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A Study Based On Methods Used In Detection of Cardiac Arrhythmia

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Abstract - *Cardiac related health problems can result in major setbacks in a person's life and are fatal at times if not detected on time. Cardiac arrhythmia is one such disorder of irregular heart rate or rhythm. The use of machine learning in the domain has been prevalent however there are still several other techniques that haven't been utilized that could provide a better accuracy in case of detecting irregular heart rates. A common problem that Deep Learning is helping to solve lately involves time series classification.*

Key Words: **Arrhythmia, Signal Processing, Deep Learning, CNN, Machine Learning, Cardiac Health Issues**

1. INTRODUCTION

Cardiovascular diseases account for a large number of deaths each year - more than any other causes representing 31% of all global deaths in 2016. [1] CVDs are often accompanied with arrhythmias.

Arrhythmia is a disorder that is caused due to the irregularity of heart beats or when a heart follows an irregular rhythm. It indicates that the heart beats quickly, slowly, or in an irregular pattern. As the blood does not flow well when it occurs, irregular heartbeats can have an impact on other organs, which can either damage or halt the organ. Arrhythmia accounts for nearly 200,000-300,000 sudden deaths per year [2] – a higher rate than that of stroke, lung cancer or breast cancer. Some forms of arrhythmia can be treated easily but the ones that cause a person to suddenly perish are a major concern for most cardiologists and researchers of the domain.

One of the many methods to detect arrhythmia is by making the use of an electrocardiogram (ECG). Doctors manually analyze the data to see if there is an issue that has been detected. The analysis may result in major delays, which isn't acceptable when a life-threatening situation occurs, hence the need for quick and automatic detection is important in such situations.

2. LITERATURE REVIEW

Although there has been significant progress in Machine learning techniques in case of detecting arrhythmia, the techniques are heavily reliant on feature extraction. Feature extraction is a part of the dimensionality reduction process, in which an initial set of the raw data is divided and reduced to more manageable groups [9]. But the process of hand crafting features is time consuming and many times not as accurate as well. On further research, it was seen that deep learning techniques contributed to a significant improvement in accuracy compared to traditional machine learning methods that were being used. To add to it, the otherwise cumbersome feature selection process is actually automated in this scenario, hence helping save a lot of time.

The paper by R. R. Janghel et al, the authors implemented seven different machine learning techniques namely, Naive Bayesian, Support Vector Machine, Decision tree, Random Forest, K-Nearest Neighbor and Ada-boost [1], however, on further literary research we noticed that despite the fair accuracy achieved by these techniques, there was still room for improvement.

One of the papers that showed us this is written by Zahra Ebrahimi et al, who reviewed various deep learning techniques namely Convolutional Neural Networks, Recurrent Neural Networks, Deep Belief Network and Gated Recurrent Unit and noted the accuracies achieved by each in the classification process of arrhythmia. The accuracy that was achieved by using convolutional neural networks was better compared to its counterparts in the research [2].

In the paper by Chris D. Cantwell et al, the authors went through multiscale cardiac electrophysiology by using predictive modeling and machine learning [1,3]. The paper used vanilla recurrent neural networks [2,3] to do this however they did mention one limitation of using it, the issue being that they can store information only for a short number of steps. They further went on to mention that long short-term memory networks can be a viable solution for this but they did not proceed with its implementation [3]. The paper by Saeed Saadatnejad et. al. proposed that an LSTM-based ECG classification provides formidable classification performance. LSTMs are shown to provide optimal performance at a lower computational cost and meet timing requirements for the same [5].

In the paper proposed by Nguyen et. al., the authors acquired data from Nihon Kohden 9620L device that was used in hospitals apart from using an ECG simulator [4].

Feature extraction was used to detect intervals of ECG signal and process signal [4,9]. They noticed a significant difference in accuracy between the simulation and real data and determined the root cause to be the presence of noise in the real data, hence resulting in the software identifying the wrong durations [4].

A major hurdle in arrhythmia detection is the non-availability of balanced datasets used for classification; imbalanced data leads to model bias. The paper proposed by D. Verma et. al. used oversampling for arrhythmia detection [6]. Instead of looking at arrhythmias in general, they focused their research on Atrial fibrillation (AF). By using oversampling, their model was able to mine more information from various classes, both major and minor, and were able to improve their results exponentially [6]. A similar paper was proposed by F. Liu et. al. and they used Ensemble Empirical Mode Decomposition (EEMD) [7]. Stacked Bidirectional LSTM used by them consisted of three layers. The SB-LSTM compared to the other implementations of LSTM in papers [5] and [6] provided 2% more accuracy [7]. In the paper proposed by Wang T. et. al., the authors worked with heartbeat classification using multilayer perceptrons and focal loss [8]. The authors elaborated upon the loss function that is needed while training a deep neural network. They mentioned that cross entropy loss, despite being the most popular loss function, does not address the class imbalance problem introduced by treating all categories equally. Hence, focal loss was used as it addresses this issue and provides an effective result [8]. One of the databases used in the paper is the MIT-BIH Arrhythmia database which helped in providing a more accurate result [8,9].

ECG data is not easily available; often the same patient data is used in various databases that leads to data leakage as each patient has a unique heart signature. In the paper by Ozal Yildirim et al, the authors used a model based on Deep Neural Networks to detect arrhythmia. The standard 12-lead ECG is recorded over a 10-second interval and the authors applied a DNN model to it. The outcome in case of each lead yielded accurate results. The focus was more on working on the various rhythm classes of heartbeats, where the authors went through 18 rhythm classes across two scenarios. The results across the two scenarios showed high accuracy, sensitivity, specificity and precision in the range of 92-96%. The ECG database, which was used in their studies, includes more than 10,000 unique subject records. The paper showed the good generalization ability of the DNN model that was used. [12]

The paper by Aurore Lyon et al focuses on the various computational techniques that have led to significant advancement in the healthcare sector. The authors elaborated on machine learning methods that used classification and methods that supported diagnosis based on the ECG. This involved analysis of the whole ECG recording instead of a single isolated beat. A challenge that could lead to overfitting is that the ratio between the amount of available training data and the number of extracted features is small, the authors mention that dimensionality reduction and feature selection helps counter this challenge. [4,9] The paper provides a thorough overview of computational methods pertaining to machine learning and 3D computer simulations that can be used for ECG analysis. [13]

The paper by M. Fikri et al provides a thorough review on the frequently utilized classification techniques used in the classification process of ECG signals. The authors do mention that deep learning techniques such as CNN and RNN, do not need to manually extract features as they are capable of extracting their own features [14].

2.1 RESEARCH GAP

Traditionally, there are two parts to the ECG classification algorithm - feature extraction and classifier [14]. To further elaborate, the use of techniques like time-frequency analysis, spectral analysis, and many others are employed to model the fluctuating patterns of the ECG. Feature selection algorithms are then used to process the extracted features to get the most relevant ones. In the end, classifiers such as random forest, neural networks are built based on the selected features [1,2,5,14]. Despite having obtained good classification performance, there are certain limitations to these methods that can't be ignored:

- The performance of these algorithms can barely be boosted. The available datasets are limited & highly imbalanced (heavily biased towards normal beats).

- Important data may be lost during the extraction process - often, real-time ECG data contains noise that needs to be removed for accurate prediction.

- In case the extraction process isn't accurate i.e. the fluctuation patterns do not reflect the actual data, the results after classification have larger errors.

There has been significant progress in machine learning techniques in case of detecting arrhythmia, the techniques are heavily reliant on feature extraction [4,9]. The process of hand crafting features is time consuming and many times not as accurate as well. On further research, it was seen that deep learning techniques contributed to a significant improvement in accuracy compared to traditional machine learning methods that were being used [1,2].

2.2 Databases

On surveying the papers, we noted the databases that were used to train the model. The most prominently occurring one is the MIT-BIH Arrhythmia database. Some papers, such as in [4], were able to access actual data from a hospital's Nihon Kohden ECG machine. Apart from that, a few papers used physionet challenge databases. Some databases that we haven't mentioned in the table below were known to be incorrectly annotated, hence causing variations in results. The table below summarizes the databases that were used in our studied research papers.

Table -1: Databases from Studied Papers

Databases from Studied Papers		
Database	**Number of Recordings**	**Description**
MIT BIH Arrhythmia	48 half hour recordings	360 Hz 2 channel ambulatory ECG
INCART	75 half hour recordings	275 Hz 12 Leads
LTAFDB	84 long term recordings	128 Hz 2 Leads 24-25 hours/recording
MIT BIH AFIB	25 long term recordings	0.1 Hz to 40 Hz 10 hours recording

3. METHODOLOGY

To detect arrhythmia, we need to understand the relevant heartbeat classes. Different types of heartbeats are labeled differently. Labeling is done for easier identification of the type of heartbeat class that is in consideration. Hence, by having knowledge of this, the results that can be ignored are understood, to get a more accurate detection result in the case of detection of an irregular heartbeat.

The main steps involved include acquisition of data, either from the databases available or from devices that can detect or read ECG signals. The data acquired through these steps undergo preprocessing. The preprocessing steps taken usually involve generalization and denoising, this helps the model in utilizing the correct signals, hence providing a comparatively more accurate detection of, in this case, arrhythmic heartbeats among normal heartbeats.

The next steps include training the model. The model is trained with the help of an optimizer for a set number of epochs. The lower the value of the loss function, the better as it indicates how much the model is deviating by. Less deviation will result in a low loss function value. Once training is done, the model undergoes testing, this is the part where we can find out the accuracy of the model and check if there is any instance of overfitting or underfitting of data.

4. CONCLUSION

Due to the global pandemic, focus of research on other sectors of health issues has reduced for the time being. Research in this domain however, still sees a steady amount of work being done. Irregularities of a heartbeat may be harmless in some cases, but it can result in some fatalities if ignored. Arrhythmias also indicate the possible presence of a more serious issue that may result in the death of an individual. The analysis of papers in the domain have shown that most researchers stick to available databases instead of opting for real time data when it comes to training the model. Another observation that was made is that deep learning techniques are less time consuming compared to machine learning techniques. The accuracy is better in the former as well.

Further work will include utilizing the knowledge obtained from the thorough paper analysis, to implement and work on a model to detect cardiac arrhythmia, using deep learning techniques. Instead of sticking to only one database, attempts to use at least two databases will be made.

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