Deep Learning-Based Algorithm for Prediction of Heart Disease using Electrocardiogram

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Abstract. Disease diagnosis in hospitals is usually carried out by experts and experienced medical practitioners. For an expert cardiologist, any anomaly over the heart rate can easily be detected using Electrocardiogram (ECG) report. ECG is reliably used as a measure to monitor the functionality of the cardiovascular system. The primary challenge in manually analyzing ECG signals lies in the intricate task of detecting and categorizing diverse waveforms and morphologies present within the signal. The change in the morphological pattern over a recorded ECG could be sometimes confusing for cardiologist and highly challenging. In this work, a single learning model is created by utilizing an adaptive implementation of 1-D Convolutional Neural Networks (1D-CNN), which combines the two primary components of classification, namely feature extraction and classification. Our system uses deep-learning techniques to predict the heart disease accurately by developing a ECG signal classification methodology. Deep CNN is used to accurately classify five different arrhythmias in accordance with AAMI EC57 standard. The CNN is trained and tested using ECG dataset obtained from MIT-BIH resulting in an accuracy of 94.31%.

Keywords: Heart Disease Prediction, Electrocardiogram, Deep Learning, 1-D Convolutional Neural Network, Feature extraction, Classification, Deep Learning

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1 Introduction

The normal heart beat rate is 60 to 100 beats per minute. It is recorded using ECG. ECG is a diagnostic test that captures the electrical activity of the heartbeat, where each heartbeat is accompanied by the propagation of an electrical impulse throughout the heart. Arrhythmia is a condition that occurs when the electrical signals to the heart that coordinates heartbeat do not work properly, causing patients heart to beat too fast or too slow or irregularly. For instance, people experiencing irregular heartbeats may feel like a racing or fluttering heart. In India, the arrhythmic patients are raising to 10 million per year. In some cases, Arrhythmia is harmless but mostly it causes serious symptoms which are potentially lethal.

The five classes of arrhythmia as proposed by AAMI EC57 [1] are Normal beat (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and unknown beat (Q). For a healthy heart, blood circulation process usually goes smoothly, resulting in a normal resting heart rate of 60 to 100 beats per minute. Identifying whether the heart rate falls within the normal range is crucial. When the heart is weakened due to disease or injury, insufficient blood circulation to the organs hampers their ability to function properly.

An ectopic rhythm refers to an irregular heart rhythm caused by a premature heartbeat. It is also known as premature atrial contraction, premature ventricular contraction, or extrasystole. Following an early beat, a brief pause typically ensues, and it is aware on the subsequent beat, which feels notably stronger. This sensation can be likened to fluttering or the sensation of a skipped heartbeat. The two most common types of ectopic heartbeats are Premature Ventricular Contractions (PVC) and Premature Atrial Contractions (PAC).

Smoking, alcohol consumption, caffeine intake, stimulant medications, and certain street drugs can either cause or exacerbate ectopic beats. However, it's important to note that ectopic heartbeats are uncommon in children who do not have congenital heart disease present from birth. Most of the extra heartbeats in children are PACs, but almost harmless. In adults, ectopic heartbeats are common. They are most commonly caused by PACs or PVCs. When they are frequent, the cause should be investigated by the healthcare provider.

Supra-ventricular arrhythmias occur in the area above the ventricles, usually in the upper chambers of the heart, called the atria. It originates from above the ventricles but below the atria, encompassing various arrhythmias like premature atrial contractions. Ventricular arrhythmias, occurring in the heart's lower chambers called the ventricles, involve small deviations in normal heartbeat, resulting in additional or skipped beats. Often, the underlying cause of these changes is unclear, but mostly harmless.

A fusion beat arises from the simultaneous firing of a supra-ventricular and a ventricular impulse, resulting in the formation of a hybrid complex. This occurrence suggests the presence of two pacemaker cell sources firing concurrently: a supra-ventricular pacemaker such as the sinus node and a competing ventricular pacemaker which generates ventricular ectopic beats.The beat which is not revealed is known as unknown beat. It represents the beat that cannot be confidently classified due to inadequate information or complexity.

The problem in manually analyzing the ECG signal is difficult because of the different wave forms and morphologies present in the signal [8]. The change in the morphological pattern over a recorded ECG could be sometimes confusing for cardiologist and highly challenging for automatic computerized system due to several reasons [10]. To deal with these aforementioned, we propose novel deep learning based algorithm for prediction of heart disease. The dataset used for this work is provided by MIT-BIH database which is large enough for training a deep neural network.

2 Literature Survey

Atrial Fibrillation, commonly known as A-Fib or AF, is the most prevalent treated heart arrhythmia. AF episodes are detected using a combination of stationary wavelet transform and support vector machine techniques [4]. Pourbabaee et. al. focused on using the deep CNN to identify the patients with Paroxysmal Atrial Fibrillation (PAF), which represents a life-threatening cardiac arrhythmia [17].

De Chazal et. al. extracted feature sets that focus on the morphology of the ECG, intervals between heartbeat and the interval that represents the ventricular depolarization and contraction of the heart [5]. They used statistical classifier which is based on supervised learning.

A-Fib, Atrial Flutter (AFL), and Ventricular Fibrillation (V-Fib) are cardiac abnormalities that can pose life-threatening risks, particularly among individuals in old age [6]. Utilizing RQA features, an ensemble of classifiers effectively classifies four classes of ECG beats, namely Normal Sinus Rhythm (NSR), A-Fib, AFL, and V-Fib. Employing RQA coefficients with ROF achieves an impressive overall accuracy of 98.37%, outperforming RAF and DT with accuracies of 96.29% and 94.14%, respectively.

In [8] and [20], the preprocessed set of ECG signal is fed to the Neural Network extracting the different type of intervals from signal with different morphologies. Rajkumar et al. proposed an intellectual based screening framework which substitutes the manual features [18] by learning a discriminative representation of raw ECG time-series signal as input domain.

Hong et al. introduced a recommendation algorithm, named Medical-History-Based Potential Disease Prediction Algorithm using deep learning techniques [7]. It predicted a patient's potential disease by analyzing the medical history, offering valuable insights to both patients and doctors. Deep learning is also applied in various fields such as Image Caption Generation [16], Recognition of Mung Leaf Diseases [15] and Diabetes Mellitus Prediction [19]. A model was proposed for predicting the onset of cardiovascular disease by leveraging historical Electronic Health Records (EHRs) to extract premorbid information of patients using an attention-based deep neural network [3]. An Automated Diagnostic System for Heart Disease Prediction utilizing χ^2 Statistical Model was proposed by Ali et al. to refine the features and to address the issues of underfitting and overfitting within the predictive model [2].

Deep learning is found to be better than the various machine learning algorithms as explicit feature extraction step is not needed. Kwon et al. developed a deep learning algorithm for identification of heart failure using ECG signals [12]. Kwon et al. used sensitivity map to determine the region that exerted the most pronounced influence on the decision-making process of the deep learning algorithm when detecting Aortic Stenosis with ECG signals [13]. Here, we use deep learning algorithm to classify the ECG signal to classify five different arrhythmias in accordance with AAMI EC57 standard. The Deep learning algorithm used is 1D convolution neural network, as it guarantees high performance in pattern recognition of signal data. The CNN automatically recognize and extract the features and produce output.

The history of the MIT-BIH Arrhythmia Database was briefly reviewed, its contents were described, and discussions were held about what was learnt regarding database design and construction [14]. Additionally, a glimpse was taken at some of the later projects that had been stimulated by both the successes and limitations of the MIT-BIH Arrhythmia Database. MIT-BIH arrhythmia database is also used to validate the algorithm that performs R-wave detection utilizing novel nonlinear transformation and a straightforward peak-finding strategy [9]. A Total Variation Denoising (TVD) based approach is suggested for locating R-peaks in the ECG signal using the MIT-BIH Arrhythmia Database [11]. Here, we used MIT-BIH Arrhythmia Database containing ECG Signals as it is commonly used in most of the work.

3 Methodology

Deep learning is the emerging trend in field of medical analysis which concerns more on biomedical signal processing. Here we use 1D Convolutional Neural Network (1D CNN). CNN is popularly called as feature leaner as it automatically learns the feature from the input data. Therefore, separate stage for preprocessing and feature extraction is not required. This paper suggests a model for heart disease prediction by performing classification of the ECG beats. Our model consists of four layers of 1D CNN with Batch Normalization and ReLU activation function, each followed by Max Pooling layer. These layers are followed by a fully connected layer (FC) and a final soft max layer as shown in 1).

The model begins with an input layer that expects data of shape (186, 1), indicating it processes sequences of length 186 with one feature per time step. The four convolutional layers perform feature extraction through filters, each followed by batch normalization to stabilize and speed up training. Max pooling layers reduce the dimensionality of the features extracted, aiding in capturing the most salient features while reducing computational complexity. The model further refines these features with additional convolutional and normalization layers before flattening the output into a vector by passing it through dense layers. Finally, the output layer, with 5 units performs classification task where the model predicts one of five possible classes. In total, the model comprises 118,597 parameters, with 118,085 being trainable, ensuring it has the capacity to learn intricate patterns from the input data.

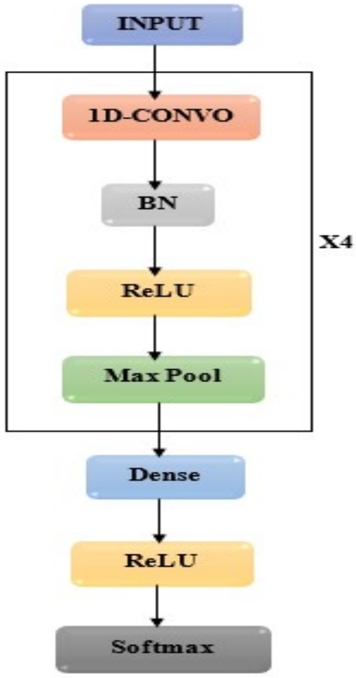

Figure 1: CNN Architecture

3.1 Dataset

The dataset used is composed of collections of heartbeat signals derived from familiar dataset that is used in heartbeat classification, the MIT-BIH Arrhythmia Dataset. The collections contain a significant number of samples suitable for training a deep neural network.

The MIT-BIH dataset comprises ECG recordings of 47 distinct subjects, captured at a sampling rate of 360Hz. It includes labeled ventricular beats from at least 100,000 instances encompassing 15 types of heartbeats. The dataset comprises 48 half-hour recordings of ECG signals, with each beat annotated by a minimum of two cardiologists. These annotations are utilized to categorize the beats into five different categories, aligning with the standards set by the Association for the Advancement of Medical Instrumentation (AAMI) EC57 as shown in Table 1.

Table 1: AAMI standard of ECG class description

Category	*Annotations*
N	Normal, LeftRight bundle branch block, Atrial escape, Nodal escape
S	Atrial premature, Aberrant atrial premature, Nodal premature, Supra-ventricular premature
V	Premature ventricular contraction, Ventricular escape
F	Fusion of ventricular and normal
Q	Paced, Fusion of paced and normal, Unclassifiable

3.2 Preprocessing

The ECG signal data acquired from MIT-BIH is split into two: Training and Test data. The proportion of number of samples in different class in the training dataset must be equal or near equal. This is because the dataset greatly affects the models behavior. The good rule of thumb is therefore to have roughly equal number of samples in every class. Therefore, we use 10000 data (2000 data each class) for training.

3.3 Convolution

When dealing with shorter segments of data and the precise location of features within these segments is not critical, 1D CNN proves highly effective at extracting valuable features. In CNN, instead of manually deciding on the filters, we specify the number of kernel filters in each convolutional layer.

A kernel serves as a weight matrix that is multiplied with input values to extract features. The neural network learns the values of the kernel filters automatically during the training process, focusing on the filters that result in the most efficient features for the specific classification or detection task. In this context, the values of the kernel filters act as weights within the CNN, and they are learnt rather than predetermined.

In convolution with a stride of 2, one sequence (sequence 2) moves step by step along another sequence (sequence 1) with a step size of 2 during the convolution process. The stride determines the number of steps taken in each convolution step, with the default value being one. The output size is smaller than the input size. To preserve the dimensions of the output to match those of the input, padding is applied, which involves symmetrically adding zeros to the input matrix.

3.4 Batch Normalization

The input dataset has numerical data of wide ranges. The data point having wider range can cause instability in neural networks. This is because, the relatively large range of inputs can cascade down through the layers in the network causing imbalance gradients. This imbalance gradient problem makes the model harder to train and it could also significantly reduce our training speed. Therefore, the data should be normalized. The normalization function will put the data in same scale and attempts to increase training speed. The Batch Normalization normalizes the output from the activation function using Equation 1.

$$z = \frac{x - m}{s} \tag{1}$$

where x is the input, m and s are the mean and standard deviation of inputs and z is the normalized output respectively.

After normalization, it multiplies the normalized output with some arbitrary parameter, g and adds another arbitrary parameter, b with the resulting product, z as shown in Equation 2.

$$(z * g) + b \tag{2}$$

This process occurs per batch basis and hence the name batch normalization.

3.5 Activation Function

The activation function used in the CNN model is the ReLu which is simple, fast, and empirically seems to work well. ReLu stands for rectified linear unit. It is quick to evaluate since it does not saturate. In a neural network, the activation function plays a crucial role in converting the aggregated weighted input of a node into its corresponding activation or output.

The rectified linear activation function, commonly known as ReLU, is a piecewise linear function that directly outputs the input value if it is positive; otherwise, it outputs zero. Due to its ease of training and tendency to yield superior performance, ReLU has become the default activation function for various neural network architectures.

3.6 Pooling

After every 1-D CNN, the data goes through Max Pool layer. In max pooling, the input data is partitioned into set of areas that dont overlap. The outputs of each region correspond to the maximum value within that region. Max pooling is all about grasping the maximum value at each spot. This would give 75% of information that is not in features.

3.7 Dense Layer

Once convolution and pooling operations are completed, dense layer is activated. The main purpose of the dense layer is to combine out features into more attributes. This results in higher accuracy for classifying the data. By combining features and attributes that offer improved class prediction, the model undergoes error calculation and subsequent backpropagation. This leads to adjustments in the weights and feature detectors, optimizing the model's performance. This iterative process is repeated multiple times to refine the model's predictions continually.

3.8 Softmax Layer

To calculate the probabilities of each target class over all possible target classes, we use softmax layer. The output probability value can be predicted in this layer. The softmax function transforms the outputs of each unit, compressing them to a range between 0 and 1. The resulting output from the softmax function represents a categorical probability distribution, indicating the probabilities associated with each class being true. The class having highest probability is chosen as the target class. Mathematically, it is represented as follows in Equation 3,

$$S(x^i) = \frac{e^{x^i}}{\sum_{j=1}^{n} e^{x^j}} \quad (3)$$

where x is the input.

3.9 Optimizer

The optimizer defines how neural networks learn. We use Adam Optimizer to optimize the output. It combines adaptive learning rates, momentum optimization, and bias correction. It efficiently adjusts the learning rate for each parameter based on historical gradients. By smoothing out oscillations and accelerating convergence, Adam enables faster and more stable training. Its adaptive nature makes it well-suited for classification and helps optimize the parameters of deep learning models effectively.

3.10 Testing and Evaluation

Once the model is created, it is tested against MIT-BIH test dataset. 3718 records is given as an input to the developed model to classify the signals among five classes of arrhythmic heart disease. The result is then fed to the evaluation model to evaluate the accuracy and loss of the developed prediction model. Accuracy is calculated as the ratio of correctly predicted instances to the total number of instances, typically expressed as percentage. It measures the model's overall correctness in predicting the outcomes of a dataset. It is calculated based on the Equation 4.

$$Accuracy = \frac{NumberofCorrectPredictions}{Totalnumberofpredictions} \quad (4)$$

4 RESULTS AND DISCUSSION

4.1 Experimental Setup

As mentioned, the classification system is built using four CNN layers with pooling layer and a fully connected layer (dense layer) in order to achieve the utter most computational efficiency for both training and testing the data. All four CNN layers consists of 64 filters. The kernel size of first CNN layer is set to 6 and the remaining layers has the kernel size 3. The dense layers consist of 64 and 32 filter each. The model was trained over 10, 20, 30, and 40 epochs.

4.2 Results

The arrhythmia classification model is trained with 10000 ECG records with 2000 for each class. We evaluated the model on 3718 ECG records. The data was trained and tested with 30 epochs. The softmax layer computes Probability for five classes for every heartbeat. Heart beat is classified to class with the highest probability. The accuracy obtained is 94.31%. The resulting confusion matrix is presented in Table 2, while the computed metrics such as precision, recall and F1 score are summarized in Table 3.

Table 2: Confusion Matrix

$Actual/Predicted$	$Class1$	$Class2$	$Class3$	$Class4$	$Class5$
Class N	696	10	11	13	12
Class S	11	695	10	13	10
Class V	13	5	709	11	8
Class F	7	12	5	708	15
Class Q	9	11	13	12	699

4.3 Inference

We have experimented with different epoch values as shown in Table 4. We found that accuracy increases with increase in epoch value up to 30. When we set the value of epoch as 40, we noticed the drop in accuracy

Table 3: Evaluation metrics

Class	*Precision*	*Recall*	*F1 − Score*
Class N	0.9457	0.938	0.9418
Class S	0.9482	0.9405	0.9443
Class V	0.9479	0.9504	0.9491
Class F	0.9353	0.9478	0.9415
Class Q	0.9395	0.9395	0.9395

percentage. Our model works better at an epoch value of 30. Accuracy and loss graph is given in Figure 2 and 3. The loss generated by this model is 0.2445 which is relatively low compared to the existing model. The accuracy obtained using this model is 94.31% which is higher than the accuracy obtained by other existing models as shown in Table 5. [12] and [13] conducted a study utilizing ECG signals that are obtained from two hospitals in Korea. They employed the Area Under the Receiver Operating Characteristic (AUROC) curve as their chosen evaluation metric.

Table 4: Experiment with different epoch

NumberofEpochs	*Accuracy*
40	93.21%
30	94.31%
20	94.09%
10	92.75%

Table 5: Accuracy comparison with the existing models

Work	*Approach*	*Accuracy*
Proposed model	1D CNN	94.31%
Rajkumar et al. [18]	CNN	93.6%
Kachuee et al. [8]	Deep Residual CNN	93.4%
Zubair et al. [20]	CNN - 3 Layers	92.7%

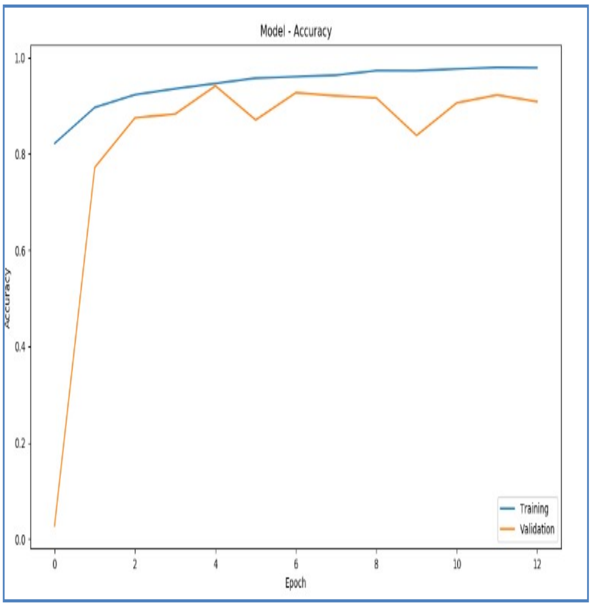

Figure 2: Accuracy Graph

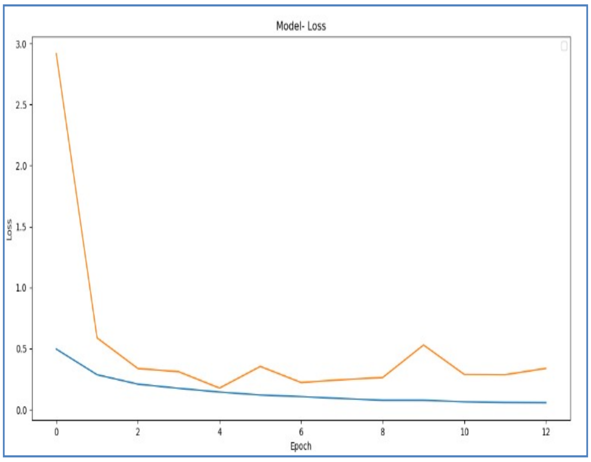

Figure 3: Loss Graph

5 Conclusion and Future Work

The manual analysis of ECG signals is a complex task due to the diversity of waveforms and morphologies present in the signal. This complexity can pose significant challenges even for experienced cardiologists. These challenges are addressed in this work by developing a single learning model that employs an adaptive implementation of 1-D CNN. This model integrates feature extraction and classification into one cohesive framework. By utilizing deep learning techniques, our system effectively predicts heart disease, achieving an impressive classification accuracy of 94.31% for five different arrhythmias, as per the AAMI EC57 standard. The work can be further enhanced and expanded by the real-time classification of ECG signals using lightweight wearable devices that monitor the heartbeat. Integrating your prediction model with wearables for real-time monitoring can revolutionize healthcare. By continuously analyzing data from wearables, the model can provide early warnings of potential health issues, enabling preventive measures and improved disease management. This continuous monitoring empowers individuals to take a more proactive role in their own health. An early alert system can also be setup to notify the doctor, if any abnormal heart rate is recorded in the wearable device.

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