WAVELET-BASED HEART-RATE DETECTION AND ECG CLASSIFICATION OF ARRHYTHMIA USING ALEXNET DEEP CNN

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CERTIFICATE OF APPROVAL

The thesis entitled as "**Wavelet-Based Heart-Rate Detection And ECG Classification of Arrhythmia Using AlexNet Deep CNN**" submitted by **S.M. Abdulla Al Hasan Tasim**, bearing Matric ID. **ET163078** and **Masum Hosen Sajjad**, bearing Matric ID. **ET163061** of session **Autumn 2020**, to the Department of Electrical and Electronic Engineering, International Islamic University Chittagong, has been accepted as satisfactory in partial fulfilment of the requirements for the degree of Bachelor of Science in Engineering and approved for the examination held on **3rd September, 2021**.

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DECLARATION

It is hereby declared that this work has been done by us and no portion of the work contained in this thesis has been submitted elsewhere for the award of any degree or diploma.

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S.M. Abdulla Al Hasan Tasim

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Masum Hosen Sajjad

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S.M. Abdulla Al Hasan Tasim

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Masum Hosen Sajjad

ABSTRACT

Effective monitoring of heart patients based on heart signals has the potential to save a large number of lives. Classification and prediction of heart diseases based on ECG signals have become increasingly important for patients and doctors over the last decade. The majority of contemporary techniques are based on custom-designed features for automatic heart rate detection and ECG signal classification. The fundamental objective of this thesis work is to calculation of heart-rate and create a comprehensive learning-based technique that can classify ECG signals more accurately. We collected all data from PhysioNet for doing this work. We calculated heart rate using the Discrete Wavelet Transform (DWT) and trained a pre-trained Convolutional Neural Network (CNN), specifically AlexNet, to classify ECG signals. To begin, we extracted a spectrogram for each of the signals and transformed them to RGB images using the Continuous Wavelet Transform (CWT); these images were then put into AlexNet and trained with minor specification adjustments. The study's findings indicate that our technique achieves an accuracy of 97.14 %.

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LIST OF ABBREVIATIONS

ECG	Electrocardiogram
DWT	Discrete Wavelet Transform
CWT	Continuous Wavelet Transform
CNN	Convolutional Neural Network

CHAPTER 1
INTRODUCTION

1.1 Introduction

An ECG or Electrocardiogram is a test that determines the electrical activity of the heart. Each heartbeat generates an electrical impulse (or "wave"). This wave induces muscular contraction and blood pumping from the heart. An ECG recording of a typical heartbeat will reveal the time of the upper and lower chambers. When the electrical impulse travels to the bottom chambers, the right and left atria or upper chambers produce the first wave, called a "P wave," followed by a flat line. The right and left bottom chambers, or ventricles, produce the next wave, called a "QRS complex." The final wave, or "T wave," represents the ventricles' electrical recovery or return to resting state. An electrocardiogram (ECG) provides two types of important information. In the first instance, a doctor may measure how long it takes an electrical wave to travel through the heart by monitoring time intervals on an ECG. The length of time it takes for a wave to move from one region of the heart to the next indicates if the electrical activity is normal, slow, rapid, or irregular in nature. Another advantage of ECG is that it allows a cardiologist to determine if certain portions of the heart are too big or overworked by monitoring how much electrical activity is flowing through the muscle [1]. In **'Fig. 1.1'** we can see a ECG of a heart in normal sinus rhythm.

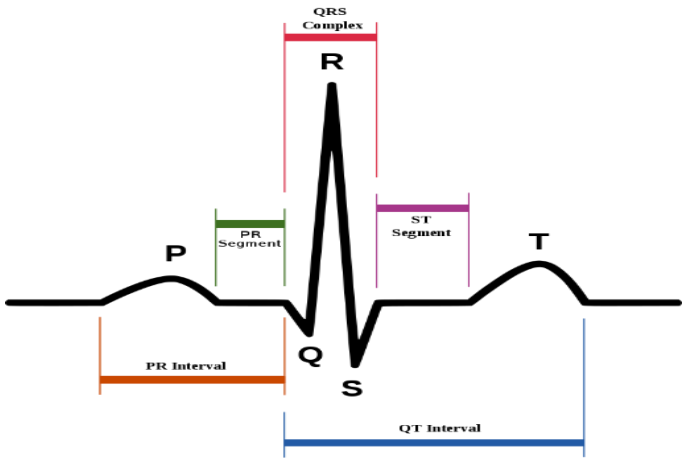

Fig. 1.1 ECG of a heart in normal sinus rhythm [2]

The technique of creating an electrocardiogram (ECG) is known as electrocardiography. An electrocardiogram is a graph of voltage against time of the electrical activity of the heart obtained by placing electrodes on the skin as shown in "**Fig. 1.2"**. These electrodes monitor the small electrical changes that occur throughout each cardiac cycle as a result of heart muscle depolarization followed by repolarization. Heart rhythm problems (such as atrial fibrillation and ventricular tachycardia), insufficient coronary artery blood flow (such as myocardial ischemia and myocardial infarction), and electrolyte disorders can cause changes in the normal ECG pattern. Ten electrodes are put on the patient's limbs and on the surface of the chest in a standard 12-lead ECG. The total magnitude of the heart's electrical potential is then determined and recorded over time from twelve distinct angles ("leads") (usually ten seconds). Thus, the amplitude and direction of the heart's electrical depolarization at each point throughout the cardiac cycle are recorded [3].

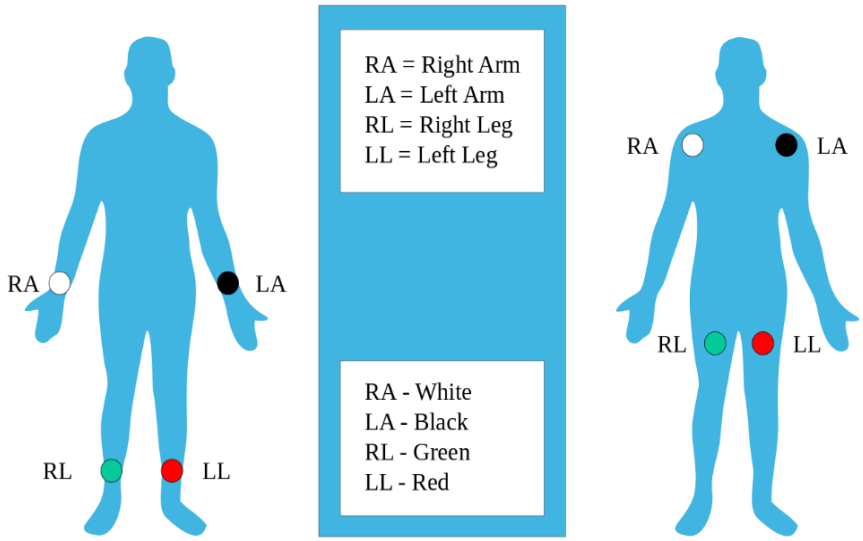

Fig. 1.2 Placement of the limb electrodes [4]

An ECG consists of three major components: the P wave, which represents the atria's depolarization; the QRS complex, which represents the ventricles' depolarization; and the T wave, which represents the ventricles' repolarization [5].

During each beating, a healthy heart undergoes an ordered sequence of depolarization that begins with pacemaker cells in the sinoatrial node, travels throughout the atrium and then

descends into the bundle of His and Purkinje fibers, spreading down and to the left throughout the ventricles. This regular pattern of depolarization results in the distinctive ECG trace. An ECG provides extensive information about the anatomy of the heart and the operation of its electrical conduction system to a skilled doctor. An ECG can be used to determine the rate and rhythm of heartbeats, the size and location of the heart chambers, the existence of any abnormalities to the heart's muscle cells or systemic circulation, the effects of cardiac medications and the operation of implanted pacemakers, among other things [6].

ECG paper is a grid on which time is measured horizontally.

- Each little square is 1 mm long and equals 0.04 seconds.
- Each bigger square has a length of 5 mm and represents 0.2 seconds.

The voltage is measured vertically.

- In voltage terms, 10 mm equals 1 mV.

The "**Fig. 1.3"** in below shows how to set up ECG graph paper and where to take measurements of the various components of the ECG wave pattern.

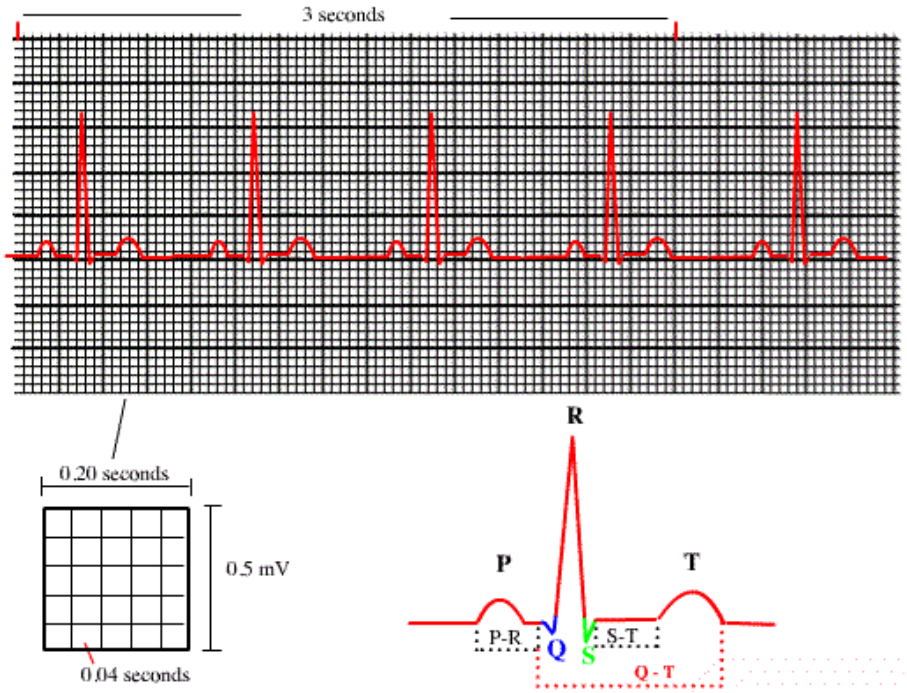

Fig. 1.3 ECG graph paper [7]

Calculating the heart rate from the ECG strip:

1. The heart rate is 300 divided by the total number of big squares between the QRS complexes when the rhythm is regular.

- If there are four big squares between normal QRS complexes, for example, the heart rate is 75 (300/4=75).

2. The second technique may be used to find the rate in the presence of an irregular rhythm. Multiply the number of R waves in a six-second strip by ten.

- For instance, if a six-second strip has 6 R waves, the heart rate is 60 (6x10=60) [7].

Classification and prediction of heart diseases based on ECG signals have become increasingly important for patients and doctors over the last decade. Due to simplicity and non-invasive nature, ECG signals have been extensively utilized to diagnose cardiac problems the majority of contemporary techniques are based on custom-designed features for automatic heart rate detection and ECG signal analysis. The fast advancement of computer technology has resulted in advancements in data gathering and computer-assisted diagnostic techniques. Due of these advancements, Heart problems can now be detected more easily. Many software's allow for the computation and extraction of ECG signal characteristics from ECG data like, MATLAB [8]. For example, large numbers of people suffer with heart problems, which in certain instances may be fatal. As a result, precise and low-cost arrhythmic heartbeat diagnosis is extremely desired [9]. Numerous researches have established arrhythmia classification methods based on automated processing and analysis of ECG data. The most critical aspects of heart illness analysis and diagnosis are feature extraction and categorization is superior. Various classification methods for ECG data have been suggested in past few years and the positive outcomes obtained. The strength of the effectiveness of ECG classification tasks relies on the feature extraction power and the classifier design. Several researchers have already described automated heartbeat categorization utilizing a multitude of characteristics to describe the ECG and classifying techniques. Heartbeat characteristics include morphology and intervals of the ECG [10]. The abundance of signal processing and neutral network approaches available for processing ECG signals motivated us to do thesis work on extracting characteristics from ECG signals in order to diagnose various heart conditions. The

fundamental objective of this thesis work is to calculation of heart-rate and create a comprehensive learning-based technique that eliminates the need for manually calculation of heart rate and identifying characteristics. We calculated heart rate using the Discrete Wavelet Transform (DWT). We collected ECG recordings from PhysioNet. From the PhysioNet, we collected MIT-BIH Arrhythmia Database and ECG-ID Database from PhysioBank ATM. The signal we collected is the length of 10 seconds. we collected 5 records from each database. The sampling rate of the MIT-BIH database is 360 Hz and the sampling rate of the ECG-ID database is 500 Hz. After that, we reduce the low and high-frequency components of the signal that is to be used for the calculation of heart rate. After removing low and high frequency we detect R peaks of the signal by Discrete Wavelet Transform (DWT) in MATLAB and calculated heart rate from the signal. In **'Fig. 1.4'** we can see Discrete Wavelet Transform process.

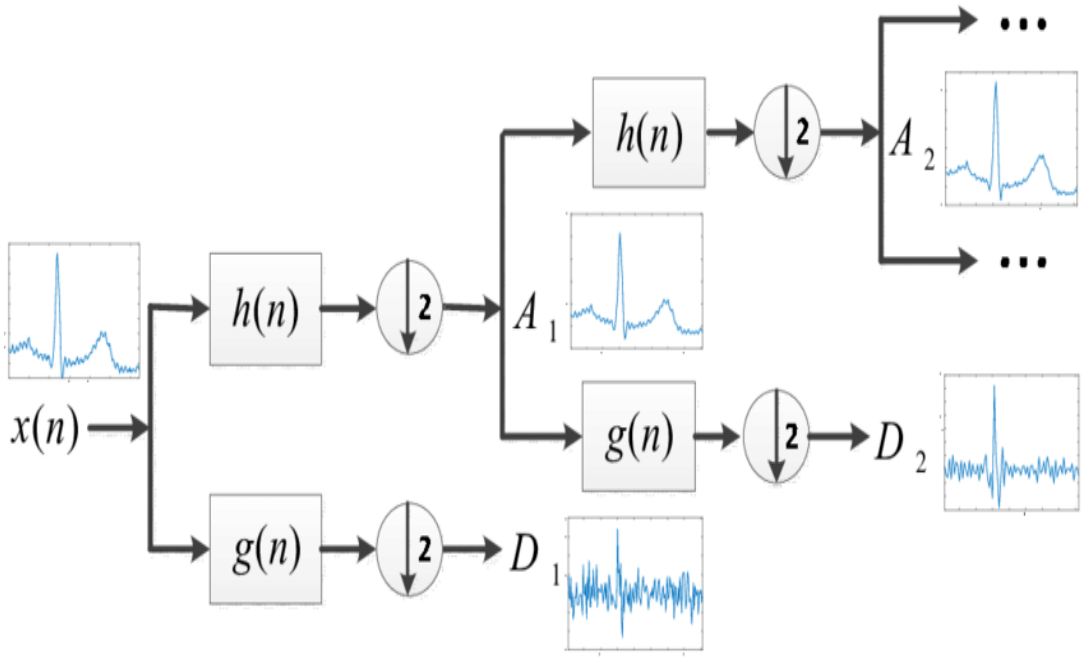

Fig. 1.4 Discrete Wavelet Transform process [11]

After calculating the heart rate, we observe if the heart rate of the patient is normal or abnormal. After calculating the heart rate, we observe if the heart rate of the patient is normal or abnormal. If the heart beats too fast or too slow than the patient has Tachycardia or, Bradycardia.

- The normal heart rhythm is 60-100 BPM. **'Fig. 1.5'** shows ECG strip of a normal heartbeat.

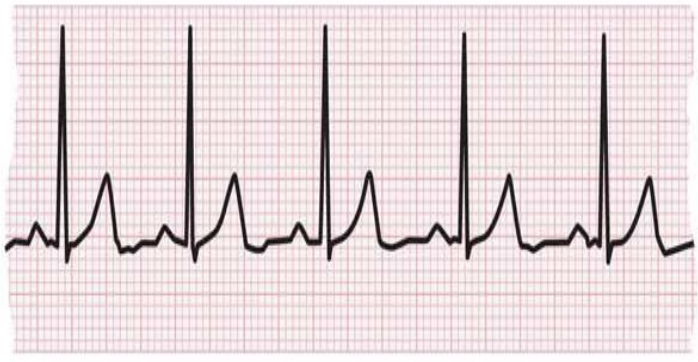

Fig. 1.5 ECG strip showing a normal heartbeat [12]

- If the heart rate is >100, then the patient has tachycardia. Tachycardia is the condition of the heart when the heart beats too fast. **'Fig. 1.6'** shows ECG strips of Tachycardia.

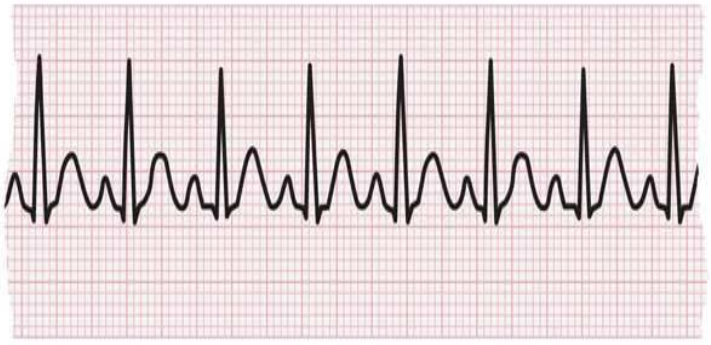

Fig. 1.6 ECG strip showing Tachycardia [12]

- If the heart rate is <60, then the patient has bradycardia. Bradycardia is the condition of the heart when the heart beats too slow. **'Fig. 1.7'** shows ECG strips of Bradycardia.

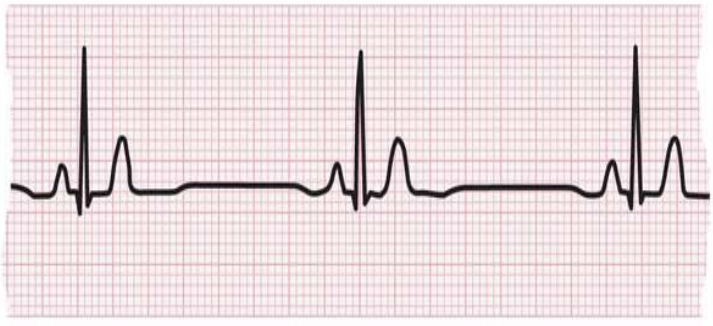

Fig. 1.7 ECG strip showing Bradycardia [13]

After Calculating the heart rate by DWT, we moved to our next process, which is the classification of ECG signal. For classifying ECG signals we used Continuous Wavelet Transform (CWT) and AlexNet deep CNN in MATLAB. Also, for this process, we collected ECG recordings from Physionet. From Physionet, we collected a total of 7 types of ECG recordings from PhysioBank ATM. We used ECG signals of seven categories:

1) MIT-BIH Arrhythmia Database.
2) BIDMC Congestive Heart Failure Database.
3) MIT-BIH Normal Sinus Rhythm Database.
4) Non-Invasive Fetal ECG Arrhythmia Database.
5) MIT-BIH Supraventricular Arrhythmia Database.
6) Intracardiac Atrial Fibrillation Database.
7) MIT-BIH Malignant ventricular Ectopy Database.

We collected a total of 357 records of ECG from PhysioBank ATM. Out of these 357 ECG recordings, we collected 96 recordings from MIT-BIH Arrhythmia Database, 30 recordings from BIDMC Congestive Heart Failure Database, 36 recordings from MIT-BIH Normal Sinus Rhythm Database, 26 recordings from Non-Invasive Fetal ECG Arrhythmia Database, 84 recordings from MIT-BIH Supraventricular Arrhythmia Database, 60 recordings from MIT-BIH Supraventricular Arrhythmia Database, 25 recordings from MIT-BIH Malignant ventricular Ectopy Database. Then we gathered all 357 records in a file where ECG recordings from all 7 databases present.

The goal of this ECG classification was to train AlexNet deep CNN to distinguish between these seven recordings of arrhythmia. We also used labels to know about ECG signals information. For our work, we process the database. We broke each ECG recordings into small signals of length 500 samples to increase the size of the database to make it appropriate to train the CNN. Each recording was broken into 15 pieces of the length of 500 samples. For equal distribution, we took 25 recordings of each type of database.

We converted all the signals which are 1D signals into images using Continuous Wavelet Transform so that they could be fed as input to AlexNet deep CNN. **‘Fig. 1.8’** shows 1D ECG signal.

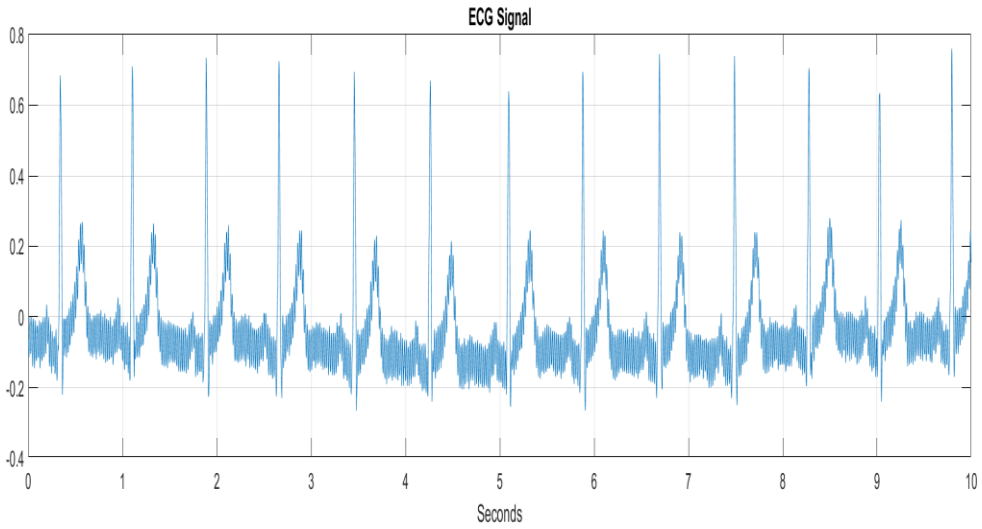

Fig. 1.8 1D ECG signal

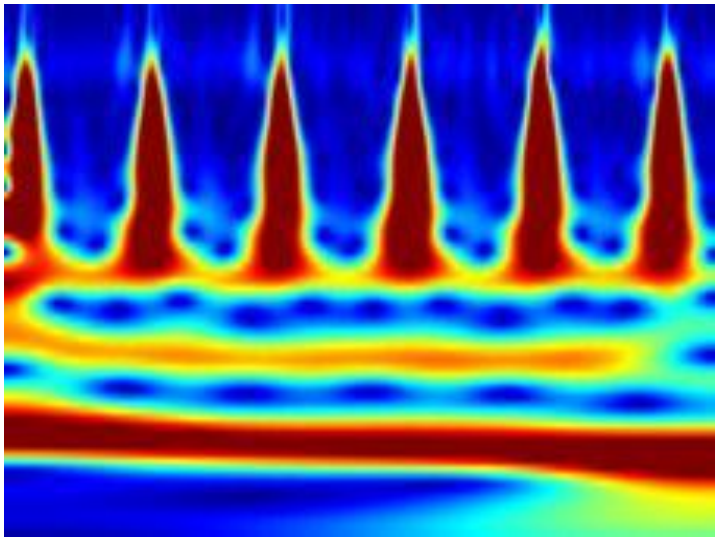

Fig. 1.9 1D signal after Continuous Wavelet Transform

'Fig. 1.9' shows the result of 1D signal after CWT process. After the conversion of 1D signals into images, we used AlexNet which was a pre-trained deep CNN for the classification of ECG signals.

The result showed that, the accuracy was 97.14%. That means 97.14% of recordings were classified correctly.

We compared our result with other methods of ECG classification in this thesis. We also elaborately discussed our work and the related theory of this work in this thesis.

1.2 Objectives

The objectives of this thesis are:

1 To calculate the heart rate from ECG recordings by using Discrete Wavelet Transform (DWT).

2 To learn about the conversion process of 1D signal to image by CWT scalogram.

3 To classify ECG signal using CWT and AlexNet deep CNN.

1.3 Chapter Outline

The chapters of this thesis are arranged in the following order:

- **Chapter 1**: This chapter is introduction, which provides a brief introduction of this work.
- **Chapter 2**: This chapter is Literature Review, which provides an overall idea of this work.
- **Chapter 3**: This chapter is Related Theory, which provides information about all the things we used in this work.
- **Chapter 4**: This chapter is Methodology, which details information about this thesis work.
- **Chapter 5**: This chapter is Result and Analysis, which shows the result of heart rate calculation and accuracy of ECG signal classification.
- **Chapter 6**: This chapter is Conclusion, which analyzes the result and conclude the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Our heart rate is similar to the velocity of Our vehicle. What we want is something that is neither too quick nor too sluggish, nor too unpredictable. Indeed, almost all of the time, heart rhythm and pace are irrelevant. And, unless anything extraordinary occurs, we are probably totally oblivious of our heart's activity. The heart rate is important because the heart's function is critical. The heart is responsible for the circulation of oxygenated and nutrient-rich blood throughout the body. When it is not functioning correctly, almost everything is impacted. Heart rate is critical in this process because the heart's function (referred to as "cardiac output") is proportional to both heart rate and blood pressure (the amount of blood pumped out with each beat). Some individuals are completely unaware of their heart's pace or rhythm, while others are acutely aware of any slight abnormality. That is not a sign of danger in the absence of symptoms. An irregular heart rate or rhythm may be detected through a physical examination, electrocardiogram, or other tests, even in healthy individuals who exhibit no symptoms [14]. “Heart rate, or pulse, is the number of times our heart beats per minute," says the American Heart Association. Our resting heart rate is calculated when we are not exercising or moving—when our heart is pumping the lowest amount of blood [15]. So, all of us need to know about our heart rate. Numerous researchers have previously reported automated categorization of heartbeats utilizing a range of ECG characteristics and a variety of classification techniques. Heartbeat aspects include ECG morphology, heartbeat interval characteristics (temporal characteristics), beat correlations, and summit values [10].

In this thesis, we calculate heart rate and also classify ECG recordings to detect arrhythmias. The heart rate calculation process objective is to calculate heart rate from ECG recordings. The ECG classification process's objective is to create an intelligent model capable of classifying ECG recording in order to detect arrhythmia. The final findings demonstrate that our model is more accurate than comparable works.

2.2 Related Work

Many researchers have worked on categorization of ECG signals. They have used several pre-processing methods, numerous feature extraction strategies and classifiers. Most of the researchers have utilized MIT-BIH arrhythmia database for ECG categorization. A survey of ECG classification given below:

1. **Shivajirao M. Jadhav, Sanjay L. Nalbalwar, Ashok A. Ghatol**: Using conventional 12-lead ECG signal recordings data, they developed an Artificial Neural Network (ANN)-based method for diagnosing cardiac arrhythmia illness and presenting it in their article. In their research, they were primarily concerned with categorizing illness into two categories: normal and abnormal. they had utilized ECG signal data from UCI to train and evaluate three distinct artificial neural network models. Their classification accuracy was 86.67 % [16].
2. **M.Vijayavanan, V.Rathikarani, Dr. P. Dhanalakshmi**: In this article, they present effective methods for classifying ECG data automatically into the normal and arrhythmia-affected (bad) categories. To illustrate the ECG signal in these categories, morphological characteristics are extracted. The probabilistic neural network (PNN) modeling method is used to represent the distribution of feature vectors for classification and to measure performance. The MIT-BIH arrhythmia database was used to gather ECG time-series signals for this study. The suggested method successfully classifies and discriminates between normal and arrhythmia-affected ECG signals with a 96.5 % accuracy [17].
3. **F. A. Naima, A. A. Timemy**: They used the discrete wavelet technique to retrieve the R location and RR interval. They utilize an FFNN trained using the backpropagation method. Their method accuracy was 95 % [18].
4. **V.K.Srivastava, Dr. Devendra Prasad**: They used discrete wavelet transform (DWT) for feature extraction and classification since wavelet transform is a two-dimensional timeframe processing technique that is well-suited for non-stationary ECG data. After that, they examined and categorized the data using neuro-fuzzy, a hybrid neural network, and fuzzy logic techniques. Their method accuracy was 85 % [19].

5. **Ahmed T. Sadiq, Nidhal H. Shukr**: The purpose of their article was to present a method for classifying cardiac arrhythmias from a normal ECG signal using wavelet decomposition and the ID3 classification algorithm. The first stage of their work was to denoise the ECG data using the Discrete Wavelet Transform (DWT), followed by the extraction of ECG characteristics from the processed signal. The algorithm Interactive Dichotomizer 3 (ID3) is used to categorize the various arrhythmias, including the typical condition. Their method accuracy was 94 % [19].
6. **X. Tang, L. Shu**: To identify ECG data, rough sets (RS) and quantum neural networks (QNN) were utilized in this study. After normalizing the data, the wavelet transforms (WT) is utilized to extract features. Then, as a preprocessor, the RS attribute reduction was used to remove superfluous attributes and conflicting items from the decision-making table while maintaining efficient information loss. Following that, they completed classification modeling and a forecasting test using QNN. Finally, when compared to the BP and RBF, the RS-QNN provides quick and accurate findings. They were able to minimize the size of feature space and the complexity of the procedure using this approach. Their method accuracy was 91.7 % [20].
7. **Jalal A. Nasiri, M. Naghibzadeh, Hadi sadoghi yazdi, Bahram Naghibzadeh:** The purpose of their research was to propose a novel method for classifying cardiac arrhythmia diseases. The suggested technique combines the methods of Support Vector Machines (SVM) and Genetic Algorithms. Their method accuracy was 93.46 % [21].
8. **Abhinav Vishwa, Mohit K. Lal, Sharad Dixit, Dr. Pritish Vardwaj**: In this article, they presented an automated classification method for cardiac arrhythmia based on multi-channel ECG data. They were primarily interested in generating highly confident arrhythmia classification findings for use in diagnostic decision support systems in this research. To categorize arrhythmia instances into normal and pathological categories, a neural network model with a backpropagation algorithm was employed. Models of neural networks were developed and validated for the MIT-BIH arrhythmia. Their method accuracy was 96.77 % [22].

9. **A. Muthuchudar, S. Baboo**: In this paper, the procedures used for diagnosis typically comprise four basic steps that must be completed to make accurate and timely conclusions regarding the type of heart disease a patient has. They are as follows: 1. Data compression 2. Defining 3. Extraction of features and 4. Classification In this paper, each step is illustrated using examples from contemporary Artificial Neural Network research. Their method accuracy was 96 % [23].

10. **R Acharya, A Kumar, P S Bhat, C M Lim, S S Iyengar, N Kannathal, S M Krishnan**: In this paper, the study looks at how an artificial neural network and fuzzy connections may be used to classify heart rhythms. The results show that the instruments employed are highly effective, with an accuracy rate of 80-85% [24].

Table 2.1 Survey of ECG Classification [25]

Researchers	Modeling Technique	Database	Accuracy (%)
Shivajirao M. Jadhav, Sanjay L. Nalbalwar, Ashok A. Ghatol	MLPNN, Generalized FFNN, Modular neural network	UCI arrhythmia	86.67
M.Vijayavanan, V.Rathikarani, Dr. P.Dhanalakshmi	Feed forward PNN classifier Trained with extracted features	MIT-BIH arrhythmias	96.5
F. A. Naima, A. A. Timemy	FFNN training algorithm Back propagation algorithm DWT-FFNN, DFT-FFNN	MIT-BIH arrhythmias	95
V.K.Srivastava, Dr. Devendra Prasad	Feed forward neuro fuzzy Combination of Fuzzy logic and MLPNN	MIT-BIH arrhythmias	85
Ahmed T. Sadiq, Nidhal H. Shukr	ID3 Decision tree Haar-ID3, Db4-ID3	MIT-BIH arrhythmias	94

X. Tang, L. Shu	QNN trained using gradient descent method	MIT-BIH arrhythmias	91.7
Jalal A. Nasiri, M. Naghibzadeh, Hadi sadoghi yazdi, Bahram Naghibzadeh	Genetic algorithm-SVM	MIT-BIH arrhythmias	93.46
Abhinav Vishwa, Mohit K. Lal, Sharad Dixit, Dr. Pritish Vardwaj	Feed forward ANN with error back propagation	MIT-BIH arrhythmia , QT and Normal sinus rhythm	96.77
A. Muthuchudar, S. Baboo	Feed forward network with back propagation algorithm as training algorithm	MIT-BIH arrhythmias	96
R Acharya, A Kumar, P S Bhat, C M Lim, S S Iyengar, N Kannathal, S M Krishnan	4-layer FFNN classifier and fuzzy classifier	MIT-BIH arrhythmias	80-85

2.3 Objective of this work

The main purpose of our work is to calculate heart rate from ECG signal automatically and also to establish a technique to classify ECG signals to detect arrhythmia more accurately. The accuracy of our ECG classification method is 97.14 %. In **Table 2.1** we showed a survey of ECG classification. From this survey, we can say that our proposed technique is more accurate and also more suitable for ECG classification than theirs.

CHAPTER 3

RELATED THEORY

3.1 Introduction

The most significant bioelectrical communication of the human body is the electrocardiogram (ECG) signal, which represents the fundamental law of heart function. The electrical activity of the heart may be determined using an ECG signal that has been appropriately processed. To make the analysis more efficient and accurate. It is particularly important in the context of cardiovascular disorders. On the other hand, the ECG signal is a non-linear, non-stationary weak signal with a high level of irregularity, making data analysis and processing more difficult. Because abnormalities aren't always periodic and don't always consistently manifest themselves, continuous ECG monitoring is necessary to track cardiac changes over time. ECG is a non-invasive, effective tool for monitoring vital signs. The discrete wavelet transform was used to extract features for various arrhythmias. The wavelet transform was used to construct a robust single-lead electrocardiogram (ECG) delineation system. The goal is to determine the accuracy of predictions in detecting and classifying cardiac arrhythmias based on anomalies in ECG signals. Because most biological systems use nonstationary signals to reflect their normal or abnormal processes, joint time-frequency analysis of physiological signals has great potential. The goal is to find important elements in ECG data that have varying time and geographical elements. The deep learning architecture model for ECG signal classification is used in the workplace. We developed and implemented a technique that combines wavelet transforms with neural networks to solve the challenge of automated heartbeat detection. For effective automated ECG analysis, this technique consists of denoising, extraction, and classification models. For the ECG type identification module, a hybrid network integrating neural networks and wavelets was developed, implemented, and analyzed. This method is based on using wavelet functions as activation functions in neural networks, which allowed the wavelet network to be more adaptable and flexible throughout the learning process due to the parameters of wavelet translation and expansion. Indeed, when compared to other neural networks, the results produced by the constructed wavelet network are excellent in terms of heartbeat classification rate. In the present work, ECG signal analysis was done and wavelet-based

ECG signal analysis was performed with MATLAB, which is a multi-paradigm programming language and numeric computing environment. Matrix manipulation, function and data visualization, algorithm implementation, graphical user building, and connecting with other languages are all possible with MATLAB [26].

In this chapter, we describe ECG signals, ECG signal interpretation methods, and The accuracy of the results was evaluated using the PhysioNet ECG Dataset, which features ECG data of people with normal sinus rhythm (NSR), arrhythmia (ARR), congestive heart failure (CHF), the non-invasive fetal disease of heat, supraventricular arrhythmia, intracardiac atrial fibrillation, malignant ventricular ectopy.

3.2 Heart Rate Determined on Electrocardiography (ECG)

Electrocardiography (ECG) is frequently utilized to detect heart rhythm abnormalities. The ECG is a graphical representation of the electrical beats of the heart. The healthcare provider attaches little bands called electrodes on the arms, legs, and chest to do the ECG. Different records of the electrical activity of the heart are taken using different combinations of these electrodes and recorded on the computer or paper. The shape and magnitude of the waves, the time between waves, the heart rate, and whether the heartbeat is regular are all examined by doctors. This examination provides crucial information about the heart and its rhythm. Though, it only reveals rhythm irregularities that occur during the procedure. During a heartbeat, there are six different waves (symbolized by the letters P, Q, R, S, T, and U) that occur in a specific order, duration, and dimension in the sinus rhythm. While there is a wide range in which alterations in heart rhythm are deemed normal, deviations from the sinus rhythm that exceed a particular threshold may indicate cardiac disease [27]. There are three fundamental components to an ECG: the P wave, which speaks to the depolarization of the atria; the QRS complex, which speaks to the depolarization of the ventricles; and the T wave, which speaks to the repolarization of the ventricles [28]. The heart rate, or the number of heart beats per minute, is represented by a cardiac cycle that lasts between 0.6 and 1.0 seconds (BPM). As a result, a normal heart rate is between 60 to 100 beats per minute. According to Einthoven's Triangle, the ECG strips are best understood from lead II or V1, which indicates the most clearly heart's rhythm [29]. **‘Fig. 3.1’** shows the normal sinus rhythm, standard waves, segments, and ranges in the ECG signal**.**

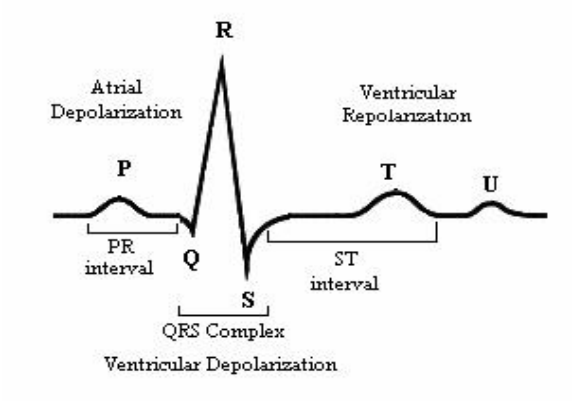

Fig. 3.1 Points and elements of ECG signal [29]

The interval between two successive QRS complexes can be used to calculate heart rate when the cardiac rhythm is regular. The heart rate is computed by dividing the number of large boxes (5 mm or 0.2 seconds) between two consecutive QRS complexes by 300 on standard paper with the most popular tracing settings. For case, in the interim between two QRS complexes is two large boxes at that point, the rate is 150 beats per miniature (bpm) (300 ÷ 2 = 150 bpm) [30]. **'Fig. 3.2'** shows the small boxes of heart rate and **'Fig. 3.3'** shows the large boxes of heart rate.

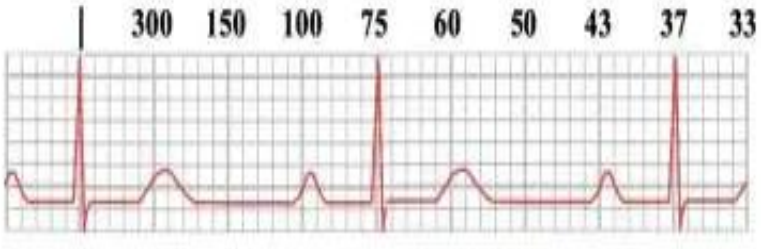

Fig. 3.2 Heart Rate boxes (Small Box) [30]

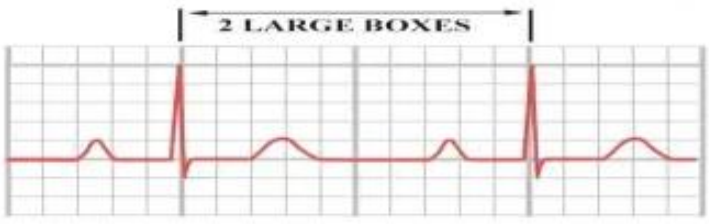

Fig. 3.3 Heart Rate Boxes (Large Box) [30]

3.2.1 The Importance of ECG Analysis

An ECG is a non-invasive, painless test that may be used to identify a variety of common cardiac issues in persons of different ages. The purpose of an electrocardiogram is to detect [31].

1) Heart rate: The most common way to determine heart rate is to examine the pulse. If your pulse is difficult to feel, or if it is too rapid or irregular to count properly, an ECG may be useful. An ECG can help a doctor detect a rapid heart rate (tachycardia) or a sluggish heart rate (bradycardia).
2) Heart Rhythm: Heart rhythm abnormalities can be detected with an ECG (arrhythmias). Any portion of the heart's electrical system might fail, resulting in several diseases. Arrhythmias can also be triggered by pharmaceuticals including beta-blockers, cocaine, amphetamines, and over-the-counter cold and allergy medicine.
3) Heart attack: An ECG might reveal signs of a prior heart attack or a current one. The ECG patterns may reveal which portion of the heart has been injured as well as the severity of the damage.
4) Inadequate blood and oxygen supply to the heart: An ECG is a test that doctors perform to evaluate if chest discomfort is caused by a reduction in blood flow to the heart muscle, such as in the case of unstable angina.
5) Structural abnormalities: An ECG can reveal information regarding heart chamber or wall enlargement, heart abnormalities, and other cardiac issues.

3.3 Interpretation of ECG Signal

Interpretation of the ECG is ultimately that of pattern recognition. Understanding the notion of what ECGs indicate is useful in understanding the patterns discovered. The hypothesis is based on electromagnetic principles and boils down to four points [31].

• A positive deflection is produced when the heart depolarizes toward the positive electrode.

• A negative deflection is produced when the heart depolarizes away from the positive electrode.

• A negative deflection is produced when the heart repolarizes toward the positive electrode.

• A positive deflection is produced when the heart repolarizes away from the positive electrode.

As a result, depending on which lead the vector points to, the overall direction of depolarization and repolarization generates a positive or negative deflection on the ECG. A normal rhythm generates four distinct entities: a P wave, a QRS complex, a T wave, and a U wave.

- Atrial depolarization is represented by the P wave.
- Ventricular depolarization is represented by the QRS complex.
- Ventricular repolarization is represented by the T wave.
- Papillary muscle repolarization is represented by the U wave.

3.4 Wavelet Transform (WT)

The wavelet transform decomposes a signal into signal coefficients obtained from a filter bank. The filter bank produces two types of coefficients: approximation coefficients and detailed coefficients. These coefficients appear to be a very effective tool for ECG signal categorization. Signals are divided into time-frequency representations using the Discrete Wavelet Transform (DWT). The DWT's main benefit is its excellent temporal and frequency localization capability, which allows it to disclose the input signal's local properties [32]. **'Fig. 3.4'** shows the Wavelet Decomposition steps.

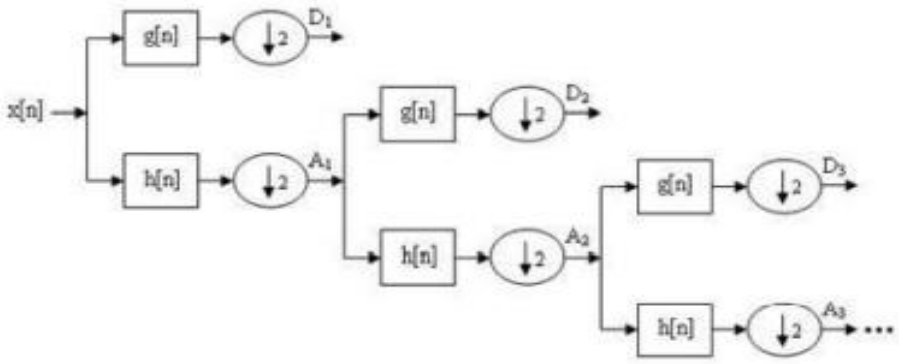

Fig. 3.4 Wavelet Decomposition Steps [33]

There are no hard and fast rules for determining which mother wavelet is ideal for a given situation, but it's a good idea to run some performance tests on various mother wavelets

before deciding on the best one to utilize. In their research, [32] chose Daubechies of 10th order (db10) with varying levels of decomposition. Because various techniques for feature selection with different cardiac beats sets generate varied outcomes, a few different researches employed different mother wavelets for decomposition based on the characteristics and the cardiac beat set used. The analysis results of several mother wavelets are collected to select which mother wavelet to utilize, and the one with the best results is chosen as the decomposition wavelet[32].

3.5 PhysioNet bank

PhysioBank is a significant and increasing database of well-characterized digital recordings of physiological signals and related data for use by biomedical researchers. PhysioBank now includes databases of multi-parameter cardiopulmonary, neural, and other biomedical signals from healthy subjects and patients with a variety of conditions that have major public health implications, such as sudden cardiac death, congestive heart failure, epilepsy, gait disorders, sleep apnea, and aging [34]. In 2012, the ILSVRC(2012) was won by Krizhevsky the developer of the AlexNet [35]. The International Wide-Scale Object Detection and Classification Competition (ILSVRC) is an annual competition for large-scale object detection and classification systems. Krizhevsky utilized neural networks, specifically convolution neural networks, as compared to other responders who used traditional characteristics and classifier training approaches. Three fully linked layers and five convolutional layers are included in the model. AlexNet's first layer is used to input a filtered picture with width, height, and depth dimensions of 227 × 227 × 3 correspondingly (red, green, blue). The last fully-connected layer links 1000 connected layers, while the other layers function as a feature extractor. AlexNet can generate a 4096-dimensional feature vector for each input picture that contains hidden layer activations before the output layer is applied. AlexNet is a massive system with 650,000 neurons and 60 million variables. The model was tested on 150,000 ImageNet data sets test photos after being trained on 1.2 million training pictures. With the aid of sustaining dropout and data augmentation, this model is highly effective at decreasing the overfitting problem. AlexNet was chosen for this research because it is the most well-studied CNN and provides a good balance of speed and accuracy. The structure of AlexNet is seen in **‘Fig. 3.5’**.

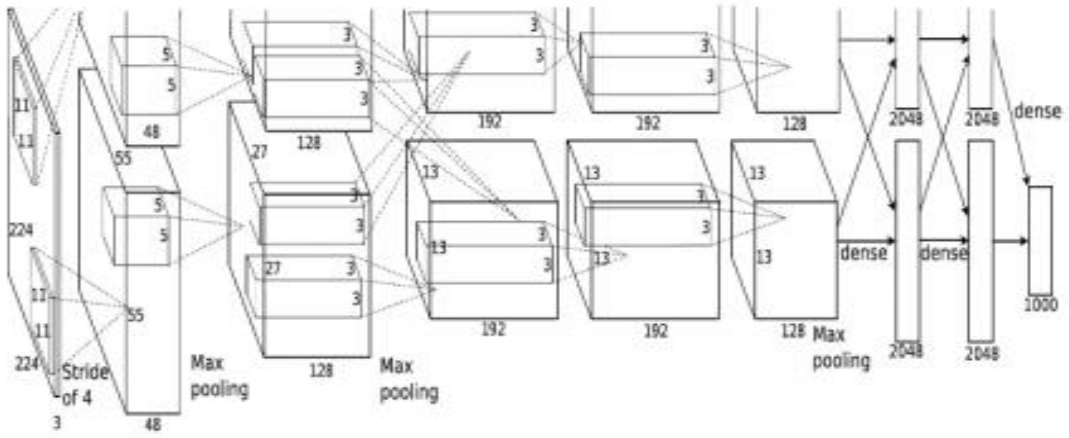

Fig. 3.5 The Architecture of AlexNet [35]

3.6 Heart disease

The term "Heart Disease" encompasses a wide range of heart disorders. Coronary artery disease (CAD), which impairs blood flow to the heart is the most common type of heart disease in the United States. A heart attack can be caused by a reduction in blood flow.

3.6.1 Symptoms of heart disease

Heart disease can be "silent," with no indications or symptoms until a person has a heart attack, heart failure, or arrhythmia. Symptoms that occur as a result of these events include:

- **Heart attack:** Discomfort, upper back or neck pain, indigestion, gastritis, nausea and vomiting, severe weariness, upper body discomfort, disorientation, and shortness of breath are some of the symptoms that might occur.

- **Arrhythmia:** Feelings of fluttering in the chest (palpitations).

- **Heart failure:** Swelling of the feet, ankles, legs, abdomen, or neck veins, as well as chest pain and tiredness [36].

3.6.2 Causes of heart failure

Many conditions that damage the heart muscle can lead to cardiac failure, including:

- **Conditions that overwork the heart:** Heart failure can be caused by a variety of conditions, including high blood pressure, valve disease, thyroid illness, renal disease, diabetes, or congenital abnormalities. Heart failure can also develop when some illnesses or conditions coexist.

- **Coronary artery disease:** Reduced blood flow to the heart muscle is caused by coronary artery disease (CAD), a condition of the arteries that deliver blood and oxygen to the heart. The heart is deprived of oxygen and nourishment if the arteries become clogged or significantly constricted.

- **Cardiomyopathy:** Harm to the heart muscle from causes other than course or bloodstream issues, such as from contaminations or liquor or sedate manhandle [37].

3.6.3 Normal Sinus Rhythm (NSR)

The sinus node of the heart controls the rhythm of a human heartbeat. The sinus node generates an electrical pulse that causes our heart muscle to contract, or beat. The sinus node can be thought of as a built-in pacemaker. Normal sinus rhythm is classified as the rhythm of a healthy heart. It implies your sinus node's electrical impulse is being appropriately delivered. Normal sinus rhythm is associated with a heart rate of 60 to 100 beats per minute in adults. Normal heart rates, on the other hand, differ from person to person [38].

3.6.4 Description of the Supraventricular Arrhythmia

Supraventricular arrhythmia is characterized by an irregular heart rate that originates above the ventricles, the heart's two bottom chambers. Supraventricular arrhythmias start in the atria, the heart's upper chambers, but not all of them. They can cause the heart to beat too quickly, too slowly, or in an uneven pattern. A person's heart rate is controlled by electrical impulses in the heart. An abnormal heart rate might result from problems with the cells that begin electrical impulses. Supraventricular arrhythmias can lead to the following symptoms:

- **Tachycardia:** Tachycardia is a condition in which the heart beats excessively quickly.
- **Bradycardia:** Bradycardia is a condition in which the heartbeat is abnormally slow.

- **An irregular heartbeat:** The heart might feel like it is skipping or adding beats begin electrical impulses [39].

3.6.5 Congestive Heart Failure

Congestive Heart Failure (CHF), also called on CHF Heart Failure, arises when the heart can no longer pump blood properly, and blood backs up into the body, particularly the liver, lungs, hands, and feet. In case of blood collects in reverse from the proper side of the heart (blood returns from the body to the proper side of the heart), the indications that ordinarily start with the swelling of the feet and lower legs d0ecline when the patient stands [27]**.**

3.6.6 Non-invasive Fetal Electrocardiography

Fetal monitoring is important to diagnose complications that can occur during pregnancy. If detected timely, these complications might be resolved before they lead to irreversible damage. Current fetal monitoring mainly relies on cardiotocography, the simultaneous registration of fetal heart rate, and uterine activity. Unfortunately, the technology to obtain the cardiotocograph has limitations. In current clinical practice, the fetal heart rate is determined using either an invasive scalp electrode, which is difficult and can only be used during labor and after the rupture of the fetal membranes, or non-invasive Doppler ultrasound technology, which is inaccurate and susceptible to signal loss, especially in women with high body mass, during motion, or in preterm pregnancies. Transabdominal electrophysiological measures are used in this study to offer non-invasive and more accurate fetal heart rate information than Doppler ultrasonography. When comparing the fetal heart rate to that acquired with an invasive scalp electrode during intrapartum monitoring, the accuracy of the fetal heart rate detection is assessed. The performance is compared to that of two commercially available devices that are likewise based on transabdominal fetal electrocardiography, as well as that of Doppler ultrasonography [40]**.**

3.6.7 Intracardiac Atrial Fibrillation

Quantitatively measuring and modeling the origin and propagation of electrical activity in the heart is a crucial field of research that will aid in the understanding and treatment of cardiac arrhythmias. AF is a cardiac rhythm disorder characterized by disorganized and fast electrical

atrial activation that replaces normal sinus rhythm, resulting in a decrease in the atria's mechanical capacity to pump blood properly. During intracardiac atrial fibrillation, when conduction is intact, the ventricles will beat frequently and quickly. The P waves, which

distribute depolarization across the atria, are replaced by QRS complexes, which refer to the three graphical deflections (Q, R, and S waves) observed on a conventional electrocardiogram. There are some symptoms of AF Palpitations, exhaustion, shortness of breath, dizziness, and chest discomfort. The resultant pooling of blood in the atria raises the long-term risk of stroke fivefold since the atria's mechanical pumping capacity is impaired [41]**.**

3.6.8 Malignant Ventricular Ectopy

There are three most commonly identified malignant that are lethal, ventricular arrhythmias in man: out-of-hospital VF, recurrent sustained VT, and dynamic equilibrium de points VT in the long QT syndrome. The mortality rate for each disease is substantial. Out-of-hospital cardiac arrest: Community-based emergency medical programs have taught us a lot about the critical syndrome of out-of-hospital cardiac arrest. First, the most prevalent etiologic kind of heart disease in those who have out-of-hospital cardiac arrest is coronary heart disease. Also, well-represented are cardiomyopathy and valvular heart disease. In every series of out-of-hospital cardiac arrest, there is a tiny and perplexing group of people who have no signs or symptoms of heart illness. Survivors of out-of-hospital cardiac arrest and advanced coronary atherosclerosis, as well as prior myocardial infarction, are more likely to have severe coronary heart disease. [42]

3.6 Conclusion

In this Chapter, we discussed about all of our work-related theory for better understanding of our work. We developed an ECG classification technique based on CWT and AlexNet Deep CNN. Also, we calculated heart rate from ECG data in this work by DWT. Our approach has the potential to be utilized as a clinical supplementary diagnostic tool due to the extremely accurate ECG categorization.

CHAPTER 4

METHODOLOGY

4.1 Introduction

This chapter provides a detailed methodology of our work. Knowing heart rate is very much important for us in order to know if our heart working properly. Without knowing this we cannot detect our heart problem. Calculating heart rate from ECG signal manually is a complex process. So, we design a process to calculate heart rate from ECG signal. Also, it is important for us to classify ECG signals to know about Arrhythmias. We design a technique to classify ECG signals more accurately from ECG recordings. At first, we design a technique for calculating heart rate from ECG signals. For this, we use the DWT process in MATLAB software. In this process heart rate is calculated by detecting R peaks of the signal. After that, we design a technique to classify ECG signals from ECG recordings to detect arrhythmias. for this technique, we use the CWT process and also used AlexNet which is a deep CNN. We elaborately discussed our method of working in this chapter.

4.2 Heart Rate Calculation Process

Calculating heart rate manually is a complex process. To remove complexity in calculating heart rate, we design a technique to calculate heart rate from ECG signal automatically. For calculating heart rate, we used Discrete Wavelet Transform (DWT) in MATLAB software. For this calculation, we used 2 types of a database from PhysioNet.

4.2.1 Data

To calculate heart rate, we use 2 types of ECG database from PhysioNet. In PhysioNet we collected the MIT-BIH Arrhythmia database and ECG-ID database from PhysioBank ATM. The signal we collected is the length of 10 seconds. We collected 5 records from each database.

The sampling rate of the MIT-BIH database is 360 Hz and the sampling rate of the ECG-ID database is 500 Hz.

We selected the .mat file format and downloaded it.

4.2.1.1 MIT-BIH Arrhythmia database

The MIT-BIH Arrhythmia Database comprises 48 half-hour samples of two-channel ambulatory ECG recordings from 47 patients examined between 1975 and 1979 by the BIH Arrhythmia Laboratory.

The recordings were digitized at a sampling rate of 360 samples per second per channel and a resolution of 11 bits throughout a ten-mV range. Each record was independently annotated by two or more cardiologists; disputes were addressed in order to produce computer-readable reference annotations for each beat (about 110,000 annotations in total) included in the database [43]. **'Fig. 4.1'** shows MIT-BIH Arrhythmia Database.

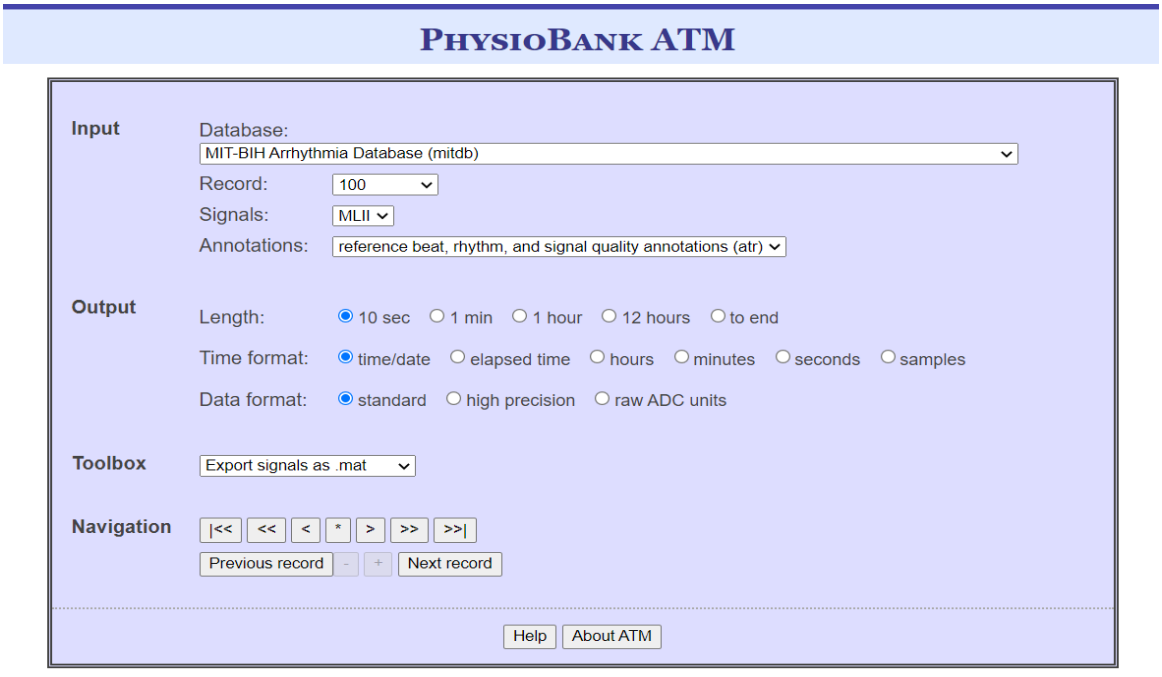

Fig. 4.1 MIT-BIH Arrhythmia Database [44]

4.2.1.2 ECG-ID database

In ECG-ID database each recording contains

- ECG lead I, captured for 20 seconds and digitized at 500 Hz with a resolution of 12 bits over a notional ten millivolt range.
- Ten annotated beats (unaudited annotations of R- and T-wave peaks from an automatic detector).
- Age, gender, and recording date information (in the .hea file for the record)

The raw ECG signals are rather noisy and contain both high and low frequency noise components. Each record includes both raw and filtered signals:

- Signal 0: ECG I (raw signal).
- Signal 1: ECG I filtered (filtered signal) [45].

From here we collected Signal 1: ECG filtered (filtered signal) for our work. The sampling rate of this database signal is 500 Hz. **'Fig. 4.2'** shows ECG-ID database.

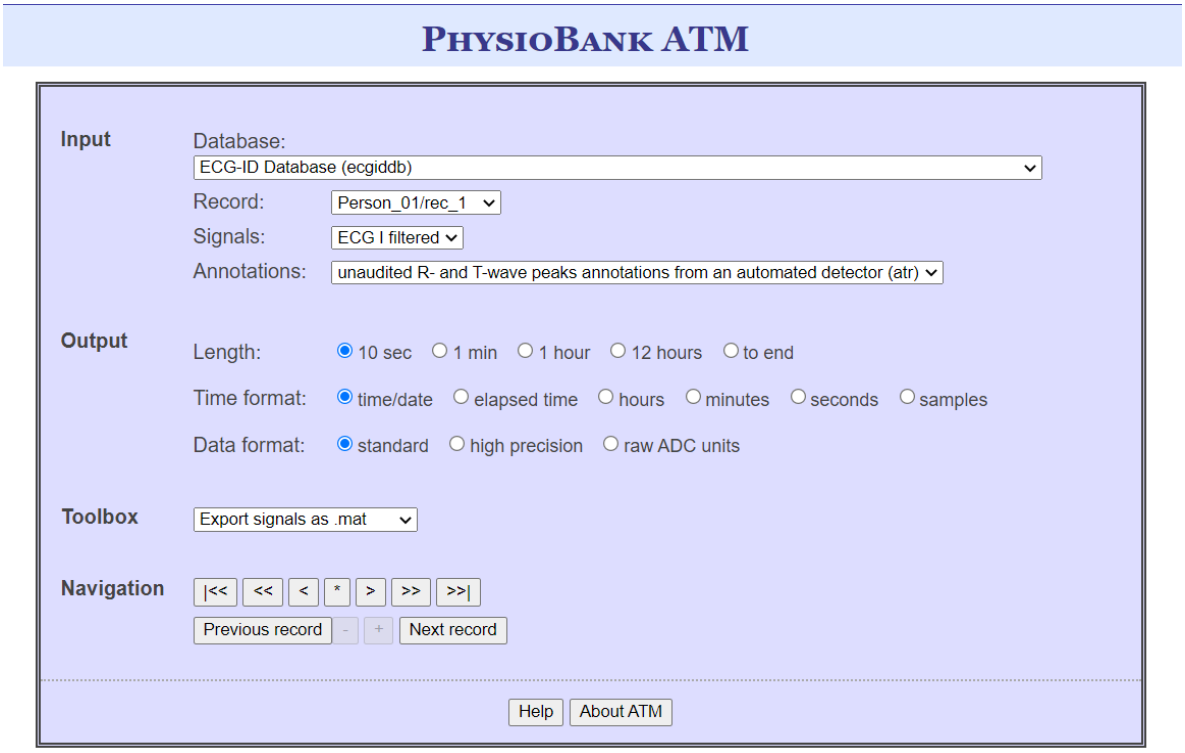

Fig. 4.2 ECG-ID database [44]

4.2.2 DWT based Heart rate calculation

After collecting the ECG recording from PhysioBank ATM we saved the .mat file in the MATLAB current directory. We used Symlet4 wavelet for ECG signal analysis. The 'sym4' wavelet resembles the QRS complex, which makes it is a good choice for QRS detection. The Symlets are nearly symmetrical wavelets proposed by 'Daubechies' as a modification of the db family. For 'sym4' the length of the filter is 8, that means in reconstruction or, decomposition filter the number of samples will be 8. **'Fig. 4.3'** shows the code for Heart Rate Calculation in MATLAB.

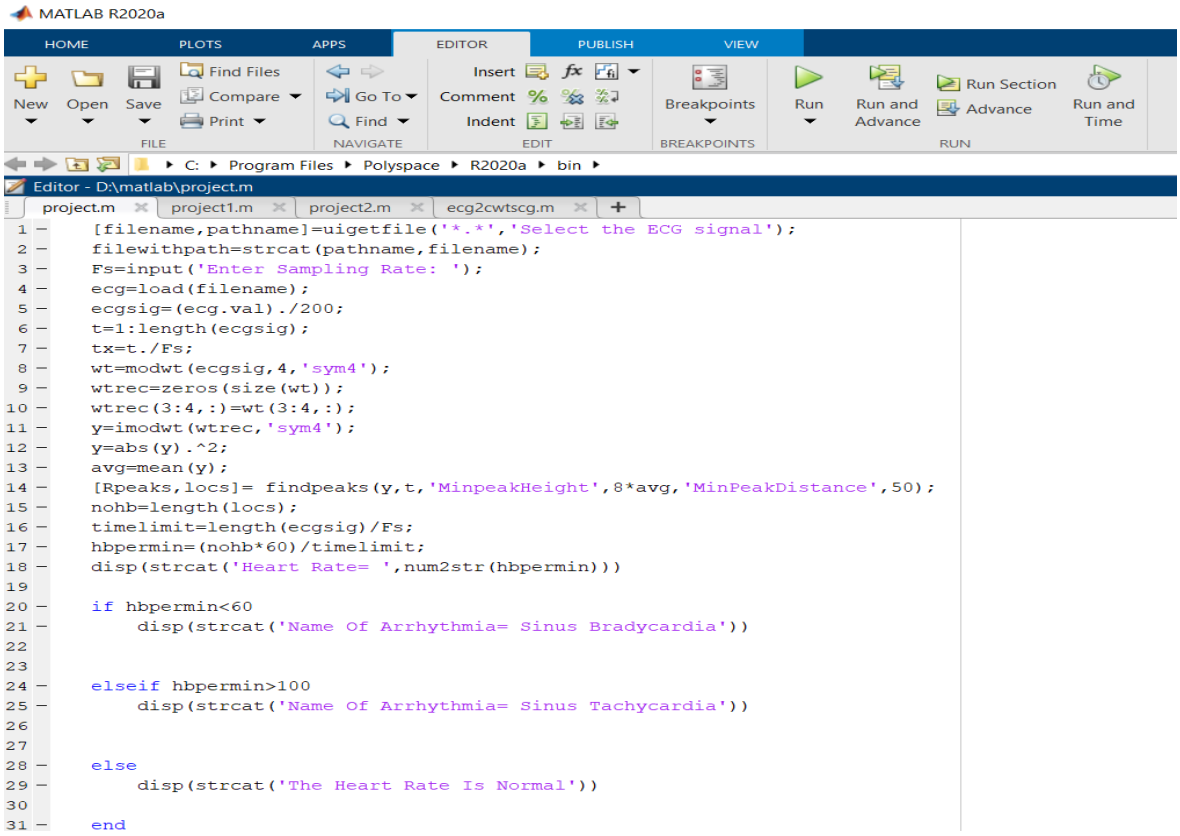

Fig. 4.3 MATLAB Code for Heart Rate Calculation.

The objective of this Discrete Wavelet Transform (DWT) based process was to eliminate all low and high-frequency components. It is band-pass filtering. Therefore, band-pass action is needed. That can be achieved with the help of wavelet transform. The wavelet transforms separate signal components into different frequency bands. The band-pass filtering can be implemented by eliminating some frequency bands. We achieved this band-pass filtering by eliminating wavelet coefficients of some lower scales (high frequency) and higher scales (low frequency) of ECG signal. For this purpose, an undecimated wavelet transform is used to get wavelet coefficients. In undecimated wavelet transform the signal length remain the same. It is similar to CWT but it is a DWT. A 4-level decomposition of ECG signal done by 'sym4' wavelet. After decomposition coefficients a_4, d_1 and d_2 were eliminated because we wanted to remove low and high-frequency elements. Only d_3 and d_4 are considered for getting band-pass filtering. Here,

- d_1 = Detailed coefficients at level 1.

- d_2 = Detailed coefficients at level 2.
- d_3 = Detailed coefficients at level 3.
- d_4 = Detailed coefficients at level 4.
- a_4 = Approximation coefficients at level 4.

Just by considering only d_3 and d_4 and taking inverse wavelet transform, we got our desired signal. R-peaks were well preserved and all the low frequency and high frequency such as P, Q, S completely removed in our desired signal. Also, the noise was removed. After that, with help of a standard peak detection algorithm in MATLAB software, we located these R-peaks. Also, we found the number of total R-peaks for a given time interval by which we calculated heart rate. In MATLAB software we wrote a standard peak detection algorithm and selected our desired data which we downloaded from PhysioBank ATM. After putting a sampling rate of 360 Hz for MIT-BIH Arrhythmia databases and 500 Hz for ECG-ID databases, the algorithm in MATLAB calculated and showed the heart rate of the person. After calculation of heart rate, we could say that the heart rate of the person is normal or abnormal. **'Fig. 4.4'** shows the Heart Rate Calculation process.

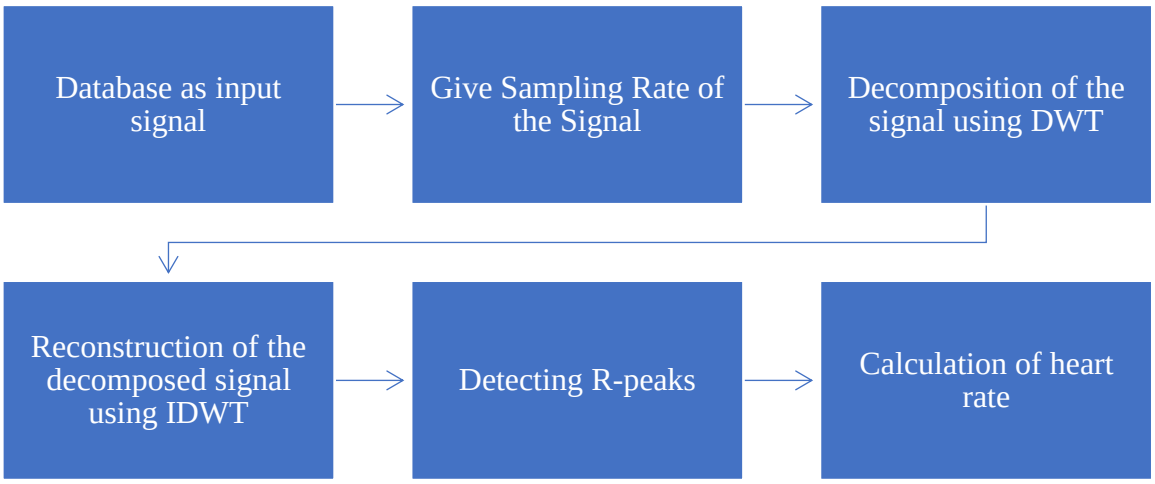

Fig. 4.4 Proposed Heart Rate Calculation process

4.3 ECG Signal Classification

Classification and prediction of heart diseases based on ECG signals have become increasingly important for patients and doctors over the last decade. Due to simplicity and non-invasive nature, ECG signals have been extensively utilized to diagnose cardiac problems the majority of contemporary techniques are based on custom-designed features for ECG signal analysis. The purpose of our work was to design a technique to classify ECG signals more accurately for detecting arrhythmias. For this work, we collected ECG database from PhysioNet. In PhysioNet, we collected 7 types of database from PhysioBank ATM.

4.3.1 Data

we collected a total of 7 types of ECG recordings from PhysioBank ATM. We used ECG signals of seven categories:

1) MIT-BIH Arrhythmia Database.
2) BIDMC Congestive Heart Failure Database.
3) MIT-BIH Normal Sinus Rhythm Database.
4) Non-Invasive Fetal ECG Arrhythmia Database.
5) MIT-BIH Supraventricular Arrhythmia Database.
6) Intracardiac Atrial Fibrillation Database.
7) MIT-BIH Malignant ventricular Ectopy Database.

We collected a total of 357 records of ECG from PhysioBank Atm. Out of these 357 ECG recordings, we collected 96 recordings from MIT-BIH Arrhythmia Database, 30 recordings from BIDMC Congestive Heart Failure Database, 36 recordings from MIT-BIH Normal Sinus Rhythm Database, 26 recordings from Non-Invasive Fetal ECG Arrhythmia Database, 84 recordings from MIT-BIH Supraventricular Arrhythmia Database, 60 recordings from MIT-BIH Supraventricular Arrhythmia Database, 25 recordings from MIT-BIH Malignant ventricular Ectopy Database.

Then we gathered all 357 records in a file where ECG recordings from all 7 databases present.

4.3.1.1 MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database includes 48 half-hour samples of two-channel ambulatory ECG recordings from 47 individuals examined between 1975 and 1979 by the BIH Arrhythmia Laboratory. The recordings were digitized at a sampling rate of 360 samples per second per channel and a resolution of 11 bits across a ten-mV range. Each record was separately annotated by two or more cardiologists; disputes were addressed in order to produce computer-readable reference annotations for each beat [46]. From here we have collected 96 ECG recordings.

4.3.1.2 BIDMC Congestive Heart Failure Database

This collection contains long-term ECG recordings from 15 individuals with severe congestive heart failure (NYHA class 3–4) (11 males, aged 22–71, and 4 women, aged 54–63). This set of patients was part of a broader research that included people who had conventional medical treatment prior to receiving milrinone, an oral inotropic drug. Additional information on the broader research group may be found in the first reference referenced above. Additional research has made use of these recordings; check the references section for further information. Each recording is about 20 hours long and contains two ECG signals recorded at 250 samples per second with a 12-bit resolution across a 10-millivolt range. The initial analog recordings were produced at Beth Israel Hospital (now Beth Israel Deaconess Medical Center) in Boston utilizing ambulatory ECG recorders with a typical recording bandwidth of about 0.1 Hz to 40 Hz. The annotation files (with the suffix.ecg) were generated automatically and have not been manually revised [47]. From here we collected 30 ECG recordings.

4.3.1.3 MIT-BIH Normal Sinus Rhythm Database

This collection contains 18 long-term ECG recordings of patients referred to Boston's Beth Israel Hospital's Arrhythmia Laboratory. The subjects in this database were determined to have no major arrhythmias; they range in age from 26 to 45 years for males and 20 to 50 years for women [48]. From here we collected 36 ECG recordings.

4.3.1.4 Non-Invasive Fetal ECG Arrhythmia Database

Fetal cardiac arrhythmias are described as any irregular fetal cardiac rhythm or regular rhythm at a rate greater than 100 to 200 beats per minute (bpm). Arrhythmias are detected in about 1% of fetuses, with approximately 10% of them being considered possible causes of morbidity. Although the majority of embryonic arrhythmias are benign, some may result in fetal hydrops and even death. This implies that up to one fetus in every hundred need careful monitoring and, if necessary, in-utero antiarrhythmic treatment. The Non-Invasive Fetal ECG Arrhythmia Database (NIFEA DB) contains recordings of 12 fetal arrhythmias and 14 control normal rhythms utilizing the non-invasive fetal electrocardiography (NI-FECG) method. Each recording included a set of four or five abdomen channels and one maternal chest channel. The sample frequency was set to 500 Hz or 1 kHz, as stated in the file headers. The publication includes comprehensive information on each fetus's diagnosis and gestational age. The following convention is used to name recordings:

ARR: arrhythmia fetus.

NR: normal rhythm fetus.

The term 'chest' refers to the single-lead maternal chest electrocardiogram that was recorded. The term 'abdominal' refers to the 4-5 raw abdominal channels captured [49]. From here we collected 26 ECG recordings.

4.3.1.5 MIT-BIH Supraventricular Arrhythmia Database

This database includes 78 half-hour ECG recordings chosen to supplement the examples of supraventricular arrhythmias in the MIT-BIH Arrhythmia Database [50]. From here we collected 84 ECG recordings.

4.3.1.6 Intracardiac Atrial Fibrillation Database

This database contains endocardial recordings from the right atria of eight individuals who were in atrial fibrillation or flutter at the time of the recordings. A decapolar catheter with a spacing of 2-5-2mm (7mm between bipoles) was inserted into four distinct areas of the heart.

Five bipolar signals were captured in each area, coupled with three surface ECG leads. The data were digitized at a sampling rate of 1kHz.The database has four entries for each of the eight patients (one for each placement). Each record's name indicates the patient (iaf1, iaf2..., iaf8) and the location of the catheter (svc, ivc, tva, afw). Eight signals are included in each record (intracardiac: CS12 - CS90, or ECG: I, II, V1, aVF). Each signal is sampled at 1 kHz with a resolution of 14 bits; the amplitudes of the signals are uncalibrated [51]. From here we collected 60 ECG recordings.

4.3.1.7 MIT-BIH Malignant ventricular Ectopy Database

This database includes half-hour ECG recordings of subjects who experienced episodes of sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation [52]. From here we collected 25 ECG database.

4.3.2 CWT Process

After collecting the database from PhysioNet we used Continuous Wavelet Transform (CWT) to convert the 1D signal into a 2D signal in order to train AlexNet deep CNN.

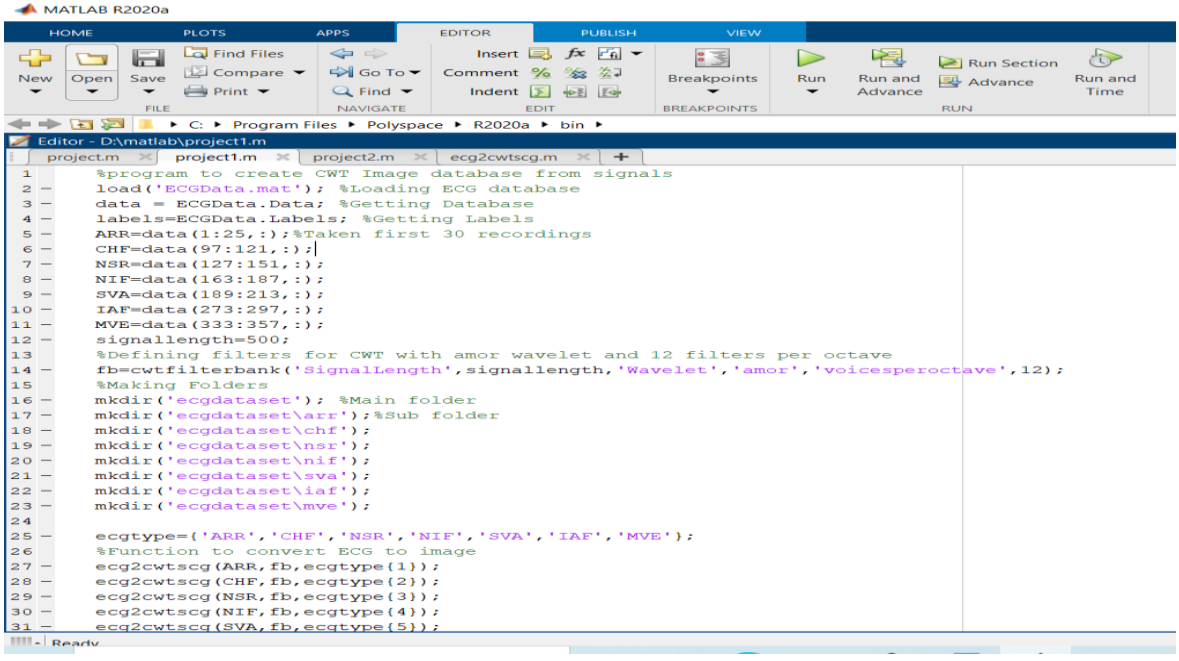

Fig. 4.5 MATLAB code for CWT process

From **‘Fig. 4.5’** we see the MATLAB code for CWT process. We collected all seven recordings in a file which is also a .mat file. We named the file as ECGData.mat. We placed the ECGData.mat file in the current working directory. Here data variable is a matrix of size 357 X 65536. It means it carries a total of 357 ECG signals of size 65536 samples each. From labels, we get types of ECG signals information. The labels are ARR, CHF, NSR, NIF, SVA, IAF, and MVE for the respective databases.

- ARR labels for MIT-BIH Arrhythmia Database.
- CHF labels for BIDMC Congestive Heart Failure Database.
- NSR labels for MIT-BIH Normal Sinus Rhythm Database.
- NIF labels for Non-Invasive Fetal ECG Arrhythmia Database.
- SVA labels for MIT-BIH Supraventricular Arrhythmia Database.
- IAF labels for Intracardiac Atrial Fibrillation Database.
- MVE labels for MIT-BIH Malignant ventricular Ectopy Database

We loaded the file in the MATLAB workspace by the load command. For our work, we preprocessed the database. Each recording is of 65536 samples. Therefore, it can be broken into small signals of length 500 samples to increase the size of the database to make it appropriate to train a CNN. We have a total of 357 recordings of 65536 samples which, is less to train a CNN. So, we took each signal and divided it into 15 recordings of 500 samples. That’s how we increase the size of the database. We also took 25 recordings of each type (ARR, CHF, NSR, NIF, SVA, IAF, MVE) to have equal distribution. Each recording is broken into 15 pieces of the length of 500 samples. Therefore, each category will provide 375 recordings of size 500 samples and the total will be 2625 recordings. Out of these 2625 recordings, we took 2170 for training and 455 for testing. 310 recordings from each type of record used for training and 65 recordings used for testing from each type of recording. Here all the data in ECG recordings were 1D. In this process, we converted all the 1D signal images using Continuous Wavelet Transform (CWT) in MATLAB software. Because AlexNet deep CNN receives input in form of images. But we had the 1D ECG signal. So, we converted the 1D signal into images with the help of CWT. For this purpose, we used CWT coefficients to convert 1D signals into 2D images. All of the coefficients were arranged

to form a CWT scalogram. Each scalogram was represented in colormap of type jet of 128 colors. Scalogram was converted into images and saved in folders corresponding to each class. We created 7 folders.

- 1st folder by the name of 'arr'.
- 2nd folder by the name of 'chf'.
- 3rd folder by the name of 'nsr'.
- 4th folder by the name of 'nif'.
- 5th folder by the name of 'sva'.
- 6th folder by the name of 'iaf'.
- 7th folder by the name of 'mve'.

In each folder we saved al of 375 images. That means:

- 375 images in 'arr' folder.
- 375 images in 'chf' folder
- 375 images in 'nsr' folder.
- 375 images in 'nif' folder.
- 375 images in 'sva' folder.
- 375 images in 'iaf' folder.
- 375 images in 'mve' folder.

We had 2625 images as a database. We resized each image of size 227 X 227 because AlexNet takes input images of this size. The image was in RGB color format. After conversion, we had total of 2625 scalogram images saved in seven folders corresponding to each category ARR, CHF, NSR, NIF, SVA, IAF, MVE.

For Continuous Wavelet Transform (CWT), we took following parameters in MATLAB software.

- For this process we used 'Analytic Morlet (amor)' wavelet. Because this wavelet has equal in time and frequency. Analytic wavelets are wavelets with one-sided spectra, and

are complex valued in the time domain. These wavelets are a good choice for obtaining a time-frequency analysis of 1D signal using CWT.

- For this purpose, we used 12 wavelet bandpass filters per octave (12 voices per octave) for CWT. That means we utilized 12 different bandpass filters to convert 1d signal into wavelet coefficients. They are well known as 12 voices per octave.

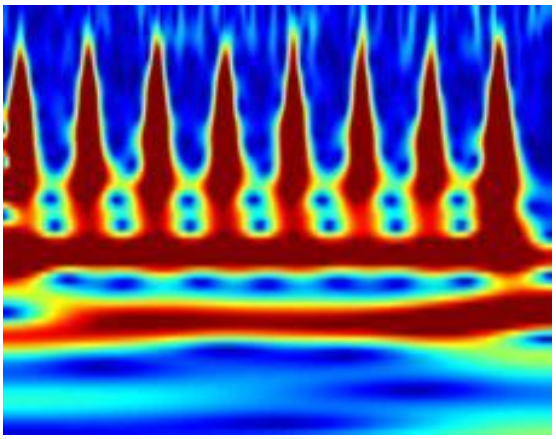

Fig. 4.6 Scalogram as 227 X 227 Image

In '**Fig. 4.6'** we can simply identify peaks of the signal. It is representation of 1D signal into 2D image using Continuous Wavelet Transform (CWT). We did same for all 2625 signals.

4.3.3 AlexNet Deep CNN For ECG classification

All of the seven folders are saved in a folder name 'ecgdataset' in the MATLAB current directory. For classification of ECG signal, we used AlexNet deep CNN, which we downloaded from 'MathWorks'. The colormap we used is jet (128) for CWT process in MATLAB. For classification of ECG signal first, we gave the path of our dataset which is 'ecgdataset' in our 2nd MATLAB program. We created 2nd MATLAB program for training and testing of ECG signals for ECG signal classification. After that, we read all of our images from the folder. Here, we defined we will take 310 images for training purposes. We use maximum epoch 8 for this classification. We were shuffling the data in every epoch. The validation frequency we used for this classification is 10. After that, we plotted training progress. For ECG signal classification we used pretrained deep CNN: AlexNet. AlexNet has been trained on over a million images and can classify images into 1000 object

categories. Actually, fine tuning a pretrained CNN to perform classification on a new collection of images is called 'Transfer Learning'. So, we used 'Transfer Learning' for this process. Transfer learning is quick and easy rather than training a CNN from scratch which requires millions of input images for better accuracy, lots of training time and high-speed efficient hardware.

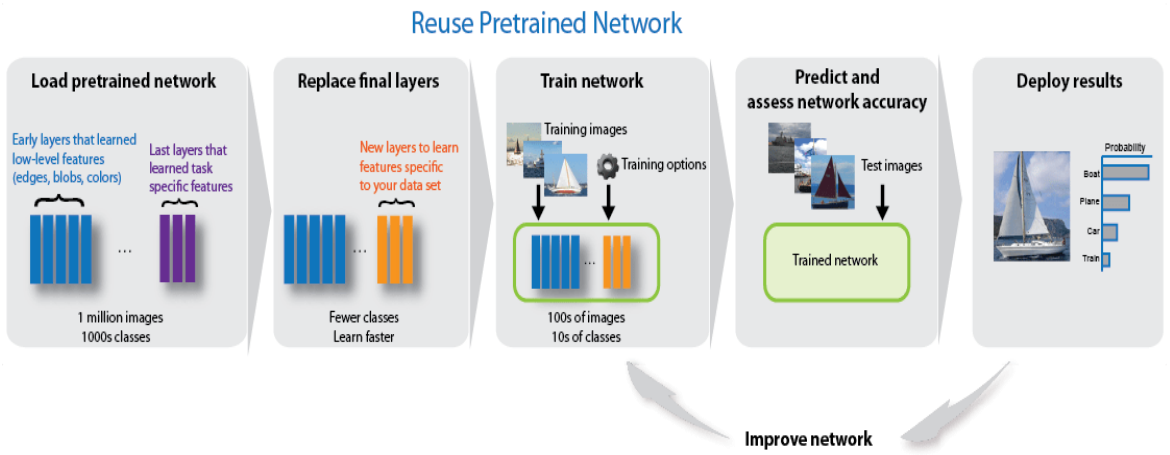

Fig. 4.7 Process of Transfer Learning [53]

In **'Fig. 4.7'** we can see the procedure of transfer learning. We can see we loaded a pretrained transfer network such as 'AlexNet' in the first step of **'Fig. 4.7'**. We preserved all its layers except the last three layers. We didn't change anything in these pre-trained layers, we changed only the last three layers. In the last three layers the 1st one is 'Fully connected layer', 2nd one is 'SoftMax layer' and 3rd one is 'Classification layer'. So, we changed this because for example AlexNet is trained for 1000 different objects. But, for our current work, the total classification objects are 7. That means we have to distinguish between 7 types of signals. So, we had to change the parameter to is the fully connected layer. We had to define the number of classes here. 2nd one is the fresh SoftMax layer. And 3rd one is the new Classification layer, which gave an output of the 7 categories. In the 2nd step in **'Fig. 4.7'**, we can see last three layers are changed and fine-tuned. In the 3rd step in **'Fig. 4.7'**, we trained this network for our new setup images and after training, it is ready to classify our new input images. We used total of 2625 signals in this process. After converting the 1D signals into images by CWT, we used total of 2170 images to train AlexNet and used 455 images for testing. After this process, AlexNet deep CNN classified our desired ECG signals

and showed the result with accuracy. **'Fig. 4.8'** shows the process of ECG Signal Classification.

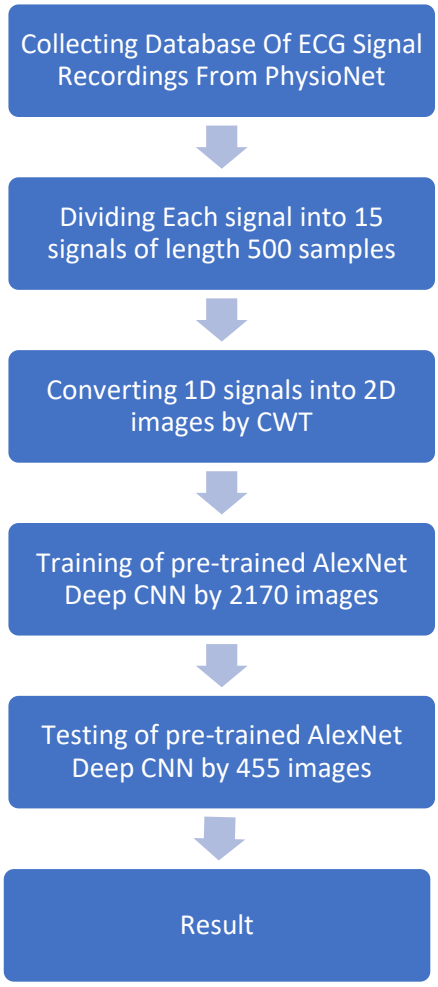

Fig. 4.8 Process of ECG signal Classification

4.4 Conclusion

In this chapter, we have discussed all methodology of our work. We used databases from PhysioNet for our work. We used DWT for our heart rate calculation process. We used CWT for the conversion of 1D signals into and images and used AlexNet Deep CNN for ECG signal classification. After all of this process, we got our desired result

CHAPTER 5

RESULT AND ANALYSIS

5.1 Introduction

In this chapter, we have discussed all methodology of our work. We used databases from PhysioNet for our work. We used DWT for our heart rate calculation process. We used CWT for the conversion of 1D signals into and images and used AlexNet Deep CNN for ECG signal classification. After all of this process, we got our desired results.

5.2 Result of Heart Rate Calculation

We used Discrete Wavelet Transform (DWT) for heart rate calculation. We established an algorithm in MATLAB software to calculate heart rate. As previously discussed, we collected 5 recordings from the MIT-BIH Arrhythmia database and 5 recordings from the ECG-ID database from PhysioBank ATM. After collecting the database, we saved the recordings by the names person_1, person_2, person_3, person_4, and person_5 for the data we collected from the MIT-BIH Arrhythmia database in MATLAB current directory. And also, we saved the recordings by the names person_6, person_7, person_8, person_9, and person_10 for the data we collected from the ECG-ID database in MATLAB current directory. After that, we run our program in MATLAB and gave the sampling rate to find heart rate.

The result of all recordings given below:

5.2.1 Person_1 Database

This database we collected from MIT-BIH Arrhythmia database. The sampling rate of this database is 360 Hz. **'Fig. 5.1'** shows the actual signal of person_1 database. It is a signal of 10 seconds.

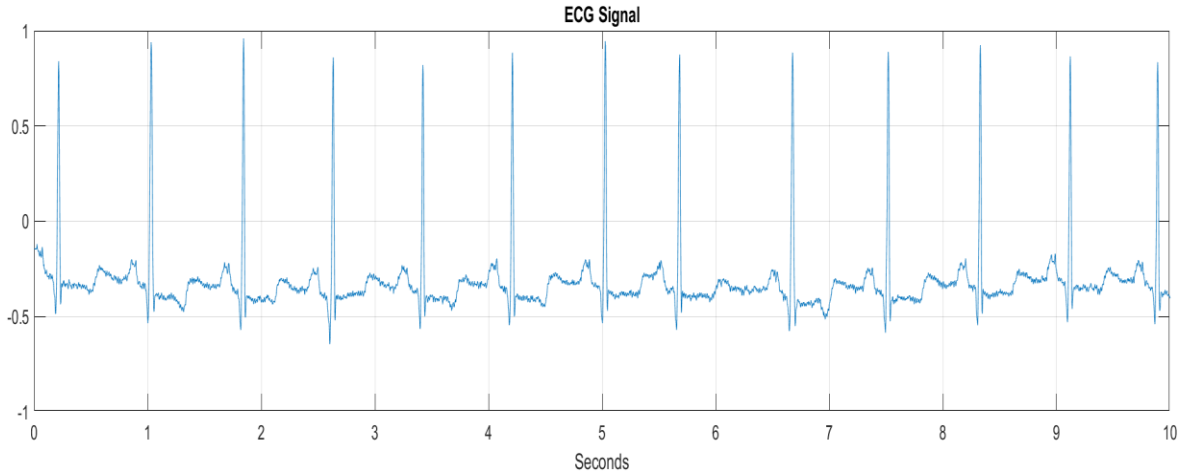

Fig. 5.1 ECG signal of person_1

'Fig. 5.2' shows the R peaks detection and Heart rate after DWT process. From **'Fig. 5.2'** we see that the heart rate of person_1 is 78. That means the heart rate of person_1 is normal.

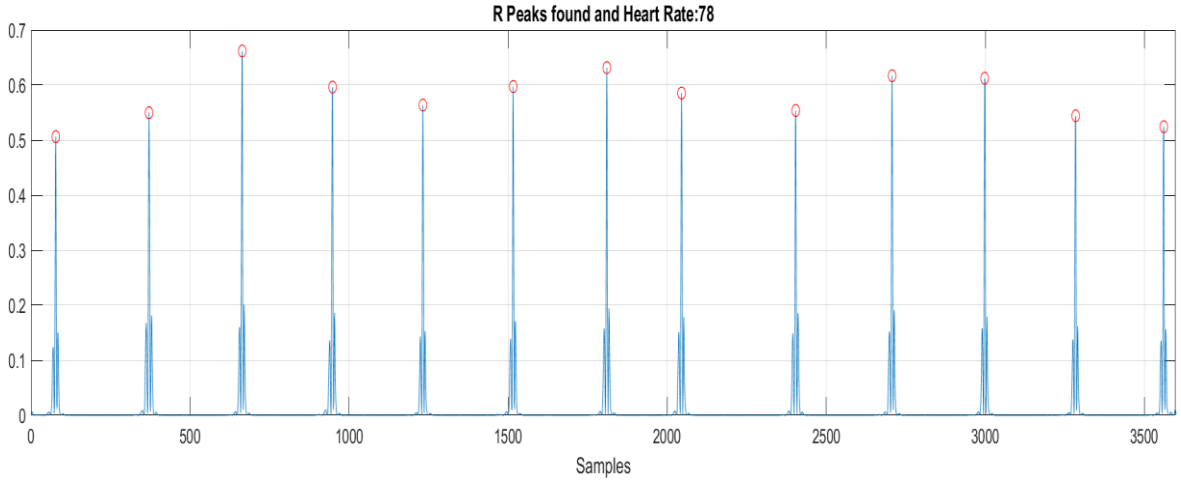

Fig. 5.2 R peaks and Heart Rate of person_1

5.2.2 Person_2 Database

This database we collected from MIT-BIH Arrhythmia database. The sampling rate of this database is 360 Hz. **'Fig. 5.3'** shows the actual signal of person_2 database. It is a signal of 10 seconds.

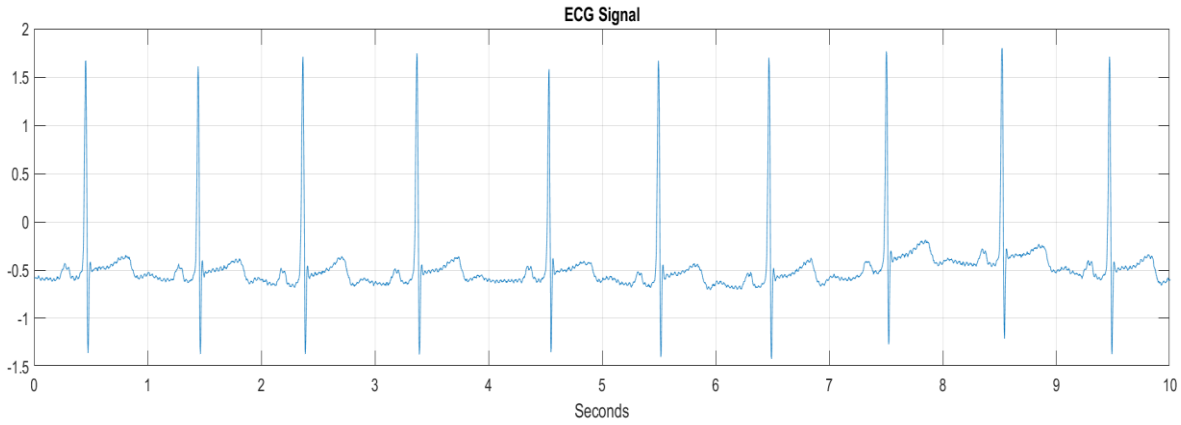

Fig. 5.3 ECG signal of person_2

'Fig. 5.4' shows the R peaks detection and Heart rate of person_2 after DWT process. From **'Fig. 5.4'** we see that heart rate is 60. The heart rate of this person is normal. But heart rate is little bit slow. That might occur because the sinus node discharges electrical impulses slower than is normal rate.

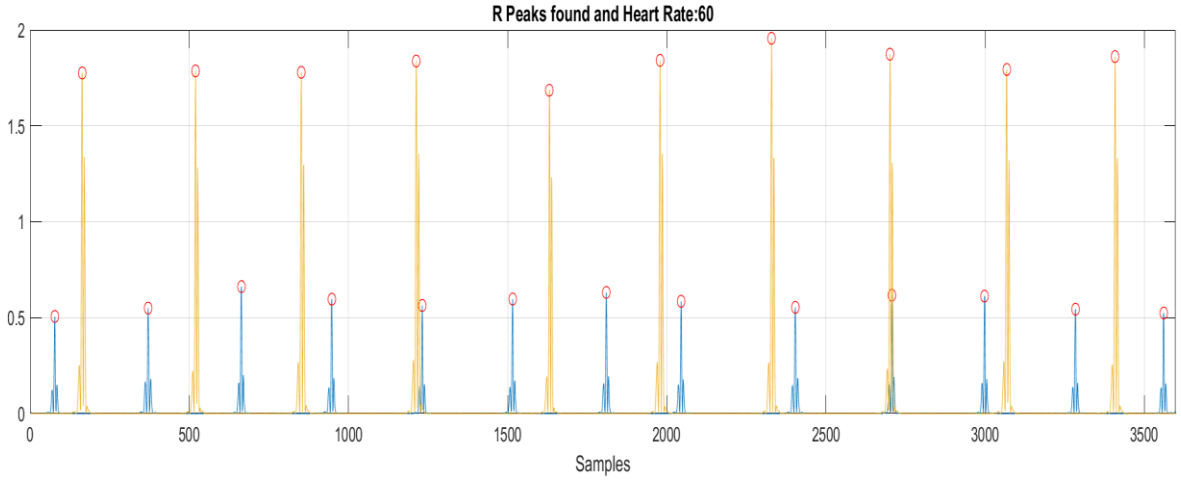

Fig. 5.4 R peaks and Heart Rate of person_2

5.2.3 Person_3 Database

This database we collected from MIT-BIH Arrhythmia database. The sampling rate of this database is 360 Hz. **'Fig. 5.5'** shows the actual signal of person_3 database. It is a signal of 10 seconds.

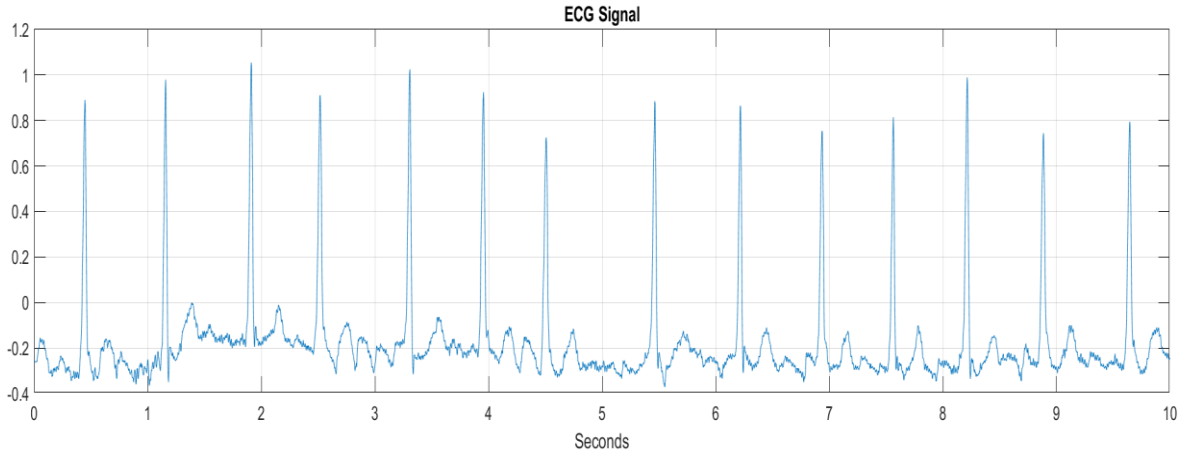

Fig. 5.5 ECG signal of person_3

'Fig. 5.6' shows the R peaks detection and Heart rate of person_3 after DWT process. From **'Fig. 5.6'** we see that the heart rate of person_3 is 84. That means the heart rate of person_3 is normal.

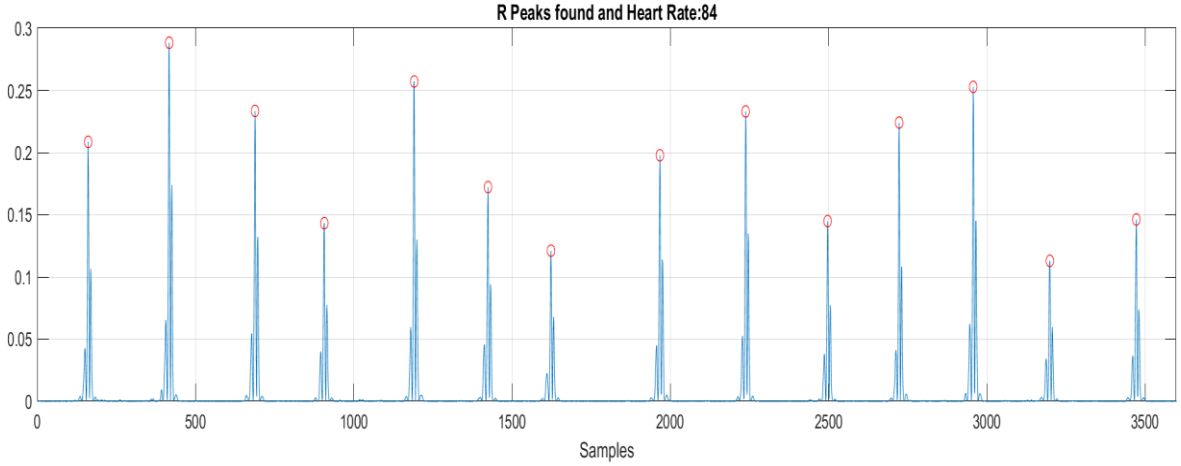

Fig. 5.6 R peaks and Heart Rate of person_3

5.2.4 Person_4 Database

This database we collected from MIT-BIH Arrhythmia database. The sampling rate of this database is 360 Hz. **'Fig. 5.7'** shows the actual signal of person_4 database. It is a signal of 10 seconds.

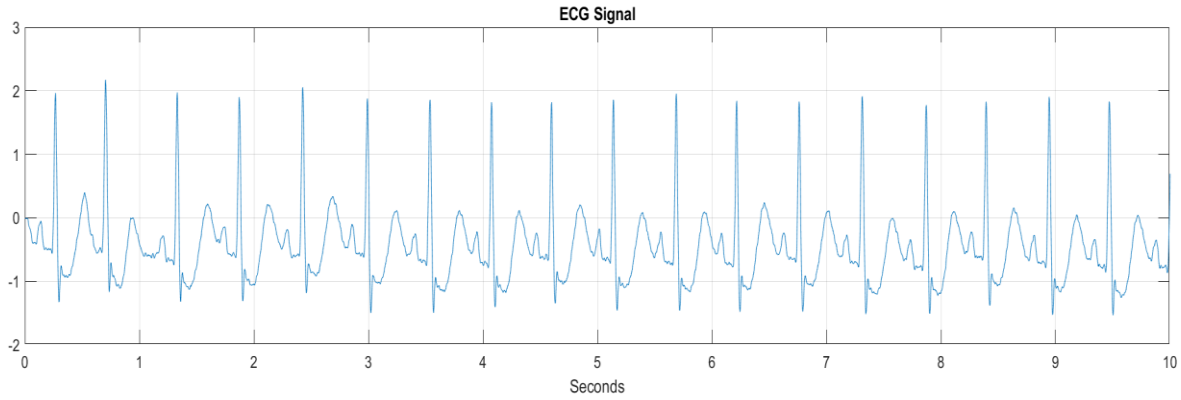

Fig. 5.7 ECG signal of person_4

'Fig. 5.8' shows the R peaks detection and Heart rate of person_4 after DWT process. From **'Fig. 5.8'** we see that the heart rate of person_4 is 108. That means the heart rate is abnormal. The heart of that persons beating too fast. Beating heart too fast (more than 100 bpm) known as **Tachycardia**.

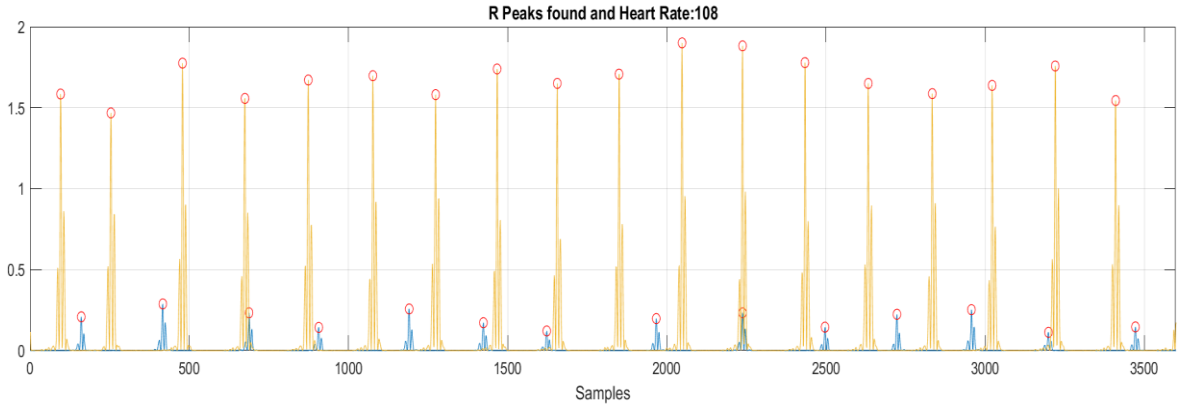

Fig. 5.8 R peaks and Heart Rate of person_4

Tachycardia may produce no symptoms or problems in some people. Tachycardia, on the other hand, if left untreated, may impair normal cardiac function and lead to severe consequences, such as:

- Heart failure
- Stroke
- Sudden cardiac arrest or death are also possible outcomes.

Drugs, medical treatments, and surgery may be used to assist regulate a fast pulse or manage other disorders that cause tachycardia.

5.2.5 Person_5 Database

This database we collected from MIT-BIH Arrhythmia database. The sampling rate of this database is 360 Hz. **'Fig. 5.9'** shows the actual signal of person_5 database. It is a signal of 10 seconds.

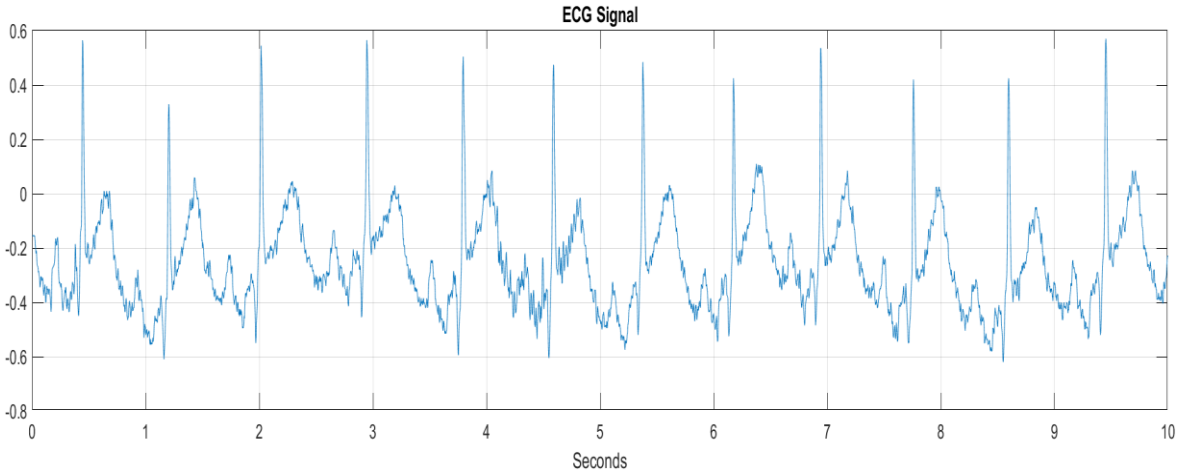

Fig. 5.9 ECG signal of person_5

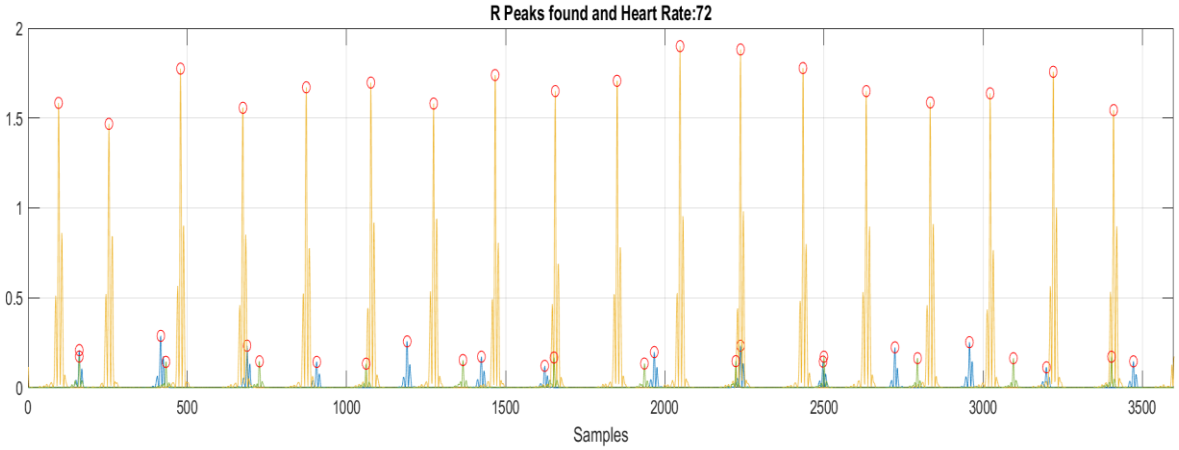

Fig. 5.10 R peaks and Heart Rate of person_5

'Fig. 5.10' shows the R peaks detection and Heart rate of person_5 after DWT process. From **'Fig. 5.10'** we see that the heart rate of person_5 is 72. That means the heart rate of person_5 is normal.

5.2.6 Person_6 Database

This database we collected from ECG-ID database. The sampling rate of this database is 500 Hz. **'Fig. 5.11'** shows the actual signal of person_6 database. It is a signal of 10 seconds.

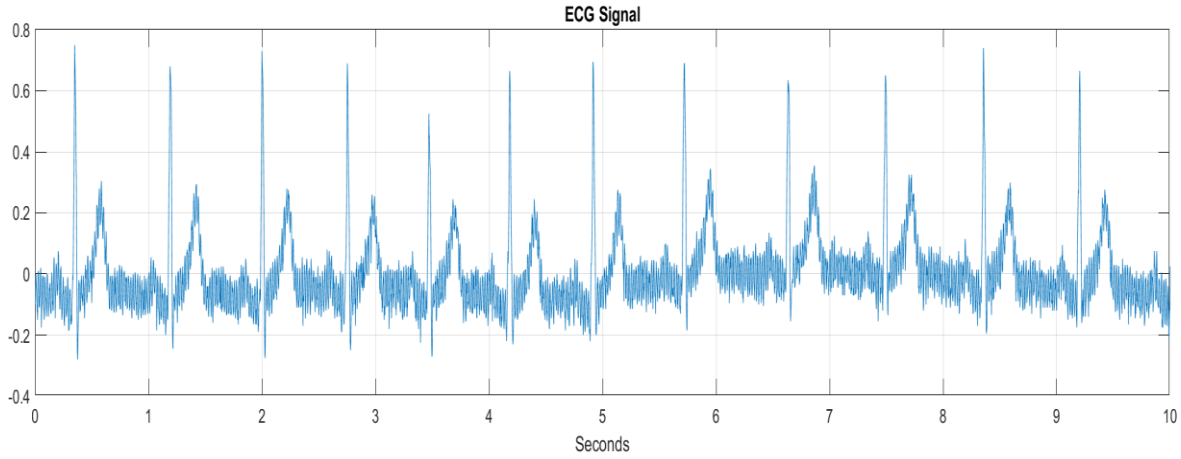

Fig. 5.11 ECG signal of person_6

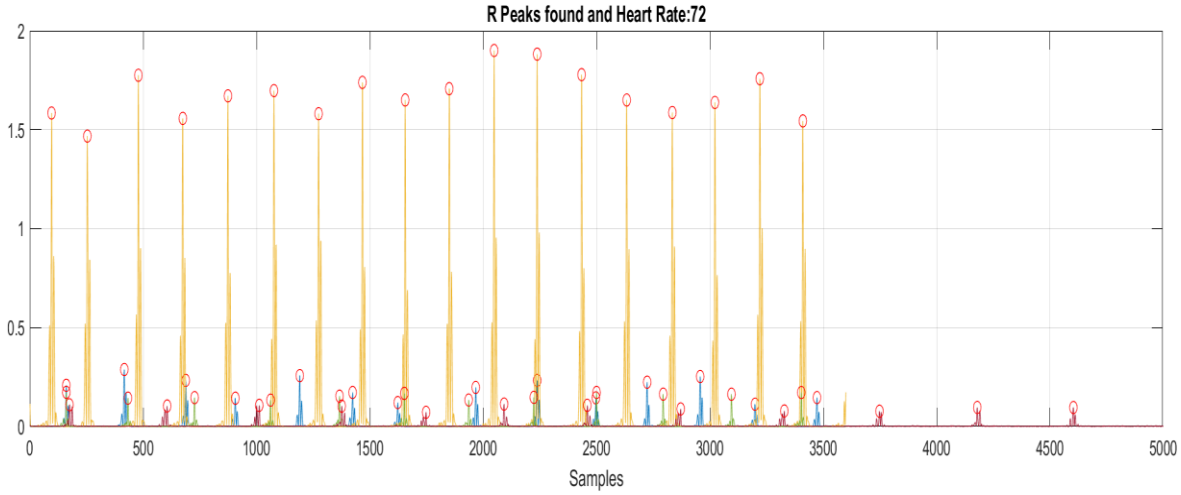

Fig. 5.12 R peaks and Heart Rate of person_6

'Fig. 5.12' shows the R peaks detection and Heart rate of person_6 after DWT process. From **'Fig. 5.12'** we see that the heart rate of person_6 is 72. That means the heart rate of person_6 is normal.

5.2.7 Person_7 Database

This database we collected from ECG-ID database. The sampling rate of this database is 500 Hz. **'Fig. 5.13'** shows the actual signal of person_7 database. It is a signal of 10 seconds.

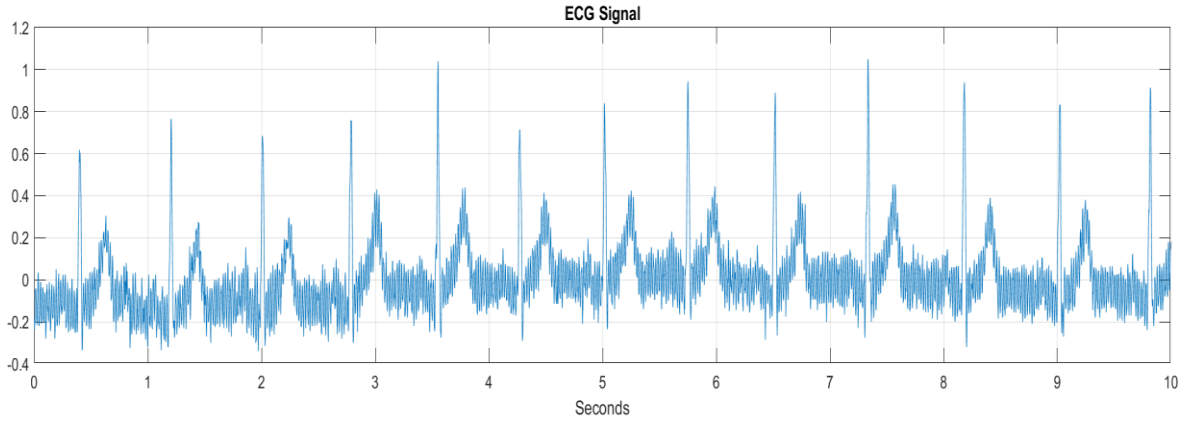

Fig. 5.13 ECG signal of person_7

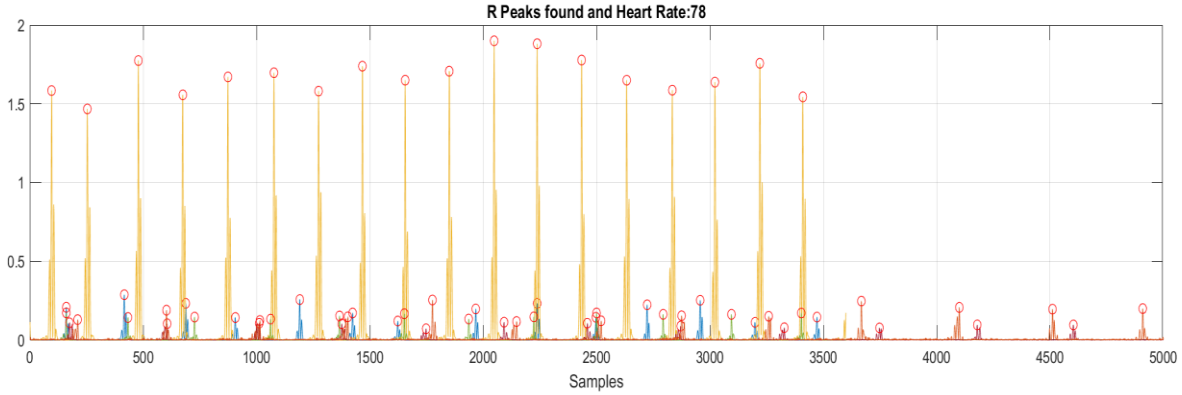

Fig. 5.14 R peaks and Heart Rate of person_7

Fig. 5.14 shows the R peaks detection and Heart rate of person_7 after DWT process. From **Fig. 5.14** we see that the heart rate of person_7 is 78. That means the heart rate of person_7 is normal.

5.2.8 Person_8 Database

This database we collected from ECG-ID database. The sampling rate of this database is 500 Hz. **'Fig. 5.15'** shows the actual signal of person_8 database. It is a signal of 10 seconds.

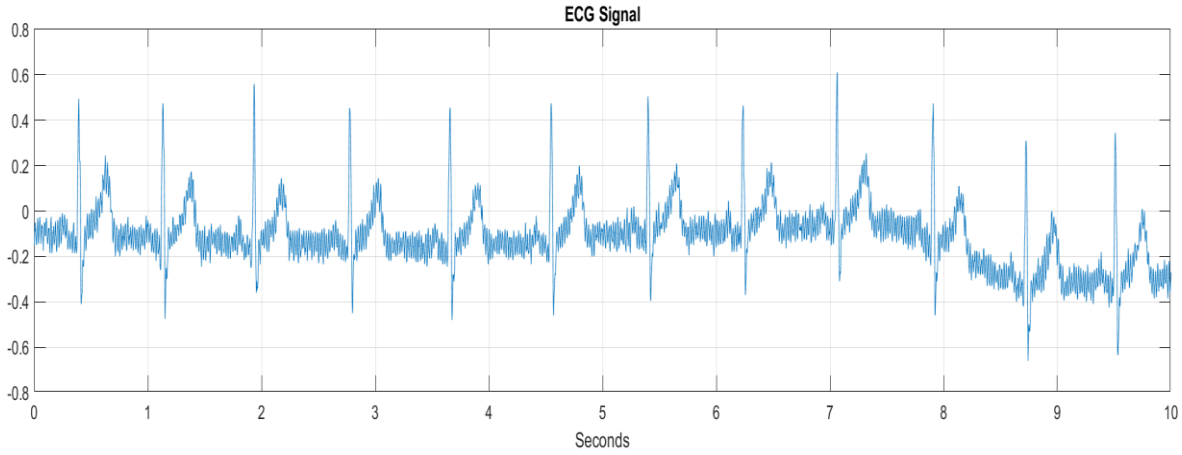

Fig. 5.15 ECG signal of person_8

'Fig. 5.16' shows the R peaks detection and Heart rate of person_8 after DWT process. From **'Fig. 5.16'** we see that the heart rate of person_8 is 72. That means the heart rate of person_8 is normal

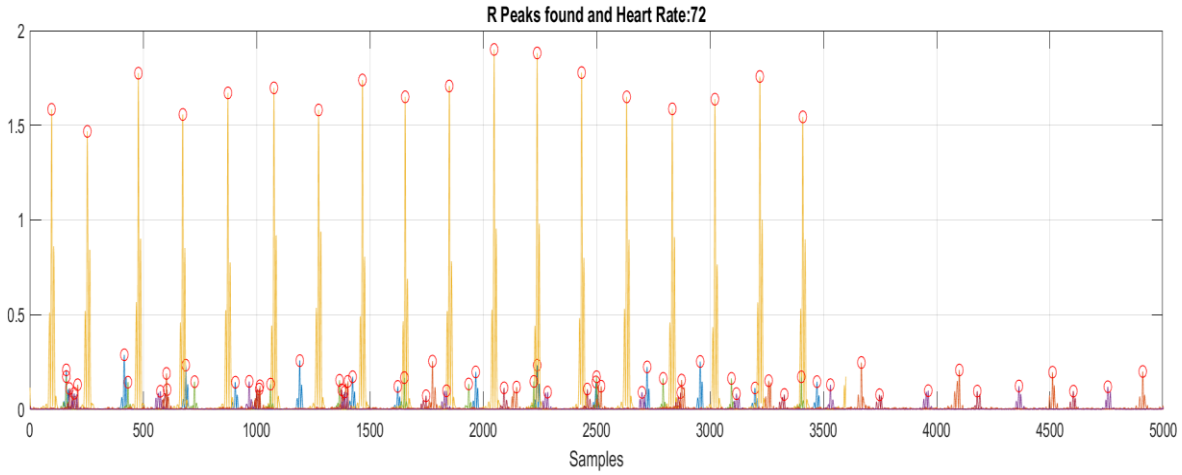

Fig. 5.16 R peaks and Heart Rate of person_8

5.2.9 Person_9 Database

This database we collected from ECG-ID database. The sampling rate of this database is 500 Hz. **'Fig. 5.17'** shows the actual signal of person_9 database. It is a signal of 10 seconds.

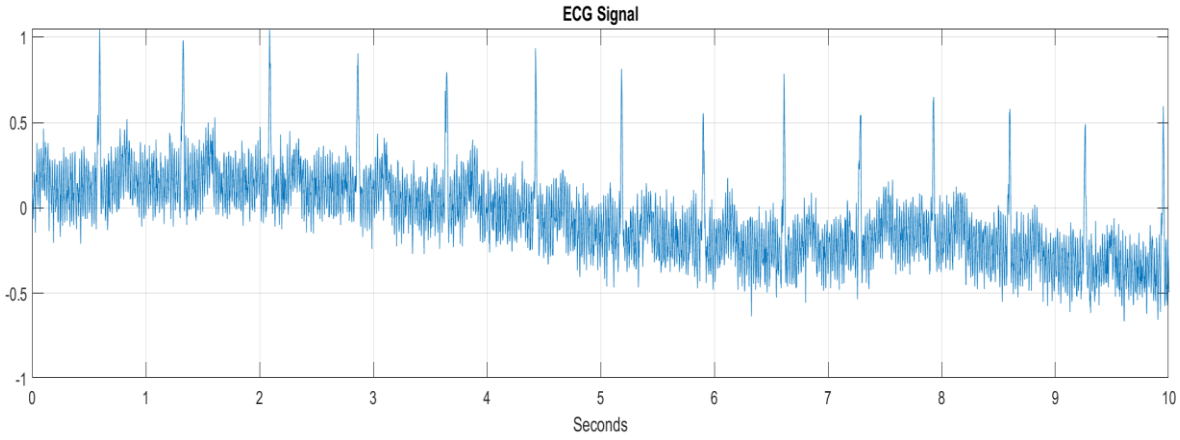

Fig. 5.17 ECG signal of person_9

'Fig. 5.18' shows the R peaks detection and Heart rate of person_9 after DWT process. From **'Fig. 5.18'** we see that the heart rate of person_9 is 84. That means the heart rate of person_9 is normal.

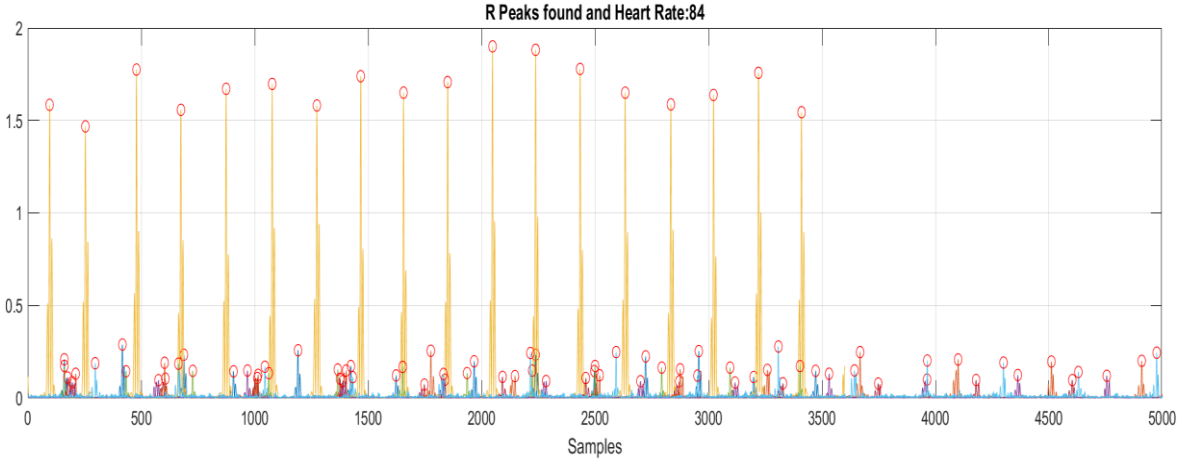

Fig 5.18 R peaks and Heart Rate of person_9

5.2.10 Person_10 Database

This database we collected from ECG-ID database. The sampling rate of this database is 500 Hz. **'Fig. 5.19'** shows the actual signal of person_10 database. It is a signal of 10 seconds.

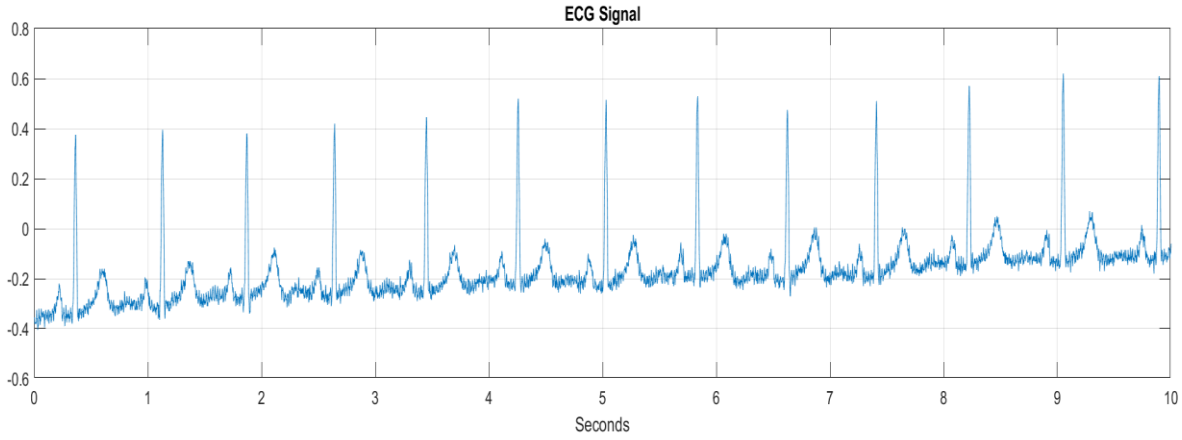

Fig. 5.19 ECG signal of person_10

'Fig. 5.20' shows the R peaks detection and Heart rate of person_10 after DWT process. From **'Fig. 5.20'** we see that the heart rate of person_10 is 78. That means the heart rate of person_10 is normal.

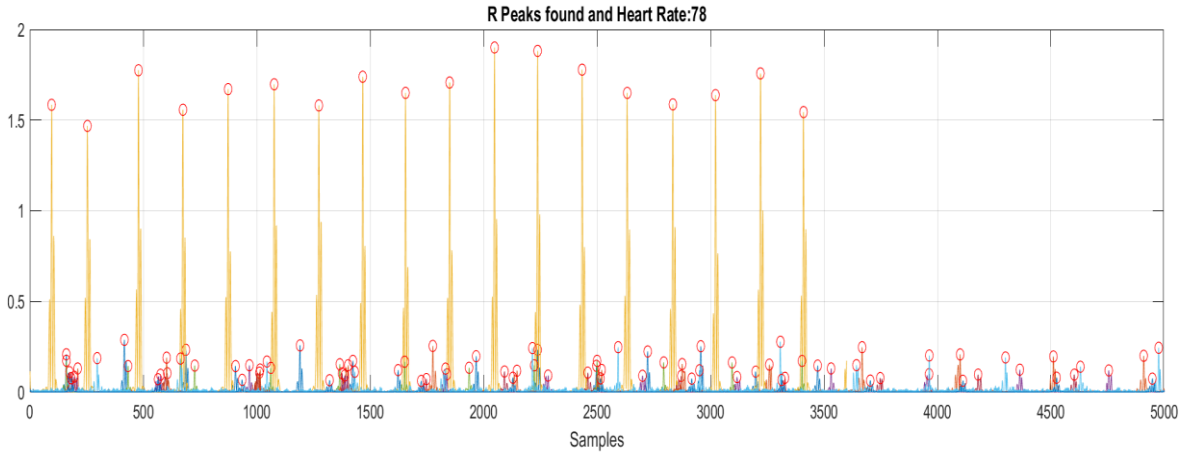

Fig. 5.20 R peaks and Heart Rate of person_10

5.3 Result of ECG Signal Classification

As previously discussed, we classified ECG signals by using Continuous Wavelet Transform and AlexNet deep CNN. At first, we took seven types of ECG recordings from PhysioNet. After that, we made a file in which, we gathered all of our ECG recordings and saved them in MATLAB's current directory by the name 'ECGData'. After that, we run our 1st program which is the Algorithm for the CWT process. After running this program, it converted all the signals into images which is the main purpose of the CWT process. After the conversion of signals into images, the program saved the images into seven different folders. The folder's names are arr, chf, nsr, nif, sva, iaf, mve. There is a total of 375 images in each folder. We had 2625 images as a database. We resized each image of size 227 X 227 because AlexNet takes input images of this size. The image was in RGB color format. After conversion, we had a total of 2625 scalogram images saved in seven folders corresponding to each category ARR, CHF, NSR, NIF, SVA, IAF, MVE. From these 2625 images, we use d2140 images for training the deep CNN and 455 images for testing for the classification process. That means we collected 310 images for training and 65 images for testing from each category. **'Fig. 5.21'** shows the result of 1D ARR signal after CWT. **'Fig. 5.22'** shows the result of 1D CHF signal after CWT. **'Fig. 5.23'** shows the result of 1D NSR signal after CWT. **'Fig. 5.24'** shows the result of 1D NIF signal after CWT. **'Fig. 5.25'** shows the result of 1D SVA signal after CWT. **'Fig. 5.26'** shows the result of 1D IAF signal after CWT. **'Fig. 5.27'** shows the result of 1D MVE signal after CWT.

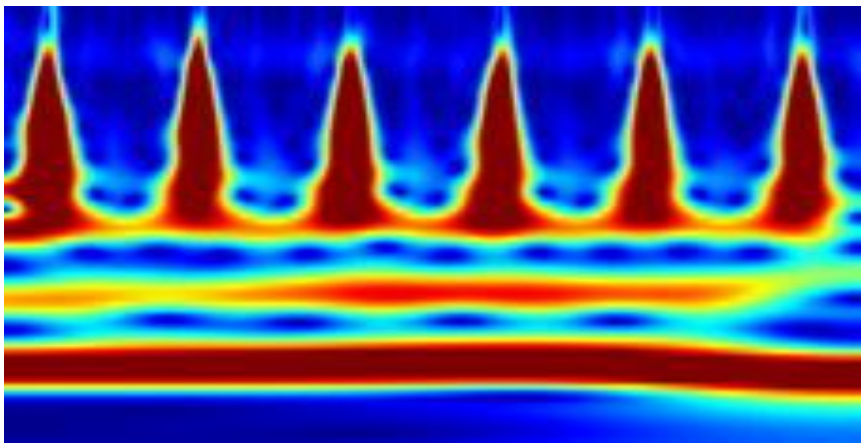

Fig. 5.21 ARR signal after CWT

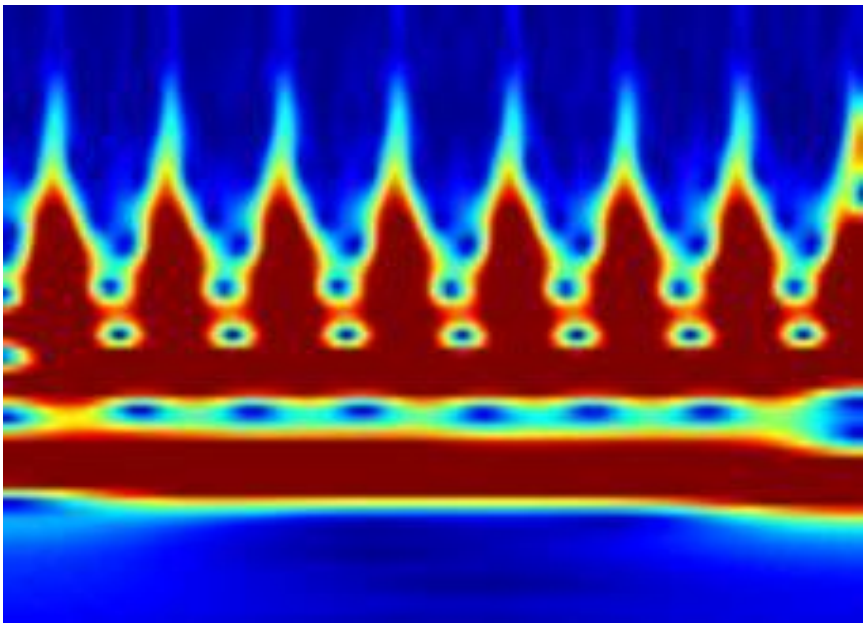

Fig. 5.22 CHF signal after CWT

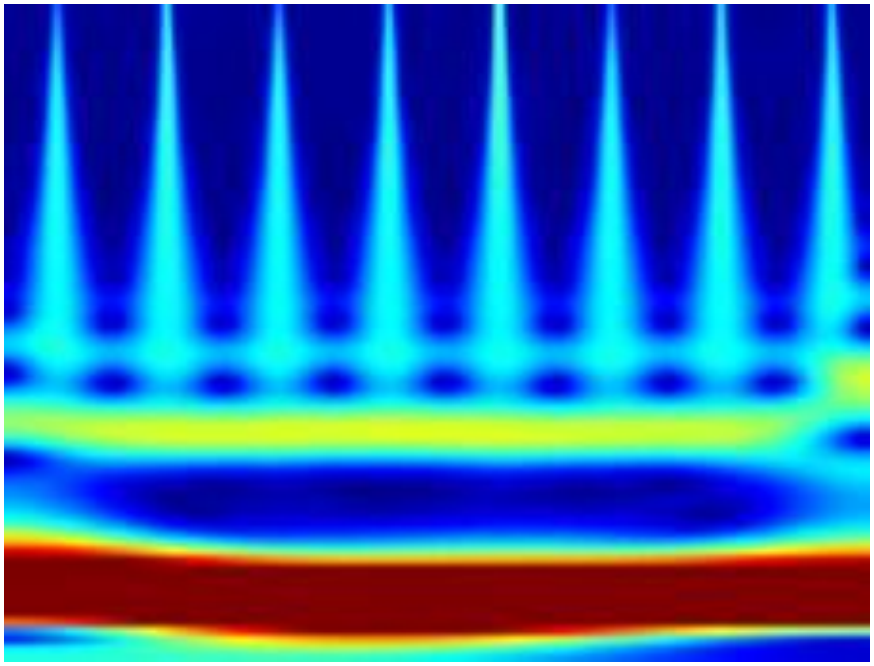

Fig. 5.23 NSR signal after CWT

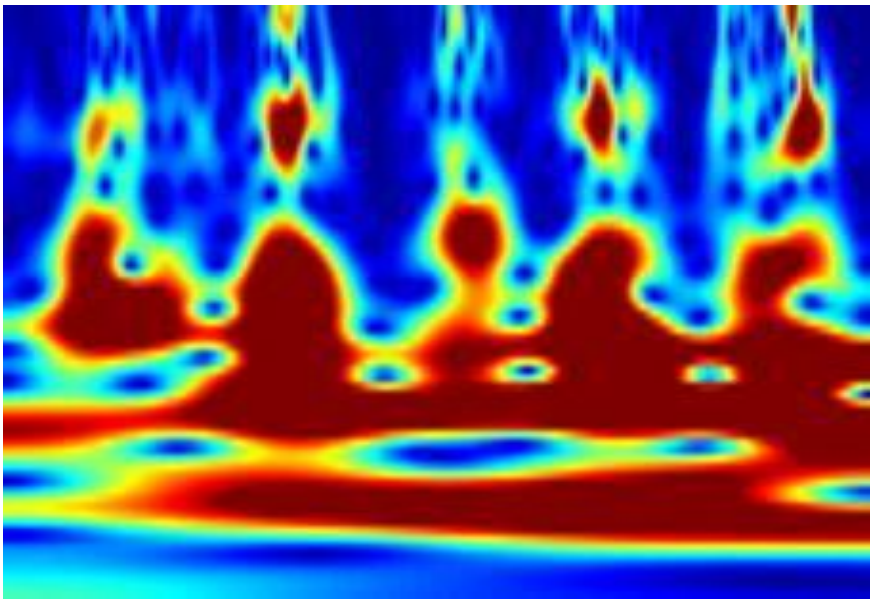

Fig. 5.24 NIF signal after CWT

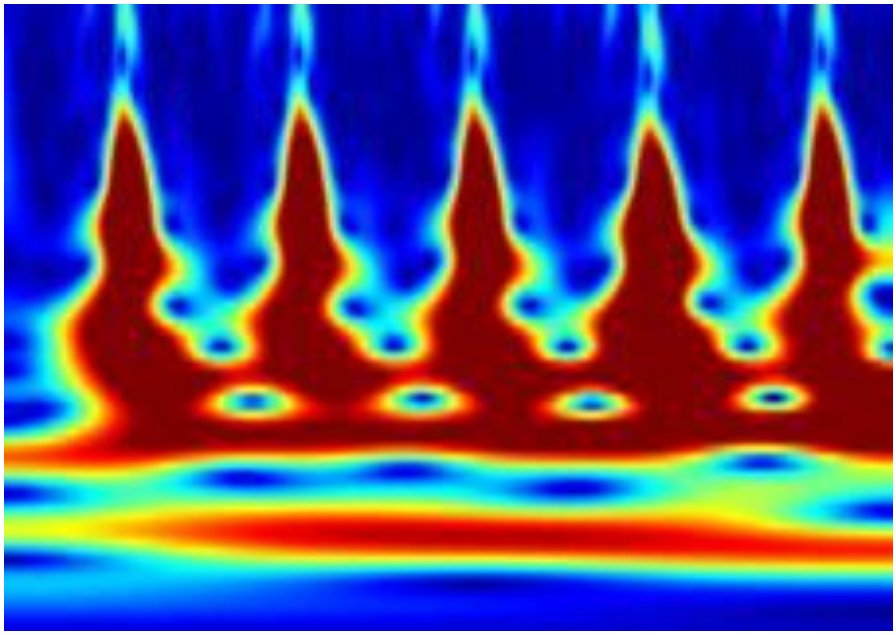

Fig. 5.25 SVA signal after CWT

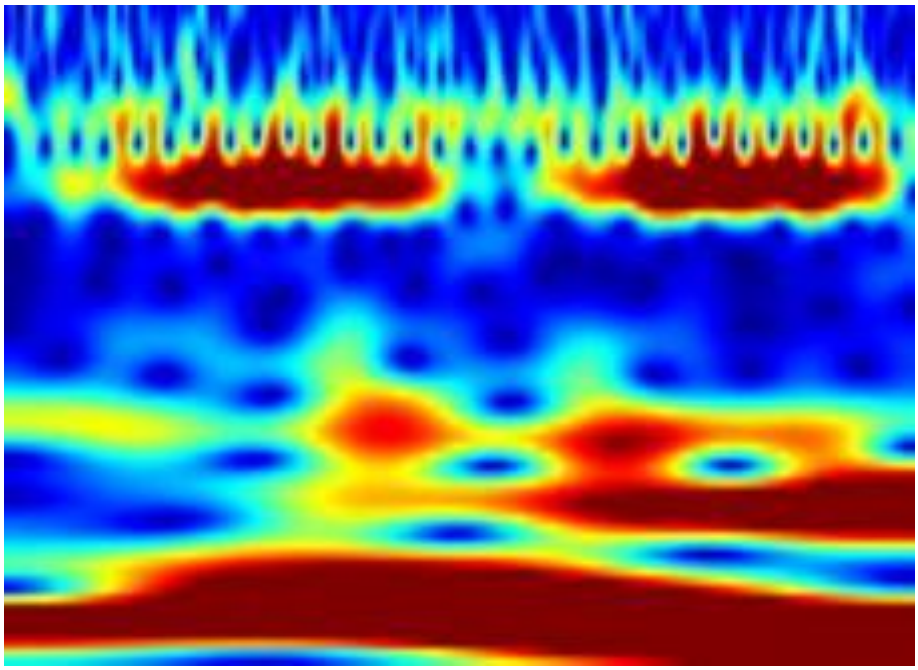

Fig. 5.26 IAF signal after CWT

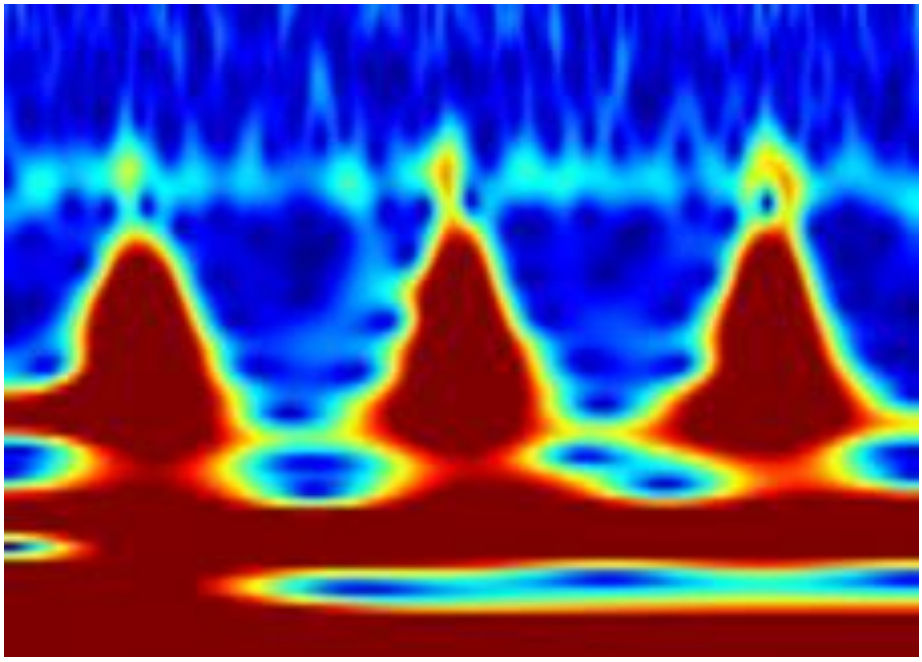

Fig. 5.27 MVE signal after CWT

After the CWT program running, we got images for all of our signals. After that we run our 2nd program in MATLAB which we created for training and testing AlexNet Deep CNN, we found a plot of 'Accuracy Vs Epoch'. This plot shown in **'Fig. 5.28'**.

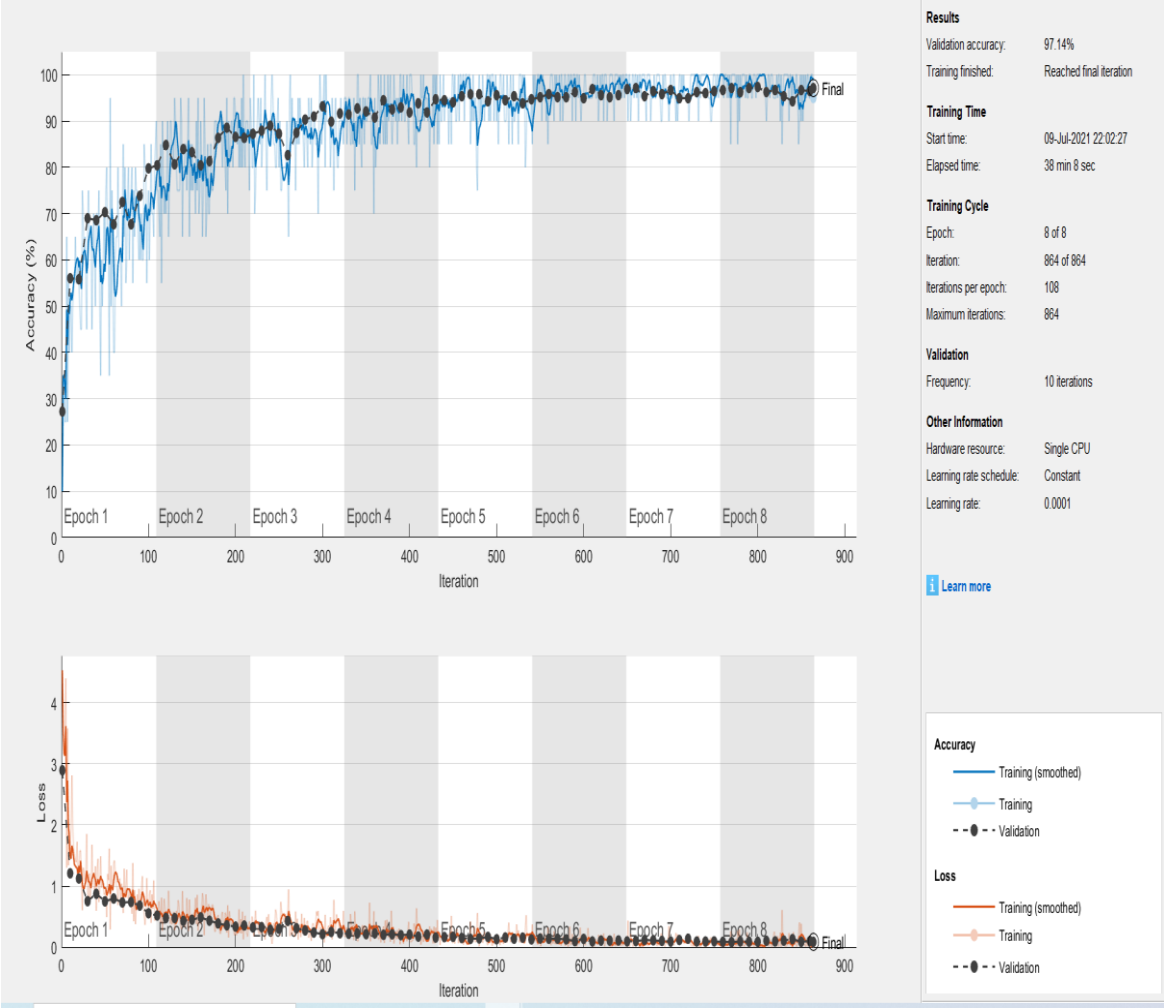

Fig. 5.28 Accuracy Vs Epoch Graph

From **'Fig. 5.28'** we see that it took 38 minutes 8 seconds for training. Here, the total epoch is 8. An epoch means training the neural network with all the training data. Iterations are the number of batches needed to complete one epoch. Here, the maximum iteration is 864, and the iteration per epoch is 108. The hardware resource is a single CPU. The learning rate is 0.0001. The frequency is 10 iterations. From the 'Accuracy vs Epoch' graph, we found total accuracy of 97.14 %. That means 97.14 % of our signal is classified correctly by AlexNet

Deep CNN. From the 2nd graph in **'Fig. 5.28'**, we see a graph of 'Loss vs Epoch'. In this graph, we see the number of misclassified signals in percentage.

Let us see the 'Confusion Matrix' for this classification. The confusion matrix is shown in **'Fig. 5.29'**.

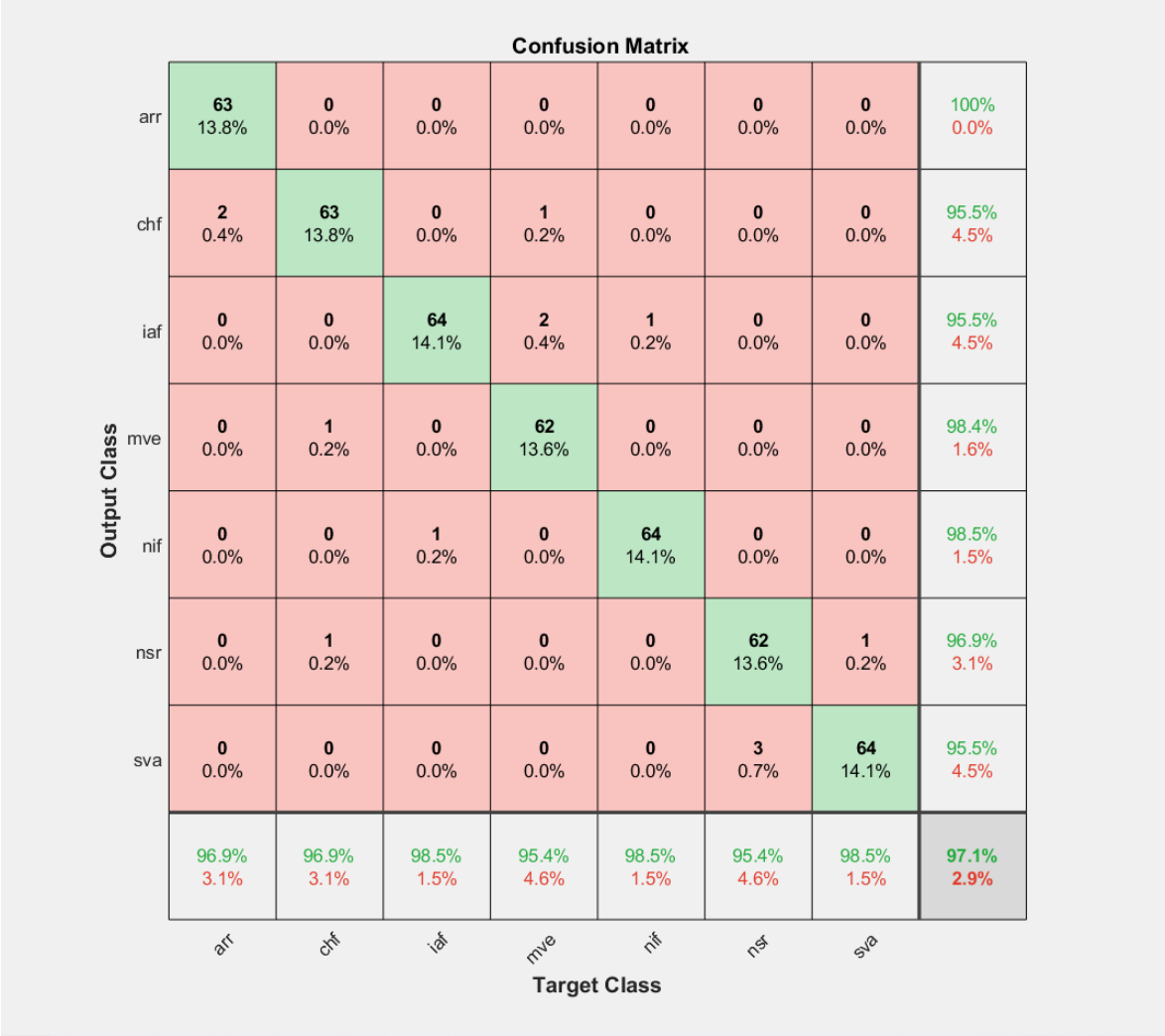

Fig. 5.29 Confusion Matrix

This is the Confusion Matrix we achieved. Here, we can see 7 classes which are arr, chf, nsr, iaf, mve, nif, sva. From the 1st column of the confusion matrix, we see that out of 65 signals 63 were classified as ARR, and 2 signals were misclassified as CHF. From the 2nd column of the confusion matrix, we see that out of 65 signals 63 signals were classified as CHF, and 2 signals were misclassified as MVE and NSR. From the 3rd column of the confusion matrix, we see that out of 65 signals 64 were classified as IAF and 1 signal misclassified as NIF.

From the 4th column of the confusion matrix, we see that out of 65 signals 62 signals were classified as MVE and 2 signals were misclassified as IAF, and 1 signal was misclassified as CHF. From the 5th column of the confusion matrix, we see that out of 65 signals 64 were classified as NIF, and 1 signal was misclassified as IAF. From the 6th column of the confusion matrix, we see that out of 65 signals 62 were classified as NSR, and 3 signals were misclassified as SVA. From the 7th column of the confusion matrix, we see that out of 65 signals 64 were classified as SVA and 1 signal misclassified as NSR. The overall accuracy of our technique is 97.14 %.

5.4 Conclusion

In this chapter, we discussed our work result elaborately. In this chapter, we discussed the results of heart rate calculation and also the result of ECG signal classification. The result of ECG signal classification shows that our technique achieves 97.14 % accuracy.

CHAPTER 6

CONCLUSION

6.1 Introduction

In this chapter we have discussed about the conclusion part of our work. We also discussed about our technique limitations and the future scope of our technique in this chapter.

6.2 Conclusion

Calculating heart rate is very important for us. Because without knowing heart rate we cannot tell if our heart is working properly or, not. If the heart rate is too slow or too fast, we need to take treatment for that. So, all of us need to calculate heart rate fast and automatically. For, that we developed a technique that can calculate heart rate from ECG signal recordings by MATLAB software. Nowadays heart disease increasing rapidly. So, all of us need to classify ECG signals accurately for detecting arrhythmia. For this, we developed a technique in our work that can classify ECG signals with 97.14 % accuracy. In this thesis, we discussed some others researchers' work. From this discussion, we can say that our technique can classify ECG signals more accurately than their technique.

6.3 Limitations

In this thesis, we introduce a technique that can classify ECG signals with an accuracy of 97.14 % which is much more efficient than other techniques. But our technique failed to achieve 100 % accuracy. We classify only 7 types of ECG recordings, but there are many more ECG recordings that need to classify for better detection of arrhythmia. For doing this work we used computer, which made this work costly. Also, we used data from the PhysioNet database. We didn't take ECG data manually from patients, which is also a limitation of our work.

6.4 Future Scope

In the future, we can develop this ECG classification technique to distinguish between more than 7 types of recordings. Also, the accuracy of our technique can be increased in the future by increasing the total number of signals recordings as well as increasing the training and testing data. Also, we can develop software for mobile which can store ECG recordings of

any person in the cloud network and can classify ECG data and calculate heart rate by taking data from there. Which will lower the cost of the ECG classification and heart rate calculation and also will save time for the classification process.

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APPENDIX

MATLAB Code for Heart Rate Calculation:

```
[filename,pathname]=uigetfile('*.*','Select the ECG signal');
filewithpath=strcat(pathname,filename);
Fs=input('Enter Sampling Rate: ');
ecg=load(filename);
ecgsig=(ecg.val)./200;
t=1:length(ecgsig);
tx=t./Fs;
wt=modwt(ecgsig,4,'sym4');
wtrec=zeros(size(wt));
wtrec(3:4,:)=wt(3:4,:);
y=imodwt(wtrec,'sym4');
y=abs(y).^2;
avg=mean(y);
[Rpeaks,locs]= findpeaks(y,t,'MinpeakHeight',8*avg,'MinPeakDistance',50);
nohb=length(locs);
timelimit=length(ecgsig)/Fs;
hbpermin=(nohb*60)/timelimit;
disp(strcat('Heart Rate= ',num2str(hbpermin)))
if hbpermin<60
disp(strcat('Name Of Arrhythmia= Sinus Bradycardia'))
elseif hbpermin>100
disp(strcat('Name Of Arrhythmia= Sinus Tachycardia'))
else
disp(strcat('The Heart Rate Is Normal'))
end
subplot(211)
plot(tx,ecgsig);
xlim([0,timelimit]);
grid on;
xlabel('Seconds')
title('ECG Signal');
```

```
subplot(212)
plot(t,y)
grid on;
xlim([0,length(ecgsig)]);
hold on
plot(locs,Rpeaks,'ro')
xlabel('Samples')
title(strcat('R Peaks found and Heart Rate: ',num2str(hbpermin)))
```

MATLAB Code for ECG Signal Classification:

Code 1:

```
function ecg2cwtscg(ecgdata,cwtfb,ecgtype)
nos=15; %number of signals
nol=500; %signal length
colormap=jet(128);
if ecgtype=='ARR'
folderpath=strcat('D:\matlab\ecgdataset\arr\');
findx=0;
for i=1:25
indx=0;
or k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='CHF'
folderpath=strcat('D:\matlab\ecgdataset\chf\');
findx=0;
```

```
for i=1:25
indx=0;
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='NSR'
folderpath=strcat('D:\matlab\ecgdataset\nsr\');
findx=0;
for i=1:25
indx=0;
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='NIF'
folderpath=strcat('D:\matlab\ecgdataset\nif\');
findx=0;
for i=1:25
indx=0;
```

```
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='SVA'
folderpath=strcat('D:\matlab\ecgdataset\sva\');
findx=0;
for i=1:25
indx=0;
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='IAF'
folderpath=strcat('D:\matlab\ecgdataset\iaf\');
findx=0;
for i=1:25
indx=0;
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
```

```
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
elseif ecgtype=='MVE'
folderpath=strcat('D:\matlab\ecgdataset\mve\');
findx=0;
for i=1:25
indx=0;
for k=1:nos
ecgsignal=ecgdata(i,indx+1:indx+nol);
cfs=abs(cwtfb.wt(ecgsignal));
im=ind2rgb(im2uint8(rescale(cfs)),colormap);
filenameindex=findx+k;
filename=strcat(folderpath,sprintf('%d.jpg',filenameindex));
imwrite(imresize(im,[227 227]),filename);
indx=indx+nol;
end
findx=findx+nos;
end
end
```

Code 2:

```
%program to create CWT Image database from signals
load('ECGData.mat'); %Loading ECG database
data = ECGData.Data; %Getting Database
labels=ECGData.Labels; %Getting Labels
ARR=data(1:25,:);%Taken first 30 recordings
CHF=data(97:121,:);
NSR=data(127:151,:);
```

```
NIF=data(163:187,:);
SVA=data(189:213,:);
IAF=data(273:297,:);
MVE=data(333:357,:);
signallength=500;
%Defining filters for CWT with amor wavelet and 12 filters per octave
fb=cwtfilterbank('SignalLength',signallength,'Wavelet','amor','voicesperoctave',12);
%Making Folders
mkdir('ecgdataset'); %Main folder
mkdir('ecgdataset\arr');%Sub folder
mkdir('ecgdataset\chf');
mkdir('ecgdataset\nsr');
mkdir('ecgdataset\nif');
mkdir('ecgdataset\sva');
mkdir('ecgdataset\iaf');
mkdir('ecgdataset\mve');
ecgtype={'ARR','CHF','NSR','NIF','SVA','IAF','MVE'};
%Function to convert ECG to image
ecg2cwtscg(ARR,fb,ecgtype{1});
ecg2cwtscg(CHF,fb,ecgtype{2});
ecg2cwtscg(NSR,fb,ecgtype{3});
ecg2cwtscg(NIF,fb,ecgtype{4});
ecg2cwtscg(SVA,fb,ecgtype{5});
ecg2cwtscg(IAF,fb,ecgtype{6});
ecg2cwtscg(MVE,fb,ecgtype{7});
```

Code 3:

```
%Training and Validation using Alexnet
DatasetPath='D:\matlab\ecgdataset';
%Reading Images from Image Database Folder
images =imageDatastore(DatasetPath,'IncludeSubfolders',true,'LabelSource','foldernames');
%Distributing Images in the set of Training and Testing
numTrainFiles=310;
[TrainImages,TestImages]=splitEachLabel(images,numTrainFiles,'randomize');
net=alexnet; %Importing pretrained Alexnet(Requires support package)
```

```
layersTransfer= net.Layers(1:end-3); %Preserving all Layers except last three
numClasses =7; %Number of output classes
%Defining layers of Alexnet
layers=[layersTransfer
fullyConnectedLayer(numClasses,'WeightLearnRateFactor',20,'BiasLearnRateFactor',20)
softmaxLayer
classificationLayer];
%Training options
options=trainingOptions('sgdm', ...
'MiniBatchSize',20, ...
'MaxEpochs',8, ...
'InitialLearnRate',1e-4, ...
'Shuffle','every-epoch', ...
'ValidationD ata',TestImages, ...
'ValidationFrequency',10, ...
'Verbose',false, ...
'plots','training-progress');
%Training the Alexnet
netTransfer=trainNetwork(TrainImages,layers,options);
%Classifying Images
YPred=classify(netTransfer,TestImages);
YValidation=TestImages.Labels;
accuracy=sum(YPred == YValidation)/numel(YValidation);
%ploting Confusion Matrix
plotconfusion(YValidation,YPred)
```