TIME SERIES CLASSIFICATION USING DEEP NEURAL NETWORKS

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TIME SERIES CLASSIFICATION USING DEEP NEURAL NETWORKS

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I certify that in my opinion the thesis submitted by Sarmad Sami MOHAMMEDALI titled “TIME SERIES CLASSIFICATION USING DEEP NEURAL NETWORKS” is fully adequate in scope and in quality as a thesis for the degree of Master of Science.

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Sarmad Sami MOHAMMEDALI

ABSTRACT

M. Sc. Thesis

TIME SERIES CLASSIFICATION USING DEEP NEURAL NETWORKS

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Karabuk University
Institute of Graduate Programs
The Department of Computer Engineering

Thesis Advisor:
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Electrocardiogram (ECG) is one of the most common and least expensive diagnostic methods used in healthcare facilities to evaluate the heart's electrical impulses. Arrhythmia is a term that refers to abnormal cardiac signals and, in most cases, it can lead to death. Arrhythmias, coming in a variety of forms, can be detected with an ECG test. Therefore, automated methods to classify arrhythmias using ECG beats has been an interesting topic for recent years.

Time series classification plays an important role in medical diagnostics by providing decision assistance for vector-shaped data collected from biomedical sensors. Traditional machine learning methods give a good starting point, but they need more feature extraction procedures and have less accuracy compared to contemporary deep learning approaches. Deep learning architectures have become the golden standard for TSC tasks, providing more accurate results and prompting research into which architecture delivers better results with faster implementation.

The aim of this study is to compare the CNN and LSTM deep learning architectures with classical ANN classifiers using the MIT/BIH Arrhythmia Dataset, a publicly available ECG dataset. The findings reveal that the best accuracy is achieved for CNN architecture used (96.17%), while LSTM resulted in comparable accuracy (94.42%) and traditional ANN (88.98%) is not as accurate as the more recent and complicated architectures. These outcomes indicate that although vector-shaped signals have relatively lower complexity compared to two or more-dimensional data like images, more complicated deep learning architectures outperform the traditional neural networks indicating exploration of high order patterns in one dimensional data improves classification accuracy.

Keywords: Deep learning, Time series classification, ECG classification, CNN, LSTM, ANN.
Science Code : 92431

ÖZET

Yüksek Lisans Tezi

DERİN SİNİR AĞLARI İLE ZAMAN SERİLERİNİN SINIFLANDIRILMASI

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Elektrokardiyogram (EKG), sağlık kuruluşlarında kalbin elektriksel uyarılarını değerlendirmek için kullanılan en yaygın ve en ucuz tanı yöntemlerinden biridir. Aritmi, anormal kardiyak sinyallerini ifade eden bir terimdir ve çoğu durumda ölüme yol açabilir. Çeşitli şekillerde rastlanabilir olan aritmiler bir EKG testi ile tespit edebilir. Bu nedenle EKG atımlarını kullanarak aritmileri sınıflandırmak için otomatik sınıflandırma yöntemleri geliştirmek günümüzde ilgi çekici bir çalışma alanıdır.

Zaman serisi sınıflandırması, biyomedikal sensörlerden toplanan vektör şekilli veriler için karar yardımı sağlayarak tıbbi teşhiste önemli bir rol oynar. Geleneksel makine öğrenimi yöntemleri iyi bir başlangıç noktası sağlar, ancak daha fazla özellik çıkarma prosedürüne ihtiyaç duyarlar ve çağdaş derin öğrenme yaklaşımlarından daha az doğruluğa sahiptirler. Derin öğrenme mimarileri TSC çalışmaları için altın standart haline gelmiş, daha doğru sonuçlar sağlamış ve hangi mimarinin daha hızlı uygulama ile daha iyi sonuçlar verdiğine dair araştırmaları teşvik etmiştir.

Bu çalışmanın amacı, açık kaynaklı bir EKG veri seti olan MIT/BIH Aritmi Veri Kümesini kullanarak CNN ve LSTM derin öğrenme mimarilerini klasik ANN sınıflandırıcılarıyla karşılaştırmaktır. Bulgular, en iyi doğruluğun (%96.17) CNN mimarisi için elde edildiğini, LSTM'nin karşılaştırılabilir doğrulukla (%94.42) sonuçlandığını ve geleneksel ANN'nin (%88.98) daha yeni ve karmaşık mimarilerle rekabet edemediğini ortaya koymaktadır. Bu sonuçlar, vektör şeklindeki sinyallerin, görüntüler gibi iki veya daha fazla boyutlu verilere kıyasla nispeten daha düşük karmaşıklığa sahip olmasına rağmen, daha karmaşık derin öğrenme mimarileri ile daha yüksek doğruluk ile sınıflandırılabildiğini ve geleneksel sinir ağlarından daha iyi performans sağladığını göstermektedir.

Anahtar Kelimeler: Derin öğrenme, Zaman serisi sınıflandırması, EKG sınıflandırması, CNN, LSTM, ANN.

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ABBREVIATIONS

ANN	:	Artificial Neural Network
CNN	:	Convolutional Neural Network
AI	:	Artificial Intelligence
CV	:	Computer Vision
DL	:	Deep Learning
SVM	:	Support Vector Machines
LSTM	:	Long Short-Term Memory
FC	:	Fully Connected Layer
FPS	:	Frame per Second
GPU	:	Graphic Processing Unit
DNN	:	Deep Neural Network
HMI	:	Human Machine Interface
DA	:	Data Augmentation
PV	:	Internal Project Validi
RBBB	:	Right Bundle Branch Block
ECG	:	Electrocardiogram
WHO	:	World Health Organization
1-D	:	One dimensional
2-D	:	Two dimension

PART 1

INTRODUCTION

According to the World Health Organization (WHO), around 17 million people die worldwide each year caused by cardiovascular disease. This represents about 31% of all deaths on the planet. According to the American Heart Association (AHA), cardiovascular disease is responsible for one in three deaths in the United States [1] .

The electrocardiogram (ECG) is a common method for monitoring heart rate and rhythm and can be used to detect many abnormalities and malfunctions in the heart's electrical system [2]. It is a crucial diagnostic tool in cardiology for detecting and analyzing patients' cardiac problems, particularly heart illnesses and life-threatening anomalies such arrhythmias [3]. It appears when the heart fails to adequately pump blood throughout the body [4]. Cardiologists monitor the heart's performance and health via ECG, a record of the electrical actions of the heart, which can be measured by placing electrodes on the skin. The ECG can be represented as time series data [5,6].

Many studies have been conducted on ECG as an input data to classify specific forms of cardiac arrhythmia. These specific cases of arrhythmia, which have been addressed in the majority of past research, are frequently dangerous arrhythmia kinds such as Myocardial Infarction (MI). Cardiac arrhythmia that can be detected in signal level has underpinnings as abnormalities in the heart and is diagnosed by an irregular cardiac rhythm. These abnormalities produce structural variances in the atria and ventricles, resulting in alterations in activation, depolarization and repolarization. ECG waveform deviates from its normal shape and size as a result of these modifications. Different forms of cardiac arrhythmia are induced by several reasons, resulting in different abnormalities in the ECG wave shape [7-9].

Arrhythmia can manifest as slow, fast or irregular heartbeat, which can be divided into life-threatening and non-life-threatening [10,11]. The diagnosis of arrhythmia is based on the identification of normal and abnormal individual heartbeats on the ECG, and accurate annotations based on the shape of the ECG. According to the Association for the Advancement of Medical Devices (AAMI) non-life-threatening arrhythmias can be divided into 5 main categories: non-ectopic (N), supraventricular (S), external (V), fusion (F), and unknown (Q) [12].

Time series classification (TSC) is a complex data mining activity that can be used in a range of real-world circumstances including medical diagnosis [13,14], recognizing human activities [15,16] categorization of sound [17] cybersecurity [18] etc. Time series data can be found in one-dimensional or multi-dimensional space and can be sampled for regular or irregular intervals [19]. Medical diagnosis is an important area of TSC that deals with human life decision support. Machine learning approaches such as multi-layered cognition, decision trees, random forests, support vector machines and deep learning (DL) architectures can be used to diagnose heart disease, a major cause of death in humans. Long-short term memory (LSTM), recurrent neural network (RNN), convolutional neural network (CNN), and their recent competitors are examples of deep learning architectures [20].

Traditional machine learning algorithms for ECG classification rely on feature extraction procedures, however deep learning architectures allow for more flexible applications that learn more signal-related properties [21]. In DL architectures, the first layers of convolutional neurons operate as feature extractors, with the succeeding fully connected layers (FCN) make the ultimate decision on ECG classes. These models deal with more variables than typical machine learning models, necessitating more memory and computing power [22]. Today's increasing computer capabilities support the use of deep learning architectures that deliver higher accuracy, but the optimal complexity for these models remains as a question.

CNN architectures have been used to detect normal and MI with a 95.22% accuracy [23]. Moreover, an accuracy of 84.54% in detecting inferior MI in ECG is acquired with a custom CNN architecture [24]. With the MIT-BIH dataset as input, four forms of arrhythmia were diagnosed with an accuracy of 99.38% by Mohammadzadeh-Asl et al [25]. Vishwa et al. used an artificial neural network (ANN) to classify the MIT Arrhythmia database of ECG into normal and pathological, with an accuracy of 96.77% [26].

The objective of this thesis is to develop a medical diagnosis model that will aid professional cardiologists by supplying information for the diagnosis of arrhythmia in a smart, cost-effective and time-saving manner. To achieve this goal, traditional ECG signal processing techniques are implemented along with the latest moderate-complexity deep learning methods to identify patterns of arrhythmia. The proposed system can recognize arrhythmia traced as a right bundle branch block (RBBB) from normal (healthy) walking and heartbeat. Among them, the normal heartbeat is the electrical waveform of the heart of a healthy adult; the rhythm beats are the artificial pulse from a device called a pacemaker. RBBB is an arrhythmia often associated with ischemic heart disease, hypertension, rheumatism, pulmonary, right ventricular hypertrophy, and toxicity of certain ECG waveform drugs. QRS lasts from 0.10 to 0.11 seconds (RBBB incomplete) or 0.12 seconds or more (RBBB complete), Prolonged ventricular activation time or rapid response time (0.03 s or more) and right axis deviation (see Figure 1 for typical waveforms) [27]. However, in addition to this, it is very simple to extend the method to categorize different types of arrhythmias.

This study investigates how the low-complexity ANN model competes with more recent architectures such as CNN and LSTM for time-series classification, to classify ECG data. Data from the MIT-BIH Standardized Arrhythmia Database are used for comparison, while performance is set as classification accuracy for the corresponding models. The remainder of the thesis is arranged as follows. General information about the dataset along with the proposed model structures are presented in Section 3, while the results are presented and discussed in Sections 4 and 5. In the last section, a conclusion is drawn.

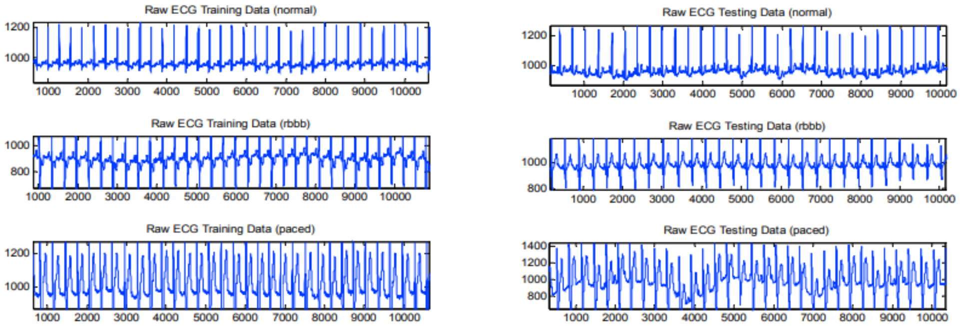

Figure 1.1. The example of different ECG recordings.

1.1. MOTIVATION

Artificial intelligence (AI) is a term used to describe systems or technologies that are designed to replicate human intelligence in carrying out goals based on information gathered from problem environments. Artificial intelligence uses machines and deep learning to enhance human capabilities in various fields. Many experiments have been conducted to develop artificial intelligence models that aim to assist human in various medical work.

Among the medical problems enhanced by artificial intelligence is the classification of medical images such as ECGs [28,29]. The ECG is also a non-invasive diagnosis, providing recordings of the heartbeat by which doctors can identify critical heart rhythms that can cause serious conditions or even death. The classic visual interpretation of an ECG can be slow and error-prone. Therefore, in recent years, a lot of studies have focused on the development of automated classifiers, a portion of it dealing with arrhythmias.

1.2. PROBLEM STATEMENT

The task of classifying the current electrocardiogram can be described as a task to determine the category to which the electrocardiogram can be assigned to a patient with arrhythmia.

- Arrhythmia is caused by a defect in the electrical mechanism of the heart.

- Cardiologists and medical practitioners manually analyze the pattern and variance in the ECG data and annotate the notes.
- Manual analysis of the ECG signal lies in the difficulty of detecting the different patterns and formations in the signal.
- As a result, a more accurate and cost-effective diagnosis of arrhythmia is required.
- In this thesis, we look at a method for classifying heartbeats using artificial intelligence techniques (using the lead, especially the use of a deep neural network).

To classify a person whether their heartbeat is regular or not, several tests are required, some of which are expensive and time-consuming. To classify arrhythmias, careful analysis of the ECG signal is required, which requires experienced doctors. In some cases, regardless of their experience and expertise, there can be some errors [30]. Deep learning models are used to classify arrhythmias with high accuracy and low error rate in this thesis. Various activation functions and deep learning methods are investigated.

This research attempts to answer the following questions covering data acquisition:
(a) How will the CNN, ANN, and LSTM models perform in grading arrhythmias for the MIT-BIH dataset?
(b) What library should be used with Python for better performance?
(c) How do the well-known deep learning architectures CNN and LSTM compare with traditional ANN?

We must evaluate the performance of the CNN, LSTM and ANN models in the classification of arrhythmias to be able to answer this research question.

1.3. AIMS OF THE STUDY

The main purpose of this thesis is to create a deep neural network (DNN) that can detect and analyze arrhythmias. The use of machine and deep learning approaches is part of the scope of this project. The key goals of this research project are as follows:

- To see if arrhythmia categorization approaches can be used in a practical way.
- To provide an overview of present research studies based on the benefits of arrhythmia categorization and future research directions.
- Based on arrhythmia classification, determine the most recent research trends and publishing interests. Study the heart rate in different arrhythmias and create a new electrical force to predict the heartbeat using deep learning techniques (using CNN, ANN and LSTM).
- Evaluation of CNN, LSTM and ANN models on the MIT-BIH time series dataset. To classify arrhythmias with a high degree of accuracy without any preprocessing other than normalization and data optimization.

This study aims to present a comparison of the well-known deep learning architectures CNN and LSTM in comparison with traditional ANN, and to apply these classifiers to MIT/BIH arrhythmia database, a freely accessible dataset including ECG recordings.

1.4. THESIS STRUCTURE

Part 1. Introduction: Contains the background, motivation, and problem statement. It also describes the aims of this study.

Part 2. Related Work: Surveys related work, highlights some of the previous work and research done in our problem area. Describes some introductory background needed for this thesis.

Part 3. Methodology: Methods used for ECG classification are described. In particular, we explain the neural network models used in this project. This section also presents the steps for classifying arrhythmias using CNN, ANN, and LSTM.

Part 4. Results and Discussion: Carefully evaluates the success of the deep learning methods employed. Comparisons are also provided to assess the optimal classifier.

Part 5. Conclusions: We provide a summary and conclusion of the results obtained in this thesis, as well as its contributions. The same part offers a short description of potential future work.

PART 2

RELATED WORK

This study focuses on detecting arrhythmias with CNN, ANN and LSTM architectures. Recently, CNNs have achieved high performance in many areas of natural language processing. We survey the most recent research and projects linked to our work in this section.

Refahi et al. use the least squares twin support vector machine, which is unlike a normal support vector machine, that is based on a non-parallel margin and gives better results compared to recent methods also running faster for diagnosing arrhythmia [31]. Singh et al. used Recurrent Neural Networks (RNN) for categorizing the abnormal and normal pulses in ECG. The main purpose of their study was to enhance the automatic distinction of irregular and regular pulses. The database MIT-BIH Arrhythmia database was used for performance categorization [32].

Zubair et al. introduced an ECG pulse categorization system by using convolutional neural networks (CNNs). The proposed model combines two basic parts, feature extraction and classification of ECG recordings. The model learnt a suitable feature extraction automatically from the raw ECG data and as a result, hand-crafted features are no longer required for efficiently categorization of ECG pulses into some classes specified by the AAMI, by using a small selection of patient-specific training data. [33].

He et al. proposed some algorithms for automatic classification of arrhythmias based on ECG data, as well as a new deep neural network-based method for automatic classification of system disturbances with deep neural networks (DNN). Two DNN models with convolution units and two-way LSTM layers were trained to extract features from raw ECG data. The obtained data is merged into a trait vector, which is then trained to perform the final classification. The algorithm is assessed using the Chinese Physiological Dataset (CPSC) test set, with F1 calculated as the harmonic mean of accuracy and recall.The overall F1 score is 0.806, with an FAF score (F-score for atrial fibrillance) of 0.914, an FBlock score of 0.879 for block segments, and FPC and FST ratings of 0.801 and 0.742 for premature contraction and ST segment shift, respectively, indicating acceptable performances [34].

Huda et al. introduced a low-cost, low-power wireless ECG monitoring system with arrhythmia detection based on autonomous learning. The flexible, fabric-based structure of the gadget, as well as its wearable nature, enables continuous monitoring while also enhancing patient comfort. The AD8232 chip is used in the ECG Analog FrontEnd (AFE), which is powered by two 450mph Li-ion batteries. The ECG signal can be sent through Bluetooth to a smart device and then to a cloud server for analysis. A deep learning model based on a one-dimensional convolutional neural network (CNN) was built in the MIT-BIH Arrhythmia database, with an accuracy of 94.03% in classifying aberrant cardiac rhythms. [35].

Wang and Li devised an automated technique for detecting the ECG signal in the diagnosis of arrhythmia. In their study, they design, build and compare an automated system that categorizes the normal sinus atrial fibrillation and other noisy signals using two distinct frameworks that integrate convolutional neural networks (CNN) with long-term memory (LSTM). Using the MIT-BIT arrhythmia dataset, their method yielded an F1 weighted score of 82%, indicating that sequencing of the two deep learning networks outperformed sequencing. Experimental results show that the CNN and LSTM series can successfully identify the ECG signals [36].

Xu et al. developed an automated arrhythmia detection model with a deep learning framework to accelerate arrhythmia diagnosis with a high degree of accuracy. They propose a new model for automatic detection of arrhythmias using a combination of a one-dimensional convolutional neural network (1D-CNN) and a repeating unit network (GRU) to diagnose five different heart rhythm disorders in ECG signals from MIT-BIH arrhythmia dataset. The proposed system exhibited high grading performance in processing variable length ECG signal data, achieving 99.45%

accuracy, 98.35% sensitivity and 99.21% specificity, and 98.95% F1-score using five-fold validation strategy. The combination of 1D-CNN and GRU networks resulted in a higher degree of accuracy compared to other deep learning networks. The proposed arrhythmia detection method has a potential to help clinicians accurately detect common arrhythmias in routine ECG testing [37].

Huang and Wu used a convolutional neural network to develop a computer-aided diagnostic (CAD) system for identifying atrial fibrillation and normal sinus rhythm from ECG readings. The proposed method considers a single heartbeat rather than a record with predefined length of seconds. Instead of the one-dimensional digital ECG output used in previous studies, this study uses convolutional neural networks to analyze the two-dimensional ECG image. The purpose of this investigation is to see if signal jitter is required for a 2D image ECG. With an accuracy of 99.23%, a sensitivity of 99.71%, and a specificity of 98.66%, the final classification produces inverted ECG signals. In unfiltered ECG signals, the best result achieves 99.18% accuracy, 99.31% sensitivity, and 99.03% specificity. The proposed CAD system has a high degree of generalizability, while it can assist clinicians in accurately diagnosing diseases and reducing misdiagnosis [38].

Zhang et al proposed a new hybrid network that integrates the convolutional neural network, long-term memory, and an attentional mechanism in their study. To assess the model provided in their study, they employed three indicators published by the Society for the Advancement of Medical Devices. The average accuracy was 99.81%, the average sensitivity was 99.36%, and the average accuracy was 99.78% after training and verifying arrhythmia data from the MIT-BIH database. As a result, they could infer that the model developed in their study could successfully assist doctors in detecting common arrhythmias during ECG evaluation [39].

Ramesh et al. offered a new way for combining several features derived from a signal using various methods while avoiding neural networks. Multiple characteristics are made up entirely of morphological, temporal, and statistical features. Each ECG signal was first preprocessed to remove the baseline before being segmented using a basic method. Furthermore, three different sets of characteristics were recovered for each heartbeat segment. The morphological features were recovered using a two-tree composite wavelet transform, while the rest were extracted using statistical measurements. In addition, principal component analysis was used to reduce the dimensionality of the set of morphological traits. Finally, a convolutional neural network classifier was used to predict the label for a particular input heartbeat using the composite and final feature vector. Simulation trials using the MIT-BIH benchmark database revealed that the suggested system had a classification accuracy of 98% on average. The improvement was roughly 5% when compared to the most recent approaches [40].

We also present the brief list of the related work mentioned in this sectin in Table 2.1 for the readers' reference.

Table 2.1 Recent studies handling cardiac arrhythmia disorder.

Authors	Methods	Accuracy
Refahi et al. [31]	SVM	91.10 %
Singh et al. [32]	LSTM	88.1 %
Zubair et al. [33]	CNN	92.7 %
He et al. [34]	DNN	92.07 %
Huda et al. [35]	CNN	94.03 %
Wang, Li [36]	CNN feed LSTM	97.8%
Xu et al. [37]	CNN-GRU	99.45%
Huang, Wu [38]	2D-CNN	99.23%
Zhang [39]	CNN-LSTM	99.81%
Ramesh et al. [40]	DTCWT-CNN	98%

PART 3

METHODOLOGY

3.1. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks do calculations in units known as artificial neurons that are dispersed over the network in layers, inspired by human brains. The external field or the previous's output layer's neuron can be to use to collect input from the specific neuron. To determine a neuron's output, all aggregated inputs are weighted, multiplied by a value assigned to each input, and then summed before being passed through a nonlinear function called the activation function, as shown in Figure 3.1. This nonlinearity allows for a more versatile output that can identify more complicated features. However, an additional value can be added to the neuron's input to provide bias to the computations, when needed, known as bias [41,42].

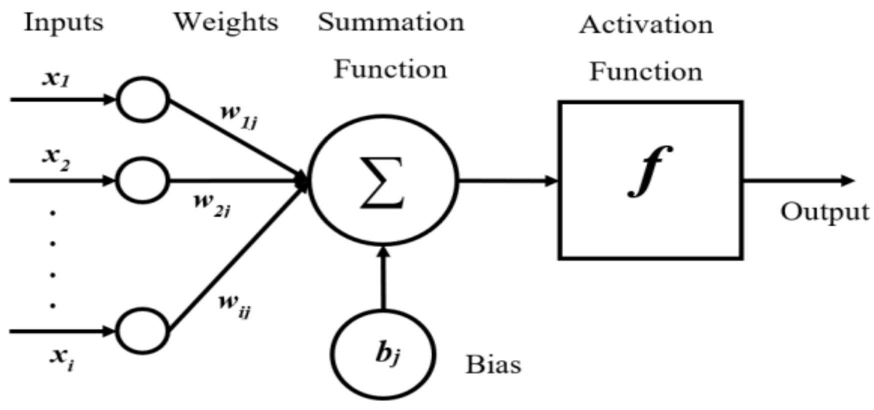

Figure 3.1. Illustration of the computations inside an artificial neuron [41].

Regardless of the type of the ANN, each of these networks has two types of computations, one executed The forward direction is defined as the direction from the input to the output pass, while the other is executed in the opposite direction, known as the reverse pass [43]. The forward pass is used to calculate the output of the network, based on its inputs, by calculating the output of each layer and use in the computations executed in the second one. In the reverse pass, the weights' values are updated through gradient descent. By measuring the deviation between the output of the ANN from the forward pass, and the intended output values from the dataset, the derivatives of the output to the weights are calculated. Gradient descent is used to recognize the position weights' value that must be updated to reduce the error, which is to the negative of the gradient descent at that position. Such an update allows the neural network to produce the intended output from the inputted values, hence, achieve the required task. By repeating this process for several iterations, the loss between the output from the forward pass and the intended output is reduced using backpropagation, which improves the performance of the neural network, until the minimum loss is reached [44,45].

3.2. RECURRENT NEURAL NETWORK (RNN)

Similar to CNNs, recurrent neural networks can handle two-dimensional inputs and output a single value per each set of inputs. However, the approach RNNs use to process these inputs is different, where the output from a previous input tuple is weighted and appended to the inputs collected from the previous layer, or the external domain. As shown in Figure 3.2, a weight value f is used to adjust the value of the output from the tuple previous to the current tuple positioned at t. During the computations of the output of the neuron at t, the output h from t-1 is included after being weighted using f. The output at this t tuple is also weighted using f and included with the inputs x of the next tuple at t+1. This process is repeated until all the tuples in the input set are processed [46,47].

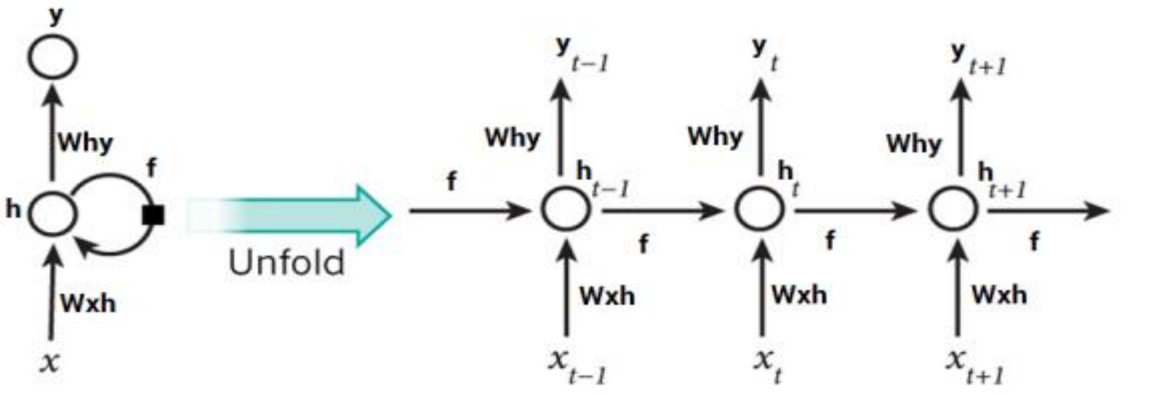

Figure 3.2. Computations in an RNN neuron.

According to the ability of RNNs to include outputs calculated from previous tuples in the computations of the current one, this type of neural networks is widely used in time series and natural language processing (NLP) applications. A phrase can be analyzed according to the effect of each word in that phrase and its position. For instance, the output of processing a negative word, such as not, can be combined with the inputs of the next word, so that the meaning of that word can be inverted. Moreover, errors can be detected by recognizing wrong combinations, when a word following another is in wrong formation, depending on the definition of the suitable form in the grammar [48,49].

3.3. LONG- SHORT-TERM MEMORY

As illustrated in the previous section, the effect of a certain output from the neuron is relative to the position of the tuple being inputted to the network, with respect to the one being processed in this instance. At instance t, the output from t-1 has more influence on the current output than that from t-2. However, in many applications including NLP, such behavior can be of significant importance in certain conditions, and of negative influence in other. Thus, a more complicated type of RNNs is being used in these applications, where the influence of a certain output is adjusted according to its importance in the current computations, rather than its position in the series. [50].

To achieve such a task, Long-Short Term Memory (LSTM) networks use gates to control the flow of the values between the input and the output. Each gate is controlled using a separate network that accepts inputs from certain position. As shown in Figure 3.3, netc is the input network that receives the values from the external domain and calculates the outputs depending on its weights. Another network netin receives a copy of these inputs in order to control the gate that defines the flow of the output from netc, through the input gate value yin. The effect of the previous output is adjusted using the forget gate values $y\phi$, which is controlled using netϕ. This output Sc is squashed using an activation function before being adjusted using the values yout acquired from the output gate, which is controlled using netout that calculates the values of the gate using the outputs collected from the previous time instance. As each gate is controlled using a different neural network, the weights of each neural network are updated during the training of the networks, so that, the appropriate decision is made based on the input values of the current time instance and the outputs collected from the previous ones [51].

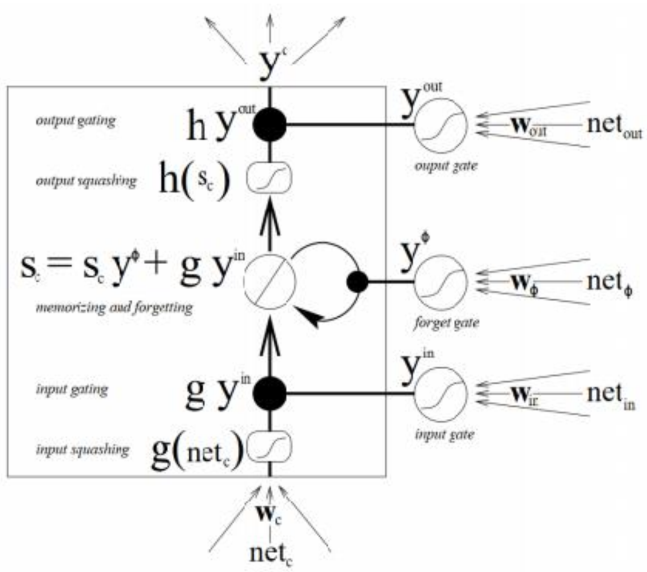

Figure 3.3. Illustration of the data flow in an LSTM neural network [51].

3.4. CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNNs) are used quite frequently in time series prediction, especially in long series. This is because CNN can model complex nonlinear models and self-adapt to the data. CNNs are universal estimators that are used in many learning tasks, and this characteristic is strongly dependent to the configuration of the network structure. A brief illustration of a CNN model is given in Figure 3.4, that is tuned for an ECG classification task.

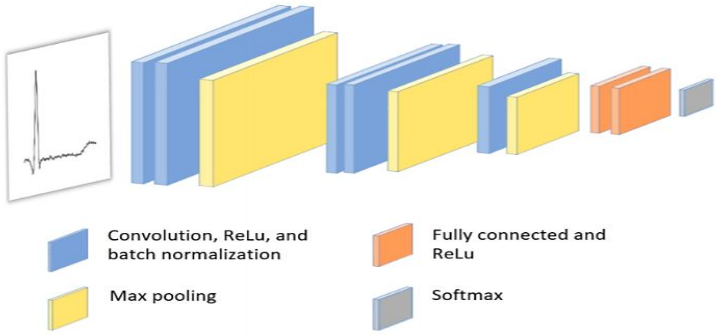

Figure 3.4. CNN model layered architecture for an ECG signal.

3.4.1. Convolutional Layers

Convolution is the mathematical process of merging two functions to create a third function. Two pieces of data are joined when this happens. In CNNs, a convolutional layer (also called as a filter or kernel) is used to generate a feature map from the input data [52].

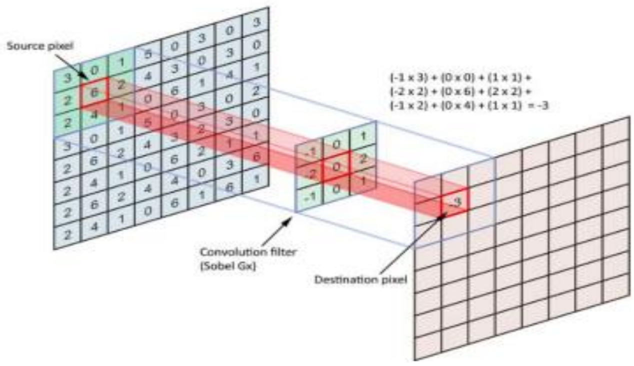

Figure 3.5. The filter is slide over the input and its output is performed on the new layer in a convolution process [52].

A dot product multiplication is performed in Figure 3.5 between a 3x3 filter matrix and a 3x3 section of the input image's matrix. The output value on the feature map is the sum of the components of the generated matrix.

3.4.2. Pooling Layers

The recovered feature sets are then sent to the pooling layer, which is one of the fundamental CNN layers. Depending on the application, pooling may compute the maximum or average. In this layer, images are shrunk down while maintaining the most significant information they carry. The dimensions of the data are reduced by the pooling layer, and the max-pooling layer also preserves the maximum value from each window[53,54] as shown in Figure 3.6.

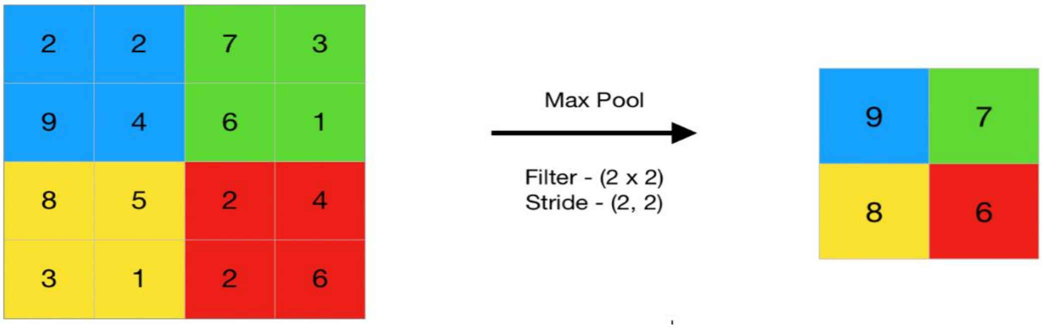

Figure 3.6. The representation of the max-pooling process [53].

3.4.3. Fully Connected Layers (FC)

The fully connected layer is the final layer. Every neuron in the previous layer is connected to every neuron in the next layer. One of the aspects of a CNN is the FC layer, which classifies the features obtained from other layers [55]. The fully connected layer with input and output layers is shown in Figure 3.7.

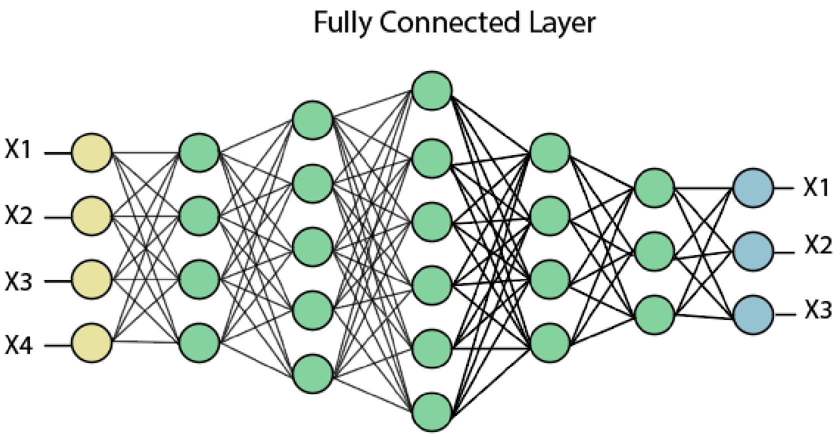

Figure 3.7. The operation of the fully connected layer.

3.4.4. Activation Functions

These functions provide non-linearity, which makes deep neural network learning easier. They also enable the learning process to deal with more difficult challenges. [56] . The systems may be tested with different activations, such as Hyperbolic Tangent (Tanh), Softmax, Exponential Linear Unit (ELU), Sigmoid, and Rectified Linear Unit (ReLU). A SoftMax activation function is used in the CNN model used in this study [57].

3.4.5. Batch Size

The number of training instances used before updating the model is referred to as a batch size. The technique is more efficient with larger batch sizes. With a small number of epochs, smaller batches function better. Larger batches, on the other hand, have more generalizations.

3.4.6. Early Stopping

This technique is one of the regularization forms, that can be used to monitor the loss to prevent overfitting on the validation set. By using early stopping, the process would be interrupted when the loss will increase inside the model [58].

3.4.7. Loss Function

The loss function is a technique to measure the performance of the network model on the labeled data. Cross-entropy and mean squared error (MSE) are both common loss functions. They define the quality of the prediction process together with the classification accuracy metrics [59].

3.4.8. Dropout Learning

In some approaches to deep neural network architecture, there is a tendency toward overfitting. This can bring about a bad shortage of samples. Dropout learning is a way to solve this issue. The dropout is a technique that has been used to prevent or reduce overfitting and improving performances [60,61].

The idea is very straightforward and profoundly successful: in each training cycle, a concealed unit is arbitrarily eliminated with a predefined likelihood (i.e. 50%), and the learning technique proceeds normally. Usually, the dropout is used after the pooling layer, also can be used after convolution layer. The dropout strategy is showed in Figure 3.8. We used a dropout of 0.4 units in this study.

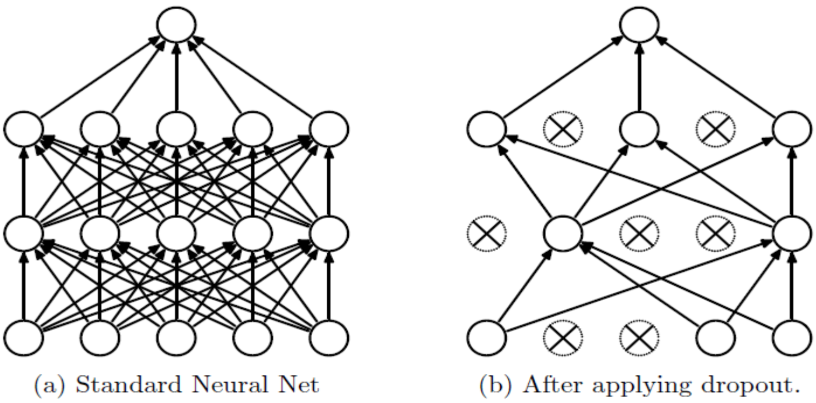

Figure 3.8. The dropout function illustrated.

3.5. MEASUREMENT AND EVALUATION

Evaluation is a process of describing corrected classification of objects (dataset) by the classifier, or to explain the accuracy of classification, and it is one of the most important components of any experiment (Confusion matrix, Accuracy, precision, recall, f1-score, ...etc).

In our study, we relied on evaluating deep learning techniques using the following scales: accuracy, specificity, sensitivity, accuracy, F-score, and recall. Basic parameters used to evaluate these metrics are explained below:

True Positives (TP): Number of correctly identified instances.
False Positives (FP): Number of incorrectly identified instances.
True Negatives (TN): Number of correctly rejected instances.
False Negatives (FN): Number of incorrectly rejected instances.

The performance measures are detailed in equations 3.1 to 3.6 as below:

Accuracy: The amount of correctly predicted classes out of a total of classes is referred to as accuracy.

$$\text{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+FN+TN}} \tag{3.1}$$

Precision: The ratio of correctly predicted values to the total number of values in a category is defined as.

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{3.2}$$

Sensitivity (Recall): The ratio of successfully identified values in a class to total values predicted in that class is known as recall or sensitivity.

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{3.3}$$

Specificity: The genuine negative rate is known as specificity (i.e., the proportion of negative tuples that are correctly identified).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \tag{3.4}$$

Detection Error Rate (DER): In a given class, the DER value is the ratio of total misclassified items to correctly classified values.

$$\text{DER} = \frac{\text{FP+FN}}{\text{TP}} \tag{3.5}$$

F-Score: The F-Score or F-Measure is the harmonic mean of precision and recall.

$$\text{F-score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Recall+Precision}} \tag{3.6}$$

3.6. DATASET DETAILS

A supervised learning dataset, known as MIT-BIH Arrhythmia Dataset is employed as a benchmark for this study [24,58]. As suggested by the AAMI, the dataset is labeled into five classes as: normal (N-0), supraventricular ectopic beat (S-1), ventricular ectopic beat (V-2), fusion (F-3), and undetermined (Q-4). Each signal in the database contains a 30-minute segment selected from 24-hour recordings of the 48-individuals, while the continuous signals are filtered over the 0.1 to 100 Hz range and then digitized at 360 Hz. Since 4 of these recordings dominantly contain paced beats, they are excluded from the learning procedure due to AAMI recommendation, because of low signal quality [59]. Therefore, the classification procedures are run over the remaining 44 recordings from the MIT-BIH arrhythmia database. A sample cardiac cycle is given in Figure 3.9.

+

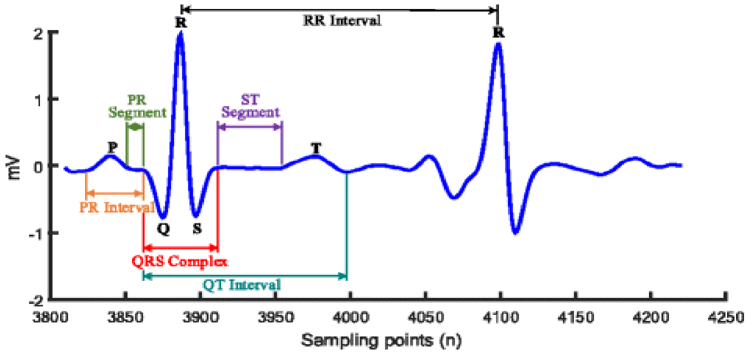

Figure 2.9. Typical heartbeats from the MIT-BIH arrhythmia database [64].

In the MIT-BIH Arrhythmia dataset, we have a total of 87,544 samples for training data and 21,892 samples for test data. Each sample consists of a time series of 187 variables [65,66]. We encoded the ".dat" files and categorized them as the above annotations. The dataset is divided into 60% training, 10% test, and 30% validation sets.

The original classes N, Q, V, S and F constitute the training set with ratios of 82.8%, 7.3%, 6.6%, 2.5%, and 0.7%, respectively. Figure 3.10 shows the percentages of ECG classes within the training set, while Table 3.1 shows the number of samples for each class. To evaluate the performance of the proposed model considering balanced categories, we choose to generate synthetic data using a smoothing procedure that uses random sampling with replacement. Thus, each category of reinforcement training data has 72,471 signals. The number of samples for the test set are also given in Table 3.2.

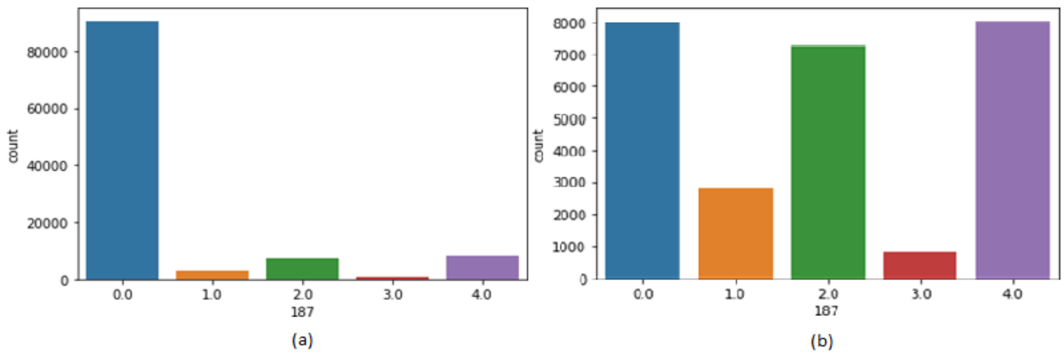

Figure 3.10. a) shows the training set with percentages of 82.8%, 7.3%, 6.6%, 2.5%, and 0.7%, respectively for classes N, Q, V, S, and F. b)We generate synthetic data using a smoothing procedure that uses random sampling with replacement. The resulting counts of samples are given in the right panel.

Table 1.1. The distribution of ECG classes within the training set.

CLASS	CATEGORY	No of Samples(Train data)
0	N	72,471
1	S	2,223
2	V	5,788
3	F	641
4	Q	6,431

Table 2.2. The distribution of ECG classes within the testing set.

CLASS	CATEGORY	No of Samples(testing data)
0	N	18,118
1	S	556
2	V	1,448
3	F	162
4	Q	1,608

3.7. PREPROCESSING

Normalization was performed before to the categorization and the augmentation steps. The dataset was normalized with the Scikit-Learn normalizer package, which converted numeric columns to a common scale of 0 to 1 without distorting the range of values. After that, NumPy library methods like squeeze, stretch, and amplify are used to enhance the samples, yielding a dataset of 2686 samples. The dataset is then split into ten percent test and thirty percent validation, yielding a 60:30:10 split ratio. The whole preprocessing flowchart is presented in Fig. 3.11.

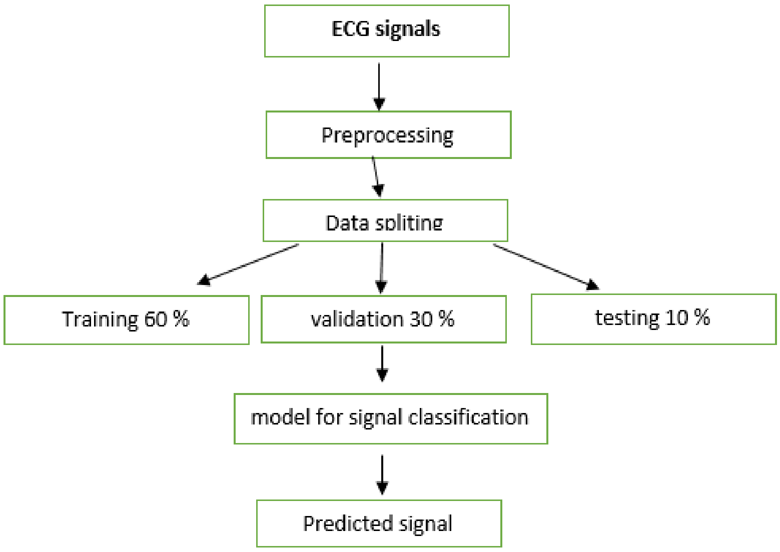

Figure 4.11. Flowchart for the model evaluation.

3.8. CLASSIFIER MODELS

Computer systems' intelligent behavior is aided by artificial intelligence. The software can learn itself in machine learning, but the learning characteristics must be established and trained appropriately by the programmer. Deep learning, on the other hand, makes use of more mathematics, neural networks, and computations to allow the computer to recognize better traits and produce accurate and valuable results [67].

In this study, three learner models are employed as CNN, LSTM, and ANN, aiming at providing a comparison with ANN, LSTM, and CNN models under a multiclass classification task for ECG signals. Corresponding model architectures are given in Tables 3.3 to 3.5. To match the vector-formatted ECG signals, a 1-D CNN model is proposed, while LSTM and ANN models are more compatible with this signal format. In common usage, CNN models handle 2-D classification tasks generally dealing with images, while special cases like single-channel time series require 1-D implementation of this well-known model.

ANNs, as a component of A computer system that analyzes and processes data in the same way that the human brain does, is assumed as an important milestone of artificial intelligence (AI) studies. It facilitates solving problems that are difficult to solve by human or statistical processes. CNN's are neural networks with one or more convolutional layers that are commonly used for image processing, classification, segmentation, and other autocorrelated data. In the realm of deep learning, LSTM is an artificial recurrent neural network (RNN) architecture. Because time series data contains lags of undetermined duration, LSTM networks are well-suited to categorizing, analyzing, and making predictions based on them.

As presented in Tables 3.3 to 3.5, the CNN model is more complicated compared to LSTM and ANN. The focus of this study is to determine if the TSC task on the MIT-BIH arrhythmia database requires the high complexity of the learning model. The high-end of this complexity spectrum is represented by CNN, while LSTM and ANN demonstrate the low-end complexity.

Table 3.3. Summary of the 1-D CNN model.

Layer (type)	**Output Shape**	**Param #**
conv1d (Conv1D)	(None, 187, 64)	768
batch_normalization	(None, 187, 64)	256
max_pooling1d (MaxPooling1D)	(None, 94, 64)	0
conv1d_1 (Conv1D)	(None, 94, 256)	82176
dropout (Dropout)	(None, 94, 256)	0
max_pooling1d_1 (MaxPooling1	(None, 47, 256)	0
conv1d_2 (Conv1D)	(None, 47, 384)	295296
dropout_1 (Dropout)	(None, 47, 384)	0
conv1d_3 (Conv1D)	(None, 47, 256)	295168
max_pooling1d_2 (MaxPooling1	(None, 24, 256)	0
dropout_2 (Dropout)	(None, 24, 256)	0
batch_normalization_1 (Batch	(None, 24, 256)	1024
flatten (Flatten)	(None, 6144)	0
dense (Dense)	(None, 50)	307250
dropout_3 (Dropout)	(None, 50)	0
dense_1 (Dense)	(None, 50)	2550
dropout_4 (Dropout)	(None, 50)	0
dense_2 (Dense)	(None, 5)	255
Total params: 984,743		
Trainable params: 984,103		

As previously stated, the five classes of arrhythmia were retrieved from the database, and then a typical 1-D CNN model was used to train the arrhythmia classifier model. This model consists of a 1D convolution of 11 filters with channel sizes of 64, 256,384, and 256 in a row. A maximum pooling layer of 2 and a dropout ratio of 0.5 were used. There are three fully connected layers of sizes 50, 50, and 5 respectively. All ReLU activation was utilized in the convolutional and fully connected layers, whereas softmax activation was employed in the final output layer. To improve CNN parameters, we used Adam's optimizer and it's trained as a 300 epochs model with early stop.

In order to train the arrhythmia classifier model, as mentioned earlier, the five categories of arrhythmias were extracted from the database and then a standard LSTM model was used. This model consists of a wrapper of a 64 filter with channel sizes 64, 32 and 64 respectively with a droupout ratio of 0.5 applied. There is a fully connected layer of size 5 in a row. ReLU activations was utilized in the convolutional and fully connected layers, however sigmoid activation was employed in the final output layer. To improve the parameters of the LSTM, it was trained as a 300 epochs model with early stop.

Table 4.4. Summary of the LSTM model.

Layer (type)	**Output Shap**	**Param #**
lstm (LSTM)	(None, 187, 64)	16896
dense (Dense)	(None, 187, 32)	2080
lstm_1 (LSTM)	(None, 64)	24832
dense_1 (Dense)	(None, 5)	325
Total params:44,133		
Trainable params :44,133		

Table 5.5. Summary of the ANN model.

Layer (type)	**Output Shap**	**Param #**
dense_9 (Dense)	(None, 187, 64)	128
dropout_12 (Dropout)	(None, 187, 64)	0
dense_10 (Dense)	(None, 187, 32)	2080
dropout_13 (Dropout)	(None, 187, 32)	0
flatten_3 (Flatten)	(None, 5984)	0
dense_11 (Dense)	(None, 5)	29925
Total params: 32,133		
Trainable params: 32,133		

As previously stated, to train the arrhythmia classification model, the five categories of arrhythmias were extracted from the database, and then the ANN model was used. This model consists of 64, 32, and 5 channel sizes, respectively. The dropout rate is 0.5. ReLU activation functions were utilized in the convolutional and fully connected layers, whereas softmax activation was employed in the final output layer. To optimize the parameters of the ANN, it has been trained as 50 epochs.

3.9. IMPLEMENTATION OF THE MODELS

The Keras and Scikit-Learn libraries for Google Colab were used for deep learning-related computations. The model was trained on Google Colab, where CNN and LSTM models were trained with 300 epochs and ANN with 50 epochs with the use of early stop. The softmax product of the cross-entropy loss is the loss function. The model employs the Adam optimizer with a learning rate of 0.0001 in each iteration, and the learning rate is exponentially decomposed by a factor of 0.2 every 300 epoch for CNN and LSTM, and 50 epoch for ANN.

PART 4

RESULTS AND DISCUSSION

4.1. CLASSIFICATION RESULTS

The classification results show that the proposed CNN model outperforms the LSTM and ANN models throughout this dataset, achieving the best accuracy score of 96.17%. This is an indicator that neural network models with less complexity fail to outperform the proposed 1-D CNN model. The precision and loss curves for this model are shown in Fig. 4.1. Having run the training procedure for 300 epochs, the early-stop function was triggered after the 124th epoch which gave the best result as 0.9617 for this setup. Table 4.1 presents all the metrics related to the classification task in detail.

Table 6.1.Summary of the results for the CNN model.

Metric	Value
Accuracy	96.17%
Loss	11.75%
Precision	0.96%
Recall	0.90%
F1-Score	0.93%

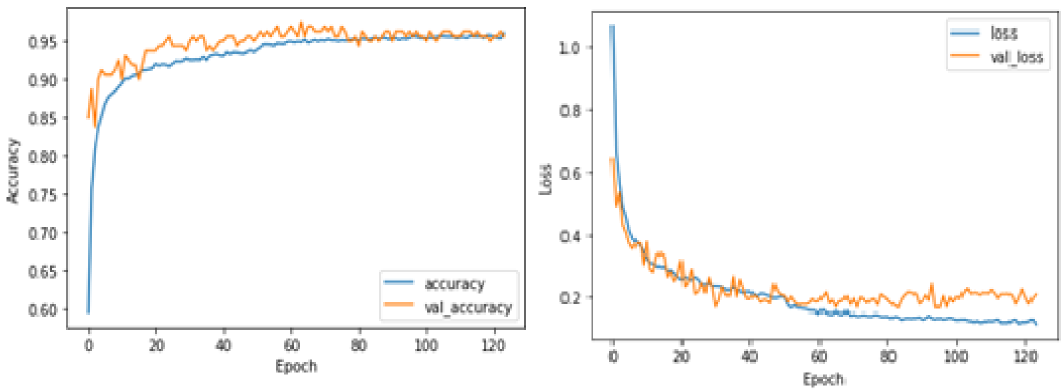

Figure 5.1. CNN model accuracy and loss curves.

After training a 50-epoch ANN model for the mentioned classification task, the best accuracy of 88.98% has been achieved. The classification metrics are given in Table 4.2 for the readers' reference, while the accuracy and loss corves for the best case are also given in Fig. 4.2.

Table 7.2.Summary of the results for the ANN model.

Metric	Value
Accuracy	88.98%
Loss	36.51%
Precision	0.87%
Recall	0.81%
F1-Score	0.83%

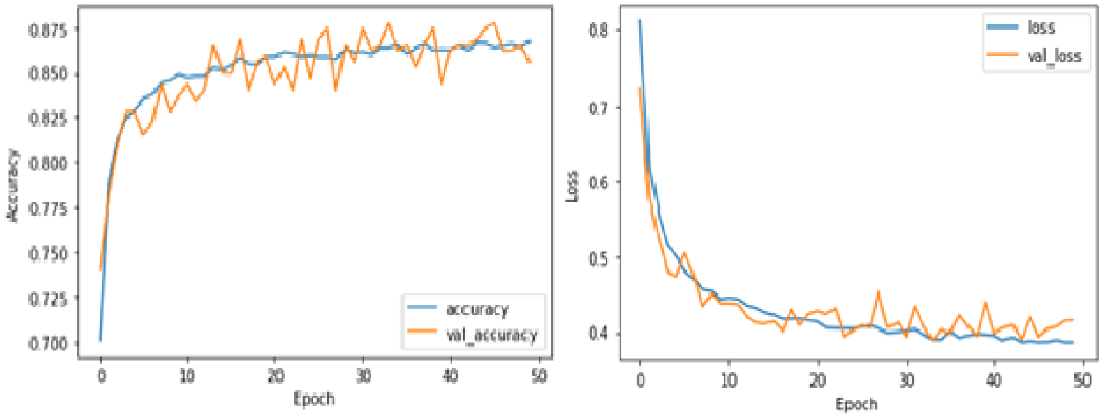

Figure 6.2. ANN model accuracy and loss curves.

After training the proposed LSTM model for 300 epochs, we achieved the best classification accuracy as 94.42%, achieved at the 82th epoch with the aid of early-stop function. Other classification metrics are listed in Table 4.3.

Table 8.3.Summary of the results for the LSTM model.

Metric	Value
Accuracy	94.42%
Loss	22.81%
Precision	0.92%
Recall	0.90%
F1-Score	0.91%

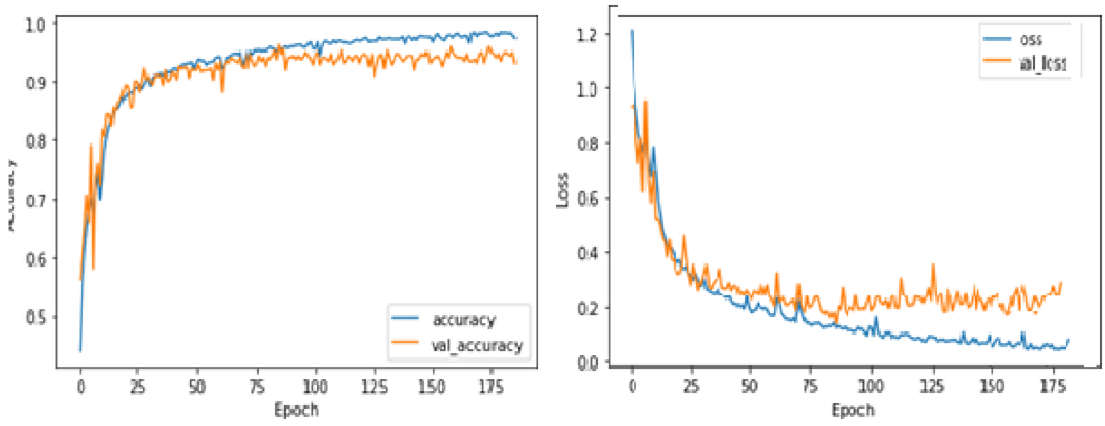

Figure 7.3. LSTM model accuracy and loss curves.

As presented in the above panels, CNN outperforms the ANN and LSTM models on the specified dataset, proving that CNN is the best classifier with a classification accuracy of 96.17%.

We also give the classification metrics for the 1-D CNN model including the success rates for the 5 classes in detail in Table 4.4. With a weighted average score of 96.17%, the most accurate results were obtained for Class 4 (unknown abnormality), while the most difficult was Class 3 (fusion) with an F1-Score of 82%.

Table 9.4.Class-dependent classification metrics for 1-D CNN model.

	Precision	**Recall**	**F1-Score**
Class-0	0.93	0.98	0.96
Class-1	0.98	0.80	0.89
Class-2	0.95	0.99	0.97
Class-3	0.96	0.72	0.82
Class-4	1.00	0.99	1.00
Accuracy			0.96
Macro Avg.	0.96	0.90	0.93
Weighted Avg.	0.96	0.96	0.96

Similarly, classification metrics through 5 classes for the ANN and LSTM models are given in Tables 4.5 and 4.6, revealing that the best F1-Scores are achieved for Class-4 and the worst metrics were for Class 3. This indicates that any of the classifier models do not display class-dependent success compared to the best classifier.

Table 10.5. Class-dependent classification metrics for the ANN model.

	Precision	Recall	F1-Score
Class-0	0.82	0.92	0.87
Class-1	0.91	0.64	0.75
Class-2	0.89	0.91	0.90
Class-3	0.78	0.60	0.68
Class-4	0.98	0.95	0.97
Accuracy			0.89
Macro Avg.	0.87	0.81	0.83
Weighted Avg.	0.89	0.89	0.89

Table 11.6.Class-dependent classification metrics for LSTM model.

	Precision	Recall	F1-Score
Class-0	0.94	0.93	0.93
Class-1	0.87	0.83	0.85
Class-2	0.95	0.97	0.96
Class-3	0.86	0.78	0.82
Class-4	0.98	0.99	0.98
Accuracy			0.94
Macro Avg.	0.92	0.90	0.91
Weighted Avg.	0.94	0.94	0.94

The achieved results indicate that low-complexity models fail to capture features in time-series data including medical disorders, while the more complicated CNN model outperforms LSTM and ANN models. On the other hand, improving the complexity of the CNN model, ensemble or cascaded models, feature extraction procedures before neural network models can improve the model's success. To prove this fact, we present a list of recent studies in Table 6. Results from recent studies indicate that better accuracy scores with CNN-based models are possible either with ensemble or cascade models with LSTM, Gated Recurrent Unit (GRU), or further preprocessed models driven with extracted features or converted signals (i.e., to 2-D).

4.2. DISCUSSION

Computer-assisted diagnosis of arrhythmias can significantly reduce cardiologists' workload, allowing them to focus more on therapy rather than diagnosis. In this research, an effective ECG classification system based on deep learning models were tested for arrhythmias by classifying a set of patients' ECG recordings.

Biomedical scientists are one step closer to the effective realization of a marketable computer-aided diagnostic system that will be anchored in clinical routines to assist clinicians and patients, thanks to state-of-the-art demonstrations of deep learning-based medical image and signal processing methods. In this perspective, it would be expected to see the deep learning applications dominating the near future, in not only medical signals and imaging diagnostics, but also in other biomedical imaging and signaling subdisciplines. [68,69].

As a type of neural network, convolutional neural networks have gained a significant popularity in image discovery. It is also successful in many tasks across classification, object tracking, and image segmentation.

As this study states out, CNN model is also a golden standard for classifying the arrhythmia disorders from ECG recordings, through a 1-D variant of it that is applicable to time series data. This result also conflicts with some recent studies stating that LSTM-based learners are the best performers in this field, as stated in Ref. [70] as 92.7% accuracy was achieved for LSTM while CNN could not exceed 88.1%. We tie this deviation with crafting a better 1-D architecture for CNN has the potential to outperform the RNN or LSTM classifiers.

4.3. A GENERAL OUTLINE OF THE STUDY

In this thesis, the MIT/BIH Standard Database for Arrhythmia, consisting of 109,446 samples, each signal containing a 30-minute segment selected from 24-hour recordings of 48 individuals are used. Continuous signals are filtered over the range of 0.1 to 100 Hz and then digitized at 360 Hz. Before the classification process, normalization was applied before the augmentation was performed. The dataset was normalized using the Scikit-Learn normalization module, which changed the values of numeric columns to a common scale with values ranging from 0 to 1 without distorting the range of values.

The samples are then augmented using NumPy library functions such as compression, stretching, and amplification, resulting from a dataset of 2,686 samples. The dataset is then split as 10% test and 30% validation, resulting in a split ratio of 60:30:10.

As previously stated, the database included samples including five classes of arrhythmia. Among the three models proposed, the 1-D CNN model with a more complex architecture emerges to outperform the proposed LSTM and ANN models, revealing that although the nature of the dataset would require classifiers with lower complexity, the model with more complex architecture has a better potential to explore patterns related with some disorders.

PART 5

CONCLUSION

5.1. CONCLUSION

In this thesis study, we tested three deep learning architectures as CNN, ANN and LSTM on a multiclass classification task. Types of arrhythmia, an irregularity related to hearth beat, are the focus of this classification task. Arrhythmia detection is an important task in bioinformatics since it can cause problems such as strokes, heart attacks, and in some cases, sudden cardiac death. Therefore, early detection and diagnosis of arrhythmias are very important. Beyond detecting arrhythmia, detecting the category of this anomaly is also an important task. Using the most prominent publicly accessible MIT-BIH arrhythmia database, we designed an automated, non-invasive framework based on deep learning architectures to primarily classify personalized ECG data as normal or abnormal hearts (with arrhythmia types).

The dataset is tested with a 1-D CNN architecture for arrhythmia classification, which was compared to the LSTM and ANN algorithms. The suggested CNN architecture with the highest complexity in its architecture, outperforms its competitors without any preprocessing other than normalization and enhancement, resulting in comparable accuracy to prior studies involving ensemble or cascade models employing LSTM, gated repetition unit (GRU), or more complex models.

As a result, the proposed 1-D CNN architecture highlights a successful model for classifying unprocessed ECG signals with acceptable model complexity, while the proposed LSTM and ANN models fail to adequately capture features related to arrhythmia disorder. LSTM is also emerging as a lightweight alternative with an acceptable trade-off by computational ordering.

5.2. FUTURE WORK

The positive results of this project encourage further research on this topic, aiming to approach it to full accuracy. Many perspectives of this task remain to be expanded. In the future, the models can be improved through larger available datasets. Another future goal is to improve the model so that it gives more accurate results in less time. Ensemble models can also improve accuracy if sufficient computational power is provided.

Finally, another interesting analysis would be knowledge transfer from one dataset to another: can train a model with these data from one dataset and performing the accuracy for classification of data from the other set? We leave this investigation for future work as well.

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RESUME

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