Myocardial Infarction Detection with Artificial Neural Network

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***Abstract*—Electrocardiogram(ECG) is an important tool in diagnosing cardiovascular diseases. myocardial infarction (MI) is one of the most common cardiovascular diseases in humans. Correct diagnosis is very important in a MI. ECG is an important tool to analyze the functioning of the cardiovascular system. ECG records the heart's electrical activity. Normal and abnormal beats of the heart are processed as electrical signals and transferred to a visual chart. However, it is quite difficult to visually interpret ECG signals. In this paper, we propose an approach that can automatically detect MI. We used the artificial neural network algorithm to detect normal and abnormal heartbeats. We used the PTB Diagnostics dataset in this project. We classified the data in two outputs, namely MI(abnormal) and healthy controls(normal). We achieved 91.2% accuracy in classification.**

***Keywords*—ECG, myocardial infarction, classification, artificial neural networks, machine learning**

I. INTRODUCTION

Myocardial infarction (MI) is caused when the blood flow to a segment of the myocardium is disrupted [2]. If blockage occurs in the coronary arteries, blood flow to the heart muscle decreases and the heart cannot receive enough oxygen. If the blood flow is insufficient, that part of the heart muscle will start to die [3]. Figure 1 shows myocardial infarction due to blockage of a coronary artery [4]. Blood clots can form due to plaque build-up in the artery. These blood clots, known as thrombus, block the artery. Therefore, the blood flow can be completely blocked. If the blood flow is blocked, a part of the heart muscle may be damaged and this damage will cause a heart attack.

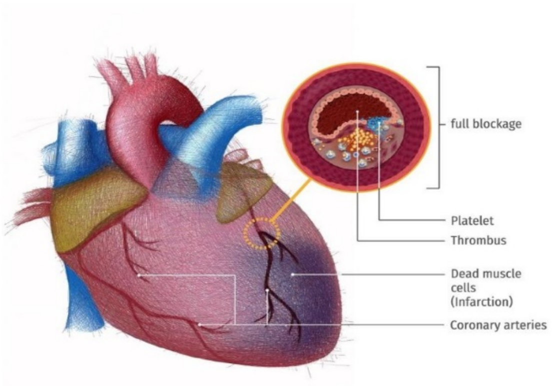

Figure 1

Most patients around the world are not aware of this congestion until they have a heart attack. According to research, about 72 percent of people with damaged heart muscle do not realize this situation. Therefore, the mortality rate in heart attacks is very high. Early diagnosis of MI is very important and treatment should be started as soon as it is diagnosed. If the heart muscles die, there is no return. Early diagnosis of MI can be conducted with ECG.

ECG is the most common method used to monitor heart health. It is used by doctors to make a diagnosis. However, ECG analysis is a difficult process and it is very difficult to detect ECG waveforms. The diagnosis may change due to minor changes in the ECG signal. So, it takes a long time to investigate and is prone to errors. According to the researches, approximately one third of the deaths in the world occur due to cardiovascular diseases. [1] For this reason, it is very important to make a correct diagnosis.

Artificial neural networks are now widely used in different clinical research and its clinical use shows high quality results especially in signal analysis such as electrocardiogram (ECG) signals. The main objective of this project is to study the applicability of artificial neural networks for the diagnosis of myocardial infarction by electrocardiogram. The main problems of every myocardial infarction detection method are complexity and a poor theoretical basis and these problems need to be solved for future developments and studies.

This study is a classification problem for artificial neural networks. There are two classes (normal and abnormal) for a ECG signal. We almost correctly detected whether ECG signals are normal or abnormal. We used a basic neural network for this study and achieved 91.2% accuracy in classification. Further researches can be done with more complex models for higher accuracy rate. These researches contribute to development of medical revolution.

The rest of this paper is organized as follows. Section II explains the datasets used in this study. Section III presents the proposed method. In Section IV, we evaluated the results and compared them with other machine learning algorithms. We have implemented other machine learning algorithms except CNN. Finally, Section V concludes the paper.

II. DATASET

We used The PTB Diagnostics dataset [7] for MI classification. The dataset includes 549 records from 290 subjects. Age distribution of samples in dataset varies from 17 to 87 with mean 57.2. While 209 subjects are male with mean age 55.5, 81 subjects are female with mean age 61.6. Each subject is represented by one to five records. Sampling rate of those records is 125 per second.

We have only worked on 200 subjects which contains 52 healthy control, 148 diagnosed as MI. The rest of the subjects have 7 another disease but we did not use those records. Because there are very few samples of diseases and number of samples is not enough for training as seen in Table 1 [7]. We have only worked on healthy and MI samples. The medical doctors and cardiologist use ECG with 12 type of leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6). In this project we used only ECG lead II because it is one of the most sufficient leads to detect the rhythm abnormalities [8].

We used a preprocessed dataset. However, the pre-processing processes are described in section III.A.

Diagnostic class	**Number of subjects**
Myocardial infarction	***148***
Cardiomyopathy/Heart failure	18
Bundle branch block	15
Dysrhythmia	14
Myocardial hypertrophy	7
Valvular heart disease	6
Myocarditis	4
Miscellaneous	4
Healthy controls	***52***

Table 1

III. METHODOLOGY

A. Preprocessing

Raw data of ECG is not suitable for training and testing. We need to process the data and extract single heart beat before using it in the neural network. For extracting steps are listed below:

- Dividing the analog ECG signals into 10 second long pieces.(Figure 2)
- Normalizing the amplitude of ECG signal between 0 and 1.
- Detecting local extremum points by using first derivative.
- Finding R-peaks points using threshold value(0.9).
- For finding nominal heartbeat period (T), detect median of time intervals between two R peaks.
- To extract single heart beat, selecting 1.2T length signal for each R-peak.
- Padding each part with zeros o make its length equal to a predefined fixed length.

After these steps, we have 14550 heart beat samples which contains 10505 MI and 4045 healthy ECG samples. Each heartbeat was examined at 1.5 second intervals. Since the sampling was done at 125 Hz, we have 187 values in this time interval. So, every beat sample is made of 187 digital value. An example can be seen in Figure 3 [6]**.** This sample is suitable for using in artificial neural network and other machine learning algorithms.

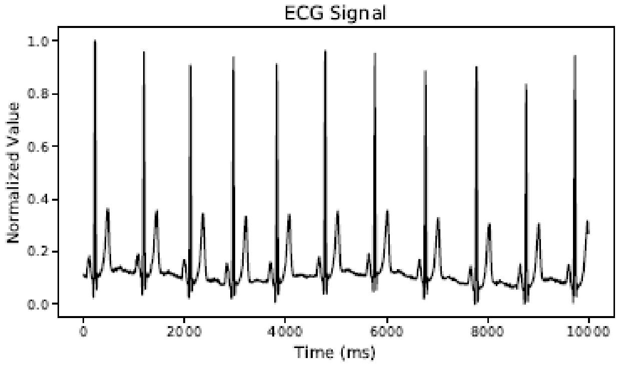

Figure 2

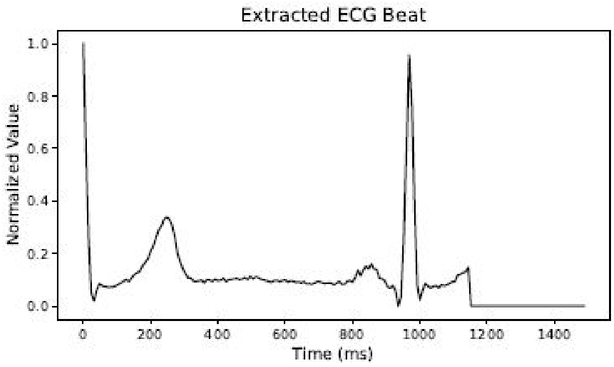

Figure 3

B. Training

The artificial neural network (ANN) classifier is created with the multi-layer perceptron (MLP) network in this study. Our network is made of 1 input layer, 2 hidden layer and 1 output layer. Input layer has 187 features (nodes). Normalization was not required because all the input features were between 0 and 1. First hidden layer has 16 nodes and second hidden layer has 8 nodes. Output layer has single node which can be binary value (0 or 1). 0 represents normal heartbeat and 1 represents abnormal (MI) heartbeats. An example for comparing normal and abnormal heartbeats can be seen in Figure 4.

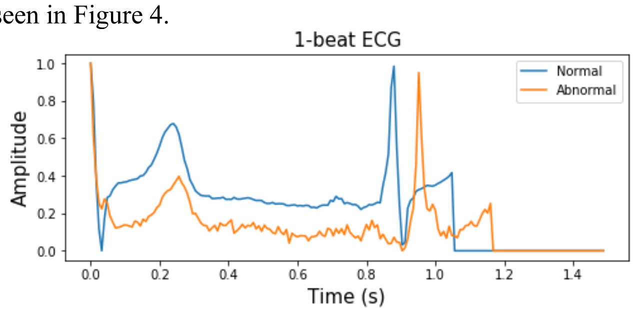

Figure 4. Normal and Abnormal Heartbeat

All layers are fully connected to the next layer. The network structure can be seen in Figure 5(a,b). We used Tanh activation function for hidden layers and we used sigmoid activation function for output layer. Cross entropy loss is used as the loss function. We choose learning rate as 0.3.

80 percent of data is used in training and 20 percent of data is used in test. We decided this percentage by trying different percentage and observing how accuracy is affected.

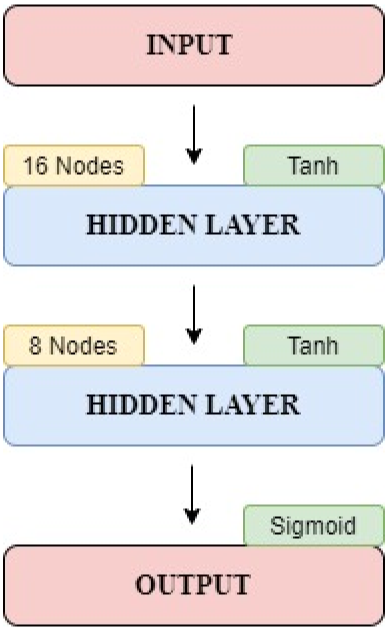

Figure 5.a. Architecture of Networks

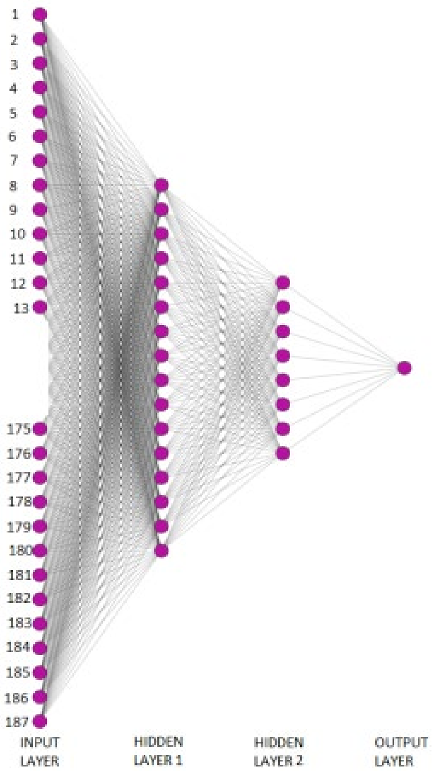

Figure 5.b. Architecture of Networks

C. Implementation Details

We used Python Jupyter Notebook in this project. In all experiments, numpy, pandas, matplotlib and sklearn libraries are used for data reading, visualization and training. The features of these libraries were used when designing the neural network structure and the structure of the learning algorithm of neural networks is designed mathematically. Training was done our personal computers.

IV. RESULTS

The algorithm was implemented with 11640 training data and 2910 test data. The number of iterations was determined to be 2800 because the rate of convergence of the model was greatly reduced in more iterations. The graph of the cost function according to the iterations is given in Figure 6.

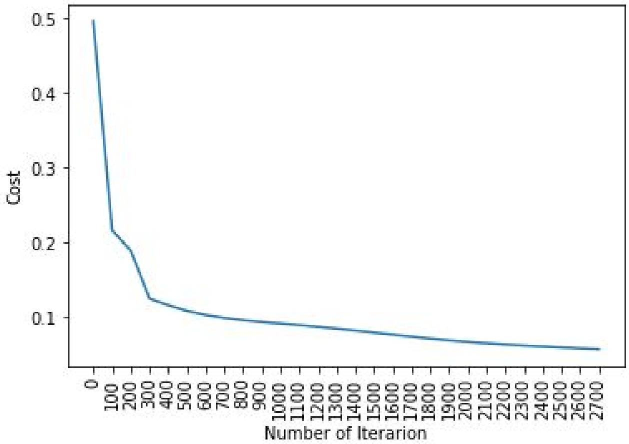

Figure 6. Cost

According to literature, tanh activation function is proposed for classification algorithms like we use. Training was implemented by using sigmoid function for hidden layers, however we could not obtain accuracy value as high as tanh function. These results can be seen in Figure 7. Also, we obtain 84 percent accuracy value for sigmoid function. That value is lower than accuracy value of our network.

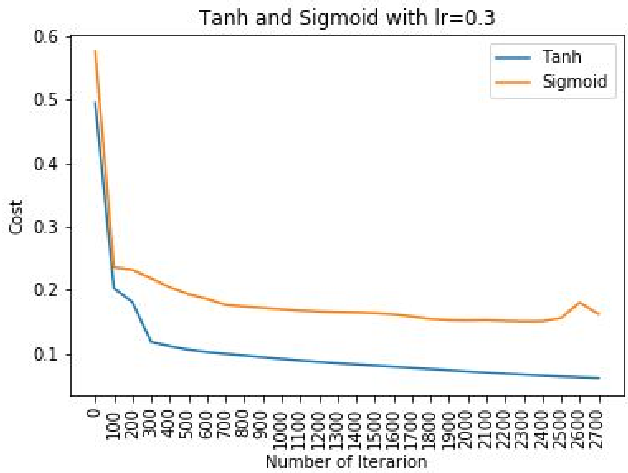

Figure 7. Comparison activation functions for hidden layers

At the end of 2800 epoch, the cost function decreased to 0.057. This value is satisfactory for training. In addition, we achieved 93 percent training accuracy and 92 percent test accuracy. Accuracy takes small changes in every training because we split the data randomly for each training and testing. Table 2 shows how number of nodes and learning rate affect accuracy value. Moreover, Figure 8 shows how number of nodes and learning rate affect cost value. Small values of learning rate take a long time for converging, it causes computational time waste. Besides, increasing the neuron numbers after 16_8 in hidden layers does not create a significant effects on accuracy and it increases model complexity.

Table 2. Accuracy Values for Different Parameters

Learning Rate \ Nodes	10_5	16_8	64_32
0.01	0.71	0.76	0.78
0.1	0.86	0.87	0.84
0.3	0.89	0.92	0.92

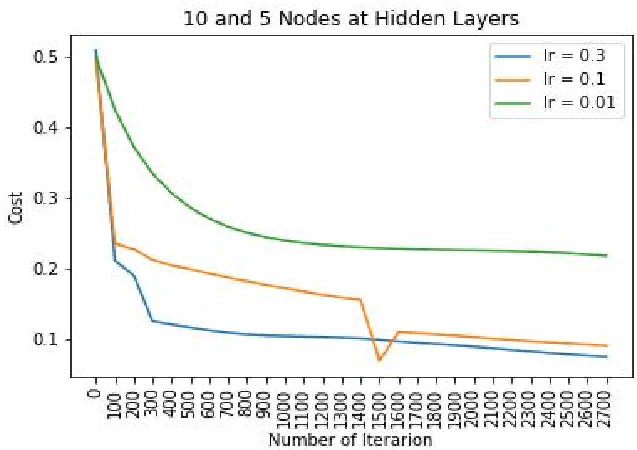

Figure 8.a

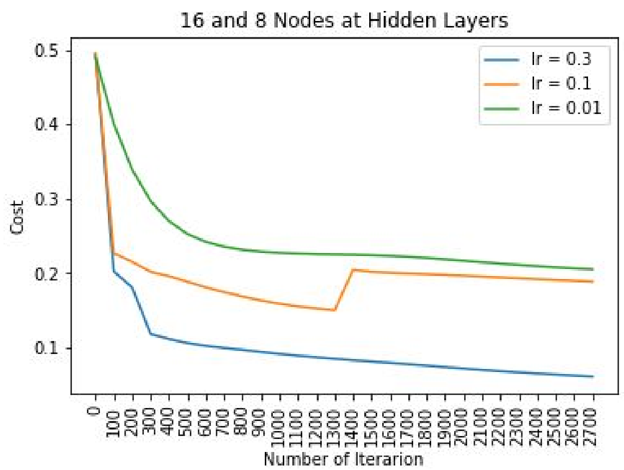

Figure 8.b

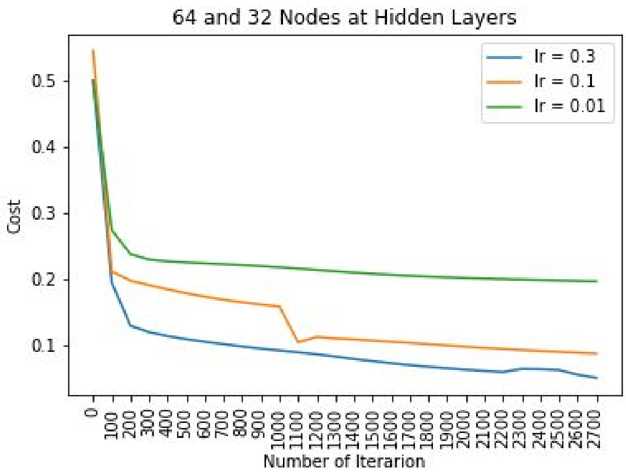

Figure 8.c

Figure 8. Number of nodes and learning rate effects on cost value

We compared our algorithm with 6 different algorithms. We have implemented other machine learning algorithms except CNN [6]. Figure 9 presents the accuracy of the proposed method and compares it with other relevant methods. The list of methods used is given below:

KNN: K-Nearest Neighbor
SVM: Support Vector Machine
GNB: Gaussian Naive Bayes
DT: Decision Tree
XGB: XgBoost
CNN: Convolutional Neural Network
MLP: Multi Layer Perceptrons (Our method)

The accuracy which we have achieved is not the best result. The convolutional neural network model has reached 95 percent accuracy. As in our study, the decision tree method reached 92 percent but Xgboost, a decision-tree based and gradient-boosting ML system, achieved the best results. Xgboost achieved a very difficult accuracy to achieve with 98 percent accuracy. Several state of art deep learning algorithms gives quite similar results with our network despite we have just create 3 layers network without any additional method like residual learning or CNN [6].

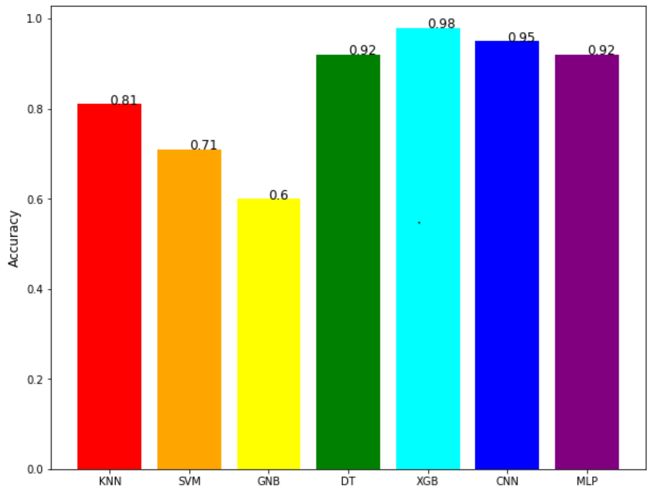

Figure 9.

V. CONCLUSION

ECG is the primary tool to diagnose the electrical activity of the heart. Any abnormalities present in the heart activity is reflected in the ECG signals. ECG signals are difficult to examine. In this study, we presented an artificial neural network based method for ECG heartbeat classification and compared it with other methods in literature. We classified the heartbeat as normal or abnormal (MI) according to the ECG of a heartbeat. As a result, we compared with other machine learning methods. Apart from these, we evaluated our model by taking samples from another dataset. The method that we proposed can be used at the clinical stage but is not sufficient alone but it will facilitate the work of doctors.

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