Arrhythmia detection and classification using convolutional neural network

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Abstract

Healthcare and Life Sciences are among severely researched domains. With the introduction of computing paradigms and possibility of leveraging computational techniques have opened new research avenues. Heart is one among the most researched organs and the reason being trivial. With the advent of computational paradigms researchers explored ways to measure the electrical activity of the heartbeat which is known as electrocardiogram (ECG). Since then ECG has become one of the most important as well as primary tests to diagnose any irregularities in the functioning of the heart. The availability of the ECG data and possibility of employing deep learning models and their robustness has made researchers venture into leveraging them to elevate the accuracy of the ECG Analysis. To date there exists no end-to-end evaluation model based on deep learning techniques. In our present work, we identify different classes of cardiac rhythm by leveraging single-lead ECG. Our results show a significant improvement in ROC (approx. 0.97). Furthermore, our results demonstrate that we can classify a wide spectrum of arrhythmias using Deep Learning Techniques which are comparable to that of cardiologists. This approach can be used to minimize the component of human misdiagnose and help improve the quality of cardiac care.

Keywords: ECG, Deep Learning, Arrhythmia, Cardiology**.**

I. INTRODUCTION

Out of the large number of deaths that occur due to cardiac issues, a significant number of deaths is cause due to Cardiac arrhythmia. Annually, millions of people die of arrhythmia and hence it becomes imperative to research on this topic. A lot of researchers have already worked on arrhythmia using many techniques like wavelets, Support Vector Machines (SVM) etc. Understanding of ECG is very essential to detect and classify Arrhythmia and involves many steps including Pre-processing ECG Signal, segmentation, peak detection / feature extraction and detection / classification.

ECG is one of the most important instruments used in cardiological practices in a clinical setup. Every year millions of ECGs are ordered worldwide. ECG's output, in clinical practices is heavily relied upon for decision making as it can help in identifying several abnormalities. Advent of ECG changed the landscape of cardiac care and introduction of computational paradigms has opened new avenues in research. [1][5-7] show that some of the conventional

ISSN: 2233-7857IJFGCN

algorithms lead to some level of incorrect diagnosis. This is also since ECG data is too complex to interpret and conventional algorithms may not scale up to handle the level of complexity. But with the advent of High-Performance Computing paradigms and possibility of implementing machine learning and deep learning algorithms, it has now become possible to use these paradigms to analyze ECG.

A lot of development that has happened over a past couple of years has paved way for deep learning models. These are the computational models with multiple layers where each layer is abstract and is designed to perform a specific task. These models have significantly increased the accuracy of techniques like speech and image recognition. These models are not just limited to speech and image but they can also be extended to research in computational life sciences and medical data analysis. Unlike conventional algorithms and machine learning deep learning and neural networks can recognize patterns from the data and interpret the features which help in feature extraction and feature engineering making them most sought after computational methods specially to interpret data like ECG.

As aforementioned, ECG Data is very complex and a lot of researchers have employed various computational methods including Machine Learning (ML) and Deep Learning (DL) Algorithms but their focus has mostly been on certain aspects of ECG analysis. Works like [5-6] have focused more on noise reduction, whereas researchers in works [7-8] have focused mostly on feature extraction ending up in detecting only a few heartbeats [9-12]. Works [13-17] detects and classify only a few types of cardiac rhythms. Most of the aforementioned works have been limited by lack of data that doesn't record / contain comprehensive cardiac rhythms.

It has been our endeavor in this work to create a novel data set that has comprehensive annotations for a wide range of rhythms. We have developed novel algorithm to detect wide range of cardiac rhythm classes. The data set contains ECG data from a single-lead ECG machine.

II. RELATED WORKS

Since the advent of newer computing paradigms like Machine Learning and Deep Learning techniques, a lot of researchers have developed lot of different techniques to detect various abnormalities, especially arrhythmia.

2.1 Detecting Arrhythmia from ECG data.

As mentioned in the previous sections, ECG signals represent the electrical activity of the heart. It is very important to study the changes in electrical signals for diagnosing arrhythmia and other cardiac abnormalities. Figure1 as shown below, shows an example of a general 2-lead ECG [18] generally, a peak can be defined as space between an apex and 2 valleys and such a peak in ECG terminology is termed as R-peak. And RR Interval (RRI) is defined as interval between 2 consecutive R-peaks. The valley on either side of an apex of the peak is studied and each such window is analyzed and features are extracted to detect arrhythmia and classify various cardiac rhythms. It becomes very trivial at this point to note how imperative it is for the feature extraction to be very accurate and effective.

ISSN: 2233-7857IJFGCN

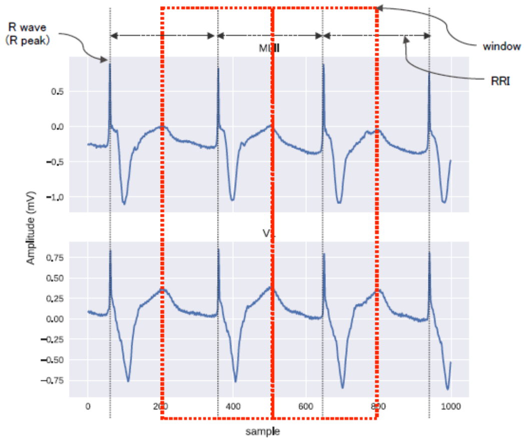

Figure 1: General Example of 2-lead ECG

Many researches have been conducted to study and detect abnormalities by leveraging computational paradigms. Most of the conventional approaches employ methods to manually extract the features from the ECG data. It is Machine Learning and Deep Learning that changed the way this type of data was being analyzed. [19] has proposed ECG classification using Conventional Neural Networks (CNN). Their model used MIT Database and focused only on VEB and SVEB. However, their approach was patient-centric which suffered from lot of variations. The work in [20] demonstrated ECG Classification by employing one-dimensional CNN. However, their approach to classification was more patient specific than being generic. Their approach to train their model was hybrid, i.e. the normal beats were recorded from the patients while the abnormal beats were emulated. Some of the other researchers who started working on a more generic approach like Zubair et al in [21] based on 1-d Convolutional Neural Network (CNN) which employed 3 layers and 1 fully connected Softmax layer. However, one of the pitfalls were that the data suffered from patient overlap in train and test data. Taking a cue from their work, researchers in the work mentioned in [22] increased the convolutional layers to 5.

Based on these works and works of many other researchers we have put forth our efforts to ensure that the data used in our work is strictly non-patient centric thus helping to clearly capture the efficiency and accuracy of our model.

III. Proposed Algorithm

The general architecture of CNN Algorithm is as shown in Figure2

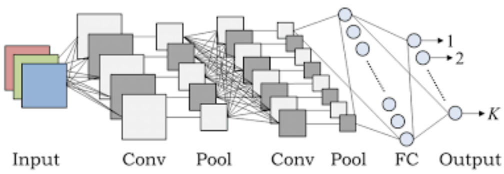

Figure 2: General Architecture of CNN

It consists of a series of input layers and pool which are connected to a fully connected layer which generates the output. The architecture is similar to the connectivity of neurons in the brain and is in-fact was inspired by the neural connection patterns in the human brain. The individual layers that perform a linear operation on the input parameters in called a convolution.

ISSN: 2233-7857IJFGCN

Generally, in the conventional Machine Learning Algorithms like Regression, we use normalization technique to scale the input to a range of value. This works well in a single layer but when want to extend the same technique to a CNN with multiple layers the input distribution gets changed at subsequent layers where each layer tries to normalize and the error propagates where the initial normalized values gets shifted resulting in "internal covariate shift". To overcome this problem, we add a normalization layer between subsequent layers thereby inhibiting the hidden / convolution layers from normalizing the values. Since these layers keep normalizing the values at each layers in batches, this technique is termed as "batch normalization" [23] generally abbreviated as batch norm. A general architecture of Batch Normalization is as shown in Figure3.

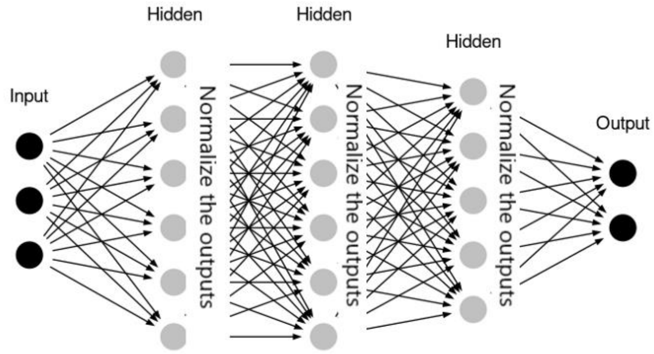

Figure 3: General Architecture of Batch Normalization

Generally, there are 4 steps involved in Batch Normalization i.e. a) batch mean b) batch-variance c) normalization d) scale and shift.

For any input batch at a normalization layer$\mathrm{B} = \{\mathrm{x}_{1,\dots,\mathrm{m}}\}$,the output of that layer will be will be $\{\mathrm{y_i} = \mathrm{BN}_{\gamma,\beta}(\mathrm{x_i})\}$ [23]. Where:

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i)$$

We have used the data from a 200 Hz ECG Monitor and have extracted a median of a 30 sec record per record to build the dataset. Most of the records are a multiplexed representation meaning there could be different classes of rhythms in a single record. We then employed the developed algorithm, as shown in Figure4, which feeds on the ECG data that is sampled at 200Hz which are raw samples of ECG. The neural network in our work consists of 30 layers and 15 residual blocks where the batch normalization is applied along with ReLU and Dropout [24]. We have trained the network by employing the random.

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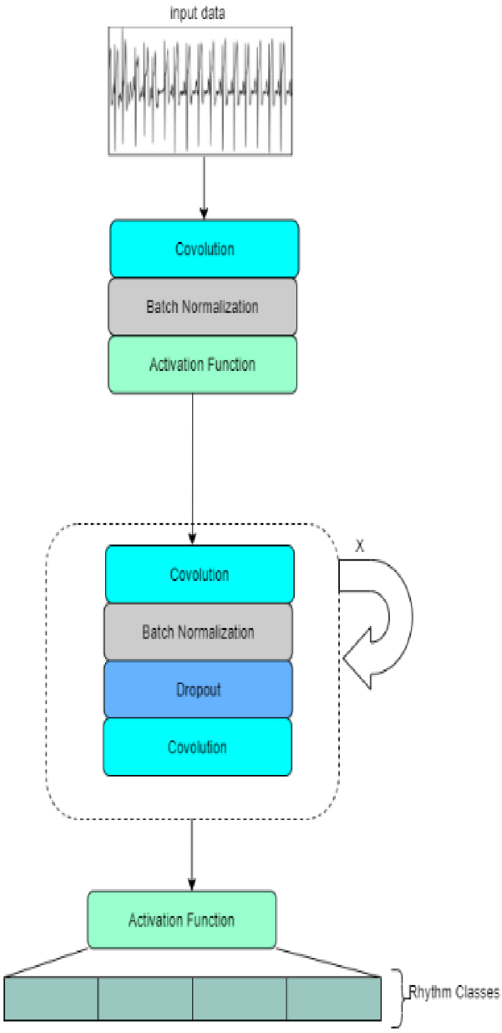

Figure 4: Proposed Algorithm

III. EXPERIMENT AND RESULT

Our work demonstrates that the accuracy of the model is around 0.97. Our study demonstrates how employing Deep Learning Methods can improve the accuracy and open new avenues for research. Figure 5 shows the AUC of the rhythm classes and we can note that the accuracy is elevated compared to the annotations.

Rhythm Class	**AUC**
AF	0.965
AVB	0.981
BIGEMINY	0.996
IVR	0.987
JUNCTIONAL	0.979
NOISE	0.947
TRIGEMINY	0.997
Average	0.978

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Table 1: Rhythm Class AUC

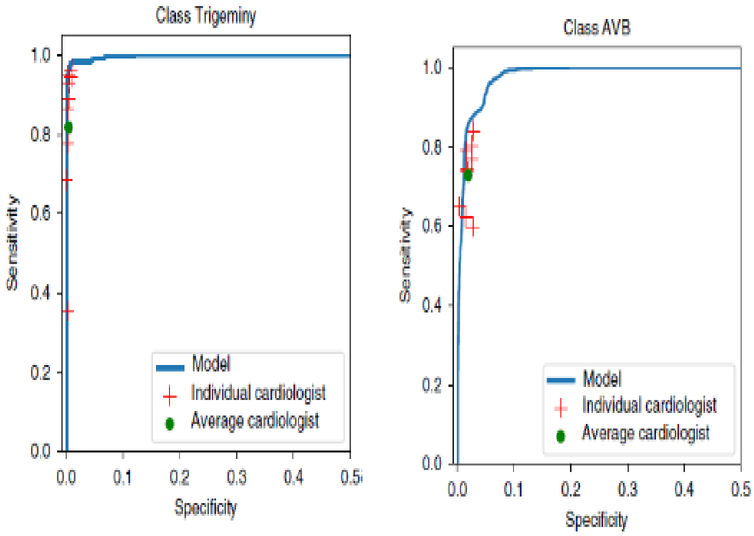

Figure 5: ROC for various rhythm classes

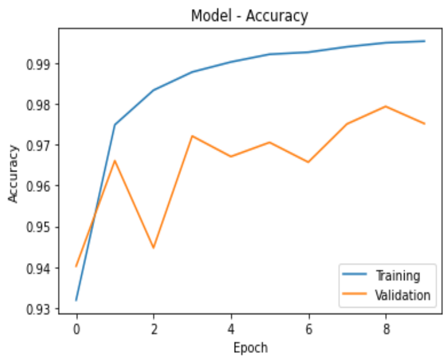

Figure 6: Model Accuracy

Figure6 shows the accuracy of the training and test sets against the number of epochs run.

IV.CONCLUSION

I believe that there is a scope for development of a more comprehensive end to end approach that employs deep learning and other neural network paradigms.

ACKNOWLEDGEMENT

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First and foremost, I wish to record my sincere gratitude to Management of Jyothy Institute of Technology and to my beloved Principal, Dr. Gopalakrishna,JIT, Bengaluru for his constant support and encouragement .

My sincere thanks to Dr. Harshvardan Tiwari, HOD, ISE, for his valuable suggestions for writing the paper

ISSN: 2233-7857IJFGCN

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ISSN: 2233-7857IJFGCN