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A Survey on Automated Detection of Cardiac Arrhythmia

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ABSTRACT

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Cardiac arrhythmia is a potentially life-threatening condition which is generally detected by a doctor with the help of an electrocardiogram (ECG). An arrhythmia is an irregular heartbeat which is caused when the electrical signals controlling the heart are at fault. In the modern world of Artificial Intelligence (AI) and Machine Learning (ML) we can automate the process of detection of such diseases to avoid manual delays in diagnosis in a world affected by COVID-19, where the medical personnel are already overburdened. Automating arrhythmia detection is a problem of classification of heartbeats into normal or the different classes of arrhythmias. It not only reduces the time for diagnosis but also reduces the possibilities of manual errors preventing accurate diagnosis. In this survey we systematically explore the various methodologies and algorithms which have been proposed prior with respect to their advantages, prediction metrics, datasets and gaps. The gap analysis sheds light on the disadvantages of the explored methods and hence provides the future scope of research for them.

Keywords: Arrhythmia detection, Artificial Intelligence (AI), Electrocardiogram (ECG), Classification.

I. INTRODUCTION

In the recent coronavirus pandemic, we have observed that the medical infrastructure that our world and especially our country has is sometimes not sufficient and hence now more than ever there is a need for automation in the medical industry. The first step towards such an automation is the automated detection of diseases and conditions.

In the modern world there has been a rise of heart related life-threatening conditions due to various factors. Cardiac Arrhythmia is one such condition. A cardiac arrhythmia is the irregularity in the normal rhythm of the heart caused by the fault in the electrical signals which are responsible for controlling the heart. It encompasses conditions like slow heart beats called as bradycardia, fast hear beats called as tachycardia and irregular heartbeats.

A regular heart beat is generally called as the Normal Sinus Rhythm (NSR). When the heartbeat deviates from an NSR, it may lead to a cardiac arrhythmia.

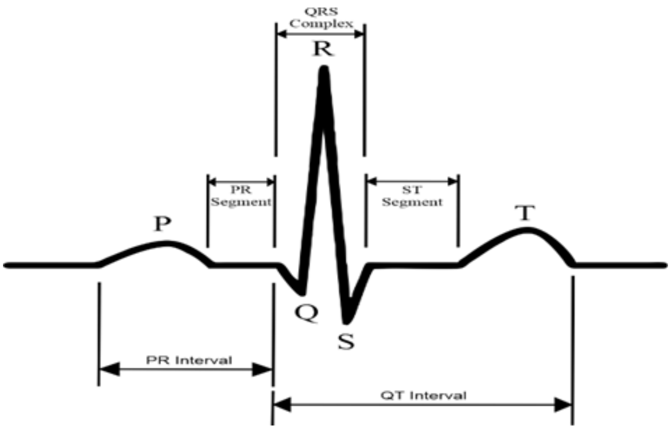

Figure 1: Normal Sinus Rhythm (NSR)

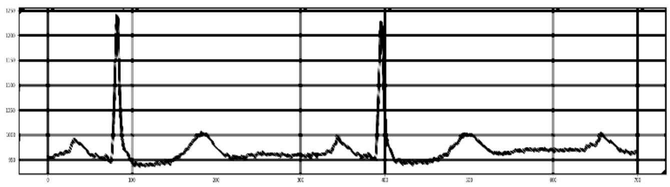

Figure 2. Plotted ECG sample from PhysioNet MIT-BIH dataset [11-12]

The different intervals and segments in the Fig. 1 are some of the parameters which are considered to determine whether the heartbeat is a NSR or not.

Arrhythmia may or may not be life threatening depending on the type and severity. Sometimes it may even go unnoticed, but in other cases it may cause life threatening effects. Hence the early detection of arrhythmia can potentially prevent any further complications. Arrhythmias are generally detected using electrocardiogram (ECG). An ECG records the electrical activity of the heart using electrodes attached to the patient's body. There are different kinds of ECG based on the number of leads used. The word 'lead' sometimes causes confusion. Sometimes it is used to mean the pieces of wire that connect the patient to the ECG recorder. Properly, a lead is an electrical picture of the heart [42].

Heart beats may be classified as Normal Beat (NOR), Left Bundle Branch Block Beat (LBBB), Right Bundle Branch Block Beat (RBBB), Premature Atrial Contraction (PAC), and Premature Ventricular Contraction (PVC) [4]. The severity of the arrhythmia depends on the beat. To detect the kind of beat a certified cardiologist manually examines the ECG report of a patient and based on the knowledge and experience determines it. This manual process is prone to errors in judgement and delays in diagnosis. Automated detection of arrhythmia would mean that this manual process can be skipped resulting in quicker and more accurate diagnosis.

Automated detection of arrhythmia is a problem of pattern recognition and classification. Hence, we can deploy different statistical, Machine Learning (ML) or Deep Learning (DL) algorithms to solve this problem. Automated detection may be achieved by recording the different intervals and segments of the ECG. Various encoding techniques and or visualization techniques maybe be employed to achieve the result as well.

In the remainder of this paper, we will be exploring various such methods that have been proposed before. In the gap analysis section, we will be exploring the disadvantages of the methods and the future scope of the same.

II. LITERATURE SURVEY

This section explores the various documented approaches for automated arrhythmia detection. The different approaches covered in this section leverage the use of Deep Learning, statistical methods, ML algorithms etc. The various approaches are grouped under the following headings – Deep Neural Networks (DNN), Signal Processing Based Approaches, Machine Learning Algorithm Approach, Feature Generation Based Approach.

A. Deep Neural Networks

Deep Neural Networks are Artificial Neural networks having various neuron layers, hence the name Deep Neural Network. The neurons in a DNN are basic functional units which perform some mathematical operation on the input it is provided with. Each neuron has a weight associated with it which determines the relevance of the output produced by it. Various neurons performing similar functions form a layer and multiple layers interconnected with each other form a DNN.

In [1] an end-to-end 34-layer DNN (33 Convolutional Neural Network (CNN) layers + 1 classification layer) approach was used by the authors to classify 12 rhythm classes using an independent dataset prepared and annotated by a consensus committee of board-certified practicing cardiologists. The data was obtained from 91,232 single-lead ECGs from 53,549 patients who used a single-lead ambulatory ECG monitoring device. Average f1 score of 0.873 was obtained which is greater than an average cardiologist (0.780) for the given custom dataset. The outcomes derived from this work were –

- Almost no pre-processing required.
- The dataset used was a custom dataset obtained from a single lead ECG, hence the study is unique as majority studies use the PhysioNet MIT-BIH dataset [11-12] obtained from a 12 lead ECG.

It is worth noting that the distinguishing factor for this method from the other DNN approaches [2-4], is that no substantial preprocessing of ECG data, such as Fourier or wavelet transforms [5-6], is needed to achieve strong classification performance.

Unlike [1], in [3] the number of Convolutional layers used are only 3. In [3] the raw ECG signal is converted to a 256 * 256 pixel RGB image, for each heartbeat post segmentation. The dataset used in [3] is PhysioNet MIT-BIH dataset [11-12], which has 5 different classes for the heart rhythms. The accuracy obtained was 99.1% for the test dataset [11-12]. The outcomes derived from this work were –

- Almost no pre-processing required.
- The number of CNN layers are considerably less and hence the algorithm works more faster and may be more suitable for real world application than [1].

Unlike [3], in [2] the raw ECG signal is segmented into a 64 * 64 pixel 2D grayscale image of a heartbeat before processing. In [2] 5 different classes of heartbeats are classified using the PhysioNet MIT-BIH dataset [11-12]. A CNN with only 3 convolutional layers is used for the same. In doing so they are able to increase the efficiency of the algorithm in real world applications. The accuracy hence achieved is 99.7 % on the PhysioNet MIT-BIH dataset [11-12]. The outcomes derived from this work were –

- Almost no pre-processing required.
- By far the highest accuracy is obtained by the use of this algorithm on the PhysioNet MIT-BIH dataset [11-12].

In [4] the time domain signals of ECG, belonging to five heart beat types from the PhysioNet MIT-BIH dataset [11-12] were firstly transformed into time-frequency spectrograms by short-time Fourier transform. Subsequently, the spectrograms of the five arrhythmia types were utilized as input to the 2D-CNN such that the ECG arrhythmia types were identified and classified finally. Using ECG recordings from the PhysioNet MIT-BIH [11-12] arrhythmia database as the training and testing data, the classification results showed an accuracy of 99.00%. The outcomes derived from this work were –

- Using pre-processing didn't seem to increase the accuracy of the algorithm.

One thing that is worth noting is that the pre-processing steps in [4] seem unnecessary as the CNN is perfectly capable of handling the raw ECG data with almost no pre-processing. In fact, it can be observed that in spite of the pre-processing steps there is no increase in accuracy as compared to [2].

B. Machine Learning Algorithms based Approaches

Machine Learning approaches use algorithms like Scalar Vector Machines (SVM), k-nearest neighbors (kNN) etc. algorithms. These approaches do not involve the use of neural networks. For such approaches pre-processing of the data is required.

These approaches tend to be faster than DNN based approaches because of the lack of neural networks.

An important part of such approaches is the feature selection and hyper-parameter tuning, as can be seen in [5]. In [5] four supervised machine learning models: SVM, KNN, Random Forest (RF), and the ensemble of these three methods are trained and tested. The inter-patient paradigm of training and testing is used here. In this paradigm the heart beats of the same patient are not present in the testing dataset if they are present in the training dataset and vice versa. As compared to the intra-patient paradigm where the heartbeats of the same patient may appear in the training and the test dataset, this paradigm helps avoid overfitting of the ML model.

1) SVM: SVM is a well-known classification technique in supervised machine learning [13-15]. Basically, SVM performs classification by constructing a separating hyper-plane in n-dimensional space (n is the number of features used as inputs) that separates different class labels by maximizing the geometric margin between the input data classes mapped in a higher-dimensional space and minimizing the empirical classification error [16,17]. SVM depends in all this classification process on the kernel functions [18], either as a linear or nonlinear classifier according to the type of its kernel function.

Essentially, the SVM is a binary classification technique. In order to be extended for a multi-classification task, two techniques are commonly used to make it possible, and these methods are one-versus-one (OVO), one-versus-rest (OVR). In the literature, SVM is one of the most popular classifiers used for other applications in biology [19], specifically for ECG arrhythmia classification [13,20–24].

In [5] the accuracy obtained using SVM is 0.83 on the PhysioNet MIT-BIH dataset [11-12] using the inter-patient paradigm. Whereas in [6] an accuracy of 96.3% is obtained using 10-fold cross-validation on the PhysioNet MIT-BIH dataset [11-12]. This difference in accuracies is due to the different pre-processing strategies that are used. In [6] Principal Component Analysis (PCA) is used, which is very good at selecting the most important features for prediction of a dependant variable. The outcomes derived from this work are –

- Pre-processing of data is required.
- The accuracy of this method is low.
- The efficiency of this approach is higher as compared to DNN based approach.

2) KNN: KNN is a common supervised machine learning technique and is considered the simplest technique used mostly for classification tasks. KNN is a non-parametric lazy algorithm because it does not use any model to fit, it is based on memory. The KNN classifies feature vectors according to the labels of the closest training samples in the feature space. The k-nearest neighbors are collected by calculating the distance (such as Euclidean, Hamming etc.) between an unknown feature vector or new sample and all the vectors in the training set [5]. In [5] the accuracy obtained by this algorithm is 0.78. The outcomes derived from this work are –

- Pre-processing of data is required.
- The accuracy of this method is very low.
- As the accuracy is this less, it is impractical to use this approach in the real world.

There are various other classifiers which can be used like a Random Forest (RF) [5], ensemble of various different classifiers [5], regression algorithms etc. A very important part of such approaches is the feature engineering aspect and the pre-processing which causes a huge difference in accuracies.

C. Feature Generation Based Approaches

These approaches use novel or specialized methods to generate features which are later classified by using ML algorithms or something similar. Feature Generation means creation of different features from the provided dataset. This may involve employing algorithms to transform the data various times, to apply different mathematical functions on it in a repeated manner etc.

In [7] homeomorphically irreducible tree (HIT) technique with maximum absolute pooling (MAP) is used to generate features on a large ECG dataset published by Zheng et al. [25,26], comprising 10-second long 12-lead ECG signals from 10,646 unique patients. A HIT is a tree in which all the nodes have a degree greater than 2. After the generation of features a Chi2 selector is used to select the most relevant 1000 features, and finally a SVM classifier is used to classify between the different classes of the heart rhythms.

HIT is a well-known hard mathematical problem with many methods presented for its solution. In [7] a HIT tree of size n = 10 is used for feature generation, and as detailed in the paper, this size may be varied with different trees to obtain different features and accuracies.

In [7] classification accuracy rates of 92.95% and 97.18% were attained for seven class (Case 1) and four class (Case 2), respectively, that were comparable with those of deep learning on the same ECG dataset. The efficiency of the approach proposed in [7] is O(n3). The outcomes derived from this work are –

- The proposed method is novel, in the sense that it uses HIT with MAP to generate features.
- The dataset used is not MIT-BIH, hence it is difficult to comment on its accuracy with respect to the other described approaches.
- The efficiency is much better when compared to the mentioned accuracy of DNN based algorithms.
- A lot of pre-processing is required for feature generation, before classification can take place.

D. Signal Processing Based Approaches

Signal processing-based approaches are those approaches which use some kind of signal processing techniques to obtain features, like Discrete Wavelet Transform (DWT) in [8], Discrete Wavelet Decomposition in [9] or Orthogonal Wavelet filters in [10].

In [8] DWT coupled with novel 1-dimensional hexadecimal local pattern (1D-HLP) technique are employed for automated detection of arrhythmia detection. The dataset used is the PhysioNet MIT-BIH dataset [11-12], from which the ECG signals of 10 s duration are subjected to DWT to decompose up to five levels. The 1D-HLP extracts 512 dimensional features from each level of the five levels of low pass filter. Then, these extracted features are concatenated to obtain 512 × 6 = 3072 dimensional feature set. These fused features are subjected to neighborhood component analysis (NCA) feature reduction technique to obtain 64, 128 and 256 features. Finally, these features are subjected to 1 nearest neighborhood (1NN) classifier for classification with 4 distance metrics namely city block, Euclidean, spearman and cosine.

Being completely mathematical, the efficiency of the approach proposed in [8] is O(n), with an accuracy 95.0% in classifying 17 different arrhythmia classes on the PhysioNet MIT-BIH dataset [11-12]. Outcomes derived from this work are –

- Being a purely mathematical approach, its very efficient when compared to the DNN based approaches.
- It has a relatively good accuracy as compared to some ML algorithms.
- The algorithm is quite complex to understand and design as compared to many other approaches.
- It is not ML based.

[10] uses the following steps: (1) ECG pre-processing; (2) wavelet decomposition; (3) features extraction; and (4) features classification.

Wavelets transforms have been proven to be an excellent tool for analyzing non-stationary physiological signals [27–30]. Several studies [31,32] have exploited wavelet-based methods for classifying heart-beats. However, these studies have employed conventional Daubechies orthogonal wavelets [33,34] for the analysis of the signals. Despite, the Daubechies wavelets have the highest regularity or zero moments

(ZMs) they are not optimal in any sense [35–38]. In [10], an optimal class of stop-band energy SBE minimized para-unitary dyadic wavelet filter banks is used, that does not have the highest regularity unlike Daubechies wavelets [39–41]. The features extracted from these decomposed ECG signals are fuzzy entropy (FuzE), Renyi entropy (RenE) and fractal dimension (FraD). These features were classified using supervised classifiers, and the best results were obtained from KNN, with an accuracy of 98% using ten-fold cross validation.

Outcomes derived from this work are –

- It uses both signal processing and ML classifiers to obtain the result.
- The optimal wavelet-based features used are found to be impressive in analysing non-stationary ECG signals [10].
- The accuracy obtained is quite comparable to the DNN based approaches which are much less efficient.

TABLE I LIETERATURE SURVEY

Approach	Title	Method	Dataset	Results
DNNs	Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network [1]	33-layer CNN	Custom	F1 score = 0.873
DNNs	Arrhythmic Heartbeat Classification Using 2D Convolutional Neural Networks [2]	3-layer CNN	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 99.7%
DNNs	Abnormal ECG Beat Detection Based on Convolutional Neural Networks [3]	3-layer CNN	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 99.1%
DNNs	ECG Arrhythmia Classification Using STFT-Based Spectrogram and Convolutional Neural Network [4]	CNN with pre-processing	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 99%
ML Algorithms based Approaches	An Automated System for ECG Arrhythmia Detection Using Machine Learning Techniques [5]	SVM	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 83%
ML Algorithms based Approaches	A novel technique for cardiac arrhythmia Classification using spectral 4 correlation and support vector machines [6]	SVM with PCA	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 96.3%
Feature Generation Based Approaches	Automated arrhythmia detection with homeomorphically irreducible tree technique using more than 10,000 individual subject ECG records [7]	HIT with MAP and Chi2 selector	Custom	Case 1- Accuracy = 92.95% Case 2 – Accuracy = 97.18%
Signal Processing Based Approaches	Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals [8]	DWT and HLP with SVM	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 96.3%
Signal Processing Based Approaches	An Efficient Automated Algorithm for Distinguishing Normal and Abnormal ECG Signal [9]	DWT, PCA with SVM	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 98.3%
Signal Processing Based Approaches	Automated heartbeat classification and detection of arrhythmia using optimal orthogonal wavelet filters [10]	Wavelet transforms with KNN	PhysioNet MIT-BIH dataset [11-12]	Accuracy = 98%

III. GAP ANALYSIS

This section explores the various gaps in the researched methods and approaches mentioned above. The topic of research being of a medical domain, the accuracy has to be high, for the algorithm to be applied in the real world. Some ML based algorithms discussed in [5], like KNN, SVM are not suitable for the task if proper pre-processing of the data isn't performed, as can be seen by the accuracies of these algorithms in [5]. For use in the real world such approaches need to rely on clever pre-processing and feature generation techniques like in [7-10].

The drawback of the feature generation techniques is that you need to have a detailed domain specific knowledge to generate meaningful features. This also means that the generated features need to be selected using feature selection techniques. Although this is not a drawback, but it adds to the complexity of the approach as compared to the other DNN based approaches. The accuracies obtained by these approaches is much better than using the ML classifiers directly, but they are significantly lower than the accuracies of the DNN based approaches.

A similar set of drawbacks and issues can be seen in approaches using signal processing on the ECG data. The signal processing techniques are highly mathematical and require a deep knowledge of the techniques to apply them for the best and effective results. The accuracies obtained by these techniques are good and they are almost comparable with the accuracies obtained by DNNs. In [8-10] the only dataset the approaches are tested on is the PhysioNet MIT-BIH dataset [11-12], and not any other dataset, which makes it difficult to comment on the effectiveness of the methods suggested.

Unlike the other approaches [5-10] most DNN based approaches yield high accuracy without almost any kind of pre-processing of the data. These algorithms have accuracies which surpass those of a certified cardiologist [1-4]. The major drawback of these algorithms is that because of using DNNs the number of parameters they have to process is large, hence resulting in higher time complexities and less efficiency. This makes it difficult to use these algorithms in the real time. Another issue with such an approach is that the way the DNN arrives at the result is not known and has to be treated like a black-box, hence it is difficult to gain confidence in these systems for detecting diseases in the real world, and hence these systems end up assisting the doctors rather than completely automating the process.

Another issue observed in [2-4] is that only the PhysioNet MIT-BIH dataset [11-12] is used; hence no comment can be made on the real-world accuracies or cross dataset accuracies for these approaches.

A major gap that can be observed in all these approaches is that there is no cross-dataset validation. This may be due to the different leads used to generate different datasets; this is a major gap as different leads produce different kinds of outputs and we cannot train the models on one lead and test on another.

This further complicates things when we want to use these methods on portable 1-lead 2-lead sensors which can be worn by the patient, as, if the model has been trained on a 12-lead dataset, then using it on the data provided by the portable 1 or 2-lead sensors may lead to inaccurate classifications.

IV. CONCLUSION

From the comprehensive survey above we can effectively say that the automated detection of arrhythmia falls under the DL & ML domain. Looking at the previous efforts in this area it can be seen that there is always a trade off between the real time efficiency and accuracy, hence leaving scope for future research and work.

The previous works have been successful in achieving high levels of accuracy at the cost of efficiency, and it may be a hindrance in real time applications. Also, the ability to accurately predict arrhythmias irrespective of the number of leads used to generate data remains unknown form the survey.

To conclude we can say that the DNN based approaches tend to give a higher accuracy at the cost of efficiency. These approaches need the least amount of pre-processing and feature generation. The ML algorithm-based approaches show less accuracies when they are used as stand-alone, that is without any pre-processing or feature generation. The ML algorithms that use pre-processing and feature generation tend to give accuracies comparable to DNN based approaches and are much more efficient than them. The complexness of such approaches is higher and the focus is more on pre-processing.

Throughout the survey we saw the dominance of the PhysioNet MIT-BIH dataset [11-12], and hence it can be concluded from the same that it is the most prominent dataset in use for arrhythmia detection. Although as stated before, this raises the question whether the methods using the MIT-BIH dataset can fare well on a 1-lead or a 2-lead ECG, as compared to the MIT-BIH dataset which was recorded using a 12-lead ECG.

As there is a trade off of efficiency and accuracy for the ML based and the DNN based approaches, an algorithm that leverages both pre-processing techniques and shallow DNNs may have a better efficiency comparable to the signal pre-processing approaches and accuracy comparable to purely DNN based approaches.

To tackle the problem of different lead ECGs, the model can be trained on a mix of datasets like MIT-BIH and the other novel datasets.

Hence, acting on the gaps identified in the gaps analysis section and observations noted in this section the developments in this area can be performed iteratively to ensure that the final model is more accurate and efficient.

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