Detection of Myocardial Infarction from 12 Lead ECG Images

A thesis submitted in the fulfilment of
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Master of Technology
in
Signal Processing and Machine Learning
by

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Dedicated to
My Parents

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Abstract

Electrocardiogram (ECG) is one of the most practiced methods used by cardiologists across the globe to detect any heart function abnormalities. ECG results are printed on paper by the ECG machines. The lab technician or attendant submits these ECG printouts to the expert physician to study and diagnose the ailments. The ECG printouts are taken round the clock, leading to a large volume of paper records that are difficult to read and may result in an erroneous diagnosis. There is a severe shortage of cardiologists in developing countries like India. Myocardial Infarction (MI) is the leading cause of the growing global mortality rate and can be detected from ECG. There is this lack of expert physicians in rural areas and the cruciality to act stat to prevent death due to MI; there is a need to detect cardiovascular diseases like MI from the multi-lead ECG images.

In the present work, we propose a method to detect MI from 12 lead ECG images with the performance of accuracy 0.8780 sensitivity 0.9286, and specificity 0.7894.

Contents

Chapter 1

Introduction

Electrocardiography(ECG) is a graphic tracing method of the electric current generated by the heart muscle during a heartbeat. The tracing is recorded with an electrocardiograph machine, and it provides information on the condition and performance of the heart. [20] The ECG machine was invented by Dutch physiologist Willem Einthoven in 1903. During the late 1960s, computerized ECG came into use in many of the larger hospitals. The conventional 12-lead ECGs are obtained by applying electrodes (also known as leads) to various parts of the body. These leads record the electrical activity of the heart, are placed at ten different locations: four on the limbs and six at different locations on the anterior surface of the chest. [20]

The ECG can be divided mainly into three parts: the P wave, which represents the atria's depolarization; the QRS complex, which represents the depolarization of the ventricles; and the T wave, which represents the repolarization of the ventricles. [15] Heartbeat of a healthy person starts with the SA node generating an electrical impulse that spreads throughout both atriums, resulting in the depolarization of atria. This signal then passes through the AV node down into the bundle of His and the Purkinje fibers. The Purkinje fibers spread this signal down to both ventricles, resulting in ventricular depolarization. [15] This complete cycle of results into characteristic ECG tracing that we obtain. To the cardiologist, an ECG conveys a lot of information about the function of its electrical conduction system and the structure of the heart. [26] The ECG image is shown in Figure 1.1.

There is an inherent problem in the ECG machine commonly used, as the ECGs are printed on paper. The lab technician or attendant submits these ECG printouts to the expert physician to study and diagnose the ailments. The ECG printouts are

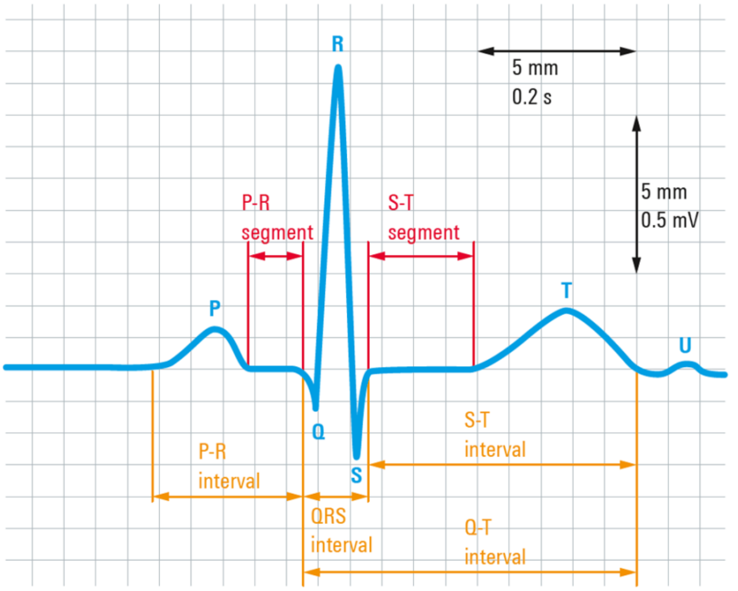

FIGURE 1.1: Single Lead ECG Image

taken round the clock, especially for critical patients. These lead to a large volume of ECG paper records, which are difficult to read and may cause erroneous diagnosis.

There is another big issue the developing countries are facing. There is a severe shortage of cardiologists in developing countries like India. Professor and HoD, Department of Cardiothoracic and Vascular Surgery, AIIMS Dr. Shiv Choudhary said that the country requires about 8,500 CTVS against the current 1,200-1,500 doctors. [21] A report on NDTV last year said that India has some 30 million heart patients, out of which 14 million reside in urban areas and 16 million in rural areas. [7] As we can see, the condition is worst in rural and urban areas where there is a lack of physicians who can interpret the ECG, diagnose and perform surgery.

Myocardial infarction(MI) is the medical name for a heart attack. When blood stops flowing to the heart muscle, it harms the heart muscle tissues, which results in a life-threatening condition. This is typically the consequence of a blockage in at least one of the coronary arteries. A blockage can create because of the development of plaque, a substance generally made of fat, cholesterol, and cell waste products. [17] It is expected that this death rate due to MI will become 23.6 million by 2030. According to a 2016 report from the American Heart Association, one out of three deaths is a heart attack. [28] The ECG is one of the best tools in the underlying assessment and triage of patients in whom any heart-related ailments, such as MI, is suspected. It is corroborative of the conclusion in around 80% of cases. [30] Therefore, as discussed above, the lack of expert physicians in rural areas and the cruciality to act stat, there is a need to detect cardiovascular diseases like MI from the multi-lead ECG images.

Usually, the 12 lead ECG consists of 2.5 seconds long data plotted in three rows and four columns, with the lead name written near them. Thus the total length of the strip is 10 seconds. Each ECG is divided into large boxes and small boxes to help measure times and distances. The standard ECG recording speed is 25 mm per second. Each large box is of length 5 mm and thus represents 0.20 seconds. There are five small boxes in each large box; hence each tiny box is equivalent to 0.04 seconds. But, a printed multi-lead ECG record also includes many annotations that contain the patient record. While taking the ECG image, we have to remove these printed characters or annotations. The 12 lead ECG chart is shown in Figure 1.2.

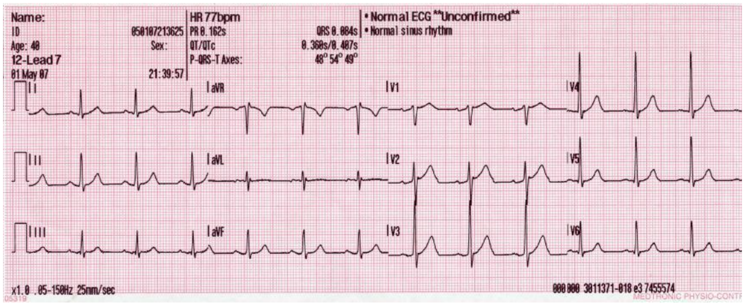

FIGURE 1.2: Scanned Multi Lead ECG Image

1.1 Related Work

In the literature, different methods are proposed, which uses different approaches to digitalize the ECG records. These methods are referred to in [3, 4, 13, 24, 25, 27]. [3] first detects the ECG background grid and then using this information [3] uses a method based on active contour modeling to retrieve the ECG graph. In [13], digital image processing methods like morphological skeletonization and binarization have been used to convert the ECG image to digital signal form. [27] used sub-channel filters followed by an adaptive filtering algorithm to get ECG binary image extraction and retrieve the 1D digital ECG data. [24] used threshold segmentation and 2D Fourier transform techniques to retrieve the signal from single lead ECG image. [25] used adaptive and iterative image processing techniques and focused on calculating heart rate from 12 lead ECG image.

Work on detecting of myocardial infarction from multi-lead ECG is done in [2, 16, 23, 29]. [2] used a 9-layer deep neural network to detect and classify five categories of heart ailments from the ECG dataset. [16], and [29] used deep neural networks to classify and localize MI from ECG signals. [16] developed an MI classifier by combining CNN and RNN, which uses a single-lead ECG signal from wearable devices. [29] used a multi-scale discrete wavelet transformation-based feature and deep neural network to detect and classify MI. For ECG classification with SVM, different feature space details are referred to in [19, 31]. Furthermore, wavelet-based multi-scale energy and eigenspace feature [23] are also used for MI classification from ECG signals.

1.2 Proposed Approach

In our thesis, we are trying to propose a method for detecting myocardial infarction from multi-lead ECG images. The technique consists of 2 steps; first, the captured images are de-skewed, and then, using various image-processing techniques, the data is retrieved. The second step is to train the deep learning model and detect Myocardial Infarction and Healthy Subject ECG. The root-mean-square error(RMSE), mean absolute error(MAE), and wavelet PRD are used to validate the data retrieval technique from images and hence measure distortions. To verify the accuracy of the model, this method is compared with the state of the art MEES approach [23]. This paper uses PTB dataset [1] for training and testing the model.

1.3 Thesis Organization

The rest of the thesis is organized in the following manner. The proposed data extraction method from ECG images and the proposed deep neural network are described in Chapter 2. The results are described in Chapter 3. Finally, a brief conclusion is made in Chapter 4 and sketch the future extensions of the present work.

Chapter 2

Proposed Method

The proposed method consists of two parts: retrieval of each lead ECG signal from the multi-lead ECG image and using this retrieved data to detect the Myocardial Infarction using a deep learning neural network. These two parts are described in detail in the following two sections. Due to the non-availability of open accessed ECG image data, we used a python library ecg_plot [9]. We modified this library function according to industry standards to create jpeg images of multi-lead ECGs. We further used python library Augmentor [5] to skew the pictures and increase the size of the data-set.

2.1 ECG Images to Plot

First of all, the multi-lead ECG images are scanned. Usually, the standard scanner works at 300 dpi resolution, and the standard ECG machine works at a recording speed of 25 mm per second. So, we will get a sampling frequency of 295 Hz from the images; that is, we can say that we will get the sampled data points at 295 Hz (=(300 dpi * 25 mm/s) / 25.4 mm). Also, the input scanned images may be skewed at some angle. So, de-skewing is done using box-detection algorithm in OpenCV [8] as shown in Figure 2.1. The resultant images might be of different dimensions. So they are resized such that the sampling frequency becomes equal to 250 Hz. The next step is to select the area of interest. As we have discussed, the multi-lead ECG image also includes many annotations that contain the patient record. Before feeding the ECG images as input to the next step, we have to remove all these printed characters or annotations. We will crop out these annotations manually. The standard multi-lead

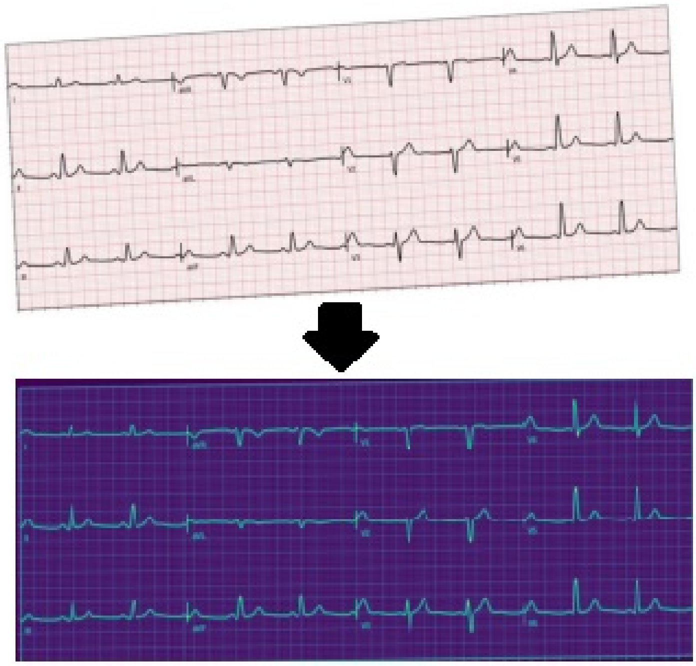

FIGURE 2.1: De-skew the ECG Image

ECG paper consists of 12 leads distributed in three rows and four columns. Each lead signal is of length 2.5 seconds, and covers 12.5 big squares as the recording speed is 25 mm/sec. So in this step, we divide the image into 12 different parts consisting of three rows and four columns. This step is flexible and depends on the standard used by the manufacturer of the ECG machine. Thus, each 12 leads images are separated, as shown in Figure 2.2. After cropping out the lead data area, 12

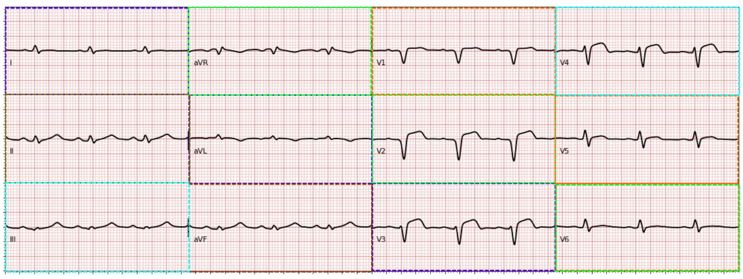

FIGURE 2.2: ECG images are partitioned and cropped

images each of different leads are obtained from each multi-lead ECG image. The ECG plot color is black on red grid lines, so we convert these images into grayscale. We use a Laplacian filter to remove any background noise and make them fainter than the primary ECG signal. A threshold of value (125/255) is selected to convert the images to binary form.

To remove any annotations still left in the images, we use a region-based segmentation from the paper [10]. The isolated pixels that do not represent the signal (printed characters) are removed from the graph. In this step, Pytesseract library [6] is also used to detect and crop out any text written on the image.

In the next step, a vertical scan is employed to find out the black pixels of thickness more than a threshold (here, we used 3), and has been recorded in an array(Figure 2.3). If no valid pixels are detected for any vertical scan, then the previous two values' average values and the following two values are taken. If the plot goes out of the bound, then the only average of the last two values is used. During

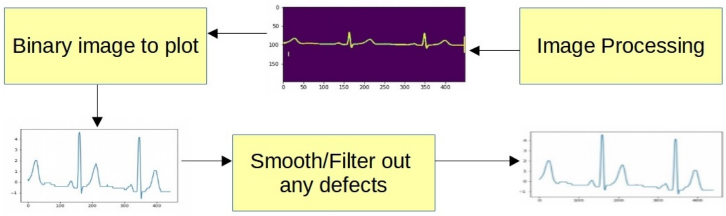

FIGURE 2.3: ECG Image to digital ECG signal(plot) conversion

image processing, we have done de-skewing and cropping work. We have also done cropping while choosing the area of interest. These steps change the length and width of the image. This changes the number of sampled data points along the time-axis(x-axis). To correct this, we use interpolation to correct this defect. Here, this work uses the ECG signal sampled at 250 Hz of 2.5 seconds, so the required number of data points is 625. We perform interpolation such that the output data is of length 625 sample points.

The signal retrieved in the above step is not smooth and may contain step like erratic changes. Hence, we apply a moving average filter of a certain length(here, 5) to smooth out any abnormalities(Figure 2.3).

For the detection of myocardial infarction, the DNN uses the shape of the ECG beat. This work uses MinMaxScaler to normalize the retrieved signal from the above step to get a zero-mean signal. The equation for normalization is shown in 2.1.

$$x[n] = \frac{x[n] - min(x)}{max(x) - min(x)} \tag{2.1}$$

Distortion analysis of the retrieved data is performed, and the original information is compared with the retrieved data to evaluate the proposed method. Various methods like Root Mean Square Error(RMSE), Mean Absolute Error(MAE), and Wavelet Percentage Root-mean-square Difference(WPRD) measures are employed to find the fidelity of the data recovered. (Figure 2.4) shows a comparison between original and retrieved data of a lead from ECG images.

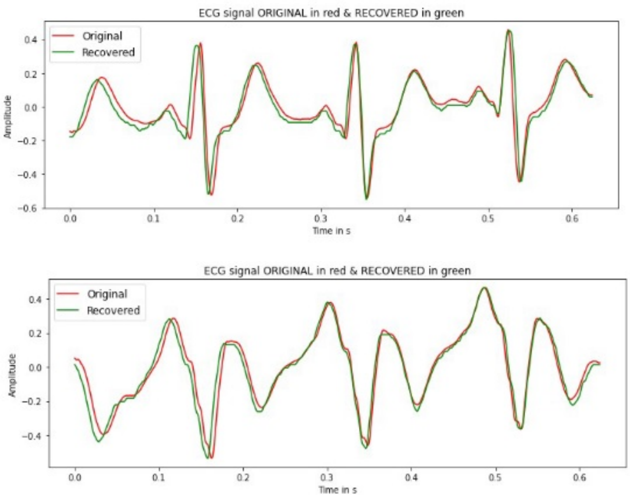

Figure 2.4: Original(in Red) vs Retrieved Data(in Green)

2.2 Detect MI using Retrieved Plot Data

We have used the PTB database [1] to train and test the DNN model. It consists of 549 records obtained from 290 patients. The database was published in 2004 and had records of 81 women and 209 men. The average age was 61.6 for women and 57.2 for men. Out of these 549 records, 80 records are of healthy ECG, and 368 records are of MI-diagnosed ECG. The rest of the records are diagnosed as ECG of bundle branch block, dysrhythmia, heart failure, valvular heart disease, myocardial hypertrophy, and myocarditis. We deleted the records belonging to this “rest” class and used data from the remaining 2 classes, namely, MI and HC.

Each record is sampled at a sampling frequency of 1000 Hz, which we have down-sampled to 250 Hz to reduce the computational power requirement. We have used 12 lead data out of the given 15 leads given in the dataset. The ECG records are raw and have various noises; hence denoising was performed using an IIR notch filter with the notch at 50 Hz and a moving average filter with a window of size 25. After that, the baseline wander was subtracted from the signal. Thus we have a total of 12 leads, with 625 samples(2.5 seconds * 250 Hz) per lead in each frame as input to the network.

TABLE 2.1: Architecture of CNN Classifier

Layers	Type	Output Shape
0	Input Layer	(625, 12)
1-3	Conv Block 1	(625, 128)
4-6	Conv Block 2	(625, 256)
7-9	Conv Block 3	(625, 128)
10	Global Avg Pool	(128)
11	Dense	(1)

The deep neural network is made from 3 CNN blocks. Each CNN block consists of 3 layers, 1d convolution layer, batch normalization layer, and a ReLu activation layer. Three such convolution blocks are used with different feature-length, as shown in Table 2.2. The 1d convolution layer finds different spatial patterns. [11] The batch normalization layer increases the training rate and prevents internal covariate shifting. [12] Finally, the last block is followed by a 1d global average pooling layer and a fully connected dense layer. The fully connected layer is used to perform the final classification. [14] Table 2.1 presents the architecture of the CNN classifier used in this study, which was constructed from three convolutional blocks.

TABLE 2.2: Architecture of Convolutional Block

Type	Filter Size	Kernel Size
Covolutional 1D	128/256/128	"Same"
Batch-Norm	-	"Same"
ReLU Activation Layer	-	"Same"

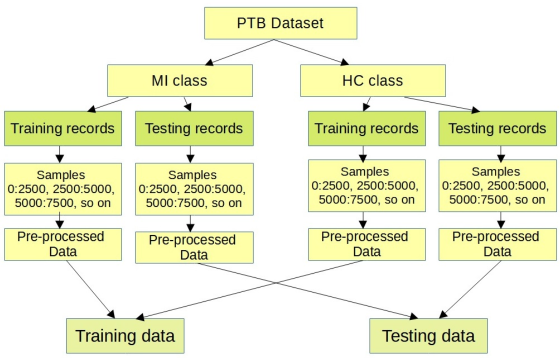

FIGURE 2.5: PTB dataset Split

The processed database is then split into training and testing parts in the 80:20 ratio, as shown in Figure 2.5. We have performed five-fold cross-validation on the model trained in this section. During five-fold cross-validation, the training part of the samples was further divided into an 80% training set and 20% validation set, as shown in Figure 2.6. In each fold, different 20% data is used for validation, and the rest 80% is used for training the model. The validation set helps prevent over-fitting of the model and performs early stopping the training process.

The model is trained on the ECG dataset as discussed above, and the data retrieved from section II is used to evaluate the model. To assess the performance of the classifier, the sensitivity, specificity, and accuracy for the MI class were computed and compared with the state-of-the-art paper [23].

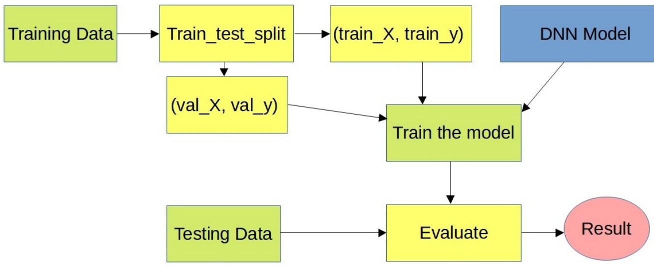

FIGURE 2.6: Training the Model

Chapter 3

Results

As discussed in Chapter 2, the PTB dataset is split into 2 parts as shown in Figure 3.1. Then, using testing records, 1927 ECG images are created with the help of a modified version ecg-plot library [9] of python.

Table 3.1: PTB Dataset Split

Class	Actual Records	Train Records	Test Records	Train Dataset	Test Dataset
Myocardial Infarction	148	118	30	5318	1372
Healthy Subject	54	42	12	1946	555
Total	202	160	42	7264	1927

Using the proposed method from Chapter 2, the ECG images were read, and the multi-lead data is retrieved. The retrieved information is compared with the original data from which the ECG images were formed. Root-Mean-Square-Error(RMSE), Mean-Absolute-Error(MAE), and Wavelet Percentage Root-mean-squared Difference(WPRD) [18] measures are calculated to find the fidelity of the data recovered and perform a quantitative comparison. The WPRD results for each lead are attached in Table 3.2. The value of Root-Mean-Square-Error(RMSE) obtained is 0.0551, and Mean-Absolute-Error(MAE) is 0.0451.

TABLE 3.2: WPRD values of each subbands for 12 ECG leads for 6 level wavelet decompositions

Coeff	I	II	III	aVL	aVR	aVF	V1	V2	V3	V4	V5	V6
cA6	0.431	0.216	0.392	0.161	0.423	0.279	0.270	0.376	0.400	0.453	0.204	0.308
cD6	0.235	0.304	0.337	0.306	0.241	0.272	0.371	0.292	0.364	0.488	0.433	0.451
cD5	0.625	0.396	0.588	0.499	0.561	0.435	0.627	0.386	0.567	0.725	0.521	0.513
cD4	0.798	0.605	0.864	0.572	0.786	0.793	0.805	0.593	0.708	0.903	0.657	0.659
cD3	1.170	1.080	0.835	0.793	0.924	1.024	1.206	0.733	1.101	1.257	0.884	0.966
cD2	1.040	1.615	1.296	1.265	1.151	1.319	1.158	0.944	1.353	1.333	0.997	1.115
cD1	0.657	1.428	0.707	0.860	0.580	0.718	0.689	0.508	0.783	2.714	0.910	1.046

The distortion measured is maximum in cD3, cD2, cD1 bands, which are usually ignored as they contain high-frequency components. So it can be concluded that the retrieved data is quite accurate and can be used to detect Myocardial Infarction.

The deep neural network is trained as described in Chapter 2 and after five-fold cross-validation, the confusion matrix, precision, recall and f1-score are calculated with the formula shown in 3.1, 3.2 and 3.3. The results are shown in Figure 3.1.

$$Sensitivity = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{3.1}$$

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives} \tag{3.2}$$

$$Accuracy = \frac{TruePositives + TrueNegatives}{TotalNumberofSamples} \tag{3.3}$$

The accuracy, sensitivity, and specificity of the model are calculated in percentage and are compared with the state-of-the-art paper [23]. The paper[11] was implemented, and the results are calculated for comparison. The results are shown in Table 3.3.

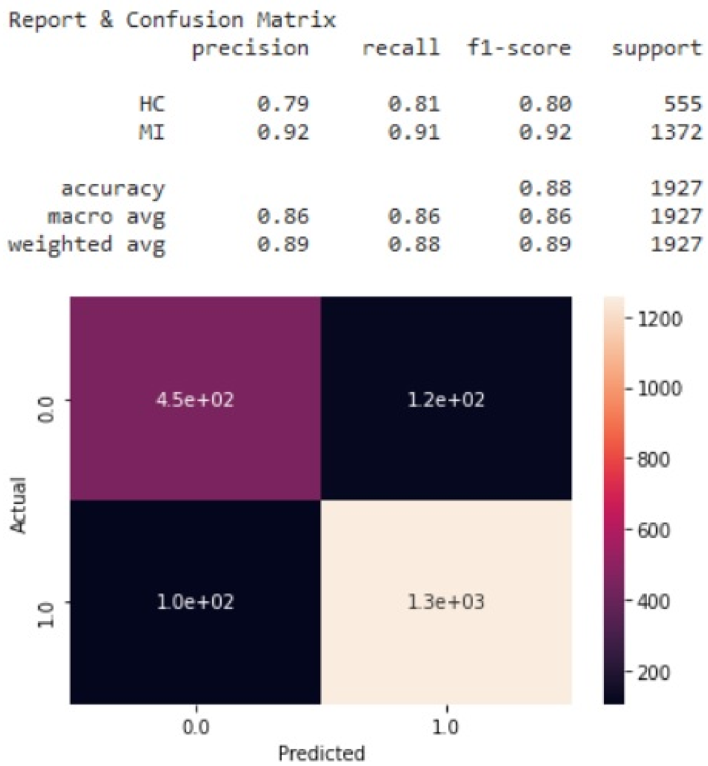

FIGURE 3.1: Confusion matrix after 5-fold Cross-Validation

TABLE 3.3: Performance comparisons with existing method

Classifiers	Sensitivity(%)	Specificity(%)	Accuracy(%)
KNN [23]	85	77	81
SVM Linear [23]	90.42	87.69	89
SVM RBF [23]	93	99	96
Implemented KNN [23]	88.23	69.81	83.07
Implemented SVM Linear [23]	81.25	84.56	81.73
Implemented SVM RBF [23]	93.53	85.77	91.31
DNN model	92.86	78.94	87.80

Chapter 4

Conclusion and Future Work

In the first phase of the MTech Project, we have developed a method to detect myocardial infarction from multi-lead ECG images using a deep neural network. The model achieved the performance of accuracy 87.80%, sensitivity 92.86%, and specificity 78.94%. We compared our proposed method with other existing methods. Our model shows comparable results with the existing models, which do not use ECG images for MI detection.

Further work could explore training the model on a larger dataset like PTB-XL [22], which consists of a dataset of 21837 12-lead ECGs. The data is taken from 18885 patients, and each record is of 10 length seconds. The designed deep neural network model can be used as a baseline model, and it can be further improved and tuned for better performance.

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