A

Project Report

on

Myocardial Infraction Predicting System

Submitted to

Sant Gadge Baba Amravati University, Amravati

Submitted in partial fulfilment of

the requirements for the Degree of

Bachelor of Engineering in

Electronics and Telecommunication Engineering

Submitted by

Shwetatai L. Bhagat
(PRN: 203120444)

Yash V. Deshmukh
(PRN: 193120326)

Vidhi M. Parashar
(PRN: 193120282)

Sameer R. Shegaonkar
(PRN: 193120336)

Under the Guidance of

Prof. (Dr.) M. N. Tibdewal

Professor, E & TC Dept.

Department of Electronics & Telecommunication Engg.

Shri Sant Gajanan Maharaj College of Engineering,

Shegaon – 444 203 (M.S.)

2022-2023

Department of Electronics & Telecommunication Engineering
Shri Sant Gajanan Maharaj College of Engineering,
Shegaon – 444203, Maharashtra, India
(Recognized by AICTE, Accredited by N.B.A, New Delhi)

Certificate

This is to certify that the project report entitled **"ECG Analysis for Myocardial Infraction Detection"** is hereby approved as a creditable study carried out and presented by

Shwetatai L. Bhagat	(PRN: 203120444)
Yash V. Deshmukh	(PRN: 193120326)
Vidhi M. Parashar	(PRN: 193120282)
Sameer R. Shegaonkar	(PRN: 193120336)

in a manner satisfactory to warrant of its acceptance as a pre-requisite in a partial fulfillment of the requirements for the degree of Bachelor of Engineering in Electronics & Telecommunication Engineering of Sant Gadge Baba Amravati University, Amravati during the Session 2022-23.

31.5.23
Dr. M. N. Tibdewal
Project Guide

Dr. P. R. Wankhede
Internal Examinar

External Examiner
External Examiner

31.5.23
Dr. M. N. Tibdewal
Professor & Head, E & TC Dept.

Dr. S. B. Somani
Principal

Abstract

Cardiovascular diseases (CVDs) have been the leading cause of death worldwide for the last decade. The electrocardiogram (ECG) is a useful tool that provides precise data on the various cardiac conditions in the human heart. current research aimed at identifying and mitigating risky cardiovascular conditions. Signal processing efficiently analyses and classify ECG signals for the early detection and diagnosis of cardiac conditions and arrhythmias.

Cardiac arrhythmia indicates abnormal electrical activity of heart can be threat to human, so it has to be automatically identified for clinical diagnosis and treatment. Because the ECG signal is nonstationary in nature, it is difficult to analyze and interpret. As a result, precise ECG signal analysis using a sophisticated instrument such as discrete wavelet transform is required. (DWT) becomes necessary. The ECG data is denoised to remove artefacts and analysed using the Wavelet Transform to detect the QRS complex and arrhythmia.

Electrocardiogram is commonly used as a diagnostic tool for the monitoring of cardiac health and the detection of possible heart diseases. With wavelet transform, this work is implemented in MATLAB software for the MIT/BIH Arrhythmia database and yields sensitivity of 99.85%, positive predictivity of 99.92%, and detection error rate of 0.221%.

In addition, it is concluded that DWT surpasses the principal component analysis technique in detecting ECG signals. The discussion of all facets of Arrhythmias are detected using heart rate, and disorders or abnormalities such as ventricular bigeminy, multiform PVC, Bradycardia, Tachycardia, and Atrial flutter are diagnosed and is presented in-depth for the first time in a review paper of this type.

Keywords: Electrocardiogram, Discrete wavelet transform (DWT), Denoising, QRS detection, Arrhythmia

.

Acknowledgement

We would like to take this opportunity to express our heartfelt thanks to our guide **Prof. (Dr.) M. N. Tibdewal** for his esteemed guidance and encouragement, especially through difficult times. His suggestions broaden our vision and guided us to succeed in this work. We are also very grateful for his guidance and comments while designing part of our project and learnt many things under his leadership. Also we would like to thank to Prof. (Dr.) M. N. Tibdewal, Head of Electronics and Telecommunication Department, all teaching and non-teaching staff of EXTC Department for their encouragement and suggestions for our project.

We extend our thanks to Dr. S. B. Somani, Principal, Shri Sant Gajanan Maharaj, College of Engineering, for his valuable support.

We sincerely thank to all our friends, who helped us directly or indirectly in completing our project work. We would like to express our appreciation for the wonderful experience while completions of this project work.

Place: SSGMCE, Shegaon

Shwetatai L. Bhagat

Yash V. Deshmukh

Vidhi M. Parashar

Sameer R. Shegaonkar

Abbreviations

CVD -cardiovascular disease

ECG -Electrocardiogram

CT -Computed Tomography

RBBB - Right Bundle Branch Block

LBBB - Left Bundle Branch Block

PAC - Premature Atrial Contraction

PVC -premature ventricular contraction

AF -Atrial Fibrillation

MI -Myocardial Infraction

IHD - ischemic heart disease

Wi-Fi - Wireless Fidelity

List of Figures

List of Tables

Contents

Chapter 1

Introduction

Because of the massive growth in the human population and medical expenditure, healthcare has emerged as one of the most critical issues for both individuals and governments. According to a World Health Organization (WHO) research, the issue of population ageing is also worsening.

Aged people often require more frequent assessments of their health status, putting a greater strain on current medical systems. As a result, there has been a surge in interest in identifying human diseases rapidly and effectively at a low cost. Due to the frequency of heart-related disease diagnosis, electrocardiogram (ECG) monitoring has been widely employed in both hospitals and medical research. The monotonous recurrence of these "PQRST" forms the ECG.

Arrhythmias are classified into three types: supraventricular arrhythmias, ventricular arrhythmias, and Bradyarrhythmias. Atrial fibrillation, atrial flutter, paroxysmal supraventricular tachycardia (PSVT), and Wolff-Parkinson-White (WPW) syndrome are examples of supraventricular arrhythmia.

It is a typical technique used in cardiac diagnosis. Figure 1.1 depicts a typical ECG trace of a normal heartbeat, including a P wave. Depending on the severity of the arrhythmia, cardiac arrest and unexpected falls may occur.

With quick diagnosis and proper analysis, arrhythmia can save many lives all around the world. This paper provides a comprehensive overview of many elements of ECG analysis, including data collecting, feature engineering, and classification using standard to advanced machine learning approaches, smart health monitoring devices, and real-time implementations with embedded architectures.

Despite the fact that there are many survey articles in the study, they only cover a few topics. As a result, this cutting-edge study provides the desired information regarding most elements of ECG analysis and serves as a valuable resource for academics working in this field.

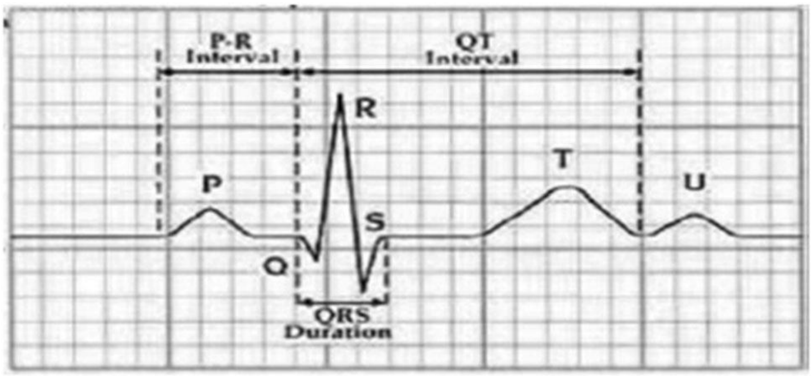

Figure 1.1 Normal ECG waveform [3]

Heartbeat patterns alter significantly over time and with different physical situations in the same person [2]. The P-QRS-T waves compose a single normal cardiac cycle of ECG signal depicted in Fig. 1 [3]. The characteristics are defined as time intervals and amplitudes [4].

The P wave is caused by atrial depolarization, the QRS complex by ventricular depolarization, and the T wave by ventricular repolarization [5]. The QRS complex is the most important and distinguishing component of an ECG that is utilized to detect the presence of a cardiac cycle [6].

1.1 Motivation

Nowadays numerous persons are mislaying their life owing to heart attack and shortage of medical attention to patient at correct stage as without warning, the heart stops. A sudden change in the heart's signaling causes sudden cardiac arrest.

A heart attack increases risk of this life-threatening condition. It can lead to death (sudden cardiac death) without immediate treatment. Most senior citizens are often neglected and are helpless in times of medical emergencies, as they are alone in their twilight years. Also, the doctors face it difficult to keep watch on each and every patient and to provide the emergency treatment at required time.

1.2 Literature review

Paper 1:

Swathy, M., and K. Saruladha. "A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques." ICT Express 8.1 (2022): 109-116.

Description:

Cardio-Vascular Diseases (CVD) are found to be rampant in the populace leading to fatal death. The statistics of a recent survey reports that the mortality rate is expanding due to obesity, cholesterol, high blood pressure and usage of tobacco among the people.

The severity of the disease is piling up due to the above factors. Studying about the variations of these factors and their impact on CVD is the demand of the hour. This necessitates the usage of modern techniques to identify the disease at its outset and to aid a markdown in the mortality rate. Artificial Intelligence and Data Mining domains have a research scope with their enormous techniques that would assist in the prediction of the CVD priory and identify their behavioral patterns in the large volume of data.

The results of these predictions will help the clinicians in decision making and early diagnosis, which would reduce the risk of patients becoming fatal. This paper compares and reports the various Classification, Data Mining, Machine Learning, Deep Learning models that are used for prediction of the Cardio-Vascular diseases.

The survey is organized as threefold: Classification and Data Mining Techniques for CVD, Machine Learning Models for CVD and Deep Learning Models for CVD prediction. The performance metrics used for reporting the accuracy, the dataset used for prediction and classification, and the tools used for each category of these techniques are also compiled and reported in this survey.

Paper 2:

Lopes, Ricardo R., et al. "Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p. Arg14del mutation carriers." Computers in Biology and Medicine 131 (2021): 104262.

Description:

The pathogenic mutation p. Arg14del in the gene encoding Phospholamban (PLN) is known to cause cardiomyopathy and leads to increased risk of sudden cardiac death. Automatic tools might improve the detection of patients with this rare disease. Deep learning is currently the state-of-the-art in signal processing but requires large amounts of data to train the algorithms.

In situations with relatively small amounts of data, like PLN, transfer learning may improve accuracy. We propose an ECG-based detection of the PLN mutation using transfer learning from a model originally trained for sex identification.

The sex identification model was trained with 256,278 ECGs and subsequently finetuned for PLN detection (155 ECGs of patients with PLN) with two control groups: a balanced age/sex matched group and a randomly selected imbalanced population. The data was split in 10 folds and 20% of the training data was used for validation and early stopping.

The models were evaluated with the area under the receiver operating characteristic curve (AUROC) of the testing data. We used gradient activation for explanation of the prediction models. The models trained with transfer learning outperformed the models trained from scratch for both the balanced (AUROC 0.87 vs AUROC 0.71) and imbalanced (AUROC 0.0.90 vs AUROC 0.65) population.

The proposed approach was able to improve the accuracy of a rare disease detection model by transfer learning information from a non-manual annotated and abundant label with only limited data available.

Paper 3:

Martis, Roshan Joy, U. Rajendra Acharya, and Hojjat Adeli. "Current methods in electrocardiogram characterization." Computers in biology and medicine 48 (2014): 133-149.

Description:

The Electrocardiogram (ECG) is the P-QRS-T wave depicting the cardiac activity of the heart. The subtle changes in the electric potential patterns of repolarization and depolarization are indicative of the disease afflicting the patient. These clinical time domain features of the ECG waveform can be used in cardiac health diagnosis. Due to the presence of noise and minute morphological parameter values, it is very difficult to identify the ECG classes accurately by the naked eye.

Various computer aided cardiac diagnosis (CACD) systems, analysis methods, challenges addressed and the future of cardiovascular disease screening are reviewed in this paper. Methods developed for time domain, frequency transform domain, and time-frequency domain analysis, such as the wavelet transform, cannot by themselves represent the inherent distinguishing features accurately.

Hence, nonlinear methods which can capture the small variations in the ECG signal and provide improved accuracy in the presence of noise are discussed in greater detail in this review. A CACD system exploiting these nonlinear features can help clinicians to diagnose cardiovascular disease more accurately.

Paper 4:

Rath, Adyasha, et al. "Heart disease detection using deep learning methods from imbalanced ECG samples." Biomedical Signal Processing and Control 68 (2021): 102820.

Description:

Heart disease (HD) is a fatal disease which takes the lives of maximum people compared to other diseases across the world. Early and accurate detection of the disease will help to save many valuable lives. The HD can be detected from medical tests, Electrocardiogram (ECG) signal, heart sounds, Computed Tomography (CT) Images etc. Out of all types of detection of HD from ECG signals plays a vital role. In this paper, the ECG samples of the subjects have been considered as the required inputs to the HD detection model.

In recent past, many useful articles have been reported for classification of HD using different machine learning (ML) and deep learning (DL) models. It is observed that with imbalanced HD data the detection accuracy is lower. With an objective to achieve better detection of HD, suitable DL and ML models have been identified in this paper and the required classification models have been developed and tested.

The Generative Adversarial Network (GAN) model is chosen with an objective to deal with imbalanced data by generating and using additional fake data for detection purpose. Further, an ensemble model using long short-term memory (LSTM) and GAN is developed in this paper which demonstrates higher performance compared to individual DL model used in this paper.

The simulation results using standard MIT-BIH show that the proposed GAN-LSTM model provides the highest accuracy, F1-score and area under curve (AUC) of 0.992, 0.987 and 0.984 respectively compared to other models. Similarly, for PTB-ECG dataset the GAN-LSTM model outperforms all other models with accuracy,

Further research work can be carried out by choosing all other different ensemble models and using other different datasets and the performance can be similarly obtained and compared. The proposed best detection methodology can also be applied to other diseases and healthcare problems.

Paper 5:

Isin, Ali, and Selen Ozdalili. "Cardiac arrhythmia detection using deep learning." *Procedia computer science* 120 (2017): 268-275.

Description:

An electrocardiogram (ECG) is an important diagnostic tool for the assessment of cardiac arrhythmias in clinical routine. In this study, a deep learning framework previously trained on a general image data set is transferred to carry out automatic ECG arrhythmia diagnostics by classifying patient ECG's into corresponding cardiac conditions.

Transferred deep convolutional neural network (namely AlexNet) is used as a feature extractor and the extracted features are fed into a simple back propagation neural network to carry out the final classification.

Three different conditions of ECG waveform are selected from MIT-BIH arrhythmia database to evaluate the proposed framework. Main focus of this study is to implement a simple, reliable and easily applicable deep learning technique for the classification of the selected three different cardiac conditions.

Obtained results demonstrated that the transferred deep learning feature extractor cascaded with a conventional back propagation neural network were able to obtain very high performance rates. Highest obtained correct recognition rate is 98.51% while obtaining testing accuracy around 92%.

Based on these results, transferred deep learning proved to be an efficient automatic cardiac arrhythmia detection method while eliminating the burden of training a deep convolutional neural network from scratch providing an easily applicable technique.

Paper 6:

K. Feng, X. Pi, H. Liu and K. Sun, "Myocardial infarction classification based on convolutional neural network and recurrent neural network", Applied Sciences, vol. 9, pp. 1879, 2019

Description:

Myocardial infarction is one of the most threatening cardiovascular diseases for human beings. With the rapid development of wearable devices and portable electrocardiogram (ECG) medical devices, it is possible and conceivable to detect and monitor myocardial infarction ECG signals in time.

This paper proposed a multi-channel automatic classification algorithm combining a 16-layer convolutional neural network (CNN) and long-short term memory network (LSTM) for I-lead myocardial infarction ECG.

They utilized the Physikalisch-Technische Bundesanstalt (PTB) database for algorithm verification, and obtained an accuracy rate of 95.4%, a sensitivity of 98.2%, a specificity of 86.5%, and an F1 score of 96.8%, indicating that the model can achieve good classification performance without complex handcrafted features.

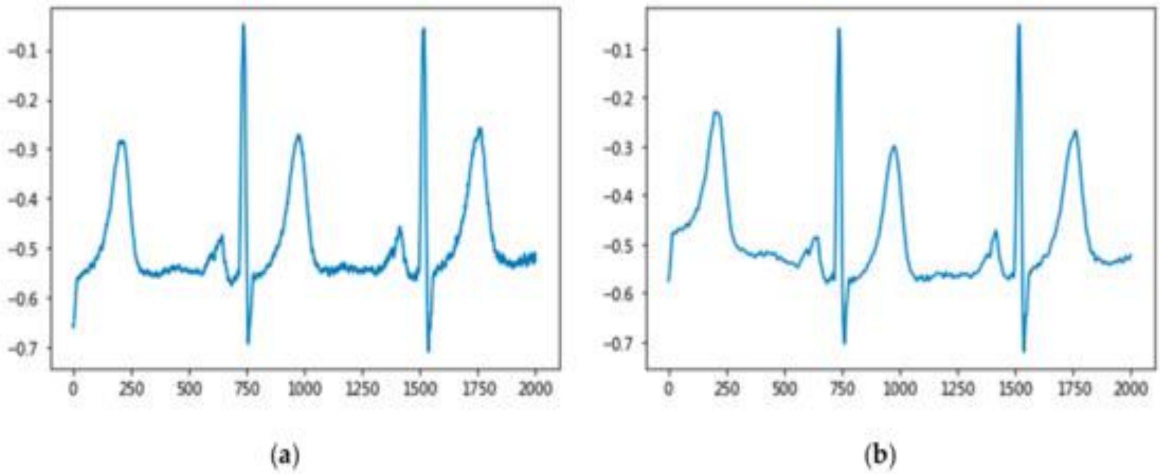

Figure 1.2 Heartbeats before and after noises were removed:

(**a**) The original ECG signal;

(**b**) ECG filtered signal by wavelet transform

Paper 7:

M. Elgendi, B. Eskofier, S. Dokos and D. Abbott, "Revisiting QRS detection methodologies for portable wearable battery-operated and wireless ECG systems", PloS one, vol. 9, no. 1, pp. e84018, 2014.

Description:

Cardiovascular diseases are the number one cause of death worldwide. Currently, portable battery-operated systems such as mobile phones with wireless ECG sensors have the potential to be used in continuous cardiac function assessment that can be easily integrated into daily life.

These portable point-of-care diagnostic systems can therefore help unveil and treat cardiovascular diseases. The basis for ECG analysis is a robust detection of the prominent QRS complex, as well as other ECG signal characteristics. However, it is not clear from the literature which ECG analysis algorithms are suited for an implementation on a mobile device.

We investigate current QRS detection algorithms based on three assessment criteria: 1) robustness to noise, 2) parameter choice, and 3) numerical efficiency, in order to target a universal fast-robust detector. Furthermore, existing QRS detection algorithms may provide an acceptable solution only on small segments of ECG signals, within a certain amplitude range, or amid particular types of arrhythmia and/or noise.

These issues are discussed in the context of a comparison with the most conventional algorithms, followed by future recommendations for developing reliable QRS detection schemes suitable for implementation on battery-operated mobile devices.

Paper 8:

P. Kora and S. R. Kalva, "Improved bat algorithm for the detection of myocardial infarction", Springerplus, vol. 4, no. 1, pp. 666, 2015

Description:

The medical practitioners study the electrical activity of the human heart in order to detect heart diseases from the electrocardiogram (ECG) of the heart patients. A myocardial infarction (MI) or heart attack is a heart disease, that occurs when there is a block (blood clot) in the pathway of one or more coronary blood vessels (arteries) that supply blood to the heart muscle. The abnormalities in the heart can be identified by the changes in the ECG signal.

The first step in the detection of MI is Preprocessing of ECGs which removes noise by using filters. Feature extraction is the next key process in detecting the changes in the ECG signals. This paper presents a method for extracting key features from each cardiac beat using Improved Bat algorithm.

Using this algorithm best features are extracted, then these best (reduced) features are applied to the input of the neural network classifier. It has been observed that the performance of the classifier is improved with the help of the optimized features.

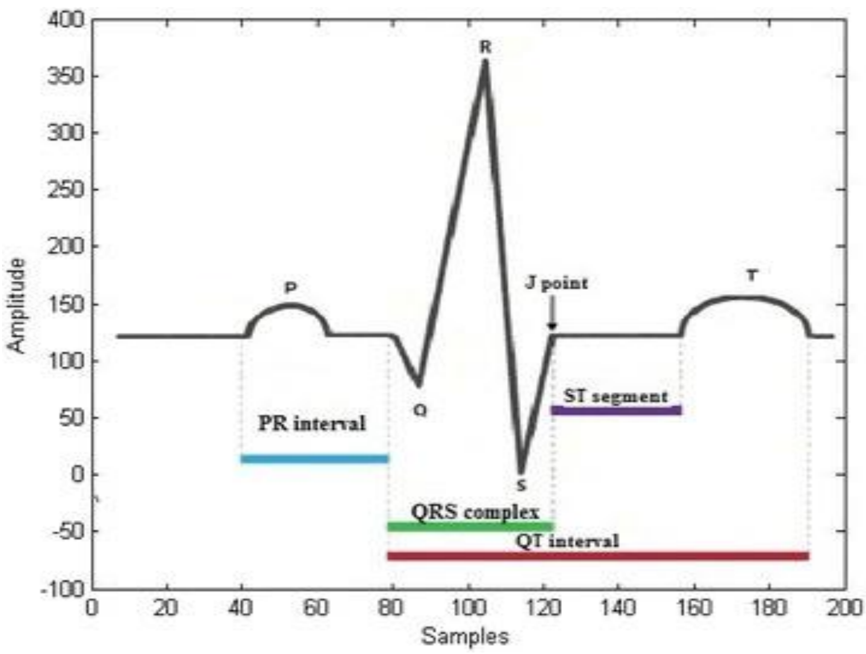

Figure 1.3 ECG Signal Intervals

1.3 Objectives

The objective of this project to develop an adaptive, sustainable, platform for electronic healthcare services increasing the computer-based diagnosis standard for medical decision support services. These are the following objective:

a. To find various possible technical solutions to predict Myocardial Infraction
b. To study the mechanism of various electronic sensors and their interfacing with microcontrollers for implementing the System for Myocardial Infraction Prediction
c. To attempt the practice of hardware as well as software system for regarding purpose
d. To significantly advance the individualization and thereby the patient's acceptance of electronic healthcare services for treatment and prevention
e. To improve patient health and provide interaction and communication as well as healthcare convenience

1.4 System Overview

A heart disease prediction system to predict whether the patient is likely to be diagnosed with a heart disease or not, using the medical history of the patient. So, a quiet significant amount of pressure has been lift off by using the given model in finding the probability of the classifier to correctly and accurately identify the heart disease.

Accurate detection of heart diseases in all cases and consultation of a patient for 24 hours by a doctor is not available since it requires more sapience, time and expertise. Nowadays, a huge amount of data pertaining to disease diagnosis, patients etc. are generated by healthcare industries.

This work aims in developing a Decision Support System in heart disease detection that uses the data mining technique having best accuracy and performance among Naïve Bayes, Support Vector Machine, Simple Logistic Regression, Random Forest & Artificial Neural Network (ANN) etc.

1.4.1 SYSTEM ARCHITECTURE:

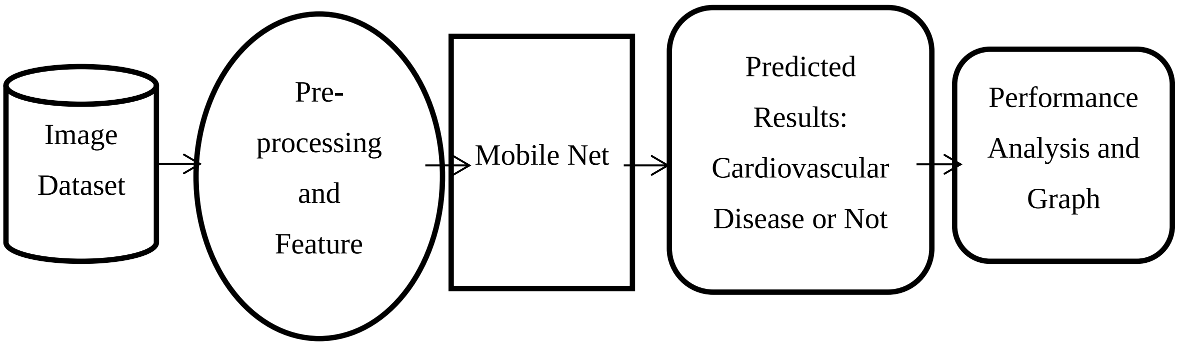

Figure 1.4 System Architecture

1.4.2 USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

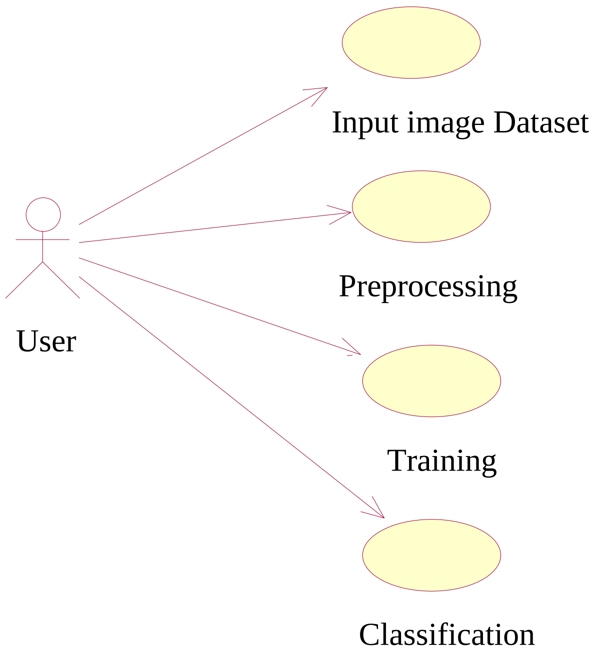

Figure 1.5 Use Case Diagram

1.4.3 CLASS DIAGRAM:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

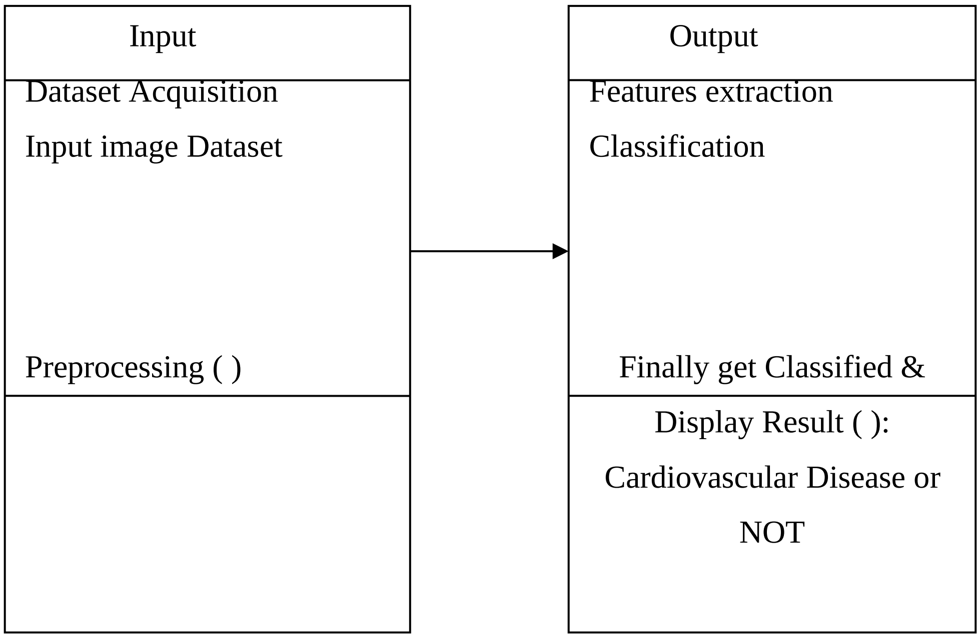

Figure 1.6 Use Case Diagram

1.5 Project Outline

Chapter 1 defines basic scenario based according to the WHO research which illustrates the need of the remedy for the problem regarding of Myocardial Infraction also specify the motivation behind the cause of project work along with literature review and a brief overview of the system designed is explained in detail.

The adopted mythology and the analysis regarding the topic is mentioned in chapter 2. The various considerable parameters are also studied in this chapter.

The Wavelet Transformation which is one of the important aspects of the project is discussed in chapter 3. It also covers the basics s of image processing and use of it in this project. The flow chart of the image processing and the types of Wavelet Transforms are discussed step by step in this chapter.

Chapter 4 includes all the ECG Speculation which is the sole of this overall phenomenon used in this project. The steps of Wavelet Transforms are explained in this section.

Chapter 5 gives the details about the ECG Pre-Processing which is unavoidable step in this project work.

Chapter 6 illustrates the Feature Extraction and Classification in order to detect the abnormalities in the ECG signals for targeting the possibilities of Myocardial Infractions in the subject are discussed.

The Prototype Implementation including used electronic components and circuit assembly is explained in Chapter 7.

Chapter 8 explained the achieved results and understanding of it in detail whereas in chapter 9 overall project work is concluded followed by used references.

Chapter 2

Methodology

Machine learning is the brain where all the learning takes place. The way the machine learns is similar to the human being. Humans learn from experience. The more we know, the more easily we can predict. By analogy, when we face an unknown situation, the likelihood of success is lower than the known situation. Machines are trained the same. To make an accurate prediction, the machine sees an example.

When we give the machine a similar example, it can figure out the outcome. However, like a human, if its feed a previously unseen example, the machine has difficulties to predict.

The core objective of machine learning is the **learning** and **inference**. First of all, the machine learns through the discovery of patterns. This discovery is made thanks to the **data**. One crucial part of the data scientist is to choose carefully which data to provide to the machine. The list of attributes used to solve a problem is called a **feature vector.** You can think of a feature vector as a subset of data that is used to tackle a problem.

The machine uses some fancy algorithms to simplify the reality and transform this discovery into a **model**. Therefore, the learning stage is used to describe the data and summarize it into a model.

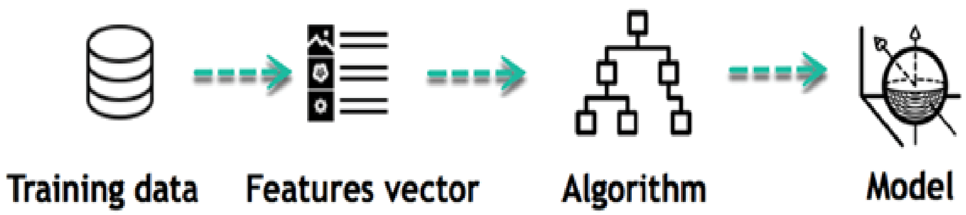

Figure 2.1 Learning Phase

For instance, the machine is trying to understand the relationship between the wage of an individual and the likelihood to go to a fancy restaurant. It turns out the machine finds a positive relationship between wage and going to a high-end restaurant: This is the model

When the model is built, it is possible to test how powerful it is on never-seen-before data. The new data are transformed into a features vector, go through the model and give a prediction. This is all the beautiful part of machine learning. There is no need to update the rules or train again the model. You can use the model previously trained to make inference on new data.

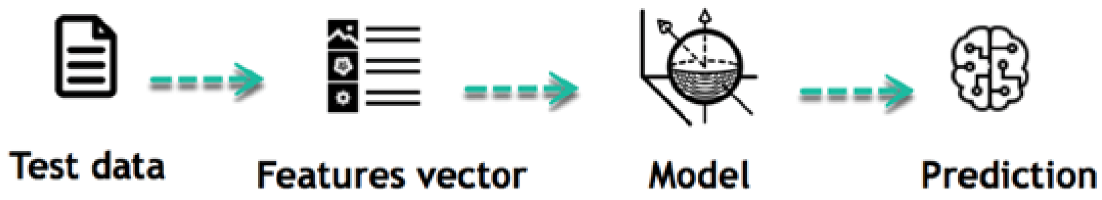

Figure 2.2 Interfacing Model

The life of Machine Learning programs is straightforward and can be summarized in the following points:

1. Define a question
2. Collect data
3. Visualize data
4. Train algorithm
5. Test the Algorithm
6. Collect feedback
7. Refine the algorithm
8. Loop 4-7 until the results are satisfying
9. Use the model to make a prediction

Once the algorithm gets good at drawing the right conclusions, it applies that knowledge to new sets of data as shown in Fig. 2.3

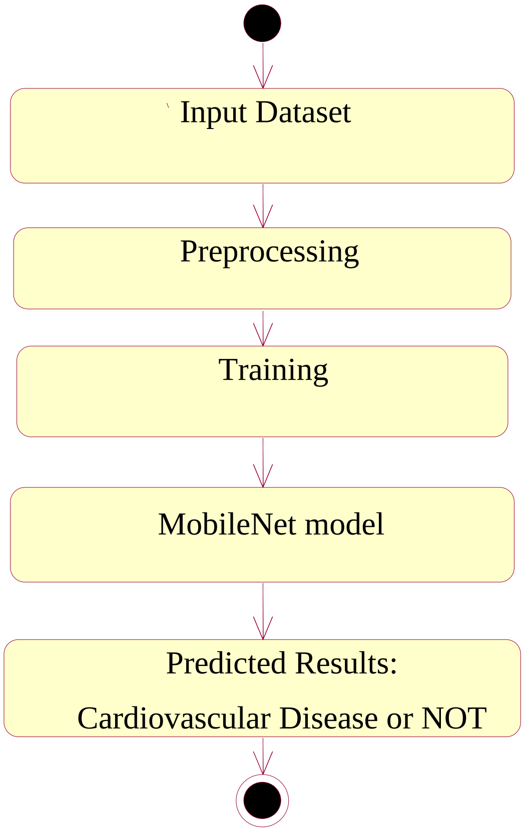

Figure 2.3 Data Flow Diagram

Chapter 3

ECG Speculation

Electrocardiogram (ECG) is a non-invasive tool for the detection and diagnosis of cardiovascular diseases, which are among one of the leading causes of morbidity and deaths around the world. CVDs accounts for approximately 31% of all the global deaths. ECG is a non-stationary signal which is a widely used for mapping heart electrical activity by using electrodes attached to the skin.

The ECG examination of nearly 30% of European Union population is conducted per year for the diagnosis of heart related diseases. Such vast practicing of ECG examination is due to its simplicity and effectiveness in diagnosing cardiovascular diseases. The ECG waveform depicts information about the health of patients. Therefore, by analyzing the underlying information of different shapes and patterns in ECG signals, cardiologists can easily interpret the different conditions 40 Progress in Signals and Telecommunication Engineering Volume 5 Number 2 September 2016 of the heart which may vary from having a minor threat to being life threatening.

According to, ECG signal classification involves four major stages: ECG Preprocessing, P-QRS-T wave fiducial points detection, feature extraction and Classification stage. In preprocessing stage ECG signal is processed for the removal of artifacts added during signal acquisition. P, -QRS-T wave detection stage aims to detect heartbeats in ECG signal, and to find out the relevant segments for feature extraction.

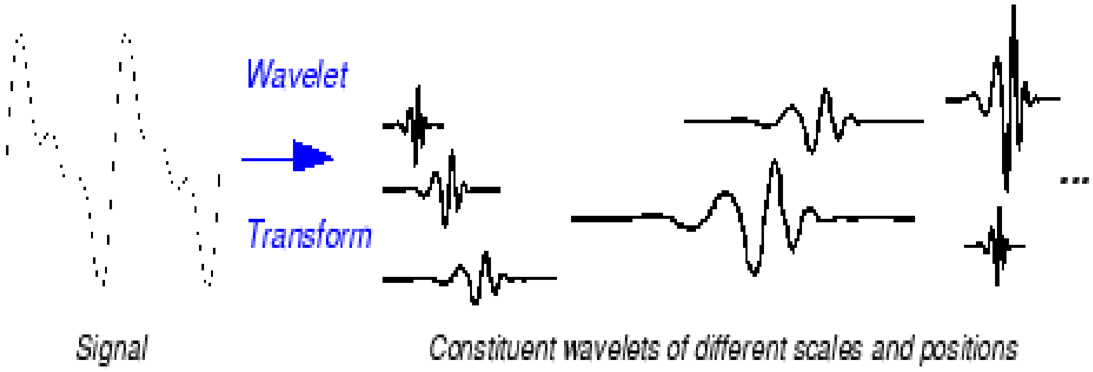

Figure 3.1 Wavelet Transform

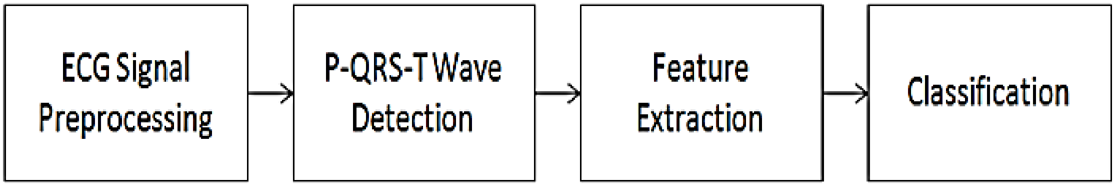

Figure 3. 2. ECG Signal Processing Stages

The feature vector formed during feature extraction stage must contain the minimum number of discriminating features for successful classification. The Classification stage comprises of one or more classifier to recognize the classes for data given in the feature vector. Choice of specific classifier may result in better classification rate than its variants for a particular heart disease. Sinus arrhythmias are mainly due to irregular electrical activity in the heart which results in improper pacing of heart.

Computer based ECG signal processing techniques effectively detects and classify abnormalities related to cardiac rhythms. Some of the major heart beat problems investigated are Sinus Tachycardia, Sinus Bradycardia, Left and Right Bundle Branch Block (RBBB, LBBB), Premature Atrial Contraction (PAC), Atrial Fibrillation, Premature Ventricular Contraction (PVC) and Ventricular Fibrillation. Most of arrhythmias do not indicate presence or absence of severe health risk; however, their proper detection is significant for proper diagnosis of cardiac disorders.

3.1 Definition:

1. **Sinus Tachycardia** is a regular cardiac rhythm in which the heart beats faster than normal.

2. **Sinus Arrhythmia** while it may seem odd to call an abnormal heart rhythm a sign of a healthy heart, this is actually the case with sinus arrhythmia. Your heart beats at a different rate when you breathe in than when you breathe out. And it’s normal. If your heart doesn’t have sinus arrhythmia, it’s a reason for concern.

3. **Sinus Bradycardia** is a cardiac rhythm with appropriate cardiac muscular depolarization initiating from the sinus node and a rate of fewer than 60 beats per minute (bpm). The diagnosis of this condition requires an ECG showing a normal sinus rhythm at a rate lower than 60 bpm.

4. **Electromyography (EMG)** is a diagnostic procedure to assess the health of muscles and the nerve cells that control them (motor neurons).

5. **Premature Atrial Contractions (PACs)** are extra heartbeats that start in the upper chambers of your heart. When the premature, or early, signal tellsthe heart to contract, there may not be much blood in the heart at that moment. That means there's not much blood to pump out.

6. **Premature Ventricular Contractions (PVCs**) are extra heartbeats that begin in one of the heart's two lower pumping chambers (ventricles). These extra beats disrupt the regular heart rhythm, sometimes causing a sensation of a fluttering or a skipped beat in the chest.

7. **Atrial Fibrillation (A-fib)** is an irregular and often very rapid heart rhythm (arrhythmia) that can lead to blood clots in the heart. A-fib increases the risk of stroke, heart failure and other heart-related complications.

8. **Ischemic Heart Disease (IHD)** It's the term given to heart problems caused by narrowed heart arteries. When arteries are narrowed, less blood and oxygen reach the heart muscle. This is also called coronary artery disease and coronary heart disease. This can ultimately lead to attack. Ischemia often causes chest pain or discomfort known as angina pectoris.

9. **Depolarization** of the heart leads to the contraction of the heart muscles and therefore an EKG is an indirect indicator of heart muscle contraction. The cells of the heart will depolarize without an outside stimulus. This property of cardiac muscle tissue is called automaticity, or auto rhythmicity.

3.2 P wave

The P wave represents the electrical depolarization of the atria. In a healthy person, this originates at the sinoatrial node (SA node) and disperses into both left and right atria.

The QRS complex is the main spike seen in the standard ECG. It is the most obvious part of the ECG, which is clearly visible. The QRS complex represents the depolarization of ventricles. It shows the beginning of systole and ventricular contraction.

3.3 The 4 types of waves seen in an ECG

The ECG parameters, such as fragmented QRS (fQRS), heart rate variability (HRV), T peak-T end (TpTe), heart rate turbulence (HRT) and T wave alternans (TWA) have predictive value for the arrhythmic events Each ECG cycles consists of 5 waves: P, Q, R, S, T corresponding to different phases of the heart activities.

There are 3 main types of ECG: a resting ECG – carried out while you're lying down in a comfortable position. a stress or exercise ECG – carried out while you're using an exercise bike or treadmill.

Normal rhythm produces four entities – a P wave, a QRS complex, a T wave, and a U wave – that each have a fairly unique pattern. The P wave represents atrial depolarization. The QRS complex represents ventricular depolarization.

3.4 Willem Einthoven discovered ECG

Willem Einthoven found the beat and built a machine that could measure the electrical current a heart creates. It weighed 600 pounds. An electrocardiogram called informally an ECG or EKG — measures the small electric waves that a human heart creates. It's been doing it for more than a century.

3.5 ECG principle

The basic principle of the ECG is that stimulation of a muscle alters the electrical potential of the muscle fibres. Cardiac cells, unlike other cells, have a property known as automaticity, which is the capacity to spontaneously initiate impulses.

3.6 ECG normal range

If the test is normal, it should show that your heart is beating at an even rate of 60 to 100 beats per minute. Many different heart conditions can show up on an ECG, including a fast, slow, or abnormal heart rhythm, a heart defect, coronary artery disease, heart valve disease, or an enlarged heart.

3.7 Abnormal ECG

An abnormal EKG can mean many things. Sometimes an EKG abnormality is a normal variation of a heart's rhythm, which does not affect your health. Other times, an abnormal EKG can signal a medical emergency, such as a myocardial infarction (heart attack) or a dangerous arrhythmia.

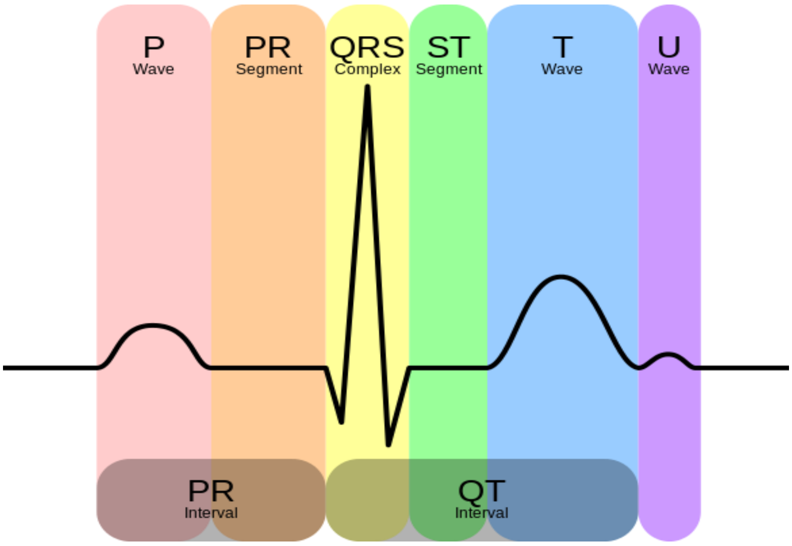

Figure 3.3. PR and QT interval

3.8 PR Interval

The PR interval is the initial wave generated by an electrical impulse traveling from the right atrium to the left. The right atrium is the first chamber to see an electrical impulse.

This electrical impulse causes the chambers to "depolarize". This forces it to contract and drain deoxygenated blood from both the Superior and Inferior vena cava into the right ventricle.

As the electrical impulse travels across the top of the heart it then triggers the left atrium to contract. The left atrium is responsible for receiving newly oxygenated blood from the lungs into the left ventricle via the left and right pulmonary veins. The pulmonary veins are red in the diagram because they are carrying oxygenated blood.

3.9 QT Interval

The QT Interval is where things get really interesting. The QRS is a complex process that generates the signature "beep" in cardiac monitors. During QRS both ventricles begin to pump. The right ventricle begins to pump deoxygenated blood into the lungs through the left and right pulmonary arteries.

The pulmonary arteries are blue in the diagram because they are carrying deoxygenated blood. The left ventricle is also beginning to pump freshly oxygenated blood through the aorta and into the rest of the body. After the initial contraction comes the ST segment. The ST segment is fairly quiet electrically as it is the time where the ventricles waiting to be "re-polarized".

Finally, the T wave becomes present to actively "re-polarize", or relax the ventricles. This relaxation phase resets the ventricles to be filled again by the atriums.

Chapter 4

Feature Extraction and Classification

The task of feature extraction is of non-trivial which aims to find out the possible smallest set of features for maximum discrimination between different classes. In literature, features for heart disease classification are classified into three classes: 1) Time based Features 2) Frequency domain-based Features 3) Time Frequency based features.

Whereas, classifiers used for recognition of cardiovascular diseases varies with approaches, which includes Artificial Neural Network (ANN), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), Fuzzy Logic System, K-Nearest Neighbor (KNN), and ensemble-based classifiers. In this section, we briefly review the features and classifiers used in literature for heart disease recognition. A comparison of feature extraction and classification techniques for heart beat classification and myocardial infarction detection are summarized in Table 6.1 and Table 4.1 respectively.

Table 4.1. Feature Extraction Approaches for the Classification of Heart Beat

Features	Author	Year	Classifier	Dataset	Accuracy
Time Domain Based Features (P,QRS,T wave Amplitude, Interval etc)	Moraes et al. [32]	2002	Mahalanobis distance	MIT-BIH	Se. 90.74% PPV 96.55%
	De Chazal et al. [2]	2003	LD & ANN	MIT-BIH	Acc. 89.00%
	Pandit et al. [33]	2014	ANN Ensemble Classifier	MIT-BIH, QT, ST-T	Se. 98.73% PPV 99.40%
	V. R. Kumar et al. [51]	2015	ANN, PSO	MIT-BIH	Acc. 92.49%
			ANN, GSA	MIT-BIH	Acc. 94.47%
	Park et al. [52]	2015	Random Forrest	MIT-BIH	Acc. 98.68%
Frequency Domain Based Features (FFT Coefficients)	Minami et al. [36]	1999	ANN	-	Se. 98.00%
	J. Gothwal et al. [37]	2011	ANN	MIT-BIH	Acc. 98.48%
Time-Frequency Domain Based Features (DWT Coefficients)	Al-Fahoum et al. [39]	1999	Radial Basis Neural Network	MITDB, YUDB, MMSDB	Acc. 97.50%
	Prasad et al. [40]	2003	Neural Network	-	Acc. 96.77%
	Yu et al. [41]	2007	Probabilistic NN	MIT-BIH	Acc. 99.00%
	Afsar et al. [42]	2008	1-Nearest Neighbour	MIT-BIH	Acc. 99.50%
	Afsar et al. [43]	2009	Pruned Fuzzy KNN	MIT-BIH	Acc. 96.75%
	Faziludeen at el. [44]	2013	SVM	MIT-BIH	Acc. 98.50%
	M. K. Das at el. [45]	2013	MLPNN	MIT-BIH	Acc. 97.50%

Table 4.2. Feature Extraction Approaches for Detection of Myocardial Infarction & ST Segment Deviation

Features	Author	Year	Classifier	Dataset	Accuracy
Time Domain Based Features	Papaloukas et al. [49]	2001	Rule Based	ESC-ST-T	Se. 92.10% PPV 93.80%
					Se. 91.09% PPV 80.09%
	Goletsis et al. [48]	2004	Multi-criteria Sorting Method	ESC-ST-T	Se. 91.00% Sp. 91.00%
	Exarchos et al. [50]	2007	Fuzzy rule based classifier	ESC-ST-T	Se. 91.00% Sp. 92.00%
	Arif et al. [34]	2010	BNN	PTB Database	Se. 97.50% Sp. 99.10% Acc. 93.70%
	Arif et al. [35]	2012	KNN	PTB Database	Se. 99.97% Sp. 99.90%
Time-Frequency Domain Based Features (DWT Coefficients etc)	S. Banerjee at el. [47]	2014	Threshold-based classifier	PTB Database	Se. 97.30% Sp. 98.80% Acc. 97.60%
	Sharma et al. [46]	2015	SVM (RBF)	PTB Database	Se. 93.00% Sp. 99.00% Acc. 96.00%

The new feature extraction method based on time-frequency domain has the combined advantages of both already mentioned approaches. It provides frequency analysis with time resolution for analyzed features. Mostly wavelet transform (WT) is used for time-frequency analysis because of its computational simplicity and interpretability in similar way as that of Fourier transform.

In a comparative study carried out, it is demonstrated that performance of wavelet transforms exhibits better result as compared to Fourier transform for the classification of ten different types of arrhythmias using MIT-BH arrhythmia database. The choice of use of specific type and order of wavelet depends on nature of application e.g. denoising of the ECG signal using debauches wavelet may give better signal to noise ratio as compared to denoising of ECG signal with symlet wavelet.

The wavelet transforms for beat classification and extracted six energy descriptors using wavelet coefficients over a beat interval. In different types of wavelets were used for the classification of four types of beats. The extracted features through debauches-4 wavelet transform achieved highest accuracy of 97.5 % using Radial Basis Function (RBF) Neural Network classifier. have presented. This method for the classification of beats using symlet-6 wavelet transform. In this study, 12 different types of beats were classified with Neural Network classifier.

The feature set included 23 derived coefficients and 2 RR interval features. This method achieved highest classification accuracy of 96.77% using MIT-BH arrhythmia database. In another study, proposed beat classification method based on wavelet transform and probabilistic neural network classifier.

They achieved the highest classification accuracy of 99.65% 1-Nearest Neighbor classifier with wavelet-based features for ECG beat classification. In the proposed approach, they extracted 11 features including one instantaneous RR interval feature to classify 6 different types of beats. They also applied Principal Component Analysis (PCA) technique to reduce the feature set from 11 to 6 features and achieved classification accuracy of nearly 99.5% with both proposed methods (with and without PCA)

The proposed a Pruned Fuzzy K Nearest Neighbor approach for cardiac arrhythmia recognition. In this method they extracted 11 features including one instantaneous RR interval feature using wavelet transform. They used 6 features after applying PCA with Pruned Fuzzy K-NN classifier and achieved nearly 97% classification accuracy for 9 different types of arrhythmias recognition. This is also extracted 25 wavelet and 3 RR intervals-based features from the ECG signal and classified three kinds of beats using Support Vector Machine.

This method achieved accuracy of 98.46%, 98.47% and 99.92% for left bundle branch block (LBBB), normal (NSR) and premature ventricular contraction (PVC) beats respectively. Another method utilizing a mixture of features has been proposed. which uses two features extraction methods for the classification of 5 different types of beats in MIT-BH arrhythmia database. This approach achieves classification accuracy of 96.9% and 97.5% for their proposed methods using multilayer perceptron neural network (MLPNN).

4.1 Time Based Features

Time based features mainly have time interval in milliseconds representing RR interval, PR interval, PP interval etc. Also, the duration or amplitude of P wave, T wave and QRS complex are used as time-based features in ECG signal analysis. These features mostly do not provide high performance due to low sensitivity. uses four features extracted from ECG wave form.

In this study we utilize

1) Width of QRS complex

2) Sum of areas under positive and negative curves

3) Total sum of absolute values of sample variations in the QRS complexes

4) Amplitude of QRS complex to classify normal and premature ventricular contraction (PVC) beats using Mahalanobis distance as classifier.

They attained sensitivity of 90.74% and positive predictive value of 96.55% using 44 records of MIT-BH database. In another approach, two features set based on 28 features are extracted from RR interval, P wave, QRS complex and T wave after the ECG segmentation.

In this classification of normal, PVC and fusion beats were obtained by linear discriminant Analysis (LDA) and Neural Network (NN) classifiers and achieved accuracy of 89.1% using both feature set. In this method feature extraction may be affected by noise and errors in calculation of onset and offset of QRS complex. Also these features have higher intra-class variations due to which this method is unable to provide very good severability among different types of QRS complexes.

The proposed method extracted 11 features from P-QRS-T waves and applied Artificial Neural Network (ANN) and Ensemble classifier using European ST, QT and MIT-BIH Arrhythmia databases. In this work they achieve average accuracy of 98.73% and 99.40% using ANN and Ensemble classifier respectively.

A myocardial infarction (MI) detection and localization method using back propagation neural network (BPNN). They used time based feature for MI detection and achieved sensitivity and specificity of 97.5% and 99.1% respectively. Whereas, for localization of MI PCA based 117, the dimensional feature vector is extracted from ST-T (0.5 seconds) segment and Q wave (0.06 seconds) region. The localization results in beat classification accuracy of 93.7%. In this approach, BPNN gives poor results due to overlapping features in case of inter related MI categories. Utilizes 36 time based features along with K Nearest Neighbor (KNN) classifier for the detection and localization of myocardial infarction (MI).

The MI detection specificity and sensitivity of 99.9% is achieved using KNN classifier. Moreover, they also used pruning algorithm for reducing storage and time for nearest neighbor search which results in the reduction of data by 93% and achieved sensitivity and specificity of 97% and 99.6% respectively.

Also, localization accuracy of 98.3% was achieved for different types of myocardial infarction. Recently, applied Random Forests for the classification of five different heartbeat classes. They extracted temporal and morphological features along with three amplitude difference features and attained the overall accuracy of 98.68% using MIT-BIH database.

4.2 **Frequency Domain Based Features**

Frequency based features are mostly computed through Fourier transform. These features have increased sensitivity but time resolution is lost during transformation process therefore it cannot specify in which portion of time the change has been occurred.

The proposed technique for the discrimination of ventricular tachycardia, ventricular fibrillation and normal sinus rhythm by observing the QRS complex changes in ECG. Their proposed technique consists of three stages. In first stage, they extracted QRS complex of each heart beat by finding the R peak using local maxima.

Then in second stage, Fourier transform is applied on the QRS window of 256 ms to calculate power spectrum consisting of five spectral components. In last stage, neural network having five inputs and two output nodes is utilized for the classification. They obtained classification sensitivity and specificity of 98%.

In another study it is detected six types of cardiac arrhythmias using Fourier transform and ANN. In their proposed work, they transformed the ECG signal into Fourier domain to remove lower frequency component which mostly represents noise. After the noise removal, features are extracted by using QRS estimates and then ANN is employed to classify cardiac arrhythmias. This method gave accuracy of 98% for cardiac arrhythmia detection on 40 records of MIT-BH arrhythmia database.

4.3 Time-Frequency Based Features

The new feature extraction method based on time-frequency domain has the combined advantages of both already mentioned approaches. It provides frequency analysis with time resolution for analyzed features. Mostly wavelet transform (WT) is used for time-frequency analysis because of its computational simplicity and interpretability in similar way as that of Fourier transform.

In a comparative study carried out, it is demonstrated that performance of wavelet transforms exhibits better result as compared to Fourier transform for the classification of ten different types of arrhythmias using MIT-BH arrhythmia database. The choice of use of specific type and order of wavelet depends on nature of application e.g., denoising of the ECG signal using debauches wavelet may give better signal to noise ratio as compared to denoising of ECG signal with symlet wavelet.

This used wavelet transforms for beat classification and extracted six energy descriptors using wavelet coefficients over a beat interval. In this study different types of wavelets were used for the classification of four types of beats. The extracted features through debauches-4 wavelet transform achieved highest accuracy of 97.5 % using Radial Basis Function (RBF) Neural Network classifier.

It has presented a method for the classification of beats using symlet-6 wavelet transform. In this study, 12 different types of beats were classified with Neural Network classifier. The feature set included 23 derived coefficients and 2 RR interval features. This method achieved highest classification accuracy of 96.77% using MIT-BH arrhythmia database. In another study, it is proposed beat classification method based on wavelet transform and probabilistic neural network classifier.

This is used 1-Nearest Neighbor classifier with wavelet-based features for ECG beat classification. In the proposed approach, they extracted 11 features including one instantaneous RR interval feature to classify 6 different types of beats. They also applied Principal Component Analysis (PCA) technique to reduce the feature set from 11 to 6 features and achieved classification accuracy of nearly 99.5% with both proposed methods (with and without PCA).

Also proposed a Pruned Fuzzy K Nearest Neighbor approach for cardiac arrhythmia recognition. In this method they extracted 11 features including one instantaneous RR interval feature using wavelet transform. They used 6 features after applying PCA with Pruned Fuzzy K-NN classifier and achieved nearly 97% classification accuracy for 9 different types of arrhythmias recognition. Also extracted 25 wavelet and 3 RR intervals-based features from the ECG signal and classified three kinds of beats using Support Vector Machine. This method achieved accuracy of 98.46%, 98.47% and 99.92% for left bundle branch block (LBBB), normal (NSR) and premature ventricular contraction (PVC) beats respectively.

Another method utilizing a mixture of features has been proposed, which uses two features extraction methods for the classification of 5 different types of beats in MIT-BH arrhythmia database. This approach achieves classification accuracy of 96.9% and 97.5% for their proposed methods using multilayer perceptron neural network (MLPNN). L. N. Sharma proposed MI detection and localization approach based on multiscale energy and eigenspace (MEES) features. They used six-level wavelet decomposition to extract 72-dimensional feature vectors. In this study only, lower frequency subbands A6, D6, D5, and D4 are used. The multiscale energy for A6, D6, D5, and D4 subbands are calculated from each lead of 12 lead ECG.

Then multiscale eigen analysis is performed to constitute the 24 remaining features of 72-dimensional feature set. In this regard, covariance matrix for each decomposition level is formulated and eigen decomposition is performed to get eigenvalues and eigenvector for approximation and detail subbands respectively.

For each of already mentioned subbands 6 dominant eigenvalues values are used as features because most of the energy is retained by them. Correlation based feature selection is also applied in this method on 72-dimensional feature set to select the optimum features subset. Support vector-based classifier with RBF kernel achieved highest accuracy, sensitivity and specificity of 99%, 93% and 96% respectively. The localization accuracy of 99.58% is achieved by using proposed MEES features with multiclass SVM classifier with RBF kernel. In another study, it is employed cross wavelet transform with threshold-based classifier for MI detection. They claimed overall accuracy of 97.6% using their proposed method.

Chapter 5

System Study

5.1 FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out.

This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

1. ECONOMICAL FEASIBILITY
2. TECHNICAL FEASIBILITY
3. SOCIAL FEASIBILITY

5.2 ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited.

The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

5.3 TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources.

This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

5.4 SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity.

The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

Chapter 6

System Analysis

6.1 EXISTING SYSTEM:

Avanzato and Beritelli proposed a deep CNN with four 1D convolutional layers for detecting three classes of cardiac abnormalities using ECG signals in the MIT-BIH arrhythmia dataset. Each convolutional layer was followed by a batch normalization layer, a rectifier linear unit (ReLU) layer activation function, and a max-pooling layer with a filter (kernel) size of 4.

A size 80 filter was used for the first convolutional layer, and the others had a filter size of 4. This architecture did not use fully connected layers for classification, but instead used an average pooling layer followed by a softmax layer.

Acharya et al. implemented a deep CNN with four 1D convolutional layers and three fully connected layers for detecting myocardial infarction using ECG signals in the PTB dataset. In this model, the leaky rectifier linear unit (LeakyRelu) was used as the activation function layer.

Each convolutional layer was followed by a max-pooling layer with a filter size of 2 and a stride of 2. The filter sizes for convolutional layers were 102, 24, 11, and 9 in order. The number of neurons for fully connected layers was 30, 10, and 2 in that order. The last fully connected layer was followed by a softmax layer.

6.2 DISADVANTAGES OF EXISTING SYSTEM:

1. The training and testing times for SqueezeNet-based algorithms were longer due to the larger size of the extracted features

2. The main disadvantages of existing system squeezenet are low classification accuracy and high computational complexity

3. Although the structural parameters are very small, it is not conducive to deployment on mobile devices

4. AlexNet is NOT deep enough compared to the later model, such as VGGNet, GoogLENet, and ResNet.

5. The use of large convolution filters (5*5) is not encouraged shortly after that Use normal distribution to initiate the weights in the neural networks, cannot effectively solve the problem of gradient vanishing, replaced by the Xavier method later

6. The performance is surpassed by more complex models such as GoogLENet (6.7%), and ResNet (3.6%)

6.3 PROPOSED SYSTEM:

The main objective of the proposed work is to develop a model for the diagnosis of cardiovascular diseases and, thereafter, to implement it. We performed the classification of ECG recordings by using ECG images from the publicly available dataset.

The proposed model is trained and tested on the ECG Images dataset of cardiac patients. This dataset consists of 1377 ECG images of different patient records with four different classes as shown. These four classes are Normal person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI).

A normal person is a healthy person who does not have any heart abnormalities. An abnormal heartbeat (arrhythmia) occurs when the electrical impulses in the heart become too fast, too slow, or irregular, so that the heart beats irregularly.

Myocardial infarction, also known as heart attack, occurs when blood flow in the coronary artery of the heart decreases or stops, causing damage to the heart muscle. The patients with History of myocardial infarction who have recently recovered from myocardial infarction or heart attack.

The proposed system uses the MobileNet Architecture as our proposed model to develop the system where, first to detect cardiovascular disease from images of electrocardiogram (ECG) tracings and, second, to predict any type of cardiac arrhythmia. For this purpose, we used trained algorithms and, thereafter, we implemented the MobileNet Architecture.

We worked with MobileNet Architecture as backend. Our goal was to develop an algorithm able to detect and classify data into different categories (normal for healthy people and cardiac arrhythmia for persons with cardiac pathologies). The learning will be directly on the ECG data without any significant preprocessing.

For performance analysis, Accuracy, Precision, Recall, F1 score were used. These measurements are based on the analysis of the data in a confusion matrix. Where the Accuracy is the percentage of positively predicted observations relative to the total number of observations.

Recall represents the ratio of positively predicted observations to all observations in the true class (should be positively estimated). Precision expresses the ratio of positively predicted observations to all observations in the predicted class (should be positively predicted). The F1 score is the weighted average of both Recall and Precision. Thus, it takes into account both of the false negatives and the false positives values.

6.4 ADVANTAGES OF PROPOSED SYSTEM:

1. To the best of our knowledge, the only work in the literature that uses the same dataset and classifies the four classes is the work.Although the extracted feature size of our proposed CNN model is the smallest, it achieved the best results on all performance measures

2. Therefore, this is an indication that our proposed model is built to learn the key features of the ECG images dataset. Thus, the advantages of the proposed model are not only the better accuracy rates, but also the lower computational costs compared to the works in the literature

3. We calculated the accuracy corresponding to each of the four classes, to evaluate our proposed model. Our work showed excellent accuracy; this is very important for easily detecting and differentiating the different classes

4. The learning process can be performed on the go with the newly-built ECG images without any fear of missing any information needed for better learning.In order to demonstrate the reproducibility of the model architecture to new data, we tested it on the test data

5. The model performance demonstrated excellent results and, therefore, one can make conclusions about the ability of our MobileNet Architecture to generalize to a new set of ECG records from a different data

Chapter 7

Prototype Implementation

7.1 MODULES:

1. Dataset
2. Importing the necessary libraries
3. Retrieving the images
4. Splitting the dataset
5. Building the model
6. Apply the model and plot the graphs for accuracy and loss
7. Accuracy on test set
8. Saving the Trained Model

7.2 MODULES DESCSRIPTION:

7.2.1 Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. Dataset is given in the model folder. The dataset consists of 1377 ECG images.

Kaggle Link:

https://www.kaggle.com/datasets/jayaprakashpondy/ecgimages

7.2.2 Importing the necessary libraries:

We will be using Python language for this. First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, numpy, matplotlib and tensorflow.

7.2.3 Retrieving the images:

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

7.2.4 Splitting the dataset:

Split the dataset into train and test. 70% train data and 30% test data.

7.2.5 Mobile Net | CNN model

Architecture:

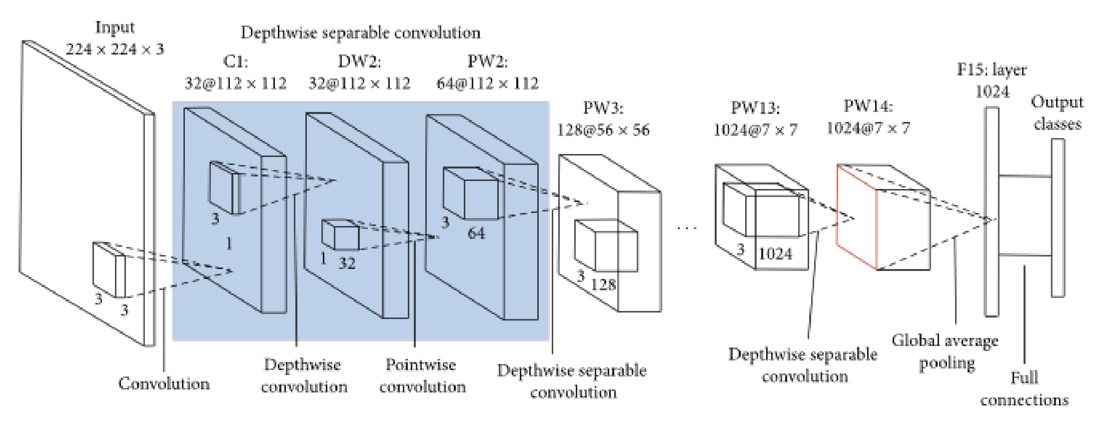

Fig. 7.1 Image Classification with MobileNet

7.2.6 MobileNet

As the name applied, the MobileNet model is designed to be used in mobile applications, and it is TensorFlow's first mobile computer vision model. MobileNet uses **depthwise separable convolutions.**

It significantly **reduces the number of parameters** when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.

A depthwise separable convolution is made from two operations.

1. **Depthwise convolution.**
2. **Pointwise convolution**.

MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

7.2.7 When MobileNets Applied to Real Life

The speed and power consumption of the network is proportional to the number of MACs (Multiply-Accumulates) which is a measure of the number of fused Multiplication and Addition operations.

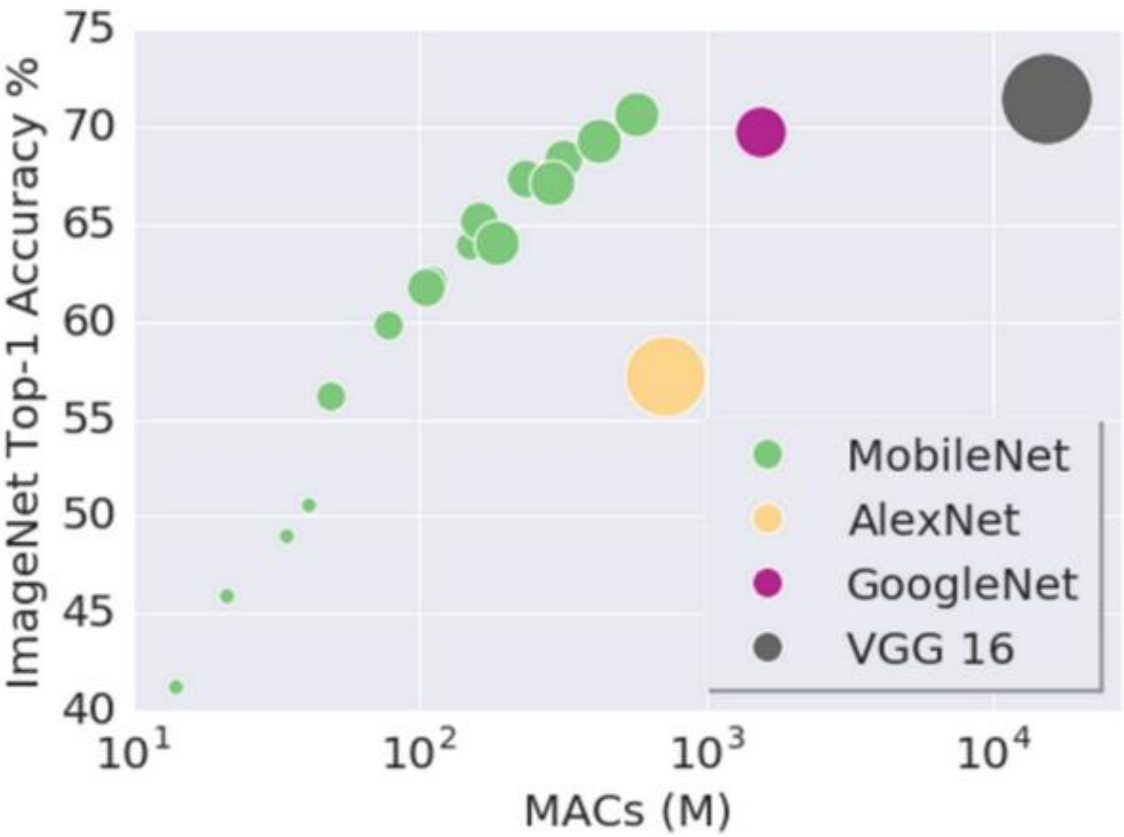

Fig. 7.2 Graph of MobileNet

7.2.8 The Architecture of MobileNet

Table 7.1 Mobile Net Filter Shape and Size

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

7.2.9 Mobilenet Layers

Depth wise Separable Convolution this convolution originated from the idea that a filter's depth and spatial dimension can be separated- thus, the name separable. We have taken the example of Sobel filter, used in image processing to detect edges. Sobel Filter, Gx for the vertical edge, Gy for horizontal edge detection

One can separate the height and width dimensions of these filters. Gx filter can be viewed as a matrix product of [1 2 1] transpose with [-1 0 1].

We noticed that the filter had disguised itself. It shows it had nine parameters, but it has 6. This has been possible because of the separation of its height and width dimensions.

The same idea applied to separate depth dimension from horizontal (width*height) gives us depth-wise separable convolution where we perform depth-wise convolution. After that, we use a 1*1 filter to cover the depth dimension.

One thing to notice is how much parameters are reduced by this convolution to output the same no. of channels. To produce one channel, we need 3*3*3 parameters to perform depth-wise convolution and 1*3 parameters to perform further convolution in-depth dimension.

But If we need three output channels, we only need 31*3 depth filter, giving us a total of 36 (= 27 +9) parameters while for the same no. of output channels in regular convolution, we need 33*3*3 filters giving us a total of 81 parameters.

Depthwise separable convolution is **a depthwise convolution followed by a pointwise convolution** as follows:

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig 7.3 Matrix

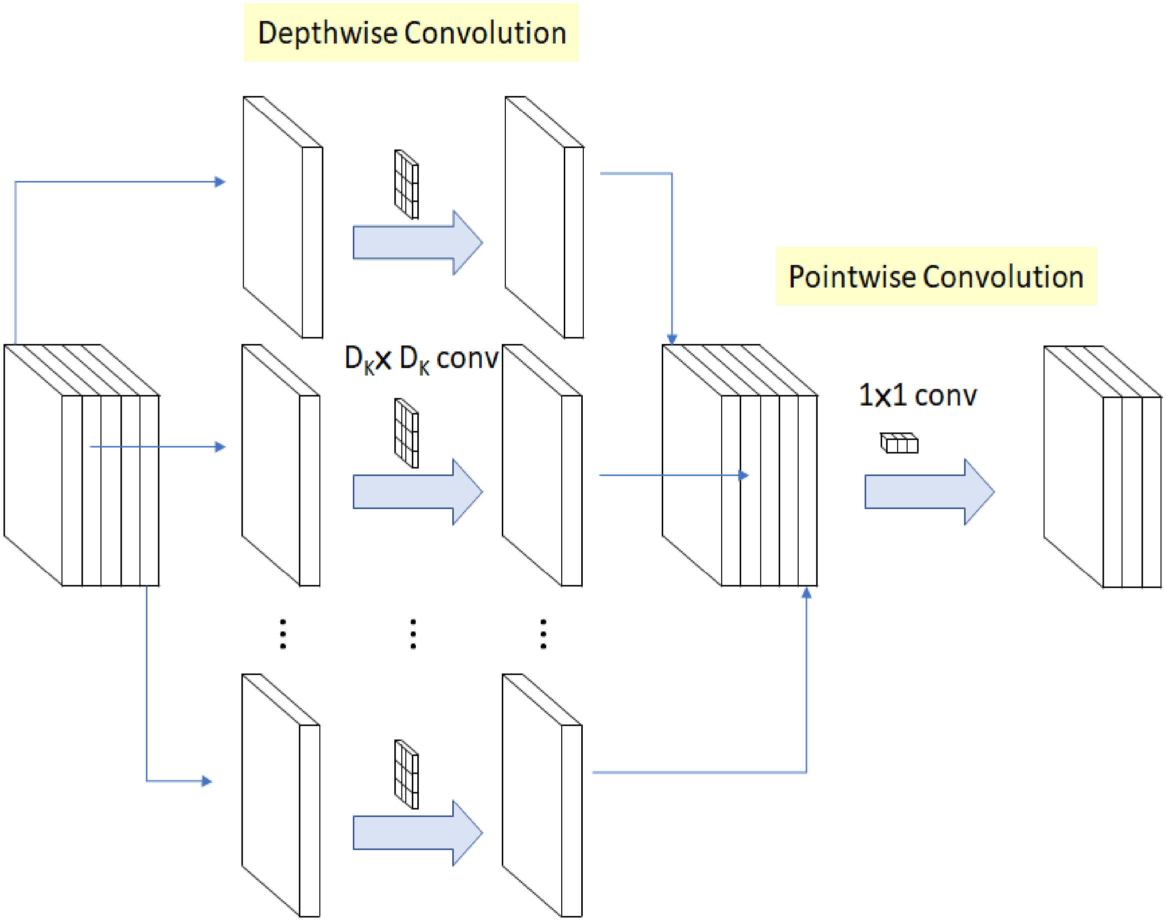

Fig 7.4 View of Depth wise Separable Convolution

7.3 Depth wise Separable Convolution

1. Depth wise convolution is the channel-wise DK×DK spatial convolution. Suppose in the figure above, and we have five channels; then, we will have 5 DK×DK spatial convolutions
2. Pointwise convolution is the 1×1 convolution to change the dimension
3. Depth wise convolution

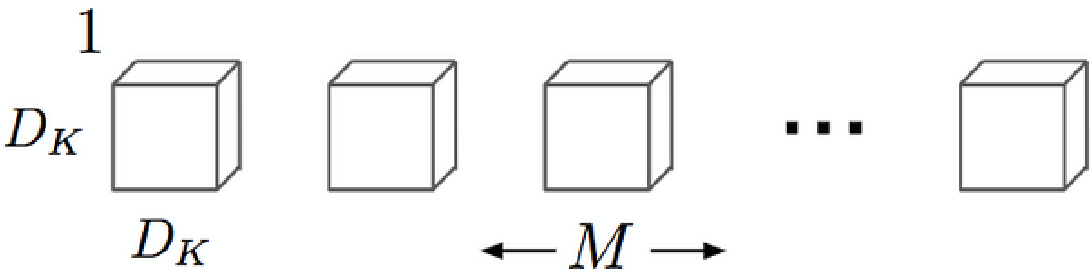

Fig 7.5 Depth Wise Convolution

7.3.1. Depth wise convolution.

It is a map of a single convolution on each input channel separately. Therefore, its number of output channels is the same as the number of the input channels. Its computational cost is

$$\mathbf{Df^2 * M * Dk^2}.$$

7.3.2. Pointwise convolution.

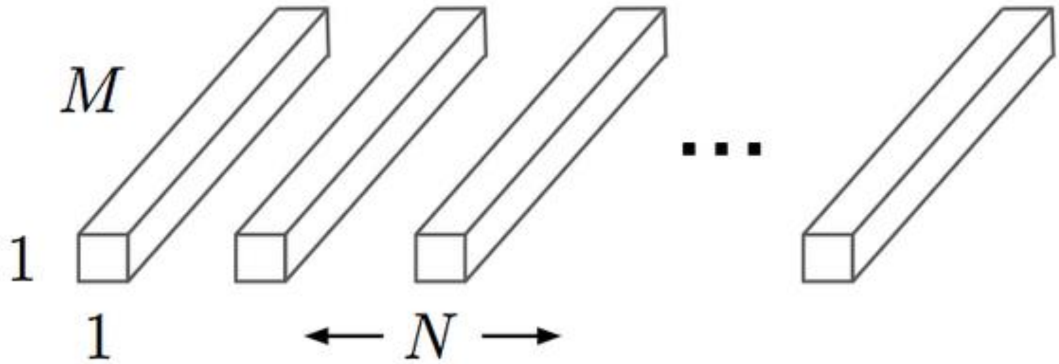

Fig 7.6 Point Wise Convolution

Convolution with a kernel size of 1x1 that simply combines the features created by the depth wise convolution. Its computational cost is

$M * N * Df^2$.

Difference between Standard Convolution and Depth wise separable convolution.

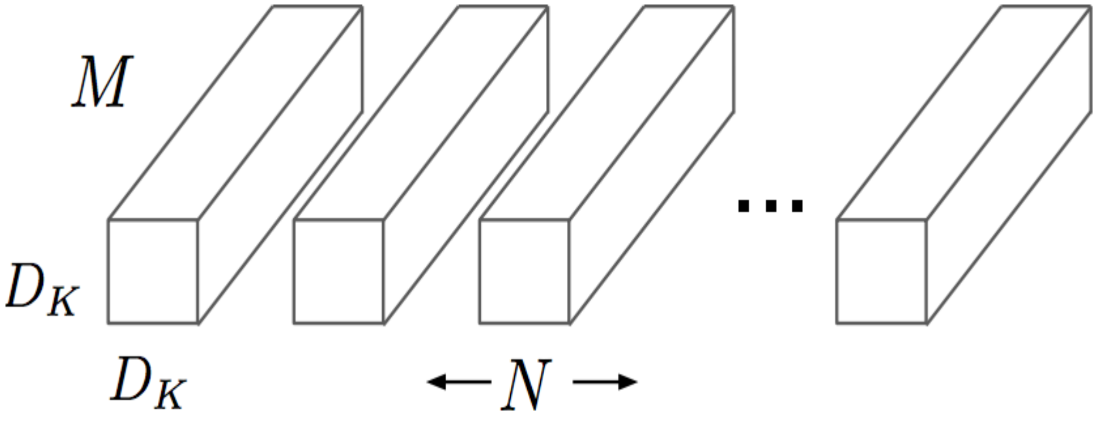

Fig 7.7 Standard wise Convolution

7.3.3. Standard Convolution.

The main difference between Mobile Net architecture and a traditional CNN instead of a single 3x3 convolution layer followed by the batch norm and ReLU. Mobile Nets split the convolution into a 3x3 depth-wise conv and a 1x1 pointwise conv, as shown in the figure.

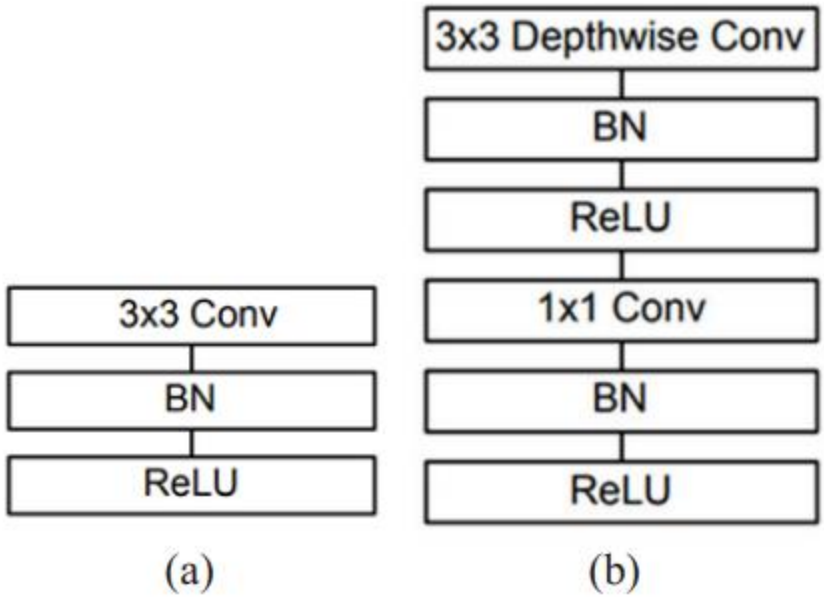

Fig 7.8 Convolution difference

(a) Depth Wise

(b) Point Wise

7.4. Building the model:

The concept of convolutional neural networks is very successful in image recognition. The key part to understand, which distinguishes CNN from traditional neural networks, is the convolution operation.

Having an image at the input, CNN scans it many times to look for certain features. This scanning (convolution) can be set with 2 main parameters: stride and padding type. As we see on below picture, process of the first convolution gives us a set of new frames, shown here in the second column (layer).

Each frame contains information about one feature and its presence in scanned image. Resulting frame will have larger values in places where a feature is strongly visible and lower values where there are no or little such features. Afterwards, the process is repeated for each of obtained frames for a chosen number of times.

In this project we chose a classic Mobile Net model which contains only two convolution layers. The latter layer we are convolving, the more high-level features are being searched. It works similarly to human perception. To give an example, below is a very descriptive picture with features which are searched on different CNN layers.

As it can be seen, the application of this model is facing recognition. If we construct the CNN from the beginning, searched features are random. Then, during training process, weights between neurons are being adjusted and slowly CNN starts to find such features which enable to meet predefined goal, i.e., to recognize successfully images from the training set.

Between described layers there are also pooling (sub-sampling) operations which reduce dimensions of resulted frames. Furthermore, after each convolution we apply a non-linear function (called **ReLU**) to the resulted frame to introduce non-linearity to the model.

Eventually, there are also fully connected layers at the end of the network. The last set of frames obtained from convolution operations is flattened to get a one-dimensional vector of neurons. From this point we put a standard, fully-connected neural network. At the very end, for classification problems, there is a SoftMax layer. It transforms results of the model to probabilities of a correct guess of each class

7.5 Apply the model and plot the graphs for accuracy and loss:

We will compile the model and apply it using fit function. The batch size will be 10. Then we will plot the graphs for accuracy and loss. We got average validation accuracy of 97.00% and average training accuracy of 91.00%.

Accuracy on test set:

We got an accuracy of 91.00% on test set.

Saving the Trained Model:

Once confident enough to take the trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like pickle. We have made sure that we have pickle installed in our environment.

Chapter 8

Result

After the successful creation and implementation of system we achieved the result as shown below:

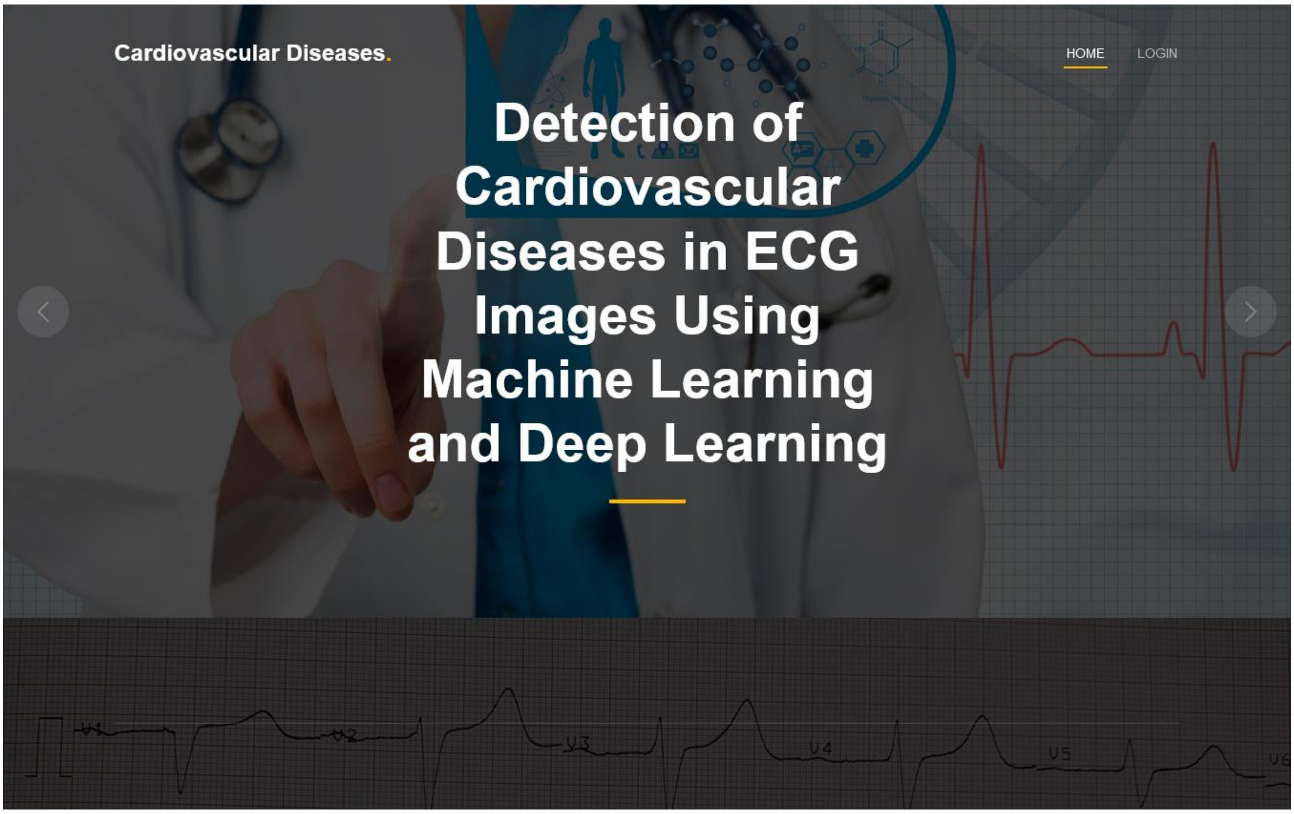

Fig 8.1 Homepage

Fig 7.6 Point Wise Convolution

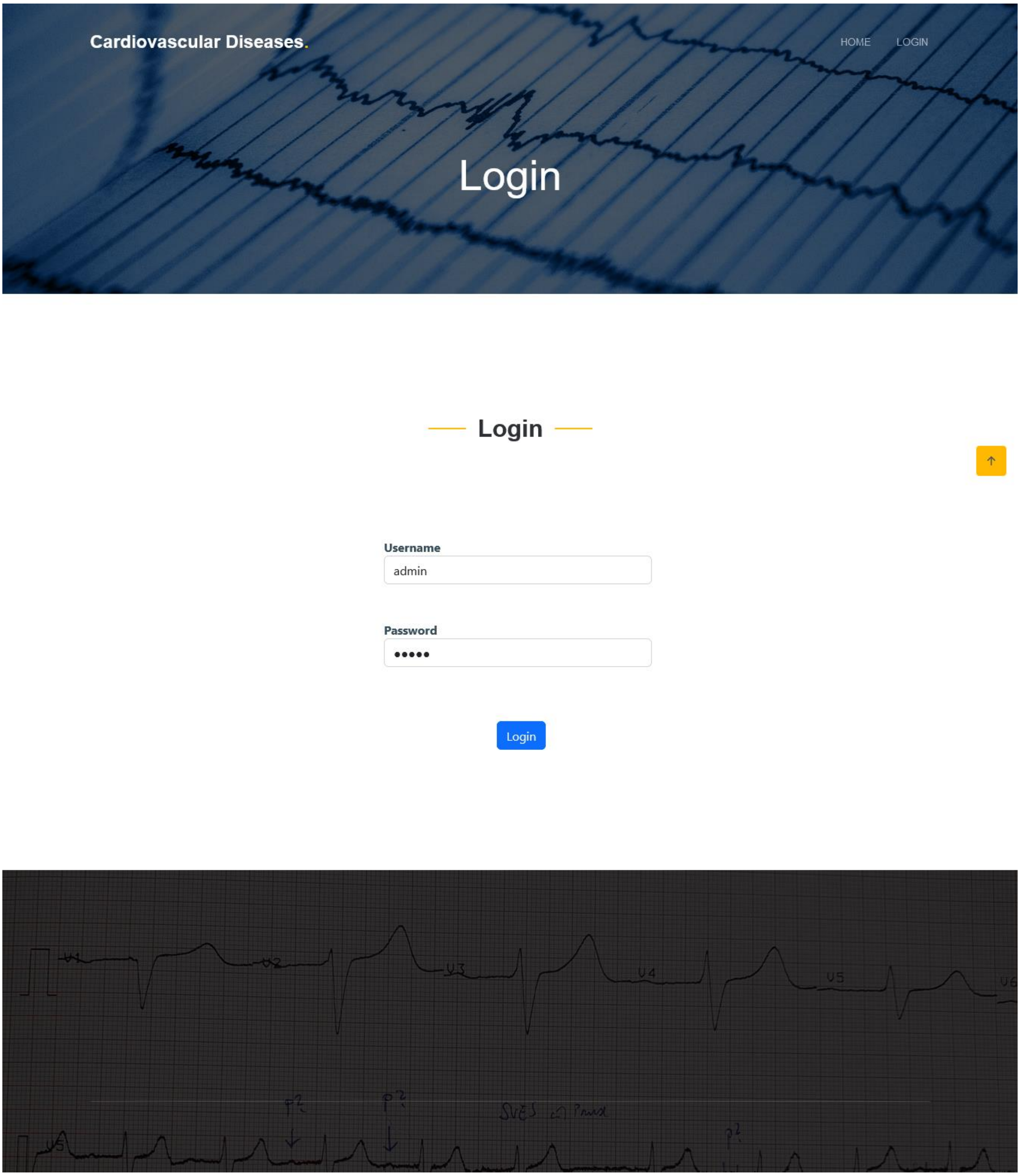

Fig 8.2 Login Window

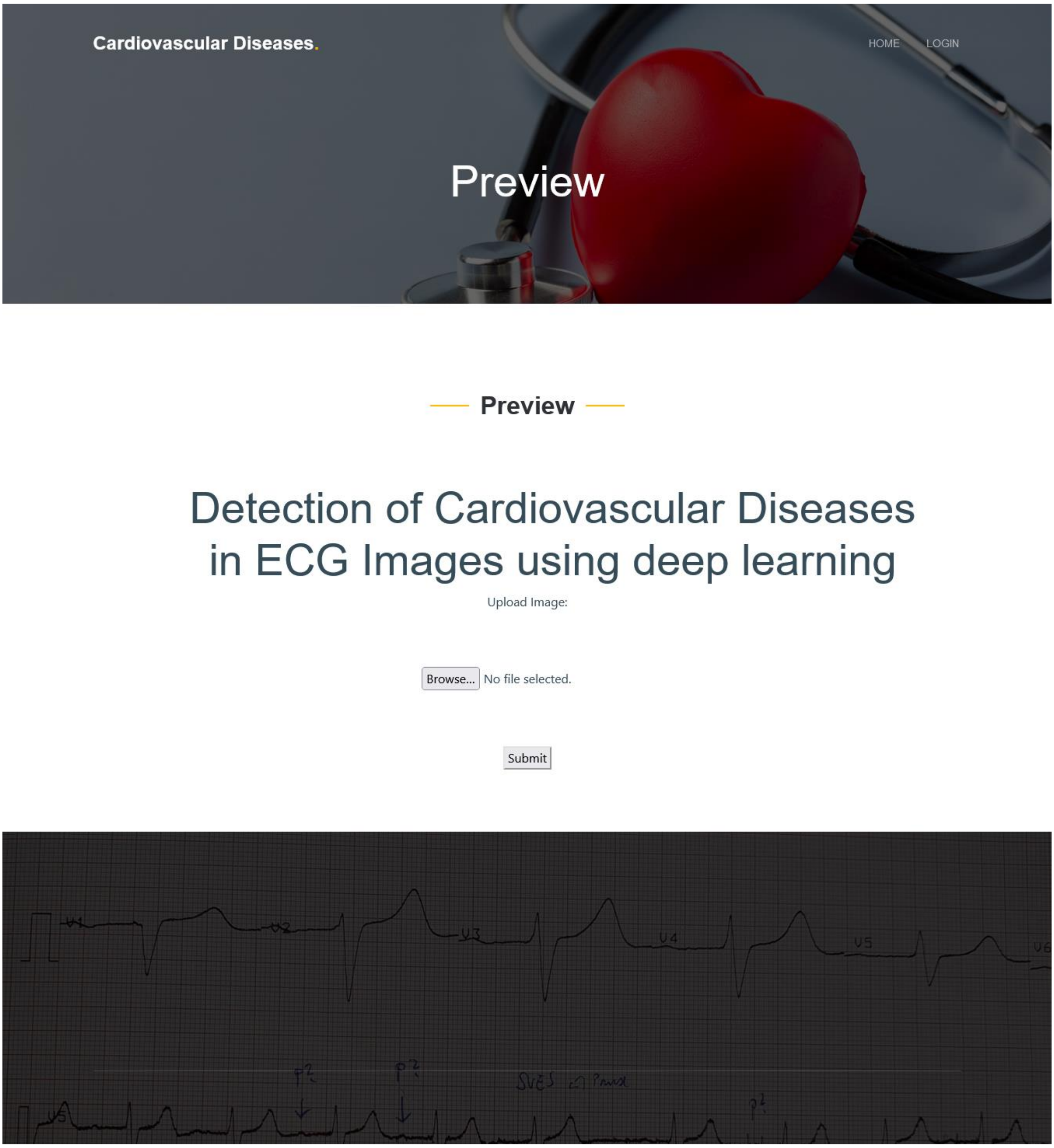

Fig 8.3 File Browsing Window

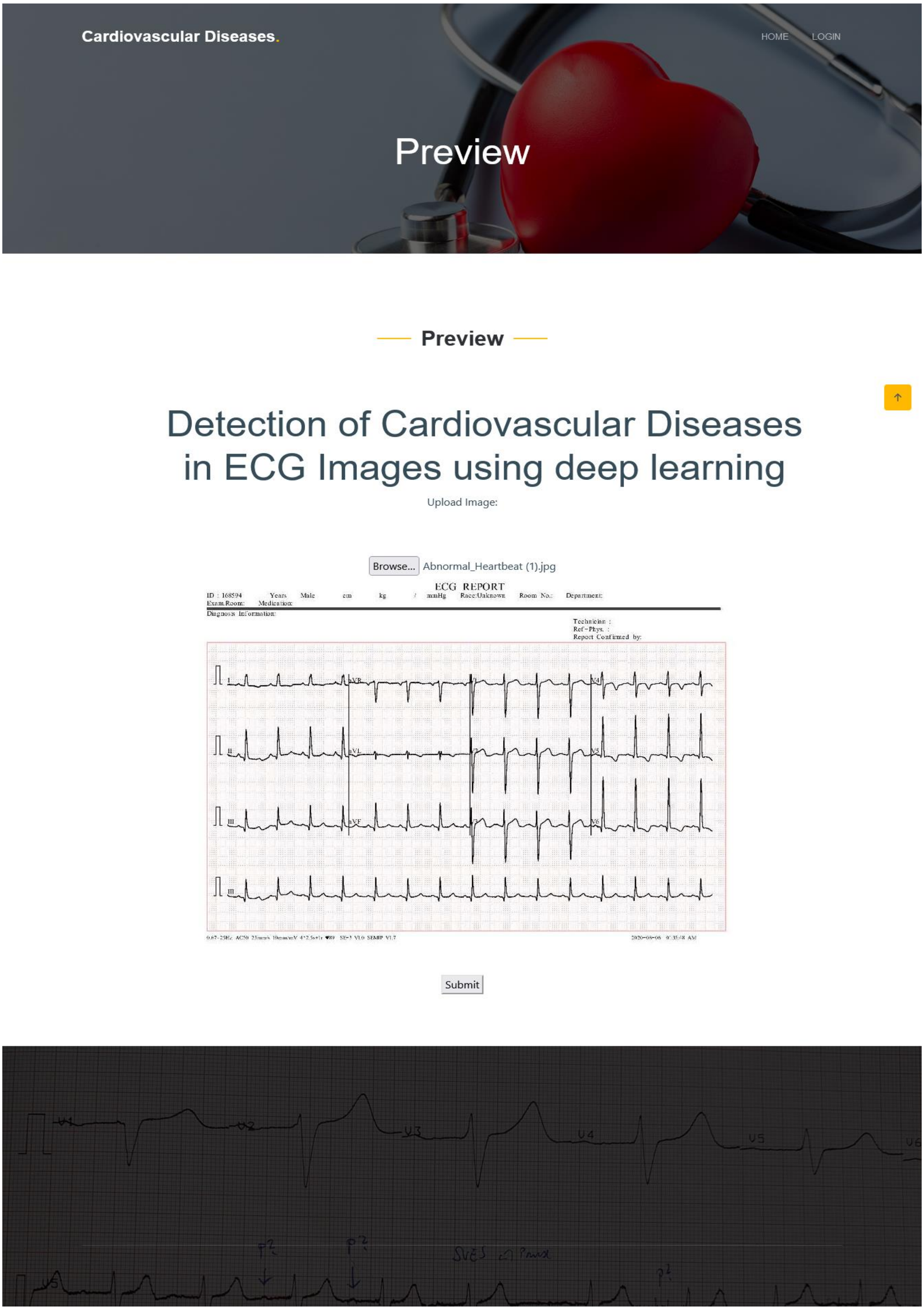

Fig 8.4 Submit Window

Fig 7.6 Point Wise Convolution

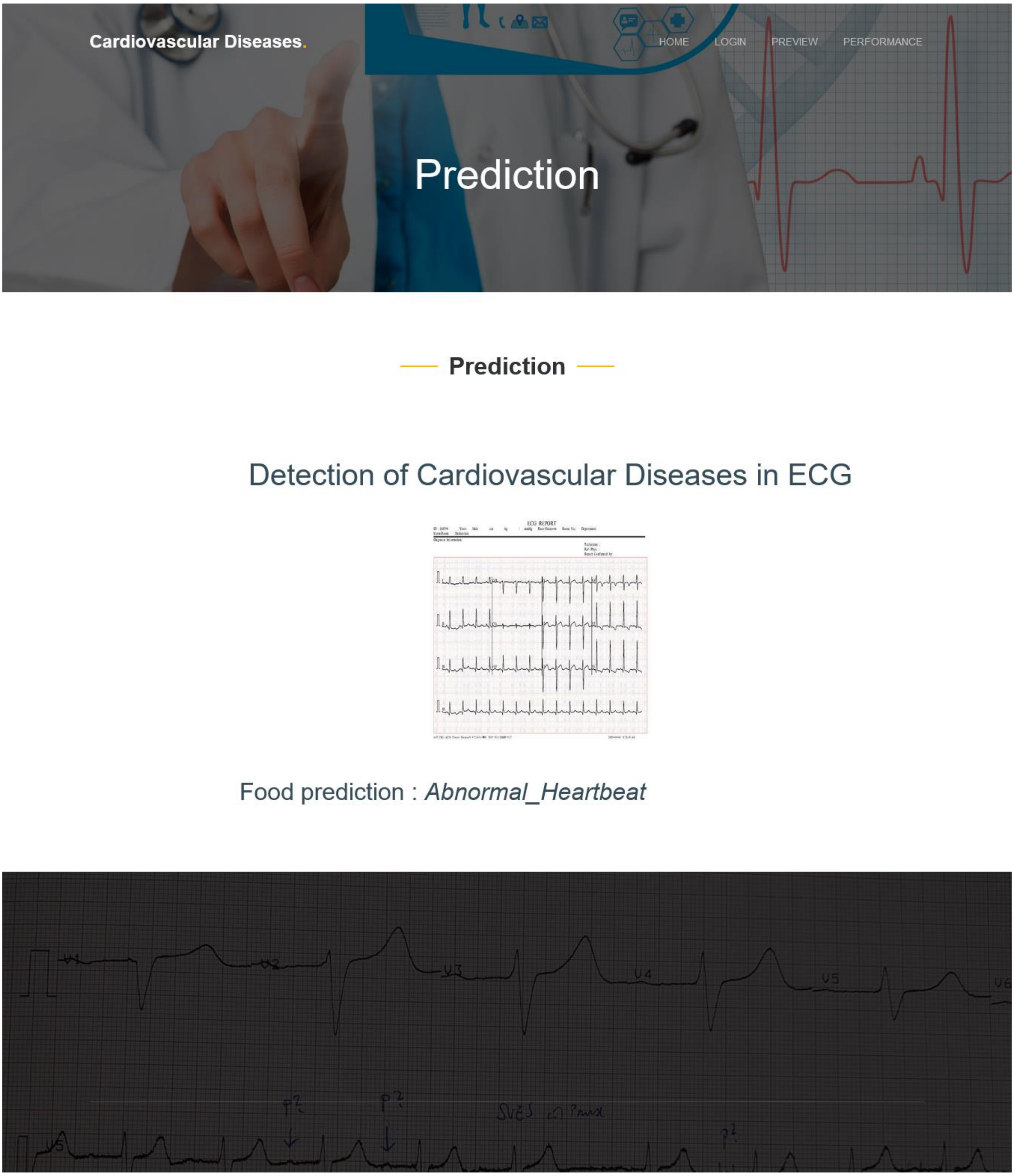

Fig 8.5 Result Declaration

PERFORMANCE ANALYSIS

Accuracy: 91.7

Precision: 84.3

Recall: 91.7

F-Measure: 91.7

Confusion Matrix

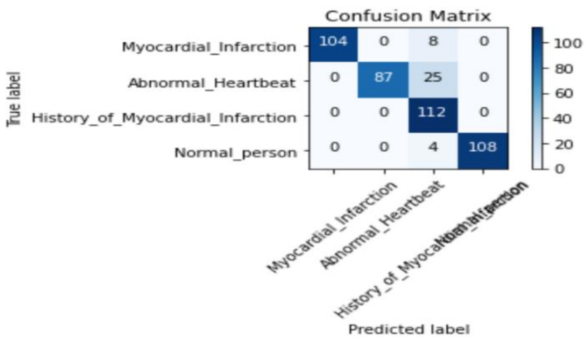

Fig 8.6 Performance Window

Fig 7.6 Point Wise Convolution

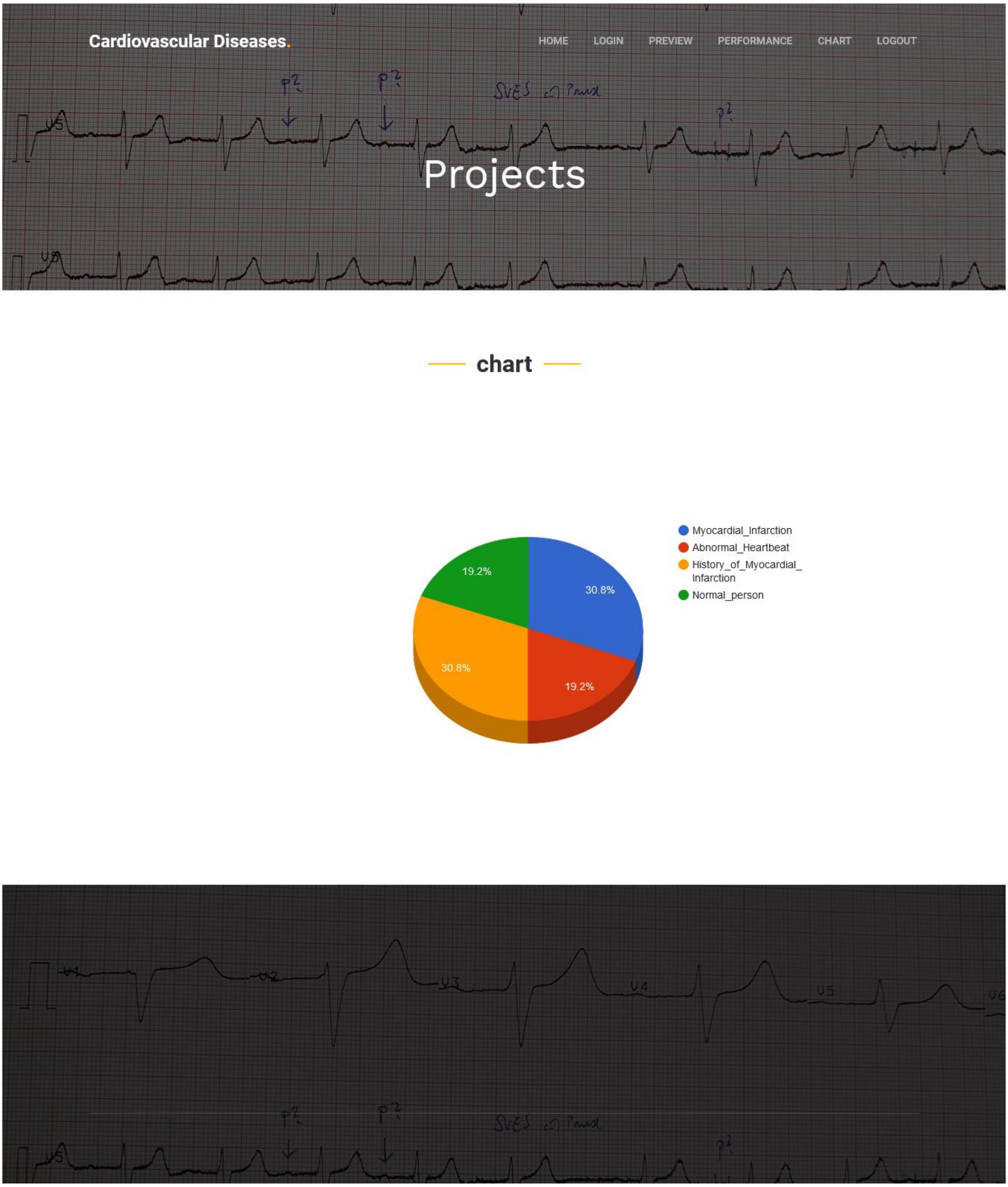

Fig. 8.7 Accuracy Scaling Window

Chapter 9

System Testing

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product.

It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

9.1 TYPES OF TESTS

9.1.1 Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application it is done after the completion of an individual unit before integration.

This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

9.1.2 Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

9.1.3 Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input: identified classes of valid input must be accepted.

Invalid Input: identified classes of invalid input must be rejected.

Functions: identified functions must be exercised.

Output: Identified classes of application as outputs.

Systems/Procedures: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration-oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

White Box Testing

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .you cannot "see" into it. The test provides inputs and responds to outputs without considering how the software works.

6.1 Unit Testing:

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

Features to be tested

- Verify that the entries are of the correct format
- No duplicate entries should be allowed
- All links should take the user to the correct page.
-

6.2 Integration Testing

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects.

The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

6.3 Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

Chapter 10

Conclusion

In this project, we proposed a lightweight CNN-based model to classify the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarc-tion, and normal person classes using public ECG images dataset of cardiac patients. According to the results of the experiments, the proposed MobileNet Architecture achieves remarkable results in cardiovascular disease classification and can also be used as a feature extraction tool for the traditional machine learning classifiers. Thus, the proposed CNN model can be used as an assistance tool for clinicians in the medical field to detect cardiac diseases from ECG images and bypass the manual process that leads to inaccurate and time-consuming results.

It is noticed that the recorded ECG signal may contain different types of artifacts which should be removed before further processing. In this study, it is found that baseline wandering, power line interferences and electromyographic noises are effectively removed by employing wavelet-based approaches.

Also, it is noticed that the accurate detection of onset and offset of QRS complex is of prime importance because most of research uses time interval-based features for the detection cardiovascular diseases which heavily rely on the reliable detection of QRS complex, P and T waves. We have noticed that overall time frequency-based features give better performance for classification of different types of hearts beats. Moreover, mixture of features also used in recent research which includes time interval based feature as well as wavelet based features for better classification of heart related diseases.

In future work, optimization techniques can be used to obtain optimized values for the hyperparameters of the proposed CNN model. The proposed model can also be used for predicting other types of problems. Since, the proposed model belongs to the family of low-scale deep learning methods in terms of the number of layers, parameters, and depth. Therefore, a study on using the proposed model in the Industrial Internet of Things (IIoT) domain for classification purposes can be explored.

References

[1] Kaur, Inderbir, Rajni Rajni, and Anupma Marwaha. "ECG signal analysis and arrhythmia detection using wavelet transform." Journal of The Institution of Engineers (India): Series B 97 (2016): 499-507.

[2] "Cardiovascular diseases," World Health Organization (WHO), 11. 06. 2021. [Online]. Available: https://www.who.int/health-topics/cardiovascular-diseases.

[3] "Common medical tests to diagnose heart conditions," Government of Westren Australia, Department of Health, [Online]. Available: https://www.healthywa.wa.gov.au/Articles/A_E/Common-medical-tests-to-diagnose-heart-conditions.

[4] M. Swathy and K. Saruladha, "A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques," ICT Express, 2021. https://doi.org/10.1016/j.icte.2021.08.021..

[5] [4] R. R. Lopes, H. Bleijendaal, L. A. Ramo, T. E. Verstraelen, A. S. Amin, A. A. Wilde, Y. M. Pinto, B. A. de Mol and H. A. Marquering, "Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p.Arg14del mutation carriers," Computers in Biology and Medicine, vol. 131, no. 104262, 2021. https://doi.org/10.1016/j.compbiomed.2021.104262.

[6] R. J. Martis, U. R. Acharya and H. Adeli, "Current methods in electrocardiogram characterization," Computers in Biology and Medicine, vol. 48, pp. 133-149, 2014. https://doi.org/10.1016/j.compbiomed.2014.02.012..

[7] A. Rath, D. Mishra, G. Panda and S. C. Satapathy, "Heart disease detection using deep learning methods from imbalanced ECG samples," Biomedical Signal Processing and Control, vol. 68, no. 102820, 2021. https://doi.org/10.1016/j.bspc.2021.102820..

[8] A. Mincholé and B. Rodriguez, "Artificial intelligence for the electrocardiogram," Nature Medicine, vol. 25, no. 1, pp. 22-23, 2019. https://doi.org/10.1038/s41591-018-0306-1.

[9] A. Isin and S. Ozdalili, "Cardiac arrhythmia detection using deep learning," Procedia Computer Science, vol. 120, pp. 268-275, 2017. https://doi.org/10.1016/j.procs.2017.11.238..

[10] H. Bleijendaal, L. A. Ramos, R. R. Lopes, T. E. Verstraelen, S. W. E. Baalman, M. D. Oudkerk Pool, F. V. Y. Tjong, F. M. Melgarejo-Meseguer, J. Gimeno-Blanes, J. R. Gimeno-Blanes, A. S. Amin, M. M. Winter, H. A. Marquering, W. E. M. Kok, A. H. Zwinderman, A. A. M. Wilde and Y. M. Pinto, "Computer versus Cardiologist: Is a machine learning algorithm able to outperform an expert in diagnosing phospholamban (PLN) p.Arg14del mutation on ECG?," Heart rhythm., vol. 18, no. 1, pp. 79-87, 2020. https://doi.org/10.1016/j.hrthm.2020.08.021.

[11] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan and C. K. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," Knowledge-Based Systems, vol. 132, pp. 62-71, 2017. https://doi.org/10.1016/j.knosys.2017.06.003..

[12] W. Jiang, S.G. Kong, Block-based neural networks for person- alized ECG signal classification. IEEE Trans. Neural Netw. 18(6), 1750–1761 (2007)

[13] M.K. Islam, A.N.M.M. Haque, G. Tangim, T. Ahammad, M.R.H. Khondokar, Study and analysis of ECG signal using MATLAB and LABVIEW as effective tools. Int. J. Comput. Electr. Eng. 4(3), 404–408 (2012)

[14] S.Z. Mahmoodabadi, A. Ahmadian, M.D. Abolhasani, ECG Feature Extraction Using Daubechies Wavelets, Proceedings of the Fifth International Conference Visualization, Imaging and Image Processing (Benidorm, 2005)

[15] I. Odinaka, L. Po-Hsiang, A.D. Kaplan, J.A. O'Sullivan, E.J. Sirevaag, J.W. Rohrbaugh, ECG biometric recognition: a com- parative analysis. IEEE Trans. Inf. Forensics Secur. 7(6), 1812–1823 (2012)

[16] X. Liu, Y. Zheng, M.W. Phyu, B. Zhao, M. Je, X. Yuan, Multiple functional ECG signal is processing for wearable applications of long-term cardiac monitoring. IEEE Trans. Biomed. Eng. 58(2), 380–389 (2011)

[17] S.A. Jones, ECG Notes: Interpretation and Management Guide(F.A. Davis Company, Philadelphia, 2005)

[18] L. Sun, Y. Lu, K. Yang, S. Li, ECG analysis using multiple instance learning for myocardial infarction detection. IEEE Trans. Biomed. Eng. 59(12), 3348–3356 (2012)

[19] Kaur, Inderbir, Rajni Rajni, and Anupma Marwaha. "ECG signal analysis and arrhythmia detection using wavelet transform." Journal of The Institution of Engineers (India): Series B 97 (2016): 499-507.

[20] W. Jiang, S.G. Kong, Block-based neural networks for person- alized ECG signal classification. IEEE Trans. Neural Netw. 18(6), 1750–1761 (2007)

[21] M.K. Islam, A.N.M.M. Haque, G. Tangim, T. Ahammad, M.R.H. Khondokar, Study and analysis of ECG signal using MATLAB and LABVIEW as effective tools. Int. J. Comput. Electr. Eng. 4(3), 404–408 (2012)

[22] S.Z. Mahmoodabadi, A. Ahmadian, M.D. Abolhasani, ECG Feature Extraction Using Daubechies Wavelets, Proceedings of the Fifth International Conference Visualization, Imaging and Image Processing (Benidorm, 2005)

[23] I. Odinaka, L. Po-Hsiang, A.D. Kaplan, J.A. O'Sullivan, E.J. Sirevaag, J.W. Rohrbaugh, ECG biometric recognition: a com- parative analysis. IEEE Trans. Inf. Forensics Secur. 7(6), 1812–1823 (2012)

[24] X. Liu, Y. Zheng, M.W. Phyu, B. Zhao, M. Je, X. Yuan, Multiple functional ECG signal is processing for wearable applications of long-term cardiac monitoring. IEEE Trans. Biomed. Eng. 58(2), 380–389 (2011)

[25] S.A. Jones, ECG Notes: Interpretation and Management Guide(F.A. Davis Company, Philadelphia, 2005)

[26] L. Sun, Y. Lu, K. Yang, S. Li, ECG analysis using multiple instance learning for myocardial infarction detection. IEEE Trans. Biomed. Eng. 59(12), 3348–3356 (2012)

[27] 12 H. B. Demuth, M. H. Beale, O. De Jess and M. T. Hagan, Neural Network Design, Martin Hagan, 2014

[28] 12 H. B. Demuth, M. H. Beale, O. De Jess and M. T. Hagan, Neural Network Design, Martin Hagan, 2014

[29] 13 M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks", IEEE Transactions on Signal Processing, vol. 45, no. 11, pp. 2673-2681, 1997.

[30] 14 Chouhan V. S., Mehta, S. S. (2007). Total Removal of Baseline Drift from ECG Signal, Computing: Theory and Appl.-ICCTA

[31] 15 Sheffield, L. T., Berson, C. A., Remschel, D. B. , Gillette, P. C., Hermes, R. E., Hinkle, L. , Kennedy, H., Mirvis, D. M., Oliver, C. (1985). Recommendations for standard of instr. and practice in the use of ambulatory electrocardiography, Circulation, p. 626A-636A

[32] 13 M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks", IEEE Transactions on Signal Processing, vol. 45, no. 11, pp. 2673-2681, 1997

[33] 14 Chouhan V. S., Mehta, S. S. (2007). Total Removal of Baseline Drift from ECG Signal, Computing: Theory and Appl.-ICCTA

[34] Sheffield, L. T., Berson, C. A., Remschel, D. B. , Gillette, P. C., Hermes, R. E., Hinkle, L. , Kennedy, H., Mirvis, D. M., Oliver, C. (1985). Recommendations for standard of instr. and practice in the use of ambulatory electrocardiography, Circulation, p. 626A-636A

[35] Xu, S.; Zhang, Z.; Wang, D.; Hu, J.; Duan, X.; Zhu, T. Cardiovascular Risk Prediction Method Based on CFS Subset Evaluation and Random Forest Classification Framework. In Proceedings of the 2017 IEEE 2nd International Conference on Big Data Analysis, Beijing, China, 10–12 March 2017; pp. 228–232.

[36] Shahin, A.; Moudani, W.; Chakik, F.; Khalil, M. Data Mining in Healthcare Information Systems: Case Studies in Northern Lebanon. In Proceedings of the Third International Conference on e-Technologies and Networks for Development (ICeND2014), Beirut, Lebanon, 29 April 2014–1 May 2014; pp. 151–155, ISBN 978-1-4799-3166-8.

[37] Gupta, N.; Dharmale, G.; Parmar, D. Heart disease Prediction using Machine Learning. J. Emerg. Technol. Innov. Res. (JETIR) 2021, 8, 2818–2825.

[38] Absar, Nurul, et al. "The efficacy of machine-learning-supported smart system for heart disease prediction." *Healthcare*. Vol. 10. No. 6. MDPI, 2022.