Detection of Myocardial Infarction in ECG Base Leads using Deep Convolutional Neural Networks

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Abstract

Myocardial infarction (MI), commonly known as a heart attack, occurs when blood flow decreases or stops to a part of the heart, causing irreversible damage to the heart muscle. It is a leading cause of mortality around the world according to the WHO reports and, therefore, it is critical to estimate the location & extent of the damaged tissue. Similarly, localization of MI is also significantly important to correctly manage the patient medically and/or surgically. In this paper we propose & implement a system in which the signals from 6 leads (I, II, III, aVR, aVL, aVF) of the ECG are used to detect the cases with MI in the lateral &Inferior walls of the heart. The use of Convolutional Neural Networks (CNN) & a novel voting scheme provides acceptably accurate estimates of MI. The proposed algorithm has been validated on MI & Normal Healthy Controls from the Physio Net dataset. This approach is robust & can be used in the clinical & research settings.

Keywords: Machine Learning, Bio Medical Signal Processing, Artificial Intelligence, ECG.

1 Introduction

Myocardial infarction (MI) or simply heart attack is a life threatening condition which occurs when there is a decrease or absent blood flow to the heart, resulting in damage to the cardiac muscles [1]. Heart receives oxygen rich blood through specialized arteries called coronary arteries. In certain conditions, there is a blockage of these coronary arteries, resulting in decrease or absent blood flow to the heart. The segment of the heart muscles, which is deprived of oxygen got damage resulting in MI. If timely treatment is not given, this damage can even be fatal [2].

Worldwide, Myocardial infarction (MI) is a leading cause of morbidity and mortality [3]. According to WHO, there are 32.4 million myocardial infarctions worldwide every year and about 17.7 million people die of cardiac diseases every year, 31% of all global deaths [4]. A lot of deaths caused by MI, can be prevented by an early treatment. There is a very narrow time frame, in which if proper treatment is given, the damage can be reversed to some extent. Therefore, in the management of MI, an early detection is crucial.

The basic, first line investigation, used to detect heart attack is ECG (Electrocardiogram). An electrocardiogram is a picture of the electrical conduction of the heart and is depicted in time vs. amplitude plot as shown in Fig I [6]. It is a non-invasive, economic mode of investigation which is performed by placing electrodes on the skin. It can measure heart rate and heart rhythm, as well as indirectly provide information about blood flow to the heart muscle. By comparing it to the normal signals obtained, clinicians can diagnose a number of heart diseases [5, 6].

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A standardized system of electrode placement for an ECG has been developed. There are a maximum of 12 leads. However, ECG can also be performed by using 6 leads. These six leads are called lead I, II, III, aVL, aVR and aVF.

The signal from these leads can be used to detect the anatomic site of myocardial infarction. Different studies have shown that ST segment elevation in leads I &aVL indicate infarction in the Lateral wall while signal in the leads II, III and aVF reflect the health of the Inferior wall [7, 8].

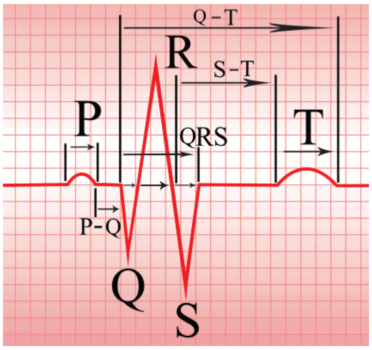

Figure 1: Components of the ECG Signal

Though ECG is a relatively simple test to perform, its interpretation requires significant amounts of training. Even after that, there is a huge room for error. As reported in [21] in which, 49% of the evaluators identified a normal ECG as ischemic and only 19% were able to correctly identify normal from abnormal scenarios. The same study [21] further reports that none of the evaluators were able to denote the correct leads, locations or amplitude of the ST-segment elevation. So a standardized, automatic method is required to interpret ECGas suggested in [20] especially in clinics where the experience, interpretation skills and/or expertise of the clinicians is below that of their counterparts in developed regions.

As seen in the [9, 10, 11], normally the ECG signal is de-noised and base line wandering is removed from the signal before extraction of features for further analysis using Artificially Intelligent systems, however as seen in [11], this process does not have a huge impact on the overall results of the system. Furthermore there is no consensus in the available literature regarding the features to be used for automatic MI detection from the ECG signals, therefore, we have followed the approach in [11] and have utilized deep learning approach for the task at hand. Also we propose that interpreting signals from multiple leads and then achieving a consensus (via voting) can achieve better results that [11]. This would reduce the misinterpretation(s) in case only signal from only one lead was evaluated.

Deep learning is a representation based learning which consists of an input layer, hidden layers, and an output layer [12]. This provides a network of systematic procedures which can be fed the raw data and the system automatically learns the necessary representations for classification. The term deep describes the multiple stages in the learning process of the network structure [12]. The deep learning neural network is trained using the backpropagation algorithm. The CNN is one of the most popular neural network techniques and provides quite desirable results [13].

A Convolutional Layers

The basic building block for any CNN is the convolutional layers which are responsible for most of the computational processing. These layers automatically extract the features from the input data.

B Rectifier Linear Unit Activation Function

Activation functions are an important part of the neural networks and are used to evaluate the excitement level of the neurons. Rectifier linear units (RELU) are interesting especially since they introduce nonlinearity in the data [17].

C Pooling Layers

Pooling function serve to down-sample and condense the features in the network thus reducing the overall computational complexity. Max-Pooling outputs only the maximum value from each kernel while sliding by a preset amount over the whole feature set. The sliding operation is called stride [17].

D Fully Connected Layer

Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular neural networks [17].

To prevent the misinterpretation in critical events such as MI, this paper proposes a system which can plausibly detect cases of MI in the lateral and inferior walls of the heart. The proposes method uses CNN and a voting scheme to demarcate MI from normal healthy controls more accurately. The rest of the paper is organized as: Section II – Dataset, Section III – Methodology, Section IV – Results, Section V – Discussion and Section VI – Conclusion.

Table 1: Characteristics of the Dataset

	MI	Healthy
Age Range	36 - 86	17 - 81
Average Age	60.37	43.4
Male	110	39
Female	38	13

2 Dataset

In this paper, we have used the Physikalisch-TechnischeBundesanstalt diagnostic ECG database [14] available on PhysioNet[22]. This database contains 12 lead simultaneous signal data for 148 patients diagnosed with MI in different cardiac regions. Also data for 52 Healthy patients is available for control purposes. The signal has been sampled at 1000 Hz. The characteristics for the patients considered in this study are provided in the Table I.

3 Methodology

A Preprocessing

In this study we only considered patients with Acute MI involving the inferior or lateral wall of the cardiac muscle. First of all the R-peak detection was carried on the ECG signals of the selected patients using Pan Thompkins algorithm [15]. Then the signal was segmented using the detected R-peaks after omitting the first & last peak in each lead. Each segment consisted of 651 samples as described in [11] (250 samples before the R-peak and 400 samples after the peak ensuring the complete P-QRS-T wave is present in each segment. Z-Score normalization [19] was applied on each segment with the aim to resolve the amplitude scaling problem. Furthermore no noise removal or base line wandering correction was performed on any of the signals before or after the segmentation. The resultant segments were further divided in 2 different sets with ratio 80:20 for training & testing purposes respectively. After the preprocessing step we had 33,796 beats for the training set and 8,449 beats were set aside for testing purposes. The training set was now shuffled in order to ensure a randomized data is being fed to the neural network. Overall we had data for 42,245 individual beats out of which 31,671 were diagnosed as having MI in the Inferior or Lateral walls while 10,574 beats were extracted from ECG records of healthy patients for control purposes.

B Network Architecture

In this work we trained 6 individual Convolutional Neural Networks with similar structure as [11]. Each network consisted of 11 layers as shown in Figure II. The Input Layer (layer 0) takes 651 inputs which is then fed to a 1-D convolutional layer with kernel size 102. Next max pooling with step size 2 and stride of 2 is applied on each feature map in layer 2. This reduces the number of neuron from 550x3 to 275x3. In layer 3 the feature map is again convolved with kernel with filter size 24, following which max-pooling similar to layer 2 is once again applied in layer 4 reducing the neurons further to 126x10. Convolution with filter size 11 is once again applied in layer 5 followed by another max-pooling in layer 6 reducing the neurons further to 58x10. A final convolution with filter size 9 is applied to this feature map in layer 7 followed by another max-pooling in layer 8. We are now left with a feature map with 25x10 neurons. This feature map is flattened and fed to a fully connected layer with output size 30. Layer 10 is again fully connected with 10 units. Finally fully connected layer # 11 has the 2 output neurons.

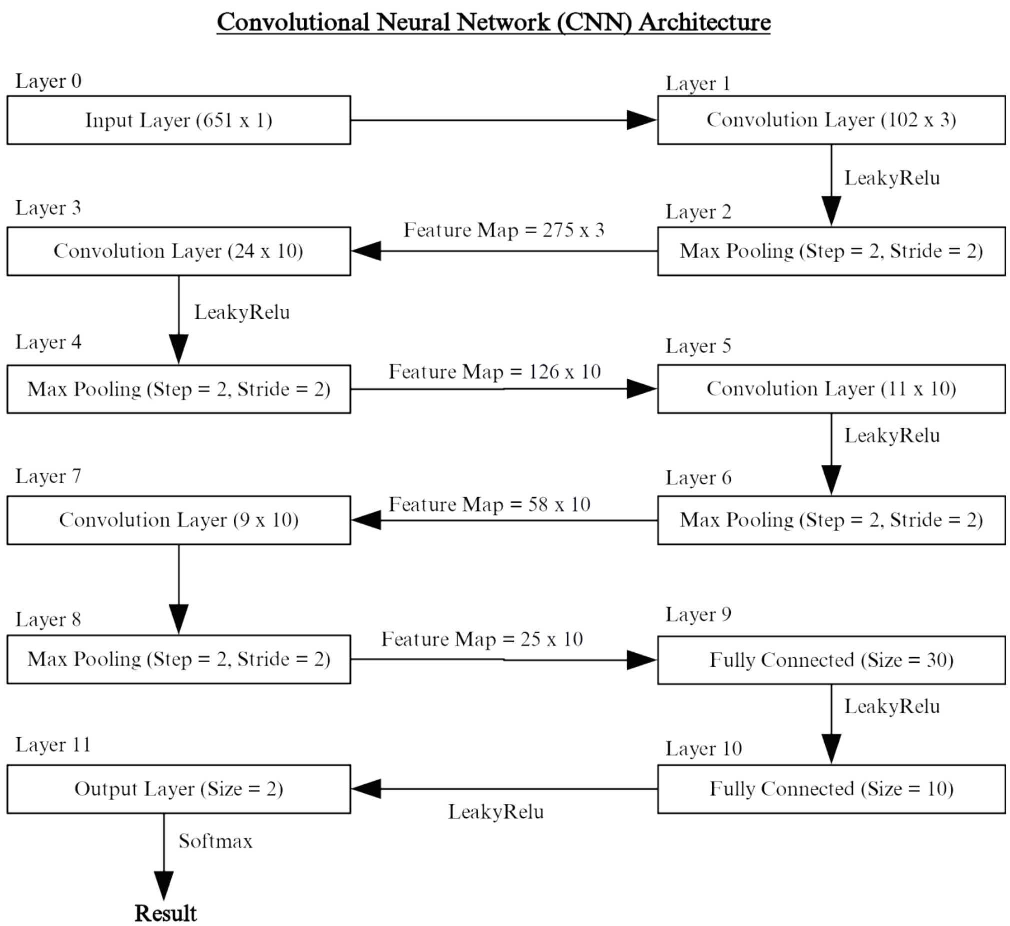

Figure 2: Convolution Neural Network (CNN) Architecture All the 6 CNNs have same architecture for respective leads

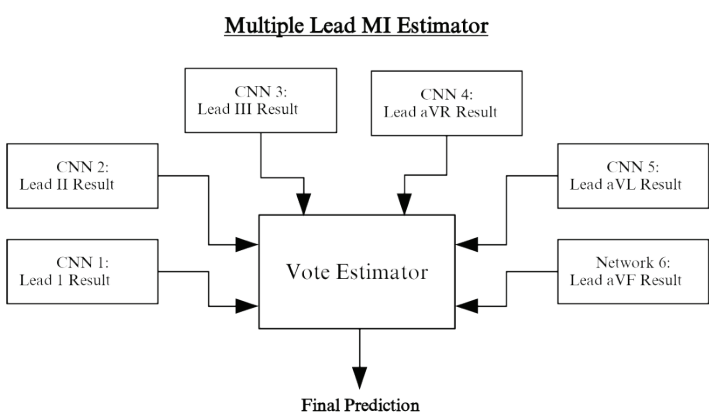

Figure 3: Vote Estimator The results of respective CNNs are input to the Vote Estimator which generates final prediction based on consensus

Table 2: MI Detection using Individual Leads

Lead	Train Accuracy	Test Accuracy	Sensitivity	Specificity	PPV	NPV
I	91.59%	92.20%	94.97%	83.86%	94.66%	84.71%
II	96.49%	96.39%	97.93%	91.74%	97.27%	93.65%
III	97.35%	97.47%	99.51%	91.31%	97.18%	98.41%
aVR	93.82%	92.46%	93.05%	90.70%	96.79%	81.25%
aVL	96.34%	97.46%	98.20%	95.21%	98.40%	94.62%
aVF	97.59%	97.82%	98.36%	96.20%	98.73%	95.12%

Table 3: MI Detection Using Multiple Leads

Votes	Accuracy	Sensitivity	Specificity	PPV	NPV
1	93.53%	100.00%	74.04%	92.06%	100.00%
2	96.84%	100.00%	87.33%	95.96%	100.00%
3	98.01%	99.95%	92.17%	97.46%	99.85%
4	98.98%	99.72%	96.77%	98.94%	99.12%
5	97.61%	97.18%	98.91%	99.63%	92.09%
6	88.83%	85.18%	99.81%	99.93%	69.11%

Leaky Rectifier Unit (LeakyRelu)[17] was used as activation functions in layers 1, 3, 5, 7, 9 and 10 and softmax was implemented in for the output layer.

C Vote Estimator

The output from the 6 individual CNN is generated as absence or presence of MI in the respective lead. These are input to the Vote Estimator (Fig III) which draws a consensus. If the presence of MI is indicated in at least 4 or more leads only then the system raises a true response.

D Training

The CNN was trained with Adam Stochastic Optimizer [16, 18] with batch size 500 for each lead. The learning rate, beta1, beta2 and decay parameters are set to 0.001, 0.9, 0.999 and 0 respectively for each network while minimizing the mean squared error. These parameters perform the following functionalities in the network [16, 18]

Learning Rate:	Helps with Data Convergence
Beta1:	The exponential decay rate for the first moment estimates
Beta2:	The exponential decay rate for the second-moment estimates
Decay:	The learning rate decay over each update

E Implementation, Testing & Validation

We ran each network for 25 epochs of training & testing rounds. After the completion of each epoch, the network was validated with the testing data for the corresponding lead.

We did not employ cross-validation in our current work. Finally after all the networks have been trained and tested with train & test beats data for their corresponding leads we once again tasked the trained networks for prediction on the test data for the respective leads. A final score for each test record was calculated based on the minimum number of networks voting the record as a healthy beat or indicating the patient had MI.

4 Results

In this study we implemented the above mentioned system using Keras® and Tensorflow® on Python®.

The algorithm was trained on a machine with Intel core i5 processor and 16 GB Ram. We also utilized nVidia GTX 950 GPU with 4 GB VRAM to aid in our training. It took approximately 200 seconds to completely train 25 epochs for each network. The training & testing accuracy along with sensitivity, specificity, PPV & NPV [19] for each lead is presented in Table II and visualized in Figure IV.

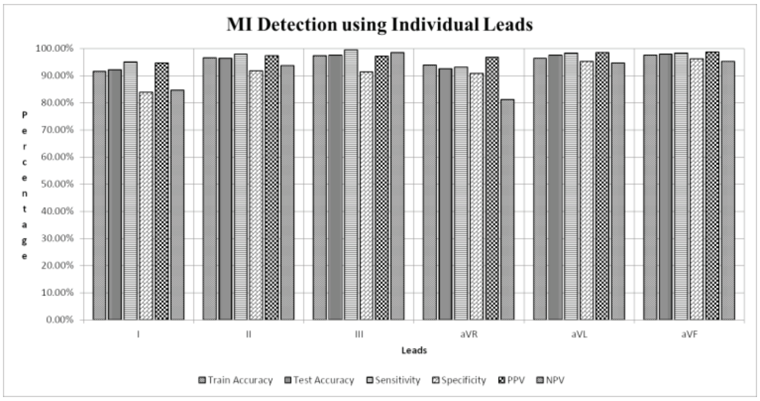

Figure 4: MI Detection using Individual Leads

It can be seen that individually each lead was able to accurately determine approximately 95% of the test data while the sensitivity & specificity figures also generally remained in high and low 90s respectively rarely rising above the 99% and 95% marks respectively.

Next step was the estimation of the test data using the novel voting scheme described above. We calculated the MI estimates from where only 1 lead marked the record as positive to where all 6 participating networks had to agree before classifying the record as a positive for the disease. The testing accuracy, sensitivity & specificity results for the voting are presented in Table III and have also been visualized in Figure V.

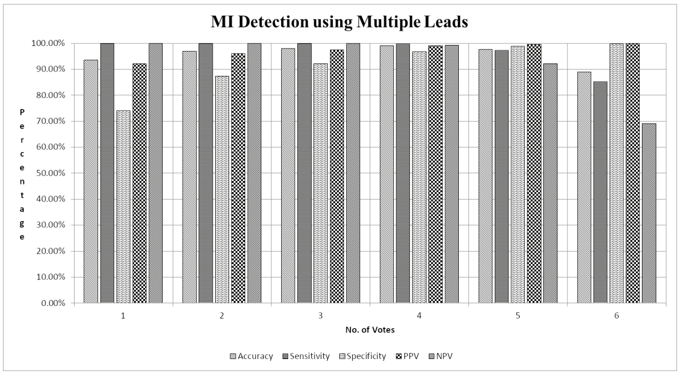

Figure 5: MI Detection using Multiple Leads

Here it can be observed that we can achieve 98 percent accuracy with the requirement of at least 3 leads agreeing on the outcome, while achieving the sensitivity at 99.9 percent mark. Requiring a simple majority i.e. at least 4 networks to agree on the outcome, we have approximately 99 percent accuracy while the sensitivity and specificity figures are also in the top half of 90 percent. However requiring all 6 leads to agree on the positive outcome, we see the changes in every category, with accuracy and sensitivity and specificity reduced to 88.83% and 85.18% respectively while increasing the specificity level to 99.81% as can be observed in Table III and visualization of the same is Fig V. The Confusion Matrix for 4 or more votes is also provided in Figure VI.

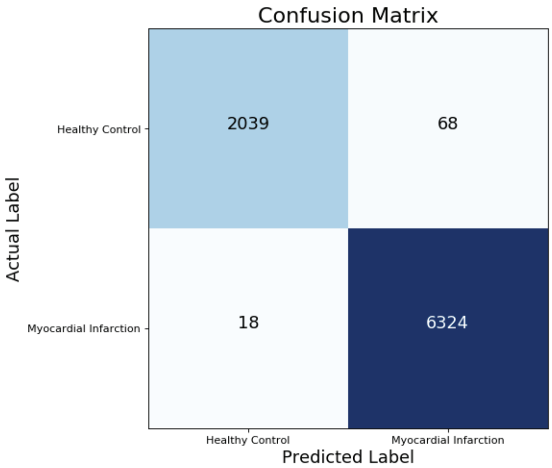

Figure 6: Confusion Matrix for 4 or more Leads

5 Discussion

The detection of MI using ECG as a non-invasive method is well established and it has been shown in literature that the response gathered through different leads of ECG can be useful in ascertaining MI s diagnosis. The experiments were designed on the above mentioned premise and the data was divided into healthy controls and MI patients and the ECG leads I, II, III, aVR, aVL and aVF were used in the algorithm.

When considering data from individual leads, it is observed that the test accuracy of more than 97% is achieved in leads III, aVL&aVF. This could be attributed to the fact that leads III and aVF represent changes due to MI in the inferior wall while the lead aVL shows changes due to MI of lateral wall. The data of the MI patients in the experiments includes samples from patients of inferior and lateral walls, as discussed in Section II. However this observation can be further exploited to localize the region of MI using the ECG base leads or all the 12 leads commonly used in emergency departments in hospitals.

To maximize the response of MI cases with higher sensitivity, a voting scheme has been adopted. The scheme considers that at least 'n' votes should favor the accuracy of final prediction and it is observed that combining the individual outputs of the respective CNN successively increases the accuracy of the proposed technique to more than 98% when n ≥4 votes favor the prediction of MI case and the confusion matrix is provided in Fug V. The constraint of maximizing sensitivity and specificity is considered during evaluation. When the condition of n ≥ 5 or n ≥ 6 votes is imposed the results show decreasing accuracy and sensitivity which construes that not all leads had voted in tandem.

Hence the empirical optimization suggests that n ≥ 4 votes should be considered in assessing the data for presence of MI will significantly improve results as compared to methods reported by other researchers.

6 Conclusion

Our work combines the concept of CNN combined with a voting scheme which uses prediction of MI from the 6 ECG leads. The results are better than the approach presented in [11] which focuses on detection of MI in the Lead II only and manages to achieve 93.53% test accuracy with 93.71% and 92.83% sensitivity and specificity respectively in the same PhysioNet dataset without baseline wander correction or applying any noise removal technique. We, on the other hand, are looking at data from the 6 base leads and the achieved accuracy, sensitivity and specificity are greater than 98%, 99% and 96% respectively when 4 or more leads vote together. Furthermore, we have limited our study to the patients with acute MI in the Inferior & Lateral walls which can be observed in the first 6 leads of the ECG signal.

Given the above 2 factors we have been able to get favorable results as compared to most recent literature. Our future approach will consider all 12 standard leads in the ECG signal and update the vote estimator algorithm to specify the probable walls where the acute MI is present in the patient and finally we also aim to validate our findings on other publically available datasets.

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