Design of Algorithm for Detection of Myocardial Infarction using ECG Signals

A project report submitted for BTP phase II

by

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Abstract

Heart disorders, such as heart attacks, strokes, and other cardiovascular problems, have increased alarmingly in India. Myocardial infarction affects 30,00,000 Indians each year. A total of 70 per cent of people die. Millions of lives can be saved by early, precise diagnosis, and the survival rate can be raised even higher. An electrocardiogram measures the electrical impulses produced by the heart (ECG). The ECG signal contains many disturbances and baseline wandering, and it must be processed in order to retrieve the information of each wave, such as P, Q, R, S, T, and, on rare occasions, U. Signal processing is very important for feature extraction and noise reduction. The primary goal of this research is to find diversions and deviations in any region of the wave, particularly the ST segment with elevation or lengthening, which accurately indicates myocardial infarction. The information that has been processed can be used in clinical trials. This paper focuses on data cleaning and pre-processing chores on the PTB-XL data-set, as well as feature extraction for training Deep Learning models for detecting myocardial infarction location and severity. For reading, extracting, and denoising the time series data, a variety of Python Tool-kits have been used.

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Nomenclature

ANN	Artificial Neural Network
CNN	Convolutional Neural Networks
DESA	Discrete Energy Seperation Algorithm
DFT	Discrete Fourier Transform
DL-LSSVM	Deep Layer Least Support Vector
DNN	Deep Neural Network
ECG	Electrocardiogram
EWT	Emperical Wavelet Transformation
FBSE	Fourier Bessel Series Expansion
HT	Hilbert Transform
KNN	K Nearest Neighbour
MI	Myocardial Infarction
PTB	Physikalisch Technische Bundesanstalt
SVM	Support Vector Machine
VCG	VectorCardioGram
WT	Wavelet Transform
BPNN	Back Propagation Neural Network
MIL	Multi Instance Learning

Chapter 1

Introduction

1.1 MYOCARDIAL INFARCTION

Myocardial Infarction commonly known as Heart Attack, happens when blood supply to a region of the heart is reduced or stopped, causing damage to the heart muscle. High blood pressure, smoking, diabetes, lack of exercise, obesity, and high blood cholesterol are just a few of the causes of Myocardial Infarction. An electrocardiogram with leads attached to various places of the body is used to detect a Myocardial Infarction.

Myocardial Infarction is divided into three types :

- Myocardial infarction with ST-segment elevation (STEMI).
- Myocardial infarction with non-ST segment elevation (NSTEMI)
- A coronary spasm, also known as unstable angina, is a condition in which the blood vessels of the heart contract

1.2 Standard 12 Lead ECG

The conventional 12-lead ECG depicts the electrical activity of the heart as measured by electrodes on the body surface.

The 12-lead ECG gives three orthogonal directions of spatial information regarding the heart's electrical activity :

- Anterior Posterior

- Superior Inferior

- Right Left

Because they are worn on the individual's arms and legs, six of the leads are referred to as "limb leads." The remaining six leads are known as "precordial leads" because they are implanted on the torso (precordium). Each of the 12 leads corresponds to a specific orientation. The leads are

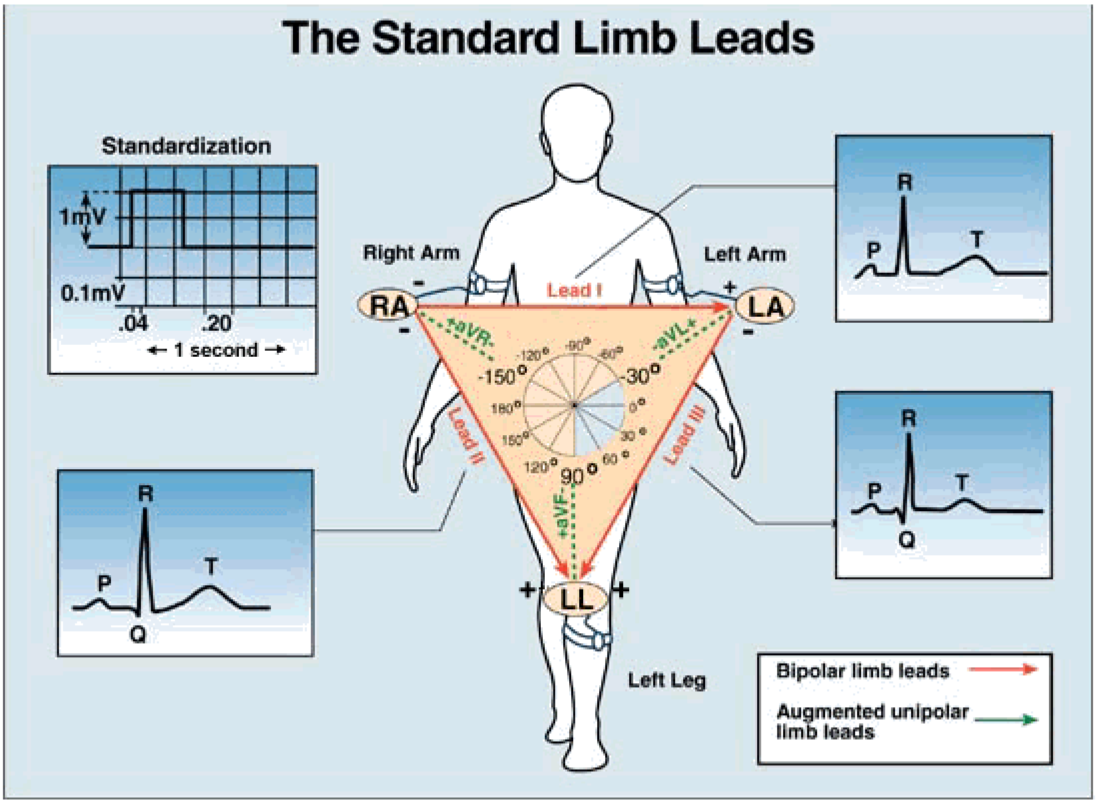

Figure 1.1: Standard Limb Leads

further divided into two parts on the basis of planes i.e. frontal plane and the horizontal plane.

- Frontal planes are divided into two parts
  - Augmented unipolar limb leads which contains aVR Lead from Right Arm to Left Arm and Left Foot(Rightward), aVL Lead from Left Arm to Right Arm Left Foot (Leftward) and avF Lead from Left Foot to Right Arm and Left Arm (Inferior)
  - Bipolar limb leads contain Lead I from Right Arm to Left Arm , Lead II from Right Arm to Left Foot and Lead III from Left Arm to Left Foot .

- Horizontal Plane only contains Unipolar Chest Leads which is further divided into two parts Posterior Anterior which has Leads V1, V2 and V3, and Right Left /Lateral which has Leads V4, V5, V6 Leads.

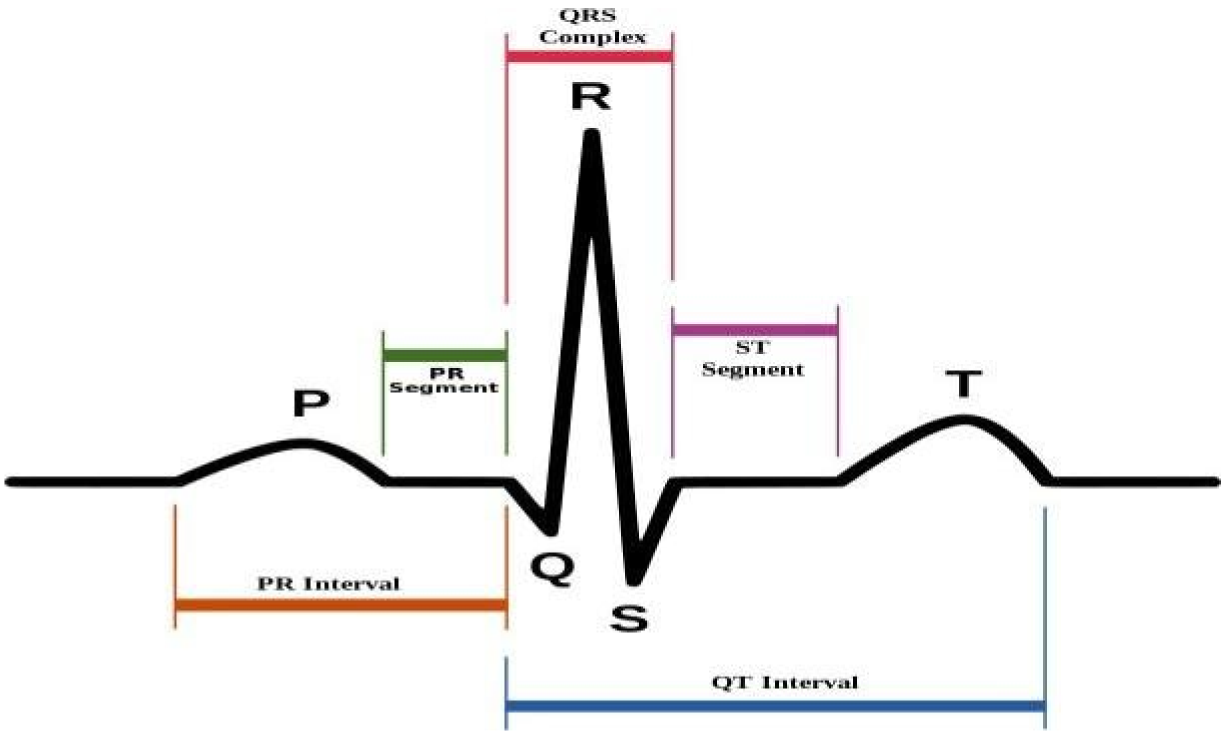

Figure 1.2: Snap Shot of Standard ECG

Pattern recognition is used to interpret the ECG. Understanding the notion of what ECG's indicate is helpful in understanding the patterns discovered. The theory is based on electromagnetic and can be categorized as follows:

- A positive deflection is produced when the heart is re polarized away from the positive electrode.
- A positive deflection is produced when the heart depolarizes toward the positive electrode.
- A negative deflection is produced when the heart re-polarizes toward the positive electrode.
- A negative deflection is produced when the heart is depolarized away from the positive electrode.

As a result, the overall direction of depolarization and re-polarization results in a positive or negative deflection on the trace of each lead. A normal rhythm generates four distinct entities: a P wave, a QRS complex, a T wave, and a U wave, each with its own pattern.

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

The patterns of these four entities are affected by changes in the anatomy of the heart and its surroundings.

1.3 Electrocardiogram Manifestations of MI

ST segment is the difference between S-peak and T-peak.
ST-elevation : New ST elevation in two contiguous leads with the cut-off points at the J-point: is greater than or equal to 0.15 mV in women or greater than or equal to 0.2 mV in men in V2–V3 leads and greater than or equal to 0.1 mV in other leads.
ST depression : New horizontal or down-sloping ST depression greater than 0.05 mV in two contiguous leads.
T-wave change : T inversion greater than or equal to 0.1 mV in two contiguous leads with prominent R-wave or R/S ratio greater than or equal to 1.

1.4 MI Localisation

- Septal MI: ST Elevation in Leads V1, V2, V3, V4 and the disappearance of septum Q in leads V5 and V6. Coronary Artery: Left anterior descending artery-Septal Branch.
- Anterior MI: ST Elevation in Leads V1, V2, V3, V4, V5, V6. Coronary Artery: Left anterior descending artery.
- Inferior MI: ST Elevation in Leads II, III, aVF and Reciprocal ST depression in I, aVL Leads.Coronary Artery: Right coronary artery (80 per cent) or Ramus circumflex (20 per cent)
- Lateral MI: ST Elevation in Leads I, aVL, V5, V6 and Reciprocal ST depression in II, III, aVF Leads. Coronary Artery: Left Circumflex.

- Right Ventricle MI: ST Elevation in Leads V1, V4R and Reciprocal ST depression in I, aVL.Coronary Artery: Right coronary artery.
- Posterior MI: ST Elevation in Leads V7, V8, V9 and high R peaks in V1, V2, V3 Leads and ST depression in V1, V2, V3 leads is greater than 2 mm.
- Atrial MI: P-Ta elevation in Leads I, V5, V6 and P-Ta depression PTa in I, II, or III. Coronary Artery: Right coronary artery.

Chapter 2

Literature Review

2.1 Feature Extraction

Muhammad Arif's propose a paper in which he used backpropagation neural networks classifiers with data collected from a 12-lead ElectroCardioGram to automatically detect and localise myocardial infarction. The goal of MI detection is to distinguish between healthy and MI-affected individuals. The task of defining the infarcted region of the heart is known as localization. The PTB database on Physio-bank was used as the ElectroCardioGrams source.T wave amplitude, Q wave, and ST level deviation, all of which are suggestive of MI, are derived from the time domain components of each beat in the ECG signal. Lead-wise principal components analysis is performed on the data extracted from the ST-T and Q wave regions of each beat for localisation. The primary components that result are utilised to identify seven different forms of myocardial infarction. The sensitivity and specificity of BPNN for beat categorization are 97.5 per cent and 99.1 per cent, respectively, for detection. [1]
The categorization of Anteroseptal Myocardial Infarction and normal patients is discussed in the paper proposed by Swati Banerjee. The extraction of diagnostic pathological characteristics from V1-V4 chest leads using a multiresolution method is proposed. For the classification and development of discriminant functions, Mahalanobish distance-based classification is utilised. Before implementing the feature extraction technique, the digitised ECG signals undergo DWT-based denoising. For the detection of R - peaks, a multiresolution technique is used with adaptive thresholding. The points of Q, S peak, QRS onset, and offset are then determined. The T wave is finally discovered. The R, Q, S, and T wave heights are computed by detecting the baseline of the ECG data. The two classes are differentiated using the computed QRS vector

and T wave amplitude. [2]
Neenu Jacob in his paper used the Cross Wavelet Transform and the Support Vector Machine to analyse and classify ECG signals. By comparing the similarities of two time-domain waveforms, the needed wave can be found. The database used as a test material is the MIT-BIH arrhythmia, which has 47 patients examined at 48 half periods. The signals have a sampling frequency of 360Hz. The cross wavelet transform (XWT) is used for wavelet coherence and wavelet spectrum classification and analysis. It studies the time domain properties by decomposing a signal into components that appear as scales. Support Vector Machines (SVMs) are a type of method that is used to separate binary sets that are linearly separable. Denoising and beat segmentation are the two main applications of the suggested approach. For decomposition and reconstruction, denoising can be done via the Discrete Wavelet Transform. The selection of frequency bands is employed for baseline wandering. As a result, the R wave peak can be located. The production of matrices is used to measure beat segmentation based on extraction characteristics such as WCS and WCOH. [3]
Marcio Jose da Silva in his paper focuses on the ECG signal filtering procedure. 60-100 beats per minute are the usual heart rate. The continuous wavelet transform is a function of the signal multiplied by the mother wavelet's scale. Discrete wavelet transforms are used for filtering, while multiresolution is used to analyse several frequency bands. It's most likely used with low pass and high pass filters to eliminate noise. Because it uses multiresolution analysis for discrete signals and continuous wavelet transform for stationary signals, the fundamental problem is an iterative procedure. [4]
The multiresolution analysis of 12-lead ECG data is proposed by Abhijit Bhattacharyya, as a method for detecting MI pathophysiology. For the time-scale decomposition of 12-lead ECG data, the method relies on the Fourier-Bessel series expansion-based empirical wavelet transform (FBSE-EWT). FBSE-EWT is used to analyse nine subband signals for each lead ECG signal. The subband signals of each ECG lead are used to calculate statistical properties such as kurtosis, skewness, and entropy. [5]
Selva Nidhyananthan et.al. developed a paper that discusses a wavelet-based method for identifying a Myocardial Infarction (MI) and determining the user's identification. The Daubechies wavelet technique is used to deconstruct the multilayer Electrocardiogram signals, which splits the ECG into distinct sub-bands. In an aberrant signal, the ST segment inversion, QRS complex, and PQ alterations are common. It noticeably alters the structure of multiscale matrices

at various levels, observing both energy and Eigenspace values. The mean and variance figures are calculated from this. The (PTB)diagnostics ECG database is used to create datasets that include both healthy control signals and various problematic signals. [6]
A study on Intelligent systems based on genetic algorithms and support vector machines for identification of Myocardial infarction from ECG data was published by Aykut Diker, Subha Velappan, and others in 2018. The major goal of this research is to discriminate MI samples from normal electrocardiogram (ECG) signals utilising morphological, time-domain, and discrete wavelet transform (DWT) features. The entire experimental work was conducted using PTBDB, an open database. GA determined 9 features to be the most important in an experimental investigation. In addition, the feature set's dimension was reduced from 23 to 9. Finally, the sensitivity and specificity were determined to be 87.80per cent and 85.97 per cent, respectively. [7]
An article was published by Chun-cheng Lin et. al. in 2015. It's utilised to locate the signals' high-frequency components. The wave is divided from the time domain functions of mother wavelets using continuous wavelet transforms. The sensitivity and specificity of the fragmented QRS complex wave were respectively 60 per cent and 65 per cent. The most significant problem found is that it produces extremely low sensitivity. [8]

2.2 MI Localisation

In Muhammad Arif's proposed paper PCA-based characteristics combined with back propagation neural network classifiers resulted in a 93.7 per cent beat classification accuracy for localisation. Because of its simplicity and excellent accuracy over the PTB database, the suggested method can be highly useful in determining the right diagnosis of MI in a practical situation. [1]
In Swati Banerjee's paper finding discriminant functions for leads V1-V4 is done using the Mahalanobis distance-based classification approach, and analysis is done accordingly. With the MIT BIH Arrhythmia database, the proposed method has sensitivity and positive predictivity of 99.8 per cent and 99.7 per cent, respectively, and 99.84 per cent and 99.98 per cent with the PTB diagnostic ECG database. Over 150 leads were examined from PTB data, each with 10000 samples, an average coefficient of variation of 3.21 was found for time plane features. This approach has a classification accuracy of 96.4 per cent. [2]
In Neenu Jacob's paper SVM is used to classify layers, and it is divided into two groups by

a hyper plane that maximises vectors between them. The separation margin has been conditioned to create two distinct components. It removes the signal's noise and baseline drifting. For SVM-based classification, the sensitivity and specificity are 89.5 per cent and 96.4 per cent, respectively. Because of the merged uncover categorization, this approach has low accuracy. [3]
In Abhijit Bhattacharyya's paper for the detection of MI from the feature vector of a 12-lead ECG, a deep neural network such as the deep layer least-square support vector machine (DL-LSSVM), which is built utilising the hidden layers of sparse auto-encoders and the LSSVM, is utilised. The experimental results show that the combination of FBSE-EWT-based entropy features and DL-LSSVM for MI detection has to mean accuracy, sensitivity, and specificity values of 99.74 per cent, 99.87 per cent, and 99.60 per cent, respectively. When compared to wavelet-based features for MI detection, the accuracy of the suggested method is increased by more than 3 per cent. [5]
In Selva Nidhyananthan's paper the SVM classifier is mostly used to distinguish between normal and abnormal signal instances. The ECG signal is authenticated using the RR interval. For 15 ECG samples, 90.42 per cent accuracy is attained for MI detection. [6]

2.3 Conclusion

A number of approaches and algorithms utilised to date were covered in this literature review, and detecting myocardial infarction is critical in clinical studies. This study gives an overview of ECG signal filtering and signal processing, as well as a detailed look at feature extraction, noise removal, and support vector machine approaches. Several disturbances, such as power-line interferences, baseline wandering, and various artefacts, may be removed from ECG signals using various wavelet transforms, and precise prediction of deviation and distractions in any of the waves can be recognised using various support vector machines. Pre-processing, segmentation or segregation, and denoising are the general approaches utilised in all signal processing, and support vector machines are used for classification and post-processing. According to the findings, the time frequency-based technique performs better in cardiovascular disorders, and wavelet-based features are utilised to classify the patients. Each article was examined for many types of performance metrics such as accuracy, specificity, and sensitivity, as well as the readings listed above.

Sl.No.	ECG	ALGORITHM	ML MODEL	PERFORMANCE METRICS			FEATURES USED
				ACCURACY	SPECIFICITY	SENSITIVITY	
1.	12 Lead	Discrete Wavelet Transform	Back Propagation Neural Network	-	99.1%	97.5%	QRS wave
2.	4 Lead	Discrete Wavelet Transform	-	99.7%	-	99.8%	R wave
3.	12 Lead	Cross Wavelet Transform	-	-	96.4%	89.5%	R wave peak
4.	12 Lead	Discrete Wavelet Transform	-	-	-	-	Filtering Process
5.	12 Lead	Fourier Bessel Series	Deep Layer Least Square Support Vector Machine	99.74%	99.60%	99.87%	ST-segment
6.	12 Lead	Daubechies Wavelet Transform	Binary Support Vector Machine	90.42%	-	-	RR Interval
7.	12 Lead	Discrete Wavelet Transform	Genetic Algorithm	87.8%	88.67%	86.97%	R and ST segment
8.	12 Lead	Continuous Wavelet Transform	-	-	60%	65%	Elimination of High

Figure 2.1: Summary

Chapter 3

Implementation

In this chapter,we have mostly worked on the PTB XL Data-set before passing it for training of different Models which includes Balancing of the Data-set then the Data Pre-Processing from the Beats after that feature are extracted from the data-set which plays important role in training the model . Then finally splitting the data into two parts first one for training the model and the second one for testing the model. In our paper we have trained two ANN models one with 12 leads/10 classes and another with 4 leads/7 classes.The reason behind the decrease in the number of classes is that the data is highly imbalanced there are classes like PMI,IPMI,IPLMI,ANI whose frequency are very small as compared to other classes and the reason behind the decrease in the leads is that the hardware implementation of 12 leads is very difficult so to make it compatible we have taken only 4 leads .

3.1 12 Leads/10 Classes ANN Model

3.1.1 Data-set Used

In this model we have used PTB-XL data-set present as open-access on Physio-net. The PTB-XL Electrocardiogram data-set is a huge collection of clinical 12-lead Electrocardiograms from 10sec long patients. The records for the ECG signals are present at sampling frequencies 500 Hz and 100Hz. For the project, I have used the ECG data recorded at a 500Hz of sampling frequency. The data-set also contains records for Normal sinus rhythm (NORM) and MI, which are divided into nine subcategories: anterior-septal MI (ASMI), Anterior MI (AMI), inferior MI (IMI),anterior-lateral MI (ALMI), inferior-posterior MI (IPMI), inferior-lateral MI (ILMI),

posterior MI (PMI), inferior-posterior-lateral MI (IPLMI), and lateral MI (LMI). The table below illustrates the frequency of each of these MI classes in the PTB-XL data-set.
The table above also shows that the dataset is highly unbalanced.

CLASSES	FREQUENCY
AMI	290
ASMI	1883
ALMI	164
IMI	2329
ILMI	393
IPMI	30
IPLMI	50
LMI	132
PMI	14
NORM	4000

3.1.2 Balancing The Data-Set

This was accomplished by oversampling classes with a lower frequency and undersampling classes with a higher frequency. In the code 'imblearn's SMOTENC' class available in Python was used for oversampling and undersampling purposes using categorical features. As a result, doing so eventually balances the initial data. Furthermore, each ECG record in the dataset was given a label.

3.1.3 Data Pre-Processing from the Beats

Using the 'wfdb' package, each ECG signal from the dataset was read into a matrix at a sampling frequency of 500Hz. Each lead/channel was separated from the signal one by one and sent to remove the trend from the time series and remove noise. The data-filtering function was created using the SciPy library's 2nd order digital Butterworth and zero-phase digital filters, which also functioned as high and low pass filters. All undesirable frequencies below 0.5Hz and above 40Hz were successfully eliminated after passing through these filters.

3.1.4 Feature Extraction from the Beats

In the code, each of the twelve ECG signal leads was sent for ECG delineation, where the Hamilton Segmenter peak detection method was utilised to detect all of the R-peaks. In the code, the inbuilt 'discrete wavelet transform method ' was used to detect the QRS-onsets, QRS-offsets, and T-peaks based on those discovered R-peaks, and the 'peak' approach to detect the Q-peaks from all the beats. The key markers of an ECG beat are Q wave, T wave, and ST level elevation or depression. The amount of the R offset relative to the iso-electric line or the matching R-onset value is used to determine whether the ST level is elevated or depressed. T wave amplitude, Q wave amplitude, QRS peak, and ST deviation measure are all time-domain features that are extracted for each beat and combined for 12-leads to generate a feature vector. Overall, each feature vector contains 144 elements extracted using different methods of standardization ranging from Mean, Standard Deviation to Variance. The number of beats of nine types of Myocardial Infarction and normal subjects is shown in the below table. A total of 35,320 ECG beats of health and nine types of MI are used in this project.

MI Type	NO. OF BEATS
LMI	3726
AMI	3598
ILMI	3488
ALMI	3555
IPMI	3540
IPLMI	3765
PMI	2896
IMI	3461
ASMI	3556
NORM	3735

3.1.5 Train-Test Split

Using the StratifiedKFold cross-validation method with shuffling allowed, the whole data was separated into training (75 per cent) and testing (25 per cent) data. The StratifiedKFold method ensures that all classes are distributed equally.

3.1.6 Model Training

Used four dense layers , every time followed by a Batch Normalisation. Since the input matrix was a column vector with shape (144, 1), Each dense layer was activated using the 'ReLU' activation function because compared to the 'sigmoid' and 'tanh' functions, 'ReLU' converges faster and helps get over the over-fitting problem. I also used BatchNormalization() layers to standardize the input and prevent generalization errors. In the end, the model contained the most crucial ’softmax layer’ or the classification layer. For training, fit the model and trained it for 300 epochs, keeping batch size = 256 (must be a power of 2). These hyperparameters had been checked and tuned up. The model showed an overall accuracy of 94.67 percent on the test data set.

3.2 4 Leads/7 Classes ANN Model

As we have seen in the above model that the the data is highly imbalanced so in this model we have tried to club some classes to make it balanced as we have seen in the above table that the frequency of the IPLMI,PMI,AMI classes are very low as compared to the other classes. For balancing we have replaced the IPLMI, PMI classes into IPMI and AMI classes into ASMI. So in this model the total number of classes present are 7 . This project work uses the PTB-XL data-set present as open-access on Physio-net. The PTB-XL Electrocardiogram data-set is a huge collection of clinical 12-lead Electrocardiograms from 10sec long patients. The records for the ECG signals are present at sampling frequencies 500 Hz and 100Hz. For the project, I have used the ECG data recorded at a 500Hz of sampling frequency. The data-set also contains records for Normal sinus rhythm (NORM) and MI, which are divided into nine subcategories: anterior-septal MI (ASMI), Anterior MI (AMI), inferior MI (IMI),anterior-lateral MI (ALMI), inferior-posterior MI (IPMI), inferior-lateral MI (ILMI), posterior MI (PMI), inferior-posterior-lateral MI (IPLMI), and lateral MI (LMI). The table below illustrates the frequency of each of these MI classes in the PTB-XL data-set.

The table above also shows that the dataset is highly unbalanced.

CLASSES	FREQUENCY
ASMI	2173
ALMI	164
IMI	2329
ILMI	393
IPMI	94
LMI	132
NORM	4000

3.2.1 Balancing The Data-Set

This was accomplished by oversampling classes with a lower frequency and undersampling classes with a higher frequency. In the code 'imblearn's SMOTENC' class available in Python was used for oversampling and undersampling purposes using categorical features. As a result, doing so eventually balances the initial data. Furthermore, each ECG record in the dataset was given a label.

3.2.2 Data Pre-Processing from the Beats

Using the 'wfdb' package, each ECG signal from the dataset was read into a matrix at a sampling frequency of 500Hz. Each lead/channel was separated from the signal one by one and sent to remove the trend from the time series and remove noise. The data-filtering function was created using the SciPy library's 2nd order digital Butterworth and zero-phase digital filters, which also functioned as high and low pass filters. All undesirable frequencies below 0.5Hz and above 40Hz were successfully eliminated after passing through these filters.

3.2.3 Feature Extraction from the Beats

In the code, firstly only the Leads I,II,VI and V5 are selected from the 12 leads and then each of the 4 ECG signal leads was sent for ECG delineation, where the Hamilton Segmenter peak detection method was utilised to detect all of the R-peaks. In the code, the inbuilt 'discrete wavelet transform method ' was used to detect the QRS-onsets, QRS-offsets, and T-peaks based on those discovered R-peaks, and the 'peak' approach to detect the Q-peaks from all the beats. The key markers of an ECG beat are Q wave, T wave, and ST level elevation or depression. The amount of the R offset relative to the iso-electric line or the matching R-onset value is used to determine whether the ST level is elevated or depressed. T wave amplitude, Q wave amplitude, QRS peak, and ST deviation measure are all time-domain features that are extracted for each beat and combined for 12-leads to generate a feature vector. Overall, each feature vector contains 48 elements extracted using different methods of standardization ranging from Mean, Standard Deviation to Variance. The number of beats of six types of Myocardial Infarction and normal subjects is shown in the below table. A total of 26,813 ECG beats of health and nine types of MI are used in this project.

MI Type	NO. OF BEATS
LMI	3938
ASMI	3800
ILMI	3863
ALMI	3804
IPMI	3771
IMI	3759
NORM	3878

3.2.4 Train-Test Split

Using the StratifiedKFold cross-validation method with shuffling allowed, the whole data was separated into training (75 per cent) and testing (25 per cent) data. The StratifiedKFold method ensures that all classes are distributed equally.

3.2.5 Model Training

Used four dense layers , every time followed by a Batch Normalisation. Since the input matrix was a column vector with shape (48, 1), Each dense layer was activated using the 'ReLU' activation function because compared to the 'sigmoid' and 'tanh' functions, 'ReLU' converges faster and helps get over the over-fitting problem. I also used BatchNormalization() layers to standardize the input and prevent generalization errors. In the end, the model contained the most crucial 'softmax layer' or the classification layer. For training, fit the model and trained it for 200 epochs, keeping batch size = 256 (must be a power of 2). These hyperparameters had been checked and tuned up. The model showed an overall accuracy of 91.21 percent on the test dataset.

Chapter 4

Conclusion and Future Work

Following thorough examination of several sorts of research publications, we now have a better understanding of ECG signal filtering and signal processing, including an in-depth examination of feature extraction, noise removal, and support vector machine approaches. Various wavelet transforms can be used to eliminate noise from ECG readings, and different support vector machines can be used to detect deviations and distractions in any of the waves. Pre-processing, segmentation or segregation, and denoising are the general approaches utilised in all signal processing, and support vector machines are used for classification and post-processing. We have also followed the trend and extracted the data from PTB XL Data-set then Balanced the given data after that Data Pre-Processing and Feature extraction from the beats parts are done and the data was split-ted for training and testing.We have trained two ANN models one with 12 Leads/10 Classes and 4Leads/7 Classes. As for the future works :

- Studying more Deep Learning Models
- Testing the Algorithm on the PTB-XL data set
- Implement for Detection of MI stages using the Model

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