ECG ARRHYTHMIA TIME SERIES CLASSIFICATION USING 1D CONVOLUTION - LSTM NEURAL NETWORKS

THESIS

MASTER PROGRAM IN ELECTRICAL ENGINEERING
MINOR IN ELECTRONIC CONTROL SYSTEM

Submitted as a partial fulfillment of
the requirements for master engineering degree

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FACULTY OF ENGINEERING
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THESIS

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Contents

List of abbreviation

CVDs	Cardiovascular diseases	**N**	Normal	**PNN**	Probabilistic Neural Networks
ECG	Electrocardiogram	**ML**	Machine Learning	**LR**	Learning rate
AAMI	Advancement of Medical Instrumentation	**DNN**	Deep Neural Networks	**1D-CNN**	One Dimension Convolution Neural Networks
R	Right bundle branch block beat	**ANN**	Artificial Neural Networks	**WT**	Wavelet Transform
V	Ventricular ectopic	**CNN**	Convolution Neural Networks	**DWT**	Discrete Wavelet Transform
F	Fusion	**RNN**	Recurrent Neural Networks	**CWT**	Continuous Wavelet Transform
SA	Sinus Node	**AV**	Atrioventricular node	**API**	Application programming interface
TF	Tensor Flow	**SVM**	Support Vector Machine	**PCA**	Principle Component Analysis
VQ	Vector Quantization	**SDWT**	stationary discrete wavelet transform	**MIT**	Massachusetts Institute of Technology
SVD	Singular Value Decomposition	**MLP**	Multi-layer Perceptron classifier	**SOM**	self-organizing map

ABSTRACT

An electrocardiogram (ECG) can be dependably used as a measuring device to monitor cardiovascular function. The abnormal heartbeat appears in the ECG pattern and these abnormal signals are called arrhythmias. A faster and more accurate result can be reached by classifying and automatically detecting arrhythmia signals. Several machine learning approaches have been applied to enhance the accuracy of results and increase the speed and robustness of models. This research proposes a method based on Time-series Classification using deep Convolutional -LSTM neural networks and Discrete Wavelet Transform to classify beats in three experiments, the first one is to classify 4 different types of Arrhythmia in the MIT-BIH Database. The second one for enhancement the first experimental results. The third one is for classifying the whole MIT-BIH database. According to the results, the suggested method gives predictions with an average accuracy of 97% in the first experiment, 99% in the second one, and 97.7% in the third experiment,without overfitting.

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CHAPTER I

Introduction

1.1 Background

According to the world health organization (WHO), cardiovascular disease (CVD) is the most common cause of death globally, taking an estimated 18 million lives each year, representing 31% of global deaths. Cardiovascular diseases can generally be divided into three groups: electrical (arrhythmia), vascular (vascular disorders), and structural (cardiomyopathies). (Heart Rhythm Society, "Heart diseases and disorders," 2017). In this work, we focused on arrhythmia. (Texas Heart Institute, "Categories of arrhythmias," 2016)

Arrhythmias are abnormal heartbeats caused by changes in the electrical current in the heart. The electrical system that controls the heartbeat is stable and produces two types of beats. Diagnoses of arrhythmias are based on determining which heart rhythms are normal and abnormal; morphology is used to classify electrocardiograms (ECGs) according to their characteristics, which is critical to make the correct diagnosis for the patient.

Typically, arrhythmias are diagnosed by electrocardiography (ECG): measuring the heart's electrical activity. Fig. 1.1 illustrates the ECG waveform with five main waves: P, Q, R, S, and T. The non-invasive and painless nature of the ECG test makes it ideal for collecting large amounts of data, which can be analyzed later. (National Heart Lung and Blood Institute, "Electrocardiogram," 2016).

Association for the Advancement of Medical Instrumentation (AAMI) divides arrhythmias into five major classes: non-ectopic, ventricular ectopic,supraventricular ectopic, fusion, and unknown. There is a wide variety of types within each class, therefore this study (in the first and second experiments) has selected heartbeats that can be categorized into four different categories, Right bundle branch block (R), Ventricular ectopic (V), Fusion (F), and Normal (N). Moreover, in the third experiment, all AAMI classes are taken. These heartbeats are usually obscured by noise in ECGs, so identifying them is difficult. (American National Standards Institute, "Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms," 2012).

Hospitals are the most common places that provide the equipment for electrocardiograms, and cardiologists perform careful evaluations of the ECGs using their knowledge and experience. The process is time-consuming and error-prone, so an automated approach can assist them in making their decision. It is highly desirable to be able to diagnose an irregular heartbeat accurately and inexpensively because this can help detect early heart problems and prevent further complications. (R. J. Martis, 2014)

Increasing global population and pressure on health facilities are driving the demand for an automatic classification system. It is also possible that some cases will require a cardiologist to be dispatched to remote areas or clinics or to remain on-site at all times in hospitals. To reach the best results, the classification model must be enhanced for a more in-depth study of classification.

There is no surprise that recent literature has focused on this topic, several authors have tested ECG arrhythmia classification using a variety of methods, including statistical methods, expert systems, and supervised neural networks. Recently, neural networks have been increasingly the subject of practical research (Lippmann, 1987). Pattern recognition and artificial intelligence are areas of study requiring real-time responses, ECG classification involves both areas.

ECG beats are classified based on features or time series. Most researchers use features extraction to analyze their models. In this time-based classification model, wavelet transform and neural networks are implemented by the Python language on Google Colab, with R peaks and network nodes as classifiers.

Other researchers used various kinds of methods for ECG classification such as Combining KNN and DWT,(Al Qawasmi, A. R., & Daqrouq, K,2010), MLP and VQ Number of beat type 2, (Sumathi, S., & Sanavullah, M. Y.,2009) and SOM with SVD Number of beat type 3,(Priyadarshini, B., Ranjan, R. K., & Rajeev A. 2012).

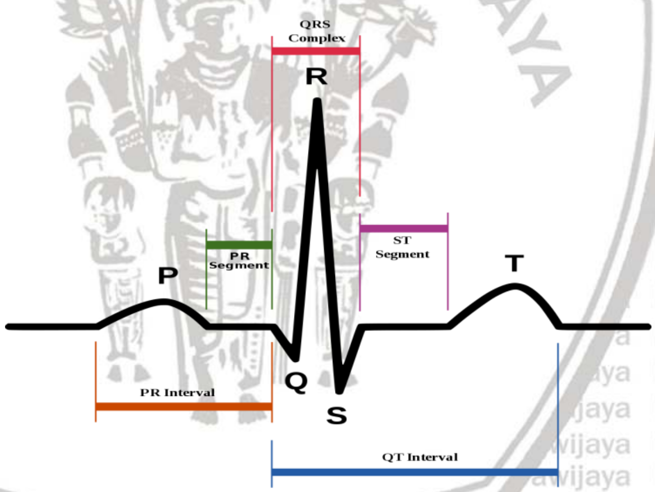

Figure 1.1 Electrocardiogram signal, waves, and segments

1.2 Problems Statement

Based on conditions we explained in section 1.1, the problems in ECG arrhythmia classification are :

1) Diagnosing types of arrhythmia can be difficult, therefore an ECG analysis needs to be done by a cardiologist.

2) Since the ECG produces a lot of data, it is time-consuming for a Cardiologist to analyze it.

3) Even if a cardiologist analyzes it, there can still be some lack of accuracy.

4) The majority of research in Arrhythmia classification is based on features classification to distinguish the beats, some of which use AAMI categories, and others that do not. However, this study focused on time series classification for intra-patient follow AAMI categories.

Three experiments are conducted to design a model for classifying types of arrhythmia using Discrete Wavelet Transform (DWT) and Neural Networks with different types of layers, including Convolution, LSTM, and Dense layers.
For model experiments one and two, we take four types of beats from the MIT-BIH database, which follows the AAMI standard, and for model experiment three we take all 12 types.

In this study, we will focus on 1,2, and 4 and aim to achieve high accuracy.

1.3 Research Objective

1) Creating an Arrhythmia classification model with high accuracy for four types of arrhythmia in the MIT-BIH database through pre-processing and building neural networks on Google Colab the platform using a new library for machine learning published by Google (2018) called TensorFlow.
2) Improving model accuracy by adjusting hyperparameters.
3) Examine the model in all MIT-BIH databases to get excellent classification for all heartbeat types, 12 types of heartbeats.
4) Comparison of results for the model with other researches to identify the most appropriate classifier.

1.4 Benefits of Research

1) By automating ECG classification, cardiologists can spend less time analyzing the beats and other non-specialist healthcare workers can easily identify cases that require urgent attention.
2) Getting good accuracy in times series-based classification is valuable for this field because most research focuses on feature-based classification.
3) The three experiments showed how changing the parameters affected the robustness of the model.

CHAPTER II

LITERATURE REVIEW

2.1 Relevant Studies

The classification of ECG arrhythmias is the subject of several publications; different methods have been used, such as statistical methods, expert systems, and supervised neural networks. Here is a review of a few of these studies.

For automatic classification of the ECG signal for the diagnosis of heart disease, Vijayavanan argued that the morphological characteristics of the ECG signal must be used to distinguish between normal and affected (abnormal) arrhythmias. This model was created using a probabilistic neural network (PNN) which captures the feature distributions and classification vectors. With 96.5% accuracy, this method provides accurate detection of arrhythmias in the ECG signal (Vijayavanan et al., 2014).

The diagnostic classification of the ECG for 12 lead was done using a combination of two pattern recognition methods proposed by Pedrycz et al, cluster analysis and feed-forward backpropagation neural networks. A cluster analysis based on Euclidean distance in parameter space was also applied to the original learning set. The classification accuracy scores ranged from 51.9% to 84.0% when it came to classifying 7 classes of ECG abnormalities (Pedrycz et al., 1991).

The description of the literature includes a review paper by Sanamdikar et al., (2015) that used modified Wavelet transforms to analyze cardiac arrhythmias and interpret ECG signals, Daubechies Six coefficient wavelet, Pan-Tompkins the algorithm, Hidden Markov models, fuzzy logic methods, neural network, support vector machine, genetic algorithm, PCA, and SVM methods. We observed that the accuracy of other methods was 98%, but the accuracy of wavelet transfer was 100%.

Also, (Silipo and Bortolan 1997), investigated the role of statistical methods and neural network architectures in an automatic ECG analysis procedure that used seven types of beats and 39 features. A neural network classifier produced 91.0%, 94.0%, and 95.0% correct classification for all 7 types, indicating a performance comparable to conventional classifiers. In terms of the neural network architectures, they produced reasonable classification results when trained using unsupervised techniques. In addition, two other characteristics were examined, such as the subjects' age and gender (Silipo and Bortolan 1997).

(Salha Samad et al., 2014) used a machine-learning algorithm to classify arrhythmias, which used Nearest Neighbors, Naive Bayes, and the Decision Tree classifier to achieve an average accuracy of 53%.

2.2 Relevant Theories

2.2.1 Heart's Anatomy, heartbeat cycle, and the Conduction System

There are two main functions of the heart: 1) Pumping blood from the lungs to the tissues of the body; 2) Pumping blood from the tissues back to the lungs. Anatomically, the heart has four chambers composed of cardiac muscles. Right and left atria to function mostly to collect blood, while right and left ventricles work mostly to pump blood around the body (Weinhaus & Kenneth, 2005).

The cardiac muscle (myocardium) forms the walls of the heart. The heart muscle performs mechanical work (=pumping blood). Electrical impulses are transmitted through specialized muscle cells to control the pumping process. ECG waveforms are formed by these impulses, called action potentials.

Electrical impulses are normally generated in the sinoatrial (SA) node, located at the upper part of the right atrium. After propagating down the right atrium with the interatrial pathways, it goes left to the left atrium to the atrioventricular node (AV). The Bundle of His provides access to the left and right ventricles through the left and right bundle branches, which terminate in Purkinje fibers responsible for contracting each ventricle. We should note that not all areas of the heartbeat are at the same speed (beats per minute). The discussed structure is shown in Figure 2.1

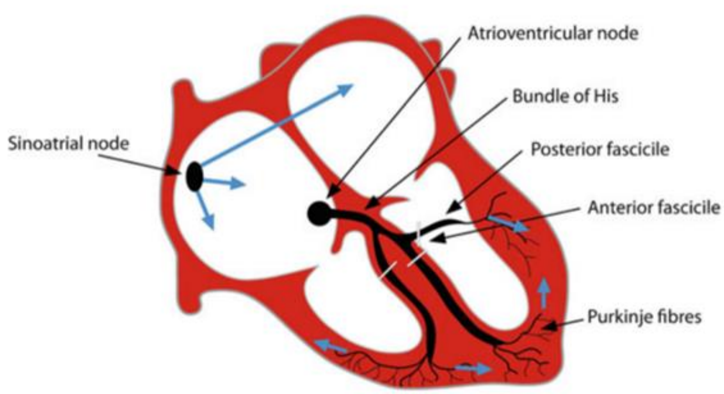

Figure 2.1 The electrical conduction system of the heart (Gacek and Pedrycz,2012)

The heart has developed a special cell system for generating electrical impulses to stay on its cardiac cycle. By releasing these impulses, the heart muscles contract mechanically. It is called the conduction system. Sinus Node (Natural Heart pacemaker) starts every heartbeat with the P-wave. Electrocardiogram waves and segments are shown in figure 1.1.

- The P-wave is the first electrical event that occurs during a heartbeat or one cardiac cycle when the atria depolarize.
- Q-waves are formed during ventricular septal depolarization. The Q-wave is a fast, small, negative wave.
- During a cardiac cycle, the R-wave is formed by ventricular depolarization. It is a fast, strong, positive wave with a large amplitude.
- S-wave is a negative, fast wave.
- The T-wave is the last wave that occurs during a heartbeat. The ventricular repolarization wave creates a positive but gradual response.

2.2.2 Electrocardiogram

It was Augustus Waller (1887) who developed the first ECG (Addison,2002). Throughout the world, it is widely used to diagnose diseases of the heart since then. The electrocardiogram records the electrical signals generated as the heart muscle contracts and relaxes. It is the result of the spread of electrical activity through the heart cells, causing their voltage to fluctuate.

An electrocardiogram, a signal-acquisition device, can be used to measure these values with electrodes attached to the skin surface. The electrodes can be placed in a variety of ways, and there are different approaches to calculating their position. Derivations allow for potential differences to be obtained in specific directions, resulting in highly correlated measurements that are variable. Each part of the ECG represents one stage of the cardiac cycle. (Taspinar,2018). ECGs are composed on graph paper (Fig. 2.2), on which voltage levels are measured comparing horizontal lines, and time interval is determined based on the vertical lines: two consecutive vertical splits cover 0.04 seconds.

Figure 2.2 Example of ECG trace

2.2.2 Wavelet Transform

The purpose of signal processing is to extract specific information from a signal. Therefore, signals are often transformed into different domains to read out the desired information more easily(Gawande and Ladhake, 2015). Wavelet transform (WT) is a remarkable mathematical method that is capable of simultaneously examining the time and frequency aspects of the signal (Haykin,2009). WT can be divided into three major types, namely continuous (CWT), discrete (DWT), and stationary discrete (SDWT).

The ECG signal has a non-stationary characteristic whose frequency response differs with time. This is because the heart generates its beats under the influence of physiological factors mediated by the brain, which vary continuously over time. Typically, WT is used to analyze instantaneous and time-varying signals While classical Fourier transform can give a general sense of the signs it represents, its expression is often not intuitive enough. Wavelet transformations can analyze signals at all scales instead of Fourier transforms. Furthermore, the time and frequency domains can be located simultaneously. This is important for the analysis of non-stationary signals. Various low-pass and highpass filters are applied to the time-domain signal in WT, which filter out the high- and low-frequency components of the signal. Whenever some frequency portion of the signal is removed from the signal, this procedure is repeated. The waves are represented by waveforms of real or complex value, which have a definite start and end, as well as a mean value of zero (as shown in figure 2.3).

To obtain the WT of a signal, compare the input signal with the extended and shifted releases of the unstretched wavelet, also referred to as the mother wavelet- equation. Equation 2.1 is an example of the mother DWT. In chapter 3, we will discuss what wavelet family we use in our model; wavelets can simultaneously deal with time and frequency, so they are suited to describing events that start and stop, such as non-stationary signals.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad a, b \in \mathbb{R} \qquad (2.1)$$

Here a and b are called Dilation (Scale) And Translation (Position) parameters respectively.

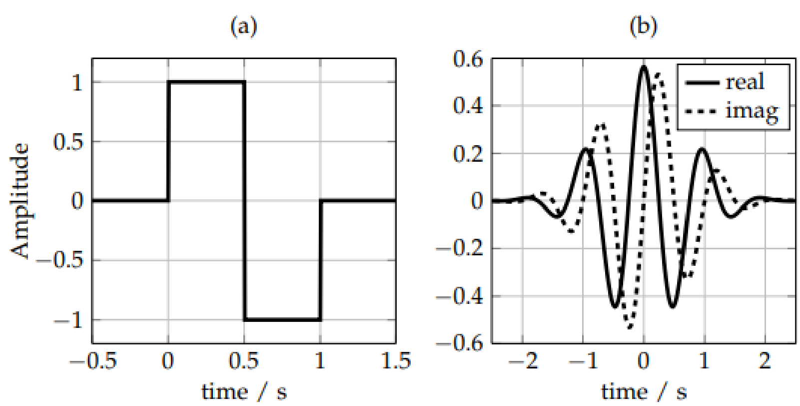

Figure 2.3 Exemplary wavelets, (a) Real valued Haar wavelet and (b) Complex valued

2.2.2 Type of Arrhythmias

Since each patient's heart mechanism differs significantly, analyzing an arrhythmia is a difficult task. There are two types of arrhythmias:

1. Rhythmic: consisting of a series of irregular beats
2. Morphological: one abnormal beat

The Association for the Advancement of Medical Instrumentation (AAMI) classifies morphological arrhythmias into five macro classes based on the location where the anomaly starts. As shown in Table2.1, the MIT-BIH database categorizes heartbeats according to the AAMI standard as follows:

Table 2.1 The Categories of heartbeats AAMI Standard (2012)

Categories	**N**	**S**	**V**	**F**
Definitions	Normal beat	Atrial premature beat	Premature ventricular contraction	Fusion of ventricular and normal beat
	Left bundle block beat	Aberrated atrial premature beat		
	Right bundle branch beat	Nodal(junctional) premature beat	Ventricular escape beat	
	Atrial escape beat	Supraventicular premature beat		
	Nodal(junctional) escape beat			
Annotations	90558	2781	7235	802

2.2.3 Discrete Wavelet Transform

Since the heart produces the ECG under the influence of brain-dependent factors that constantly change, the signal is non-stationary. To characterize them, a simple approach would be to use a time-domain analysis, which would consider factors such as the duration of the QRS complex and the R-R interval. An alternative method is to perform a frequency field analysis using a Fourier transform, which is compatible with small amplitude and duration changes in ECGs of any patient. In reality, the latter is not entirely applicable because an assumption of an evenly distributed frequency in the signal is not accurate: only the constant periodic signal is applicable. We are concerned about the frequency of the signal as well as the specific portion of the signal displaying that frequency when representing the ECG signal.

The DWT employs a wavelet as the basis function instead of a sinusoid as in the Fourier Transform. Wavelets are functions that have a finite duration: their amplitude is set at zero, increases, then decreases. Since wavelets only exist in a specific time interval, they are more localized in time than sinusoids. There are two ways to manipulate the wavelet: by changing its location or by changing its scale (Figure 2.4). Convolutions are highly valuable if the wave is the same shape as the signal at a point. The transform also results in a low value if wave and signal are not well correlated. In the continuous wavelet transform (CWT), this is done continuously, and for the discrete wavelet transform (DWT), it is done in discrete steps (Addison, 2002)

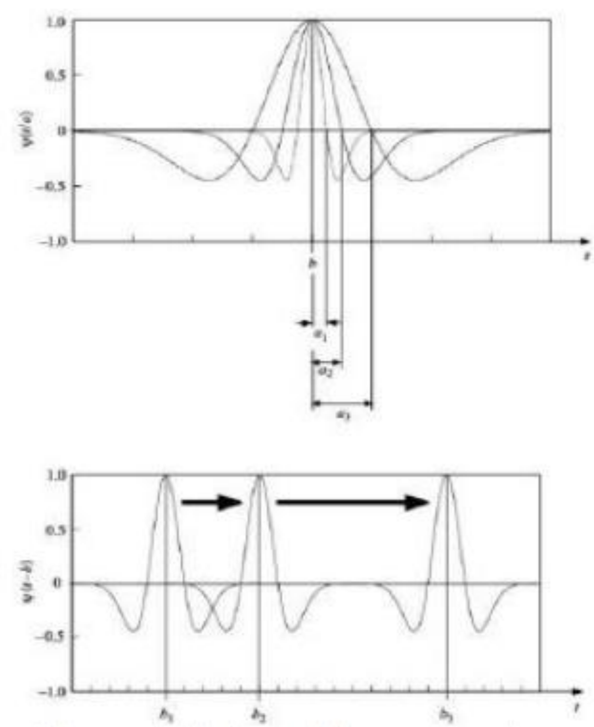

Figure 2.4 Two possible manipulations with wavelets: a) Translation (or location) and b) Scale, (Addison,2002)

As a result, DWT outputs the signal at different bandwidths, so that at each level of analysis, the output is high if there is a strong correlation between the signal at that scale and the wavelet. Many wavelet types exist, and the choice of the right one depends on how similar the shape is to the part of the ECG we want to analyze. (Taspinar, 2018). See figure 2.5.

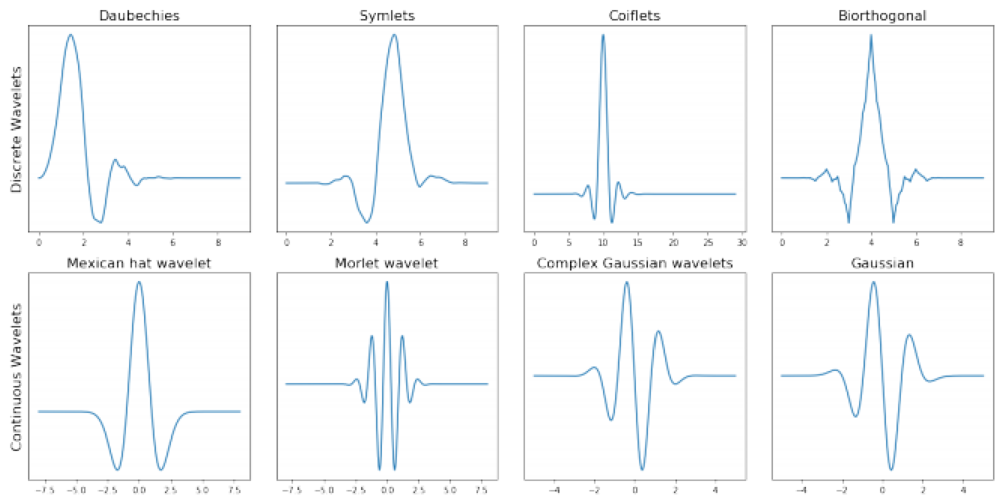

Figure 2.5 Wavelet families (Taspinar,2018**)**

The DWT is usually implemented as a Filter-Bank (Fig. 2.6), which means it is implemented as a cascade of high-pass and low-pass filters; filter banks are extremely efficient in splitting a signal into several sub-frequency bands. Two sets of coefficients are returned by the DWT; the approximation coefficients and the detail coefficients. Approximation coefficients correspond to the output of the DWT's low pass filter. A high pass filter of the DCT is used to generate the detail coefficients. The wavelet transform is applied again on the coefficients of the previous DWT to obtain the wavelet transform of the next level, which can be repeated at every level of the system. The original signal is also sampled down by a factor of 2 at each successive level.

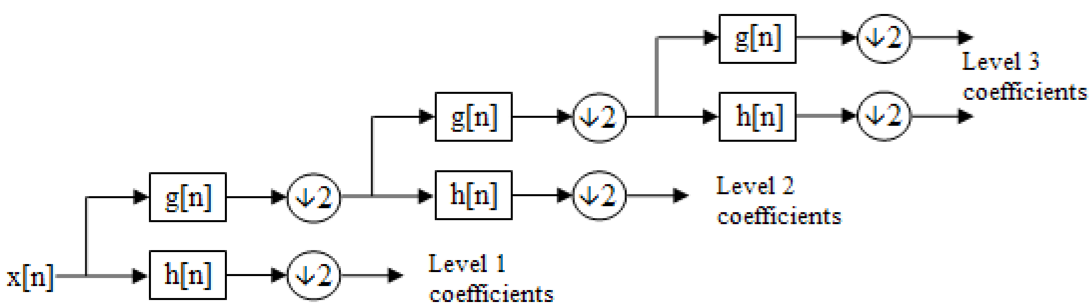

Figure2.6 Filter bank; three-level DWT

2.2.4 Discrete Wavelet Transform (DWT) family

The Symlets family consists of orthogonal wavelets that are compactly supported, which were introduced by I. Daubechies as modifications to the DB family, and their properties are almost the same. Symlets are the most symmetrical and least asymmetrical. Figure 2.7 shows the Symlet wavelet and scaling functions for orders 2 to 8. (Sorkhabi et al.,2014).

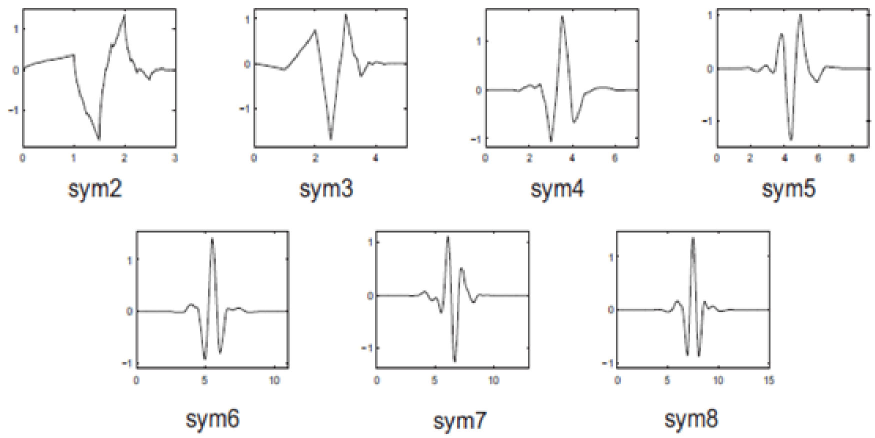

Figure 2.7 The Symlet wavelet and scaling functions, (Sorkhabi et al.,2014).

In this research, Symlet 4 is used to extract R peaks shown in figure 2.8 the scaling function ϕ(t) and wavelet function ψ(t). (Shalchyan, V et al., 2012)

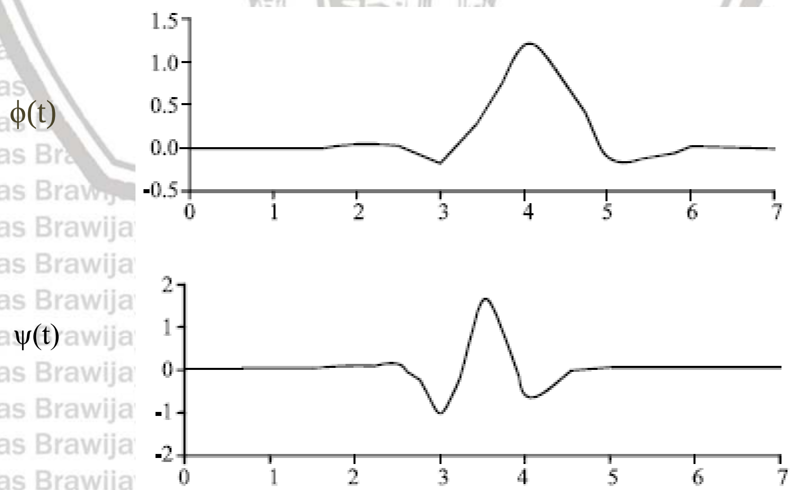

Figure 2.8 Symlet 4 scaling function and wavelet function. (Shalchyan, V et al., 2012)

2.2.5 Neural networks

An artificial neural network is an interconnected set of nodes, similar to the vast networks of neurons in the brain. It consists of a circular knot and an arrow, where each circular node represents an artificial neuron cell and the arrow represents a connection from the output of a neuron cell to another input. Artificial neural networks (ANN) (Gawande and Ladhake,2015), are generally presented as systems of interconnected "neurons" which are Exchange messages with each other. Communications have numerical weights that can be adjusted based on experience, making neural network input adaptive and self-learning. Artificial neural networks (ANNs) are useful in application areas such as pattern recognition, classification, etc. . The decision-making process of the ANN is holistic, based on the features of input patterns, and is suitable for the classification of biomedical data. A neural network can be characterized by 1) its pattern of connections between the neurons (called its architecture), 2) its algorithm of determining the weights on the connections (called its training, or learning algorithm), and 3) its activation function (Haykin;2009).

Traditional machine learning algorithms use only input and output layers, and at most one hidden layer. The use of more than three layers (including input and output) is referred to as deep learning. Figure 2.9 distinguishes between simple NN and deep learning NN, simple neural networks contain only one hidden layer as well as the input and output layers, while deep learning neural networks contain more than one hidden layer. In this case, there are four hidden layers between the input and output layers.

The main benefit of a Deep Neural Network (DNN) is its ability to recognize more complex features due to the number of hidden layers it contains. This DNN function makes it capable of handling high-dimensional large data that has a large number of features. Deep learning networks end with an output layer: a logistic, or softmax, a classifier that assigns a likelihood to a particular outcome or labels (Acharya et al., 2016).

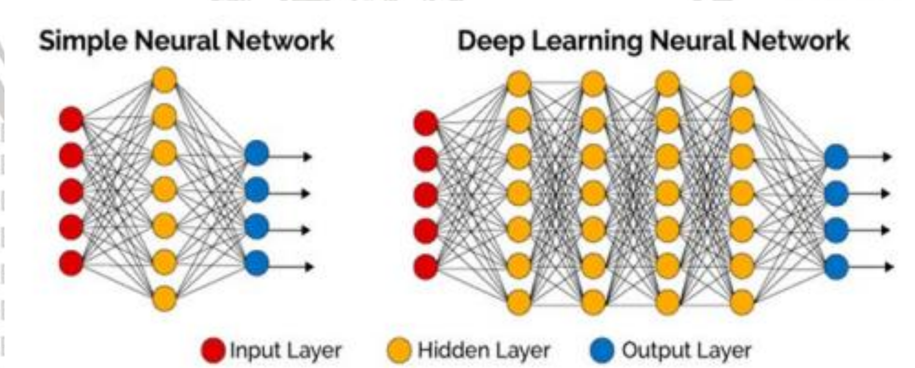

Figure 2.9 Comparison between the simple neural network (NN) and deep NN; (Acharya et al.,2016)

2.2.6 Convolutional Neural Networks (CNNs)

An artificial convolutional neural network extracts hierarchical features using the convolution process. Conventionally, CNNs were designed to work with two-dimensional data, which is used for image recognition. Fukushima and Miyake proposed the predecessor of Convolutional Neural Networks (CNNs) in 1982 (Fukushima et al.,1982). Machine learning and computer vision processes rely on convolutional neural networks (CNNs). Two-dimensional Convolutional Neural Networks (2D-CNNs are designed to handle multidimensional input and overcome the high number of parameters required in a standard Feedforward Neural Network (FNN), figure 2.10 is a comparison between FNN and CNN.

Alternatively, a modified version of Deep Convolutional Neural Networks (1D-CNN) has recently been proposed and has immediately achieved cutting-edge performance levels in a variety of applications, such as personal biomedical data classification and early diagnosis (S. Kiranyaz;2016), structural health monitoring, anomaly detection, and identification in power electronics, and electric motor failure detection (O. Avci;2017).

Because of their low computational complexity, 1D-CNNs are often preferred to their 2D counterparts when treating 1D signals due to some of the following reasons: (1) computational complexity is low; (2) they are especially suitable for real-time and low-cost applications due to their low computation requirements.

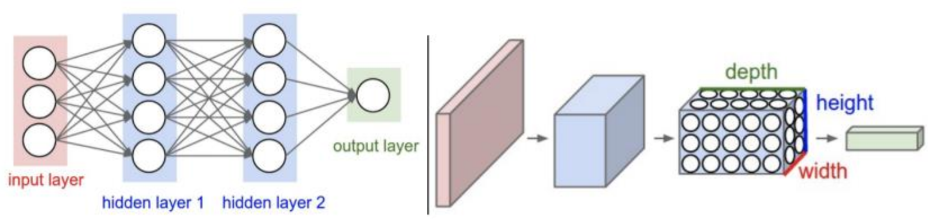

Figure 2.10 Comparison of FNN versus CNN. In CNN each layer has 3 dimensions: depth, height, length (visual recognition)

Convolutional layers are the building blocks of CNNs. It is composed of a set of filters (or kernels) whose parameters are learned during training. Typically, a single filter consists of a multi-dimensional array with the same height, length, and width as the input layer.

2.2.7 Forward and Back Propagation in CNN-layers

Let the input to convolution layer of length n be represented by x and let the kernel of length k be represented by h. Let the kernel window be shifted s positions (number of strides) after each convolution operation. Then convolution between x and h for stride s is defined as

$$y(n) = \begin{cases} \sum_{i=0}^{k} x(n+i)h(i), & if\ n = 0. \\ \sum_{i=0}^{k} x\big(n+i+(s-1)\big)h(i), otherwise. \end{cases} \quad (2.2)$$

a) Activation Function

Activation functions can be either linear or non-linear. If the inner product of the input x to a neuron and its weight w set is denoted by net then the output of the neuron is some function f of the net (denoted by y). Non-linear activations enable the network to learn complex mappings and there exist multiple non-linear functions to choose from and hence a decision has to be made while designing an ANN or in this case a CNN.

$$net = w^T x \qquad (2.3)$$

$$y = f(net) \qquad (2.4)$$

A popular activation function is ReLU (Rectified Linear Unit) the input-output relation is shown in Figure 2.8, the output of the ReLU function is equal to the input value for inputs that are greater than 0. For all other input values, the output is 0.

$$y = max(0, net) \qquad (2.5)$$

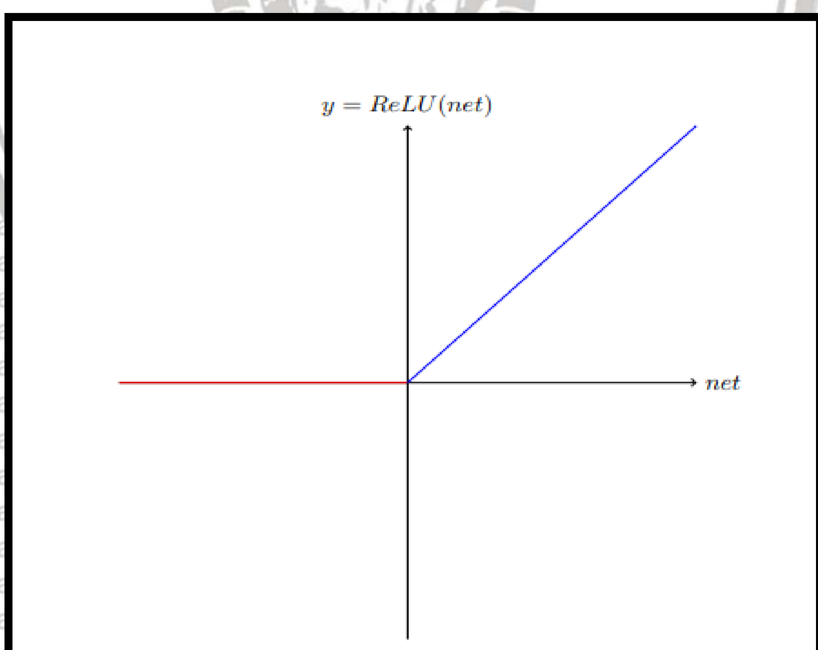

Figure 2.11 the input-output relation in ReLU function

b) Dropouts

Using dropouts is a way to prevent overfitting, which is a phenomenon in which inputs are memorized instead of learning general traits of the inputs. Neurons that drop out mean that the next layer will receive zero inputs. There can be several neurons in a layer, and whether a neuron drops the output or not is determined by its dropout rate.

c) Loss Function

The loss function describes the deviation of the predicted output from the target output. Categorical problems and multiclass problems refer to classification tasks with more than two labels. The model can estimate the probability of an example belonging to each class label. Therefore, in this study, we will use categorical cross-entropy. It is often desirable to minimize the cross-entropy for the model across the entire training dataset. To calculate this, average cross-entropy is calculated for all training examples.

$$CE = -log\left(\frac{e^{s_p}}{\sum_{j}^{C} e^{s_j}}\right) \tag{2.6}$$

CE: Cross Entropy.

C: number of classes

Sj: output vector

Sp: Where Sp is the CNN score for the positive class.

Our objective is to minimize the loss function, ADAM optimizers can be used to reduce the loss function.

2.2.8 Long Short Term Memory(LSTM)

A Long Short Term Memory network is a special kind of RNN that can learn dependencies over time. Hochreiter & Schmidhuber (1997) introduced them. A long-term dependence problem is avoided with LSTMs. Based on the fact that important events in a time series can be delayed, the LSTM network is well suited for categorizing, processing, and making predictions. During training for neural networks, weights are adjusted proportionally to the partial derivative of the error function in each iteration.

The issue is that the gradient can be vanishingly small in some cases, which effectively prevents the weight from changing. If this happens, the neural network may be prevented from training further. With LSTMs, the vanishing gradient problem that is associated with conventional RNN training can be avoided, The relative sensitivity of the gap length is one advantage of LSTMs over conventional RNNs shown in Fig 2.12. LSTMs generally consist of a cell, an input gate, an output gate, and a forget gate.

There are three gates in the cell that control how information enters and leaves the cell (Greff's 2017).

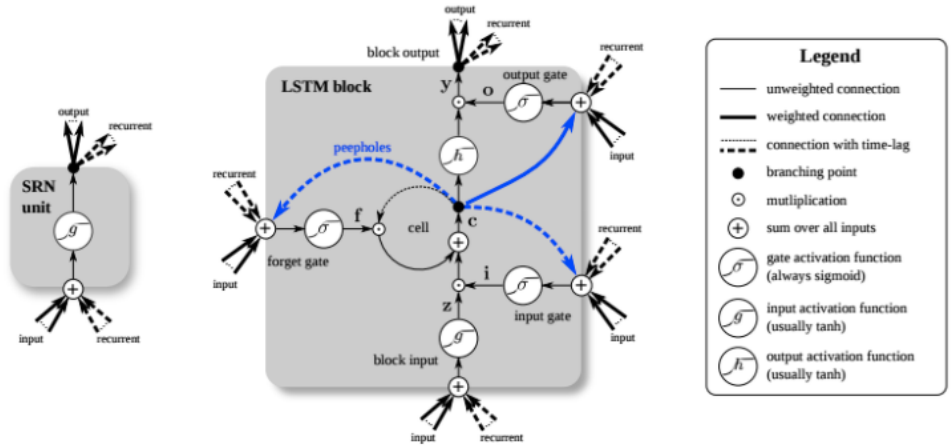

Figure 2.12 comparing a simple recurrent network to an LSTM cell (Greff,2017)

2.2.9 Dense neural network

The dense layer contains a fully connected network of neurons; each is connected to every neuron from the previous layer, as shown in figure 2.13. Its purpose is to classify the features that have already been extracted from the previous layers. It is used at the end of the model.

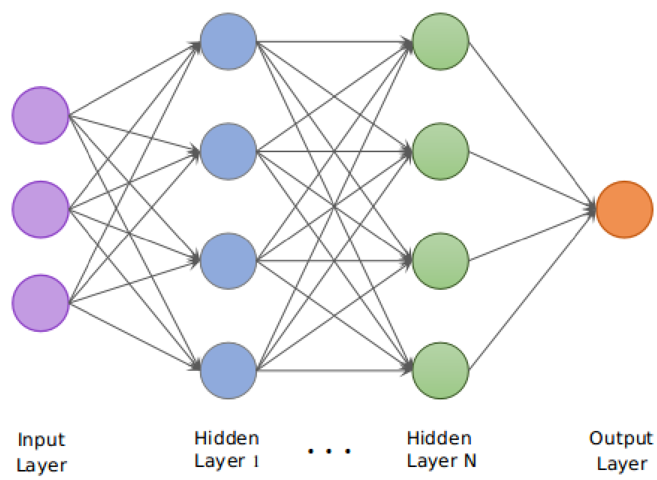

Figure 2.13 Dense Layer architecture

CHAPTER III

RESEARCH CONCEPTUAL FRAMEWORK AND HYPOTHESIS

3.1 Research Conceptual Framework

According to the review of literature on the classification of Arrhythmia ECG signals, most researchers are focusing on Feature-based Classification(Annama et al.,2020). For this study, we decided to investigate the arrhythmia classification method using time series. Figure 3.1 illustrates the conceptual framework for the study.

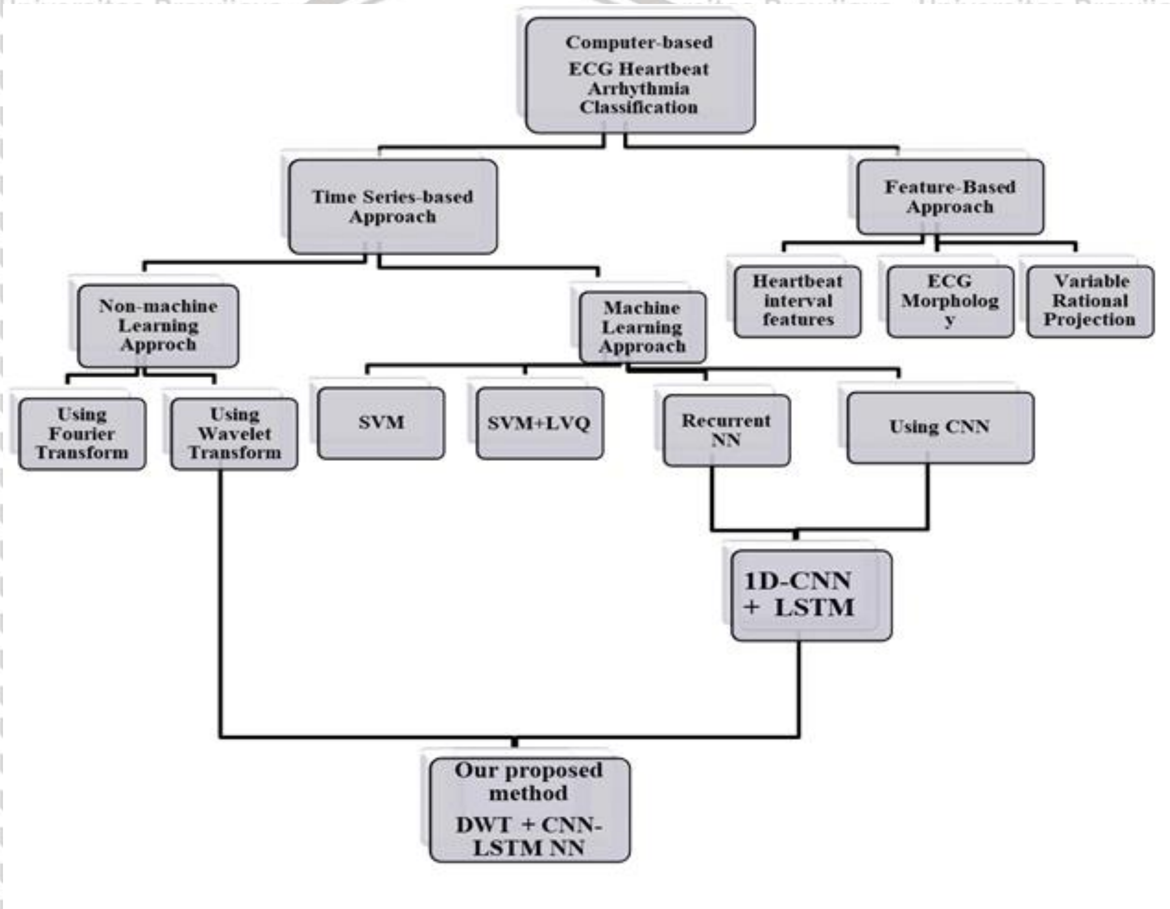

Figure 3.1 Conceptual Framework

3.2 Hypothesis

1) High accuracy can be achieved with Time-series classification instead of featuring extraction classification in arrhythmia classification problems.
2) The combination of DWT and NN will yield good results in classification problems (for our purposes assume CNN+LSTM layers).

CHAPTER IV

RESEARCH METHODS

4.1. Problem Identification

Taking advantage of the ECG, one of the most cost-effective and accurate methods for diagnosing cardiovascular diseases, we can determine the heart's electrical behavior. The ECG is a representation of the heart's electrical activity, which includes the regular and calm contraction of the heart muscles. Various cardiovascular diseases can be diagnosed using an analysis of the ECG waveform. There are five major waves of P, Q, R, S, and T in an ECG. Measurement of the RR-Interval, which is representative of the variety of heartbeats, is one of the most essential parts of the ECG analysis. Through the ECG classification, health care costs can be minimized by allowing the appropriate general practitioners to refer only those with serious heart problems to the hospital. Heart disease can also be detected early with the aid of ECG classification, shortening hospital waiting lists. An arrhythmia results from a disturbance in the heart's electrical conduction system. People of all ages suffer from arrhythmias. In many cases, arrhythmias require constant monitoring and an accurate diagnosis. As a result, we need a non-invasive, accurate, and robust technique. To classify the beats of the MIT-BIH database, we propose the use of discrete wavelet transforms and neural networks.

4.2 Data preparation

4.2.1 Data source and collection

As a basis for the classification of ECG beats, we used the MIT-BIH arrhythmia database. There are 48 ECG records for 48 patients in the MIT Arrhythmia Database available on Physiobank. Each ECG record lasts 30 minutes. The Arrhythmia Laboratory at BIH studied the data between 1975 and 1979. 25 men and 22 women aged 32 to 89 years took part in the study. In-patient records accounted for about 60% of the data. Annotations are included with this dataset along with markings for normal and abnormal beats. 360 Hz is the frequency used in these recordings. Lead II is the lead type that was used to record most of the ECG signals in the MIT-BIH database, figure 4.1 shows the MIT-BIH record 100, figure 4.2 shows the single beat after splitting. A team of cardiologists independently annotated each record. Each annotation corresponds to the peak of the R wave of a single beat so that the beat detection problem has been implicitly solved in this case (Moody and Mark, 2001).

AAMI (2012) recommends standardizing the evaluation of arrhythmia detector algorithms on their performance on five major categories of heartbeats: normal, supraventricular ectopic beats, ventricular ectopic beats, fusion beats, and unclassified beats.

In this research, we used 4 different categories – 'N', 'R',' V', and 'F' - to classify them. Table 2 displays the four arrhythmia classes used in this study in the first and second experiments, and table 1 lists the AAMI classes used in the third experiment.

Table 4.1 Heartbeat classes chosen in the study in experiment 1

Class	Name	Definition
N(0)	Normal beat	Normal
R (1)	Right bundle branch block beat	Happened when a block in the right bundle of the electrical conduction system in the heart.
V(2)	Premature ventricular contraction	Happened where the heartbeat is initiated by Purkinje fibers in the ventricles rather than by the SA node
F(3)	Fusion	Fusion beats occur when electrical impulses from different sources act on the same area

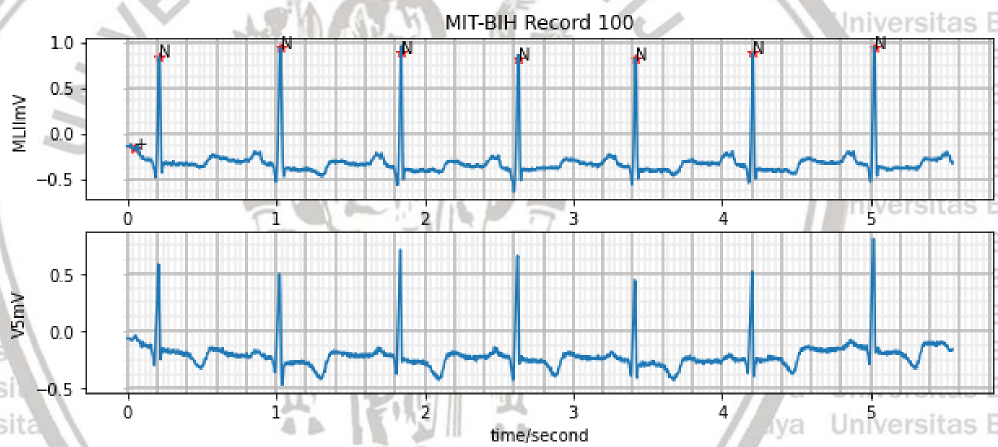

Figure 4.1 MIT-BIH record 100

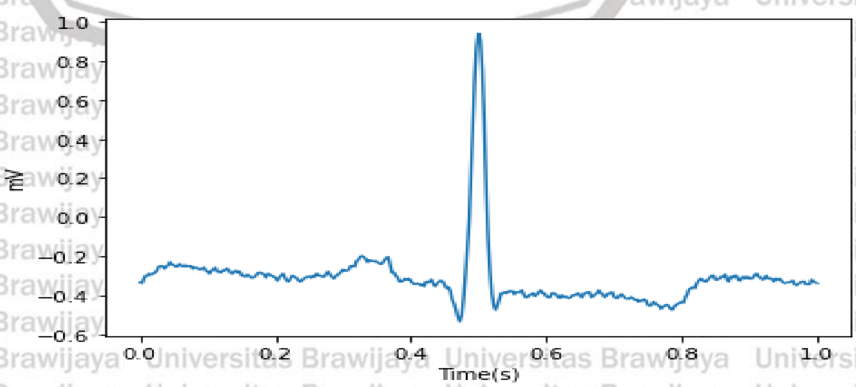

Figure 4.2 One ECG cycle from MIT-BIH DataBase

In figure 4.3 the four beats, we choose in experiment 1.

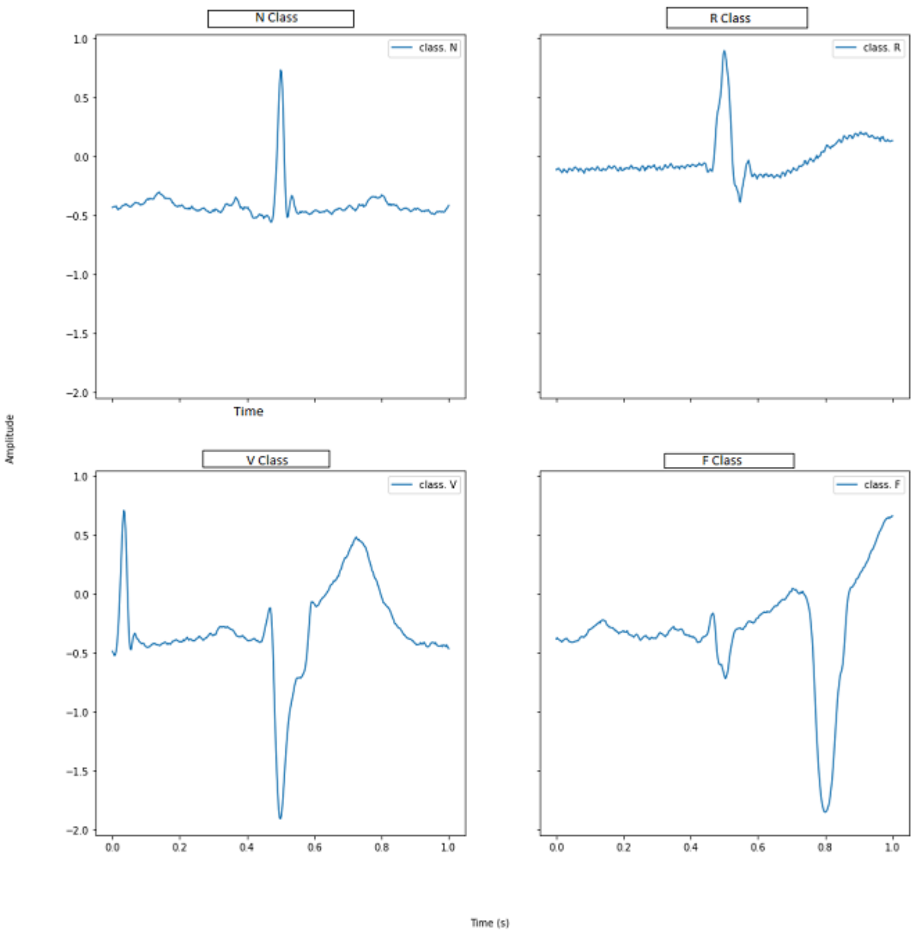

Figure 4.3 The Four beats that chosen in the 1st experiment

4.2.2 Data preprocessing

The N class is more populated than any other: it accounts for 89% of the dataset. Overbalancing can result in inconsistent training and poor quality algorithms. This problem is solved by replicating the data from model 1 and augmenting the data from models 2 and 3. There were two dataset configurations considered, the first involved building the validation set randomly from the dataset, and the second involved building the test set.

During training and validation, the samples are randomly selected for each category in experiments 1, 2, and 3, with different ratios shown in Chapter 5.

4.3 Design of Proposed Solution

This research was organized into two stages based on its design:

First: Data preparation: R detection using the annotation file in the data set, and selecting the window around R to ensure it's the peak we want. The window will be 500 ms to +500 ms around R.

Second: Wavelet Transform; in this study, DWT coefficients are fed to the deep learning model, we will use the Symlet family from Discrete Wavelet Transform.

Figure 4.4 illustrates the Workflow for Exp.1,2, and 3 . It will also be used for the Enhancement Model 1. We will start by taking the ECG signal from the MIT-BIH database and choosing one of the four-beat types (in exp.1&2). Using the native Python waveform database (WFDB) package, we will then identify the peaks based on the data file annotation. An interval of one second is suggested for taking a window centered on the peak of the R. To convert each pulse of ECG signal into a coefficients matrix, discrete wavelet transforms will be applied. We recommend using the symlet4 family. MinMaxScaler will be used for normalization.

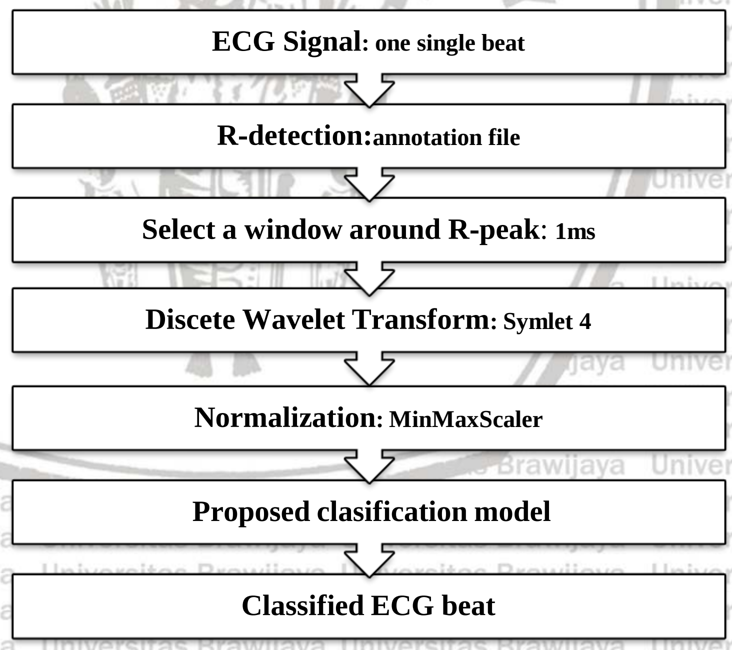

Figure 4.4 System WorkFlow. Source: by Researcher

In this study, we proposed to apply two 1D convolution layers and an LSTM layer, and then two dense layers would be applied to the outputs. The proposed model is shown in figure 4.5. Note that the three experiments use this architecture with various hyperparameters and samples of data.

In Figure 4.5, we see the input from the previous stage which is normalized coefficients of DWT feed to the first layer from the 1D CNN had 32 filters, and the second one had 64 filters, kernel size 5, and an LSTM layer with 256 units (neuron). These three layers used the ReLU as the activation function. We provide convergence stability to the model by using 64 filters in the second layer of 1D CNN. In this study, Rectified Linear Unit is used as the activation function. It was used to decide the output by mapping it to some values, like 1 and 0, based on the function of the model. Fully connected layers consist of two dense layers, the first dense layer with 64 units and ReLU activation function, and the second dense layer with 4 units and Softmax activation layer, which predicts output class probabilities. As you will see in Chapter 5, the dropout layers and learning rate as well as other hyperparameters will differ between experiments.

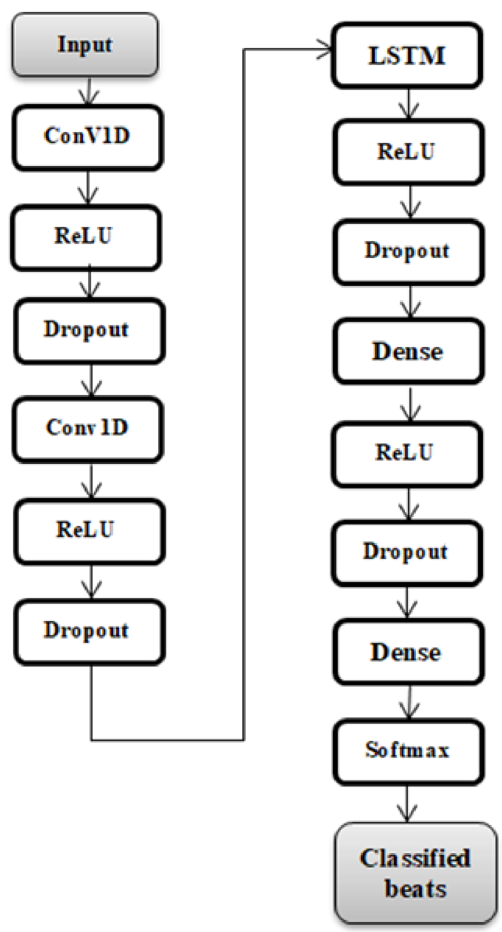

Figure 4.5 The Architecture Of The Proposed Networks

4.4 Implementation

We used Keras and Tensor Flow for Python 3.7 to implement the proposed model to train it for 50 epochs on Google Colaboratory. The Softmax output is the loss function from cross-entropy loss. Adam optimizer with a learning rate of 0.0001 in Exp.1 and a learning rate of 0.001 in Exp.2 and 3, that decays exponentially by a factor of -0.001 are used in this model.

a) Google Colab is a free cloud-based Jupyter notebook environment. You can write and execute code in Python on Colab, create/load from/to Google Drive, import/export notebooks from/to your Google Drive, and integrate Python, TensorFlow, Keras, OpenCV on Colab. Colab notebooks run on Google's cloud servers and have access to Google's GPUs, which means you can use Google hardware regardless of the power of your machine, you only need a browser.

b) TensorFlow is an open-source platform for building and deploying ML models, with a special focus on deep learning.

c) Keros is an ML (machine learning) API (Application Programming Interface) written in Python and running on TensorFlow. It provides essential abstractions and building blocks for developing machine learning solutions.

4.5 Evaluate the performance of classification

To evaluate the performance of classification we used many parameters including precision, recall, and F-score.

1. The precision of a test represents the fraction of positive results among all false-positive results plus true-positive results.

$$precision = \frac{tp}{tp+fp} \qquad (4.1)$$

2. Recall is the percentage of true positives over a total number of true positives plus false negatives).

$$recall = \frac{tp}{tp+fn} \qquad (4.2)$$

If the Precision and Recall are both equal to ***1*** then we said that the classifier is perfect.

3. The F1-score measures the accuracy of the model on a dataset. A great model mean F-score=***1***.

$$F1 = \frac{tp}{tp+\frac{1}{2}(fp+fn)} \qquad (4.3)$$

Where :

tp : Number of true positives values .

fn : Number of false negatives values.

fp : Number of false positives.

CHAPTER V

RESULTS

The research was separated into three experiments each one is divided into three parts, here we will examine the results of each of them, the three parts are data set preparation, discrete wavelet transforms coefficients, and then the classification results. In the following sections, we will show the results for the three experiments and the three stages of each one.

5.1 Experiment One Results

In this experiment, we tested our model on four beats from the MIT-BIH database (N, R, V, F) see table 5.1, in the following results for the three stages at experiment 1.

5.1.1 The Dataset Upsample (Stage one)

According to the dataset, the N class comprises 89% of the whole dataset. Due to this overbalancing, poor-quality algorithms can result from the training process. The problem is solved by duplicating the data and doing an up-sample (as we did in Experiment one) or augment the data(as we did in Experiments two and three) to overcome this problem.

Here are two dataset configurations we have considered. Firstly, we created the test set, followed by the validation set, which was randomly selected from the dataset.

Table 5.1 shows that each category is randomly sampled 2000 times for training and validation (90:10%, respectively). Within class F, there are only 1784 samples, so it is randomly repeated to produce 2000 samples. The frequency distribution for the various labels before and after upsampling is shown in Figures 5.1 and 5.2.

Table 5.1 Traning and Validation Dataset used in the experiment (1)

Class heartbeat			Traning Data	Validation data	# of each class in all database
N	**0**	**Normal beat only**	2000	14000	75011
R	**1**		2000	1420	7255
V	**2**		2000	1460	7129
F	**3**		1420	361	1784

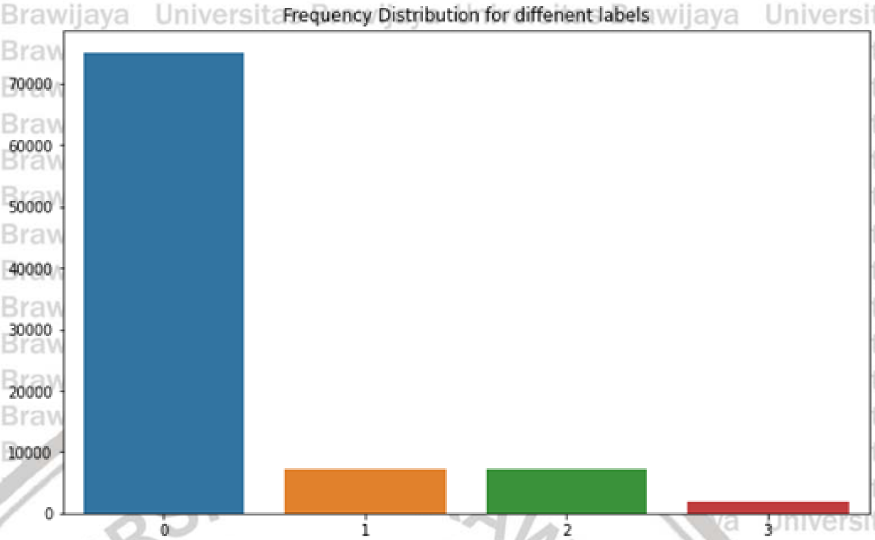

Figure 5.1 frequency distribution before up-Sample

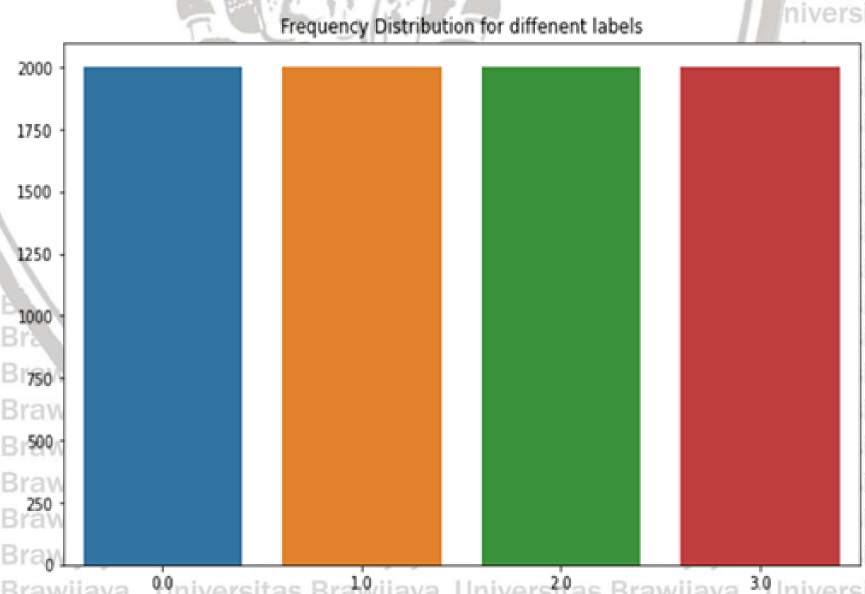

Figure 5.2 frequency distribution after up-Sample

5.1.2 The Discrete Wavelet Transform coefficients (stage 2)

The Scalogram For Discrete Wavelet Coefficients in Figure 5.3 shows the detailed coefficients in experiment 1.

The original signal which beats here is multiplied along the x-axis with wavelets so we start from Lower(4) coefficient when the wavelet is compressed capturing details in the high-frequency range, and Higher(0) coefficient when the wavelet is expanded capturing details in the low-frequency range. These coefficients are fed to our Deep Learning model, and help the model to predict the beat class with better accuracy.

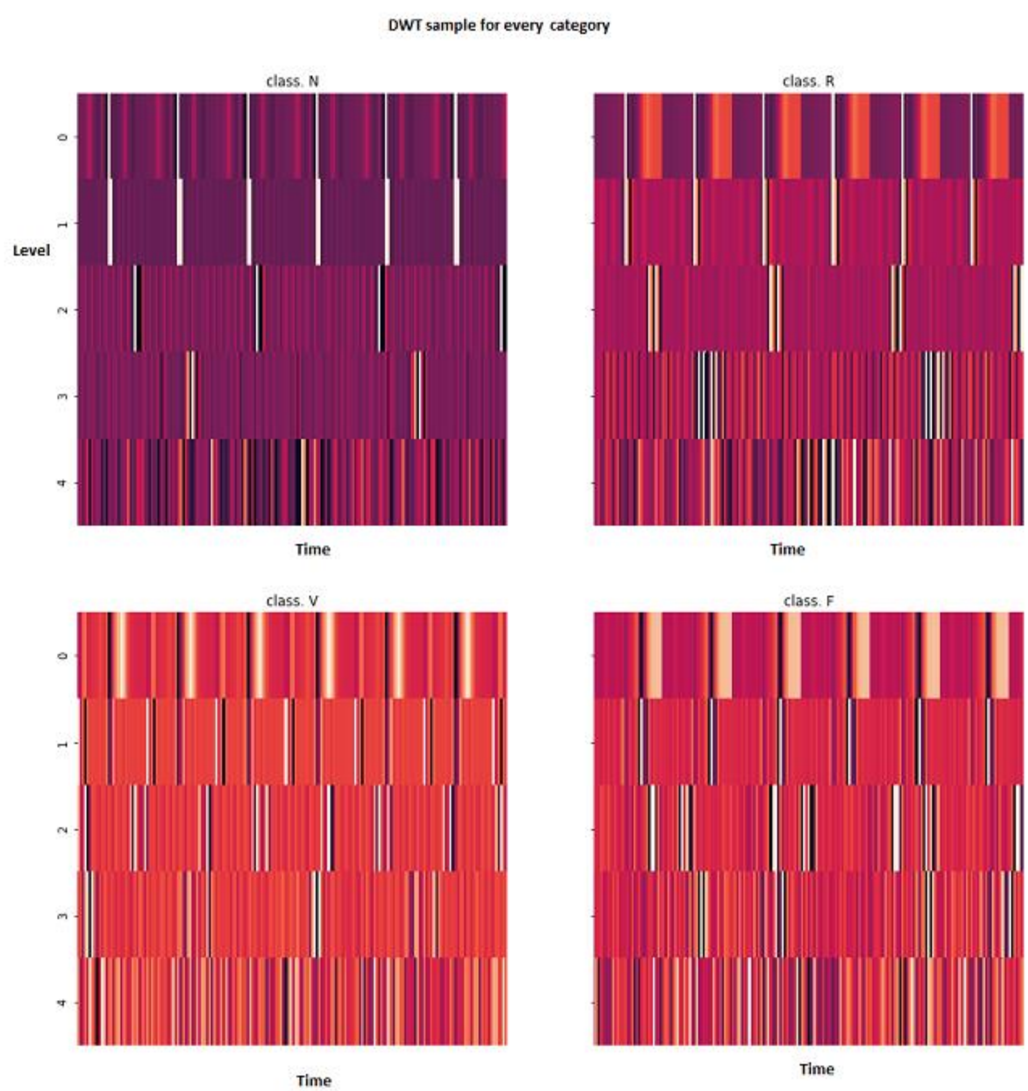

Figure 5.3 The Scalogram For Discrete Wavelet Coefficients for experiment 1

5.1.3 The evaluation of the classifier in Exp.1 (stage three)

Our goal is to show the results of evaluating the proposed classifier in section 4.3, applying it to the dataset for experiment 1, and showing the results on both training and testing datasets for each experiment respectively.

A. Training Set Results: In Section 4.3, the arrhythmia classifier was evaluated on 8000 heartbeats (2000 for each class). Figure 5.4, which shows the confusion matrix for the applied classifier, indicates that the model can classify and distinguish between different classes with an overall accuracy of 99%. The Classification Report for the training data is shown below, as shown in Figure 5.5. The performance is excellent, F1 score and recall are almost 1.0

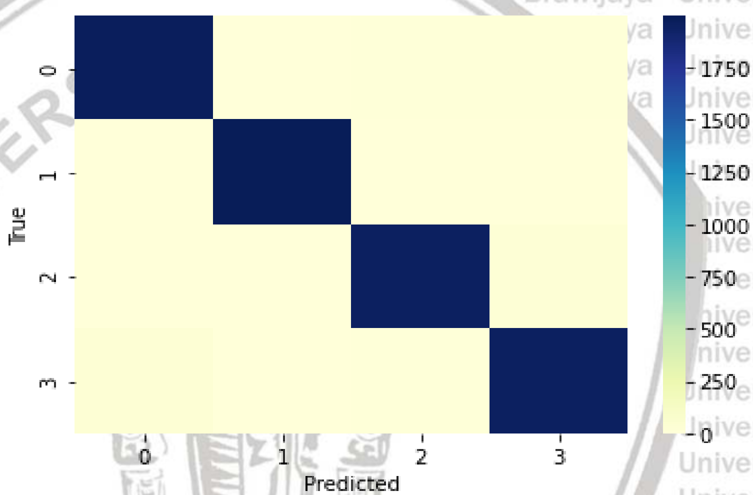

Figure 5.4 The Confusion Matrix For Applying The Model On The Training Set

	precision	recall	f1-score	support
0	0.98	0.99	0.98	2000
1	1.00	1.00	1.00	2000
2	0.99	0.98	0.98	2000
3	0.98	0.98	0.98	2000
accuracy			0.99	8000
macro avg	0.99	0.99	0.99	8000
weighted avg	0.99	0.99	0.99	8000

Figure 5.5 The Classification Report On The Training Data

B. Testing Set Results: When we evaluated the arrhythmia classifier in Section 4.3 on 18236 heartbeats, we got 97% accuracy. Based on Figure 5.6, it appears that the model provides accurate predictions and classifies four different classes when applied to the testing set. The Classification Report in Figure5.7 shows that the testing data perform well. The F1score and Recall numbers are very close to 1, which is their optimal number.

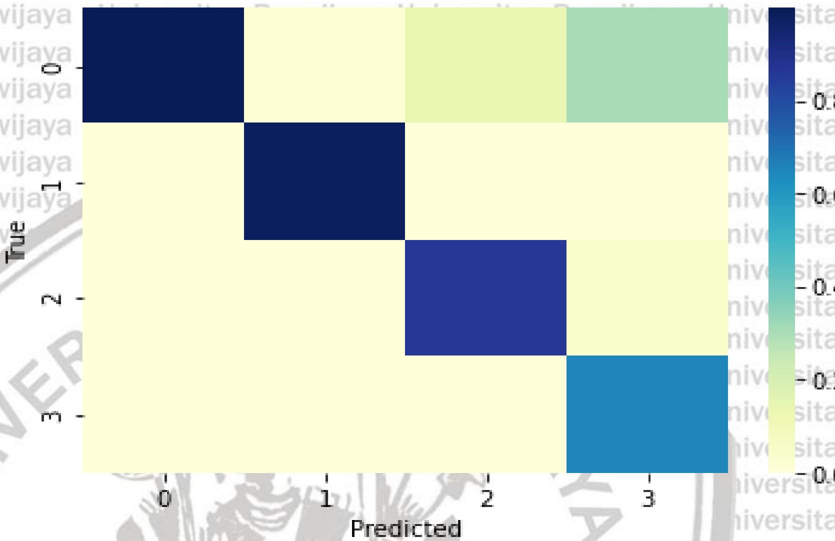

Figure 5.6 The Confusion Matrix For Applying The Model On The Testing Set (exp.1)

	precision	recall	f1-score	support
0	1.00	0.97	0.99	14990
1	0.98	0.99	0.99	1422
2	0.86	0.98	0.91	1461
3	0.65	0.94	0.77	363
accuracy			0.97	18236
macro avg	0.87	0.97	0.91	18236
weighted avg	0.98	0.97	0.98	18236

Figure 5.7 The Classification Report On The Testing Data (exp.1)

5.2 Expermint Two Results

In this experiment, we tested our model on four beats from the MIT-BIH database as experiment one but we made a little change in the heartbeats types, we used S instead of R (see table 2.1). Also, we made enhancements to the model we changed hyperparameters, and the data was augmented in this experiment. in the following results for the three stages at experiment 2.

5.2.1 The Data Augmentation (Stage one)

To enhance Exp.1, we use data augmentation, we take one sample of ECG waveform and augment it. Figure 5.8 shows the data used in exp.2. Note that in the enhancement model we took 10000 samples per category. with the categories 0: N, 1: S, 2: V, 3: F'. we replace R with S only, as 20%:10% for testing and validation data respectively.

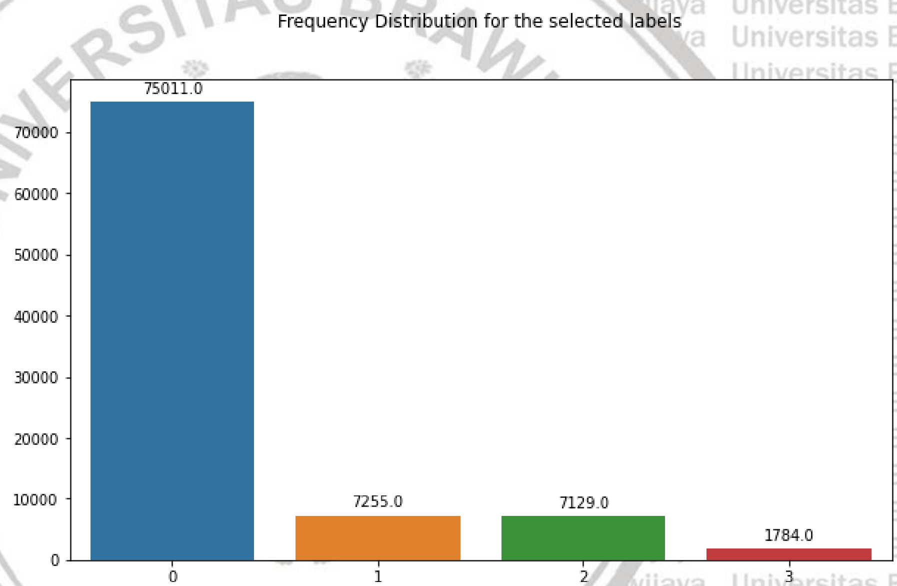

Figure 5.8 The frequency distribution for the data for the enhancement model

5.2.2 The Discrete Wavelet Transform coefficients (stage 2)

The Scalogram For Discrete Wavelet Coefficients in Figure 5.9 shows the detailed coefficients in experiment 1, The original signal which beats here is multiplied along the x-axis with wavelets so we start from Lower(4) coefficient when the wavelet is compress capturing details in the high-frequency range, and Higher(0) coefficient when the wavelet is expanded capturing details in the low-frequency range. These coefficients are fed to our Deep Learning model, and help the model to predict the beat class with better accuracy.

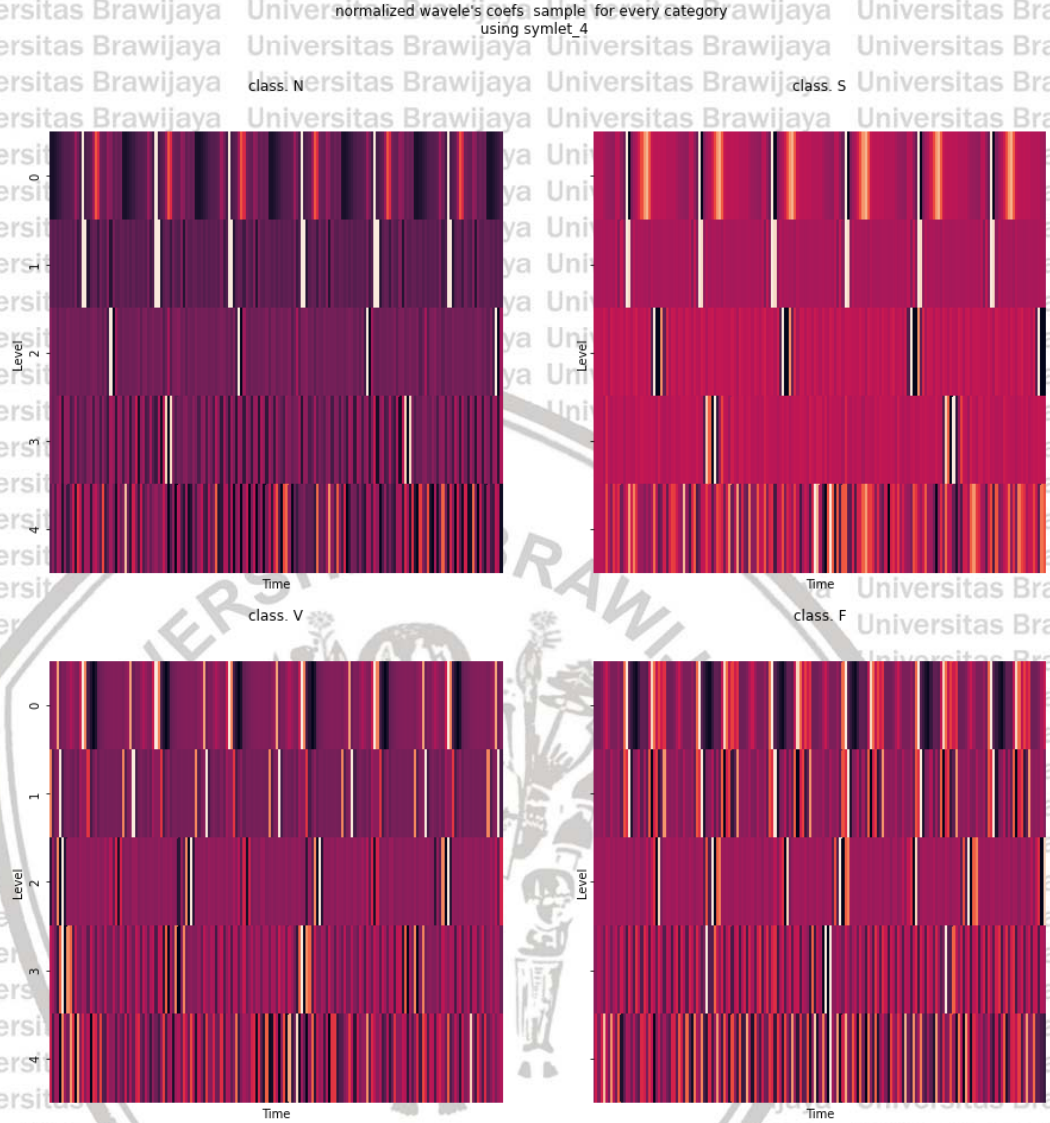

Figure 5.9 The Scalogram For Discrete Wavelet Coefficients for experiment 2

5.2.3 The evaluation of the classifier in Exp.2 (stage three)

Here we discusses the results of evaluating the proposed classifier in section 4.3, applying it to the dataset used in experiment 2, and showing the results from both training and testing datasets for each experiment.

A. Training Set Results: The arrhythmia classifier in Section 4.3 was evaluated using 72943 heartbeats (10000 from each class). Figure 5.10, which shows the confusion matrix for the applied classifier, can make accurate classifications and determine between the different classes to an overall accuracy of 99%. The Classification Report on the Training Data is shown in Figure 5.11. The performance is excellent, the F1 score and Recall are almost 1.

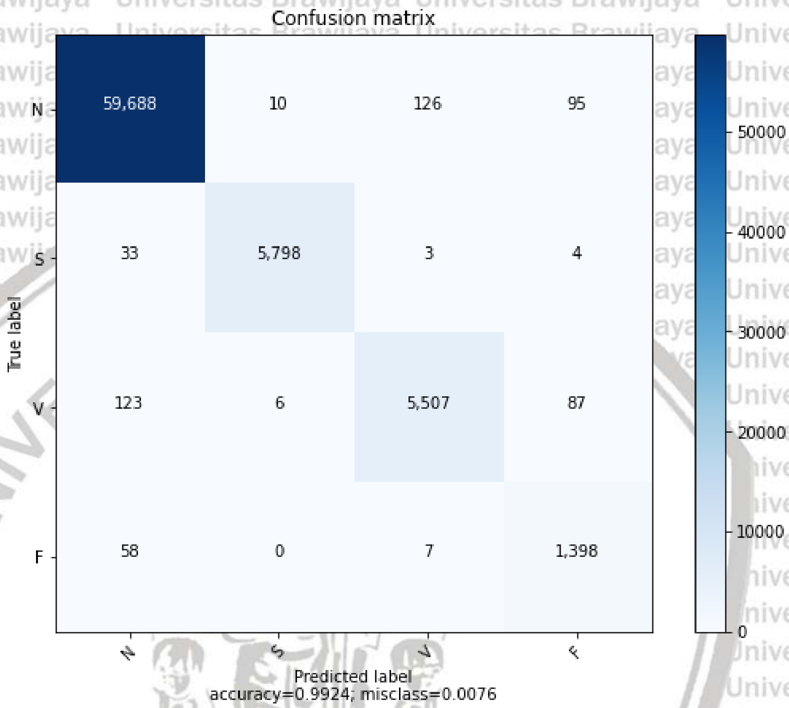

Figure 5.10 The Confusion Matrix For Applying The Model On The Training Data (exp.2)

Figure 5.10 shows that for example, the predicted N class are 59688 beats are true classified, 33 was classified as S class, 123 beats as V class, and finally, 58 beats were classified as F class.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	59919
1	1.00	0.99	1.00	5838
2	0.98	0.96	0.97	5723
3	0.88	0.96	0.92	1463
accuracy			0.99	72943
macro avg	0.96	0.98	0.97	72943
weighted avg	0.99	0.99	0.99	72943

Figure 5.11 The Classification Report On The Training Data (exp. 2)

B. Testing Set Results: A "98.99% accuracy" result was observed when the arrhythmia classifier of Section 4.3 was used to analyze 18236 heartbeats. According to the confusion matrix in Figure 5.12, the model gives accurate results and classifies four classes when applied to the testing set. Furthermore, the Classification Report in figure 5.13 shows that the performance of the testing data is excellent. Both F1score and Recall are close to 1, which is an ideal number for them. By changing the hyperparameters and the samples that were already taken, we did a clear enhancement in Experiment1.

Figure 5.12 shows that for example, the predicted S class are 1407 beats are true classified, 4 was classified as N class, 4 beats as V class, and finally, 0 beats were classified as F class.

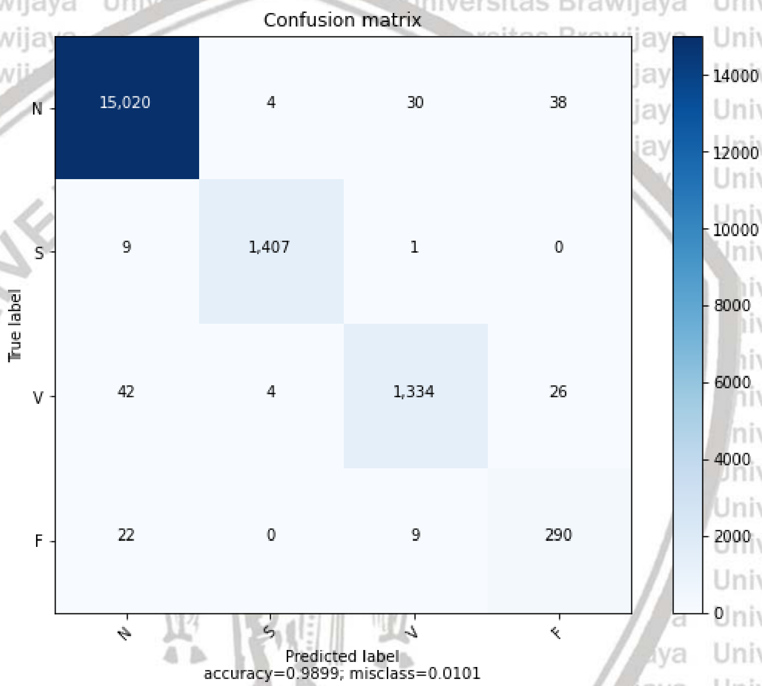

Figure5.12 The Confusion Matrix For Applying The Model On The Testing Set (exp.2)

	precision	recall	f1-score	support
0	1.00	1.00	1.00	15092
1	0.99	0.99	0.99	1417
2	0.97	0.95	0.96	1406
3	0.82	0.90	0.86	321
accuracy			0.99	18236
macro avg	0.94	0.96	0.95	18236
weighted avg	0.99	0.99	0.99	18236

Figure 5.13 The Classification Report On The Testing Data (exp.2)

5.3 Expermint Three Results

In this experiment, we tested our model on all beats from the MIT-BIH database which is 12 beats divided into four major types (N, S, V, F) see table 2.1. Also, we changed hyperparameters, and the data was augmented in this experiment. In the following results for the three stages at experiment 3.

5.3.1 The Data Augmentation (Stage one)

A frequency distribution is illustrated in Figure 5.14 for experiment 3. Here, we took all AAMI categories 30000 samples each, and 20% on testing, and 10% on validation data.

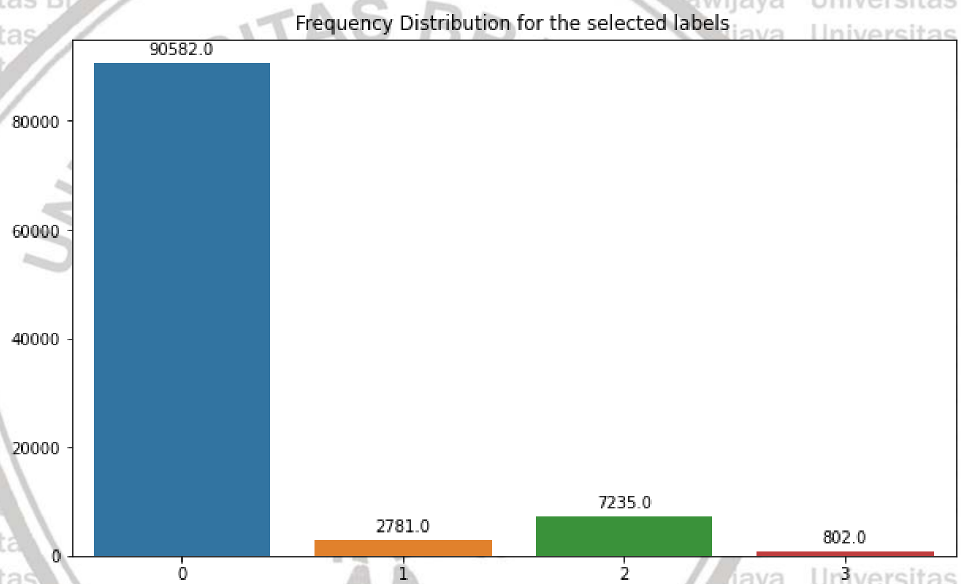

Figure 5.14 The frequency distribution for the data for the second model

5.3.2 The Discrete Wavelet Transform coefficients (stage 2)

The Scalogram For Discrete Wavelet Coefficients in Figure 5.15 shows the detailed coefficients in experiment 1, The original signal which beats here is multiplied along the x-axis with wavelets so we start from Lower(4) coefficient when the wavelet is compressed capturing details in the high-frequency range, and Higher(0) coefficient when the wavelet is expanded capturing details in the low-frequency range.

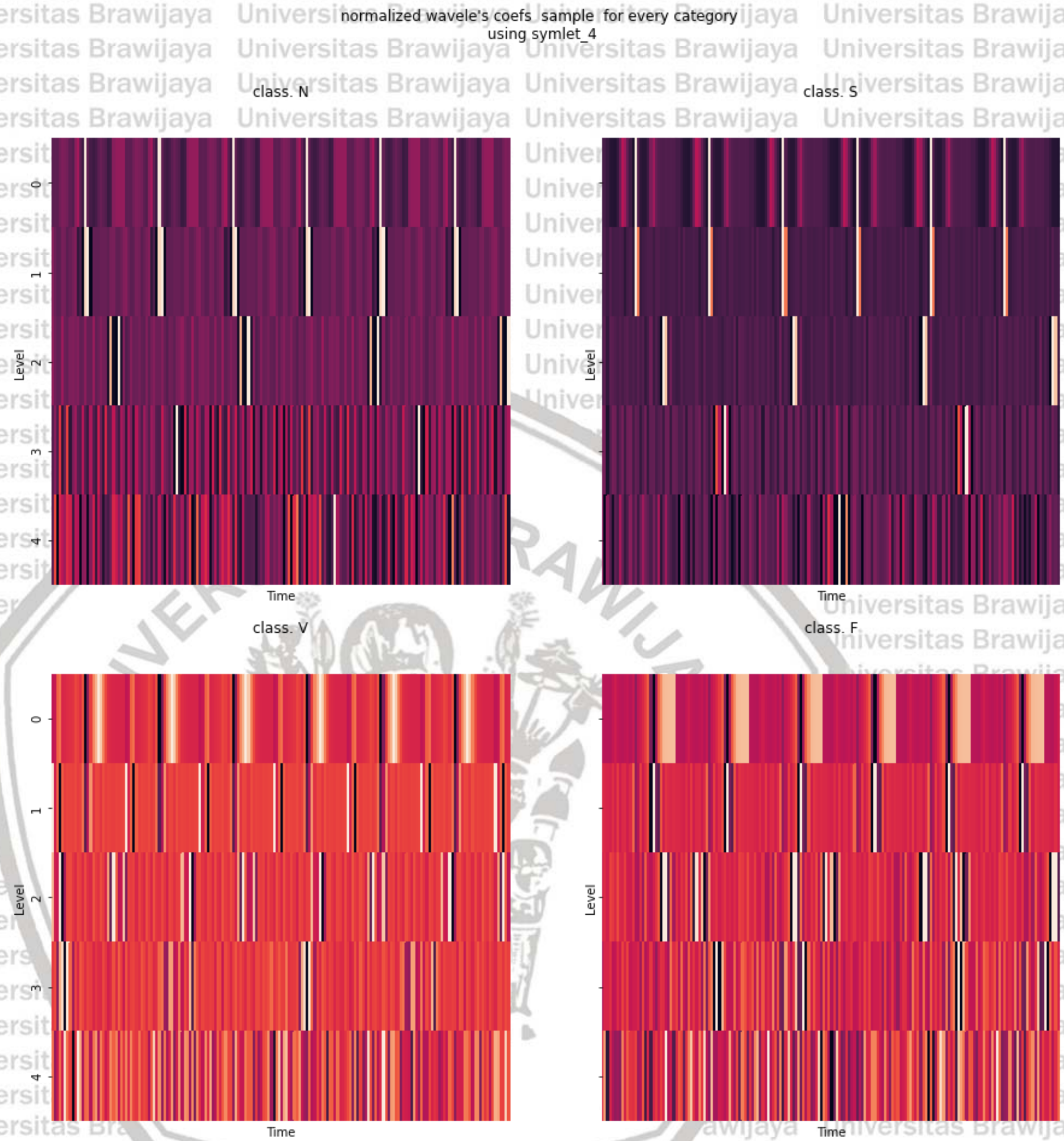

Figure 5.15 The Scalogram For Discrete Wavelet Coefficients for experiment 3

5.3.3 The evaluation of the classifier in Exp.3 (stage three)

The purpose of this section is to discuss the results of the evaluation of the proposed classifier, applying it to the dataset for experiment 3, and showing the results on both training and testing datasets for the experiment.

A. Training Set Results: Using the arrhythmia classifier in Section 4.3, 81000 heartbeats were evaluated (30000 from each class). On the confusion matrix found in Figure 5.16, the model can classify and distinguish between the different classes with

98.2% accuracy in the testing set. Figure 5.17 shows the classification report on training data, F1 and Recall are both excellent.

Figure 5.16 shows that for example, the predicted V class are 5120 beats are true classified, 19 was classified as S class, 45 beats as N class, and finally, 10 beats were classified as F class.

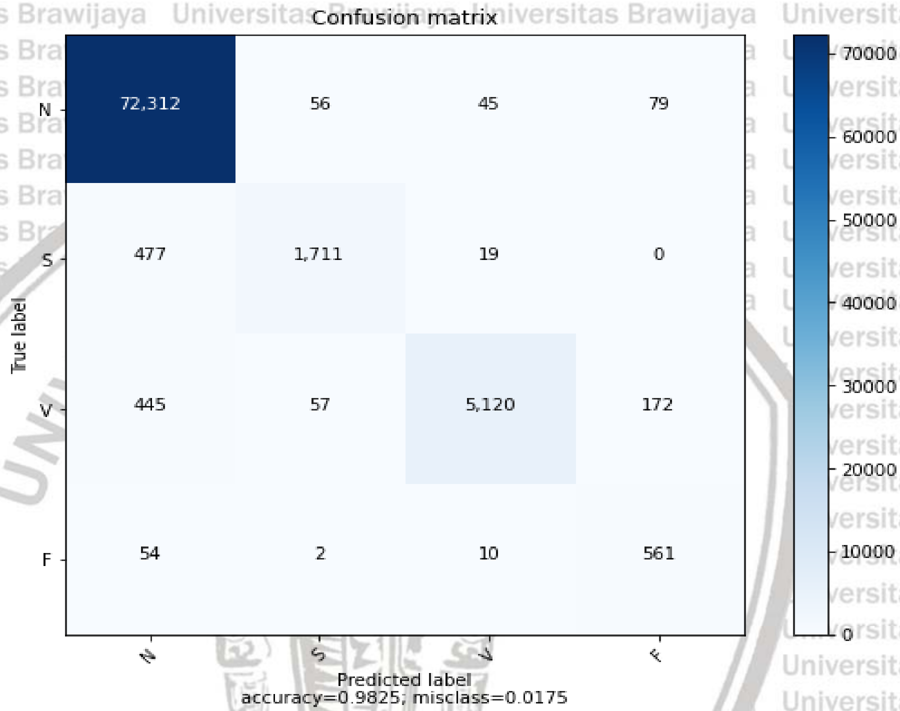

Figure 5.16 The Confusion Matrix For Applying The Model On The Training Data (exp. 3)

	precision	recall	f1-score	support
0	0.99	1.00	0.99	72492
1	0.94	0.78	0.85	2207
2	0.99	0.88	0.93	5794
3	0.69	0.89	0.78	627
accuracy			0.98	81120
macro avg	0.90	0.89	0.89	81120
weighted avg	0.98	0.98	0.98	81120

Figure 5.17 The Classification Report On The Training Data (exp.3)

B. Testing Set Results: Using 20280 heartbeats, we tested the arrhythmia classifier described in Section 4.3. We achieved 97.7% accuracy. When the model is applied to the testing set, the confusion matrix in Figure 5.18 appears to give accurate predictions and classify four different classes. Also, in figure 5.19, we see a very good performance from the testing data. Both F1score and Recall are close to 1, which is an ideal number for them.

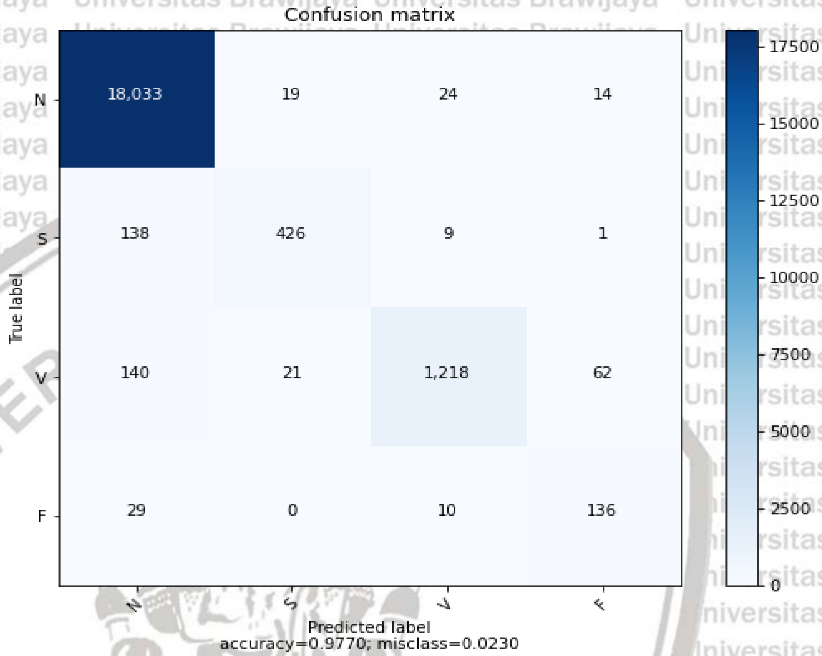

Figure 5.18 The Confusion Matrix For Applying The Model On The Testing Set (exp. 3)

Figure 5.18 shows that for example, the predicted N class are 18033 beats are true classified, 138 was classified as S class, 140 beats as V class, and finally, 29 beats were classified as F class.

	precision	recall	f1-score	support
0	0.98	1.00	0.99	18090
1	0.91	0.73	0.81	574
2	0.96	0.83	0.89	1441
3	0.65	0.80	0.71	175
accuracy			0.97	20280
macro avg	0.87	0.84	0.85	20280
weighted avg	0.97	0.97	0.97	20280

Figure 5.19 The Classification Report On The Testing Data (exp. 3)

5.4 Summary

To classify arrhythmia beats for the MIT-BIH database, we implemented one classifier model and tested it three times, changing the hyperparameters and data amount, as well as the beat categories. We test three experiments:

1) Experiment One: Classified 4 beat types (Normal only, R, V only, F),

2) Experiment Two: Improvement for experiment number 1 (Nonly, S, V only, F)

3) Experiment Three: Classified 12 beat types into four major AMMI categories (N, S, V, F)

In the first model, we get 97% without overfitting, we do not do data augmentation but just upsample, and we use the discrete wavelet transform in all experiments. (Alqaisi, Y. Muslim, M. Rahmadwati, 2021). Furthermore, we get 99% without overfitting in enhancement experiment 1 by doing data augmentation and raising the number of samples, while making minor changes to the hyperparameters. In the third analysis, we obtain 97.7% without overfitting from all data and all types of beats as AAMI standards. Here is a comparison between the three experiments and the hyperparameters used in Table 5.2.

Table 5.2 The hyperparameters used in the three experiments

Model	beats	Dropout	Epochs	LR	The Data	Accuracy %	Macro-average	weighted average
1st model	4	0.5	50	0.0001	Up-sampled	**97**	0.91	0.98
2ed model	4	0.2	50	0.001	augmented	**99**	0.95	0.99
3rd model	12	0.2	50	0.001	augmented	**97.7**	0.85	0.97

Table 5.3 displays a comparison between our work and others, although we employ a time-series method, not a feature extraction one.

We mean by feature extraction in ECG, extract the segments and intervals between points such as RR interval, the amplitude of P, R, and T wave, also QRS offset. And that happened by many methods such as machine learning and non-machine learning, statistical, wavelet transforms, etc. In another hand, this research used annotation files to detect R peaks.

The table has shown that our proposed model (CNN+LSTM+DWT) achieve high accuracy in the three experiments.

Table 5.3 Another works on the topic of arrhythmia

Work	Approach	Average Accuracy (%)
This work: 1st EXP./2ed /3rd	**CNN-LSTM +DWT**	**97/99/97.7**
M. Kachuee (2018)	DR- CNN	93.4
Martis (2013)	DWT + SVM	93.8
Acharya (2017)	Augmentation + CNN	93.5
Li (2016)	DWT + RF	94.6
Yeh et al., (2012)	Clustering	94
Lin et al., (2008)	Morlet Wavelet+ AWN	90
Korurek and Nizam (2008)	ACO-based Cluster,kNN	94

CHAPTER VI

CONCLUSIONS AND SUGGESTIONS

6.1 Conclusions

Three experiments were conducted in this study. In the first experiment, we selected four beats from the MIT-BIH database and classified them using a time series model based on deep learning (1D-CNN+LSTM), and DWT to prepare the data for analysis. There was a 97% accuracy rate. With the second experiment we improved output to 99% after changing hyperparameters and with the third experiment, we applied the proposed model to all MIT-BIH databases (12 beat types) for Arrhythmia following the AAMI standard and achieved an accuracy.

According to our problem statements the results of our research shows the following:

The model solved the difficulties of diagnosing types of arrhythmia and the needing for analysis by a cardiologist. by showing that no need for a cardiologist to analyze the ECG data and diagnosing types of arrhythmia, we can do that using the model of classification.

The model solved the time-consuming by a Cardiologist to analyze data. by computerized classification that offers a very high speed in deal with ECG data. The program takes **26.761**s to **36.234s** in the prediction of the classes.

The model solved the problem of lack of accuracy, the model achieved very high accuracy in the three experiments from (97-99)%.

The research is focused on Time-series Classification following AAMI categories which added value to this field. Because The majority of research in Arrhythmia classification is based on features classification to classify the beats, some of which use (AAMI) categories, and others that do not.

Based on the research hypothesis we find that :

In our study, Deep Learning and Discrete Wavelet Transform combine to achieve high classification accuracy. Using the proposed model (1D-Convolution, LSTM, and Dense) we improved the Time series classification approach to achieve high classification accuracy, as well as to announce that the proposed model is reliable in classification tasks with time-series data.

By doing this, we reduced the time taken by cardiologists to detect arrhythmia, helped non-specialist health workers distinguish between the different types of arrhythmia heartbeats, and detected them faster.

6.2 Suggestions

Therefore, based on our study, it is possible to increase the third experiment to 99% or 100% accuracy. Additionally, researchers might find it interesting to test this proposed model on another data set. The Time series approach can also be used to experiment with other classifiers due to the lack of research in this area.

In summary, we achieved our goals when designing an arrhythmia classification model. The model was also applied to part of the samples and the whole dataset.

This method uses a time series instead of a feature extraction method, and it has proven to be reliable, reducing the time needed for the health workers to classify the arrhythmia beats.

Deep learning demonstrates a very good ability to predict and classify problems. Furthermore, we encourage the researcher to test more ML algorithms.

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