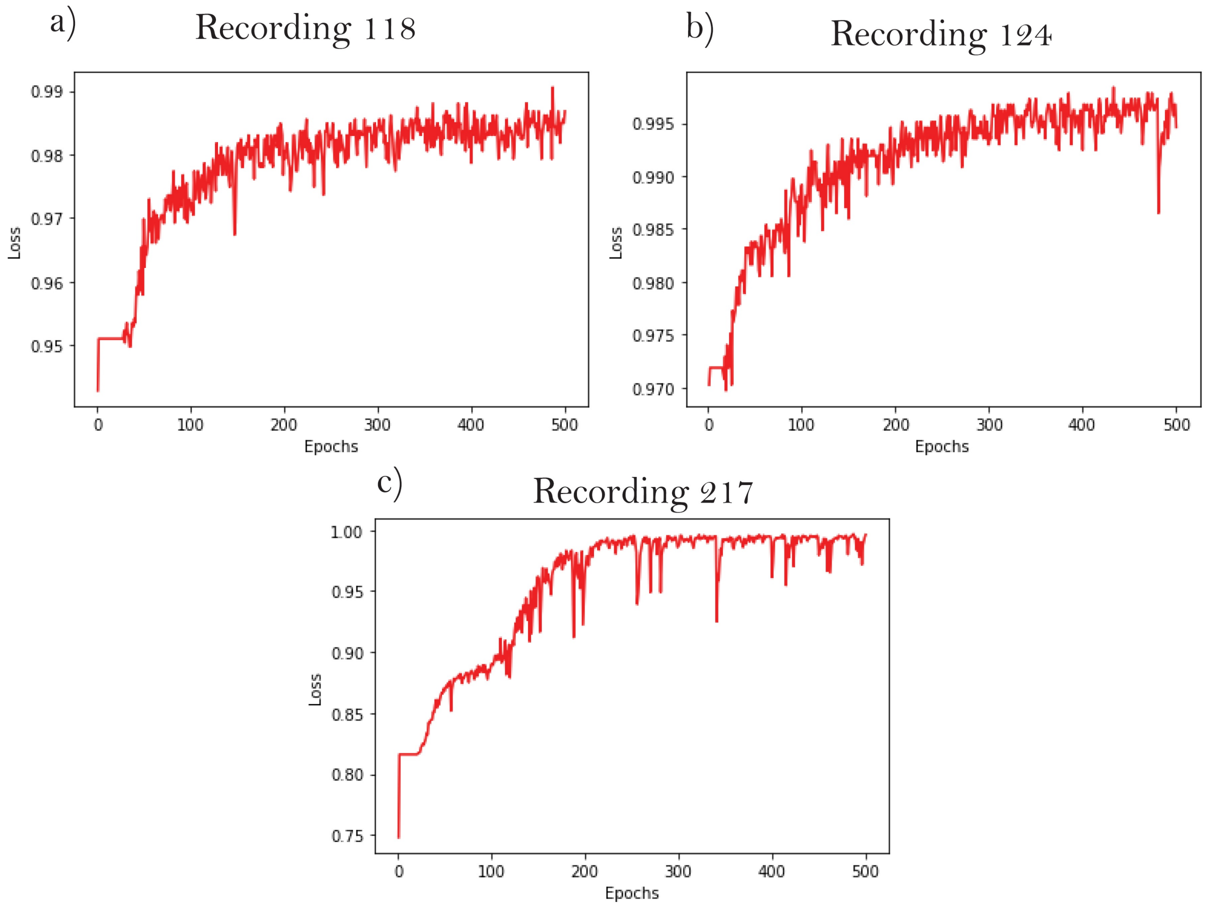

Figure 5.2: Training accuracy of the best experiment with its respective 3 recordings tested: a) recording 118, b) recording 124 and c) recording 217.

5.3 Deep Learning using HNN

Our method offers an accuracy rate of up to 99% using deep learning using a hybrid neuron with CNN and RNN for the same application. Although the existing approaches generally anticipate discriminatory characteristics, our proposed method shows a positive appreciation of the results.

In addition, the following table 5.1 shows the performance of the hybrid neural network structure, using the 3 records of the MIT-BIH arrhythmia database and taking the average of all the records used; The selection criteria of the records is due to the fact that in these three records the data record was obtained with the same medical equipment, they also provide valuable information to be classified in the super classes mentioned in Chapter 2.

Table 5.1: Deep Learning with CNN and RNN Performance

Register	Precision	Recall	fl_score	error	Accuracy
118	97.37319	97.51098	97.31636	0.02781	0.98
124	98.96637	99.11727	99.01582	0.01639	0.99
217	98.78265	98.79154	98.78629	0.01963	0.99
overall	98.37407	98.47326	98.37283	0.02128	0.99

Also, the Table 5.2 compares the performance of the results with other authors who used different classifiers. The records of database recording D were chosen because they have a big variety of data that easily cluster into the superclasses (see Table 3.1), in addition to the records having a considerable and imbalanced variety compared to the other database recordings of the MIT-BIH Arrhythmia.

With machine learning approaches, the ANN methodology is not sophisticated, is of low computing cost and achieves competitive accuracy with earlier studies where more complex and computationally expensive techniques are utilized (see Table 5.2). One of the key benefits achieved from our technique is related to the grouping by superclasses, which makes our neural network cheap computational cost, non-complex, competitive and achieves an accuracy of up to 99% .

Table 5.2: Performance of the results with other authors who used different classifiers.

Author	Year	Method	Accuracy	Reference
Kiranyaz S et al.	2019	CNN	97%	[45]
Zahi X. et al.	2018	CNN	90%	[49]
Rangappa V. et al.	2018	KNN	98%	[53]
Nanjundegowda R. et al.	2018	DNN	98%	[63]
Scire A. et al.	2019	FCB	89%	[64]
Our Method	2022	HNN	99%	

The literature technique was compared to our HNN-based keras dense methodology, which produced encouraging results despite using a more complex neural network than was indicated. Table 5.2 shows that our technique is competitive and yields excellent results while using a simple and affordable computation cost strategy.

Rangappa V. et al. [53] proposed a three-step technique for classifying five different kinds of ECG beats. The PanTompkins algorithm (PTA) was employed in the initial stage to find spikes in the ECG readings. In the second stage, three interval characteristics are extracted and merged with higher-order ECG statistics. The K-Nearest Neighbor (KNN) approach is employed in the third stage to categorize the ECG beats. This method accurately classified heartbeats as normal or abnormal.

The MIT-BHE arrhythmia database, which has a huge collection of ECG signals for both sinus rhythm and arrhythmia rhythm, was one real-world database from which the ECG signal was gathered. The tag values and sinus and normal rhythms that were utilized during testing and training are also stored in the database. The outcomes showed that the proposed technique is up to 98.40% accurate in segregating the signals. The authors note that utilizing different methods, illness stages may be raised and peak detection can be enhanced. Superclasses were expanded and the method was enhanced utilizing deep learning, which was done in this thesis to achieve an accuracy of up to 95%.

The categorization of arrhythmias using the hybrid ECG T wave properties was proposed by Nanjundegowda R. et al. [63]. The three steps of the classification system are feature extraction, windows technique, and classification. Differential entropy (DE), maximum magnitude RMS ratio, and autoregressive feature based on Yule Walker and Burgs technique are only a few of the features that are employed throughout the feature extraction phase. The Deep Neural Network (DNN) classifier was employed during the classification stage. This classifier effectively distinguishes between normal and abnormal data. The experimental findings shown that the proposed classifier outperforms current classifiers like NN and SVM.

The suggested DNN classifier had an accuracy of about 98.33% after 100 iterations. Precision, sensitivity, and specificity are just a few of the assessment measures used to gauge performance in this situation. The objective classification method, which was applied to the current thesis using the superclasses to identify an objective classification with relevant characteristics and give as Result up to 99% accuracy, is used together with the appropriate characteristics in the subsequent work to further improve the accuracy of the classification.

Scire et al. [64] use supervised learning to identify heartbeats and categorize arrhythmias. The system makes use of a window-based function definition that may be executed by an embedded asymmetric multicore processor that has a core specifically designated for hardware-assisted pattern matching. In terms of the accuracy attained in recognizing anomalous occurrences, the authors assessed the system's performance in comparison to a number of other existing systems. According to the results, the suggested embedded system has a high detection rate that, in some cases, is on par with the precision of the newest generation algorithms running on conventional processors. It is therefore suggested that as further work for this thesis, an embedded system that incorporates learning be created. deep and categorize arrhythmias in this manner without requiring a base in between.

The lack of an embedded system for real-time ECG signal identification is one of this research thesis's constraints, necessitating the use of a database for the suggested method to effectively detect cardiac arrhythmias. The suggested system is not user-friendly, meaning that only someone with a basic understanding of Python programming will be able to use the proposed software. As a result, it is incorporated in future work to make the system user-friendly.

Chapter 6

Conclusions and Future Work

6.1 Conclusion

Cardiovascular disease has surpassed all other causes of human morbidity since the beginning of the present decade. Manual analysis is time-consuming, costly, and prone to human error due to the abundance of ECG data. This degree thesis research diagnoses and detects cardiac arrhythmias in long-term ambulatory electrocardiographic recordings using deep learning characteristics derived from a hybrid neural network comprised of two types of neural networks, recurrent neural network and convolutional neural network achieving an optimal balance between performance and computational cost in the diagnosis of cardiac arrhythmias. The method exploits the potential of CNNs and RNNs to represent features, which is a nonlinear dimensionality reduction technique often used in machine learning. Central to this objective are the signal elicitation from the database, signal preprocessing, and signal segmentation. In addition, we evaluate the efficacy of several tactics used to achieve the same aim. As a method for representation learning, our HNN-based algorithm can automatically extract discriminative features from the data. This involves QRS segmentation of the signal using the R peak as a reference. For the purpose of validating this capacity, accuracy scoring is applied and compared to the conventional artificial intelligence methodology to demonstrate that the proposed method is promising.

This thesis degree work concludes by proposing the development of a deep learning approach capable of detecting heart arrhythmia, providing a collection of meaningful beat features (superclasses) that enable successful diagnosis in the study of cardiac arrhythmia. Additionally, a demonstration of the application of deep learning principles to the behavior analysis of biomedical data is made, this model identifies superclasses of cardiac arrhythmia with an accuracy of up to 99 percent. The model presented in this paper compares with some of the techniques already available in the literature, yielding promising findings with accuracy similar to that of conventional methods, in addition, fewer computing resources are required for this method with the best detection performance and lowest computational cost.

6.2 Future Work

Future research will investigate novel characterizations and classification algorithms at the software level, as well as the incorporation of an embedded system at the hardware level. Future software releases will also include ways to improve interpretability and reduce computing costs, making the system more user-friendly.

6.3 Scientific Dissemination

Previous research presented in: The international conference on computational science and its applications (ICCSA 2022). With the work entitle: ”ECG-Based Heartbeat Classification for Arrhythmia Detection Using Artificial Neural Networks”

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Appendices

Appendix

GitHub Repository

All the codes and work carried out for the present research project can be found at the following GitHub repository:

https://github.com/EduardoCepedaM/Deep-Learning-for-ECG

International Conference ICCSA 2022

Certificate of attendance of a previous research presented at: The international conference on computational science and its applications (ICCSA 2022). With the work entitle: ”ECG-Based Heartbeat Classification for Arrhythmia Detection Using Artificial Neural Networks”

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