IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Arrhythmia Classification With Artificial Intelligence Techniques

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Abstract **-**Cardiovascular diseases like arrhythmia are a sig- nificant health concern worldwide, affecting both elderly and young population due to lifestlye changes. Early diagnosis of cardiac arrhythmia using Electrocardiogram (ECG) by trained cardiologists is vital to prevent heart ailments and save lives. With the growth of wearable and standard ECG monitoring devices and a dearth of qualified cardiologists required to analyse the vast amounts of data collected, automated arrhythmia detection by Machine Learning (ML) and Deep Learning (DL) techniques have become very popular in recent years. In this study, we have reviewed the literature and described standard ML and DL studies in ECG arrhythmia classification. While ML techniques do demonstrate very good metrics, ML classifiers like SVM, k- nearest-neighbours, Decision Trees, etc. need preprocessing and hand-crafted feature extraction. DL methods which use networks like Convolutional Neural Networks (CNN), Long-Short-Term- Memory (LSTM) do not need any feature extraction as they automatically learn the features by themselves. Recent studies in DL have demonstrated very high performance metrics without the need for feature extraction. While some DL techniques do need noise filtering and determination of other features like the QRS complex, many of them can work with raw ECG signals and hence are ideally suited over their ML counterparts for real time ECG classification. DL networks can also be used as feature extractors and combined with ML classifiers. We thus conclude that state-of-the-art DL methods offer inherent advantages and flexibility over ML methods for automated arrhythmia classifica- tion. This review aggregates the niche features of leading ML and DL studies in this field which interested researchers can benefit from.

Index Terms—Arrhythmia, ECG, SVM, kNN, Decision Tree, Feature Extraction, CNN, LSTM, MIT BIH

I. INTRODUCTION

The transition from healthy to sedentary lifestyle has led to tremendous increase in number of cases of cardiovascu- lar diseases worldwide primarily in low income and middle income countries including India ([1]). Irregular heartbeats, or arrhythmias, coronary artery disease, heart attack, heart failure, stroke, deep vein thrombosis and pulmonary embolism, vascular disease are some of the most common types of car- diovascular diseases ([2]). According to surveys conducted by WHO, cardiovascular diseases are one of the prominent causes of death globally, calculating an estimated 17.9 million lives yearly ([1], [2]). The mortality rate has increased substantially as there is less advancement in the domain of heart diseases prediction systems. According to studies it has also been observed that people who are suffering from coronary heart diseases including arrhythmia are more vulnerable to Covid- 19 viral infections ([3]).

Arrhythmia, commonly referred as cardiac arrhythmia, is a cardiovascular condition in which there is high occurrence of irregular or abnormal heartbeat ([4]). It can be either too fast– above 100 beats per minute in adults known as tachycardia or too slow – below 60 beats per minute called as bradycardia. Apart from these there are other types listed as below: a premature or extra beat, supraventricular arrhythmias, atrial fibrillation (AFib), atrial flutter, paroxysmal supraventricular tachycardia (PSVT), Ventricular tachycardia (VT), Ventricular fibrillation (VFib), etc ([5]).

Arrhythmia needs early diagnosis and one of the recom- mended ways to detect the state of this disease is Electrocar- diogram (ECG). It is a graph depicting the electrical activity of the heart (voltage vs. time) measured using electrodes, which is a continuous sequence of depolarization (activation) of the ventricles and repolarization (recovery) occurring in each heartbeat ([6]). Experienced cardiologists monitor ECG data and perform diagnosis. There exist varied waveforms of ECG corresponding to different types of arrhythmia. As the amount of ECG data is growing exponentially due to low cost monitoring equipment and wearable devices (like the Apple Watch), there is no efficient way of monitoring this cardiovascular disease because the analysis is time consuming. Also in India, there is a dearth of qualified cardiologists to perform arrhythmia diagnosis. One of the additional short- comings of ECG is in terms of variability. Many findings shows that patients suffering from same class of arrhythmia show different ECG signal patterns and also patients with different arrhythmic conditions show the presence of the same ECG waveforms ([7]). The morphology and spatio-temporal characteristics of ECG are highly dynamic and vary from individual to individual. It is influenced by many factors like age, sex, health of the patient, ECG recording conditions etc. which decide the strength of the signal and outcome of the prediction. Accurate and timely detection of arrhythmia is vital to prevent severe life threatening complications in the future. Hence there is a need of an automated system which can assist medical practitioners to diagnose and provide timely treatment. To address this, there is an emergence of new machine learning (ML) and deep learning (DL) techniques that can make the process of detection and prediction easier, reliable and cost effective ([8]–[10]). By automating the process of arrhythmia detection and classification, the vast amounts of ECG data generated can be reliably classified without manual intervention. The process of detection is also affected by bias of individual doctors hence the process of automation can augment manual diagnosis. Hence in this review, we aim to give an overview of the leading ML and DL techniques for arrhythmia classification and highlight the differences between them. We analyze the existing literature on these topics ex- tensively and describe the leading techniques in detail. Since there exist a large variety of ML and DL studies on arrhythmia classification, it can be a daunting task to go through them and gather information. Many data science researchers interested in arrhythmia classification might be familiar with ML and DL algorithms and their usage but not the medical literature and jargon related to arrhythmia, this review is aimed to make the review process easier. In addition, the existing reviews either comment on ML or DL techniques alone and not both of them. We review both approaches with a tilt towards DL as the method of choice.

The paper is organized as follows. In the next section we briefly describe the methodology of writing this review, followed by sections on the ECG description, types of arrhyth- mia, datasets and final sections on ML and DL algorithms for classification. We end with a summary of our recommenda- tions for future research in Conclusions.

II. MATERIALS AND METHODS

There exist detailed review articles on deep learning tech- niques for arrhythmia classification in the literature ([11]– [15]). References [11], [12] review the ML literature for ECG classification. They also describe arrhythmias and preprocess- ing methods to classify ECG. Reference [12] also reviews the literature for feature selection and extraction in detail. References [13]–[15] deal with DL techniques and describe studies related to various DL architectures. Reference [14] also contains techniques other than ECG in cardiology. Reference

[15] has a comprehensive review of most of the DL related studies of arrhythmia classification, along with highly detailed tables listing the key features of each study. Reference [13] contains a systematic description of the major DL techniques. Starting from these papers, we extracted the studies that seemed most relevant to us from each review and studied them. In addition, we obtained highly cited

papers from internet searches and SemanticScholar. In addition, we also went through different journals and obtained the latest articles in this field. Our review not only combines the existing review articles together, but we have also described a few articles.

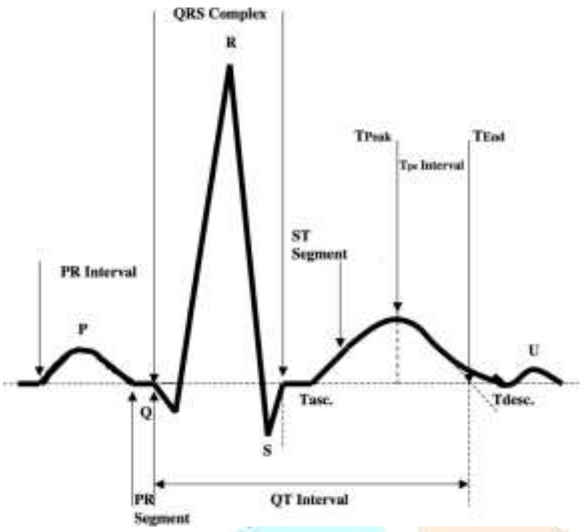

Fig. 1. An ECG waveform showing a cardiac cycle (taken from [16])

which are not found in any of these previous reviews. There is another aspect which sets our review apart from the existing articles. The previous reviews have surveyed a large number of articles but have provided very little description of the actual techniques used. We chose to restrict ourselves only to the most relevant studies and have described the most important aspects of these studies in good detail. There are some unique aspects about each study that sets them apart from the others and we have described those aspects in detail. Some of the very common aspects in all studies like the use of common activation functions, preprocessing steps, etc have been omitted and only the aspects that set each study apart from others are highlighted.

III. ECG AND ARRHYTHMIA

The heart is made of tissue that periodically polarizes and depolarizes resulting in pumping of blood across the body. A normal cardiac cycle consists of depolarization and repolarization cycles of the heart muscles leading to variation in electrical activity, which can be measured. The non-invasive cardiac diagnostic tool Electrocardiogram (ECG) is a graph of this electrical activity. A conventional ECG is measured by ten electrodes placed on the skin, which form 12 leads that record the heart activity from different views. By studying the ECG waveform, experienced cardiologists can determine if the heartbeat is healthy or abnormal. The latter case is called arrhythmia and can be usually detected due to abnormalities in the waveform. Arrhythmia leads to irregular electrical activity which manifests itself in the ECG. We describe the ECG signal and different types of arrhythmia in the next sub-sections.

A. *The ECG signal*

In Figure 1, a normal ECG waveform depicting a single heart beat is shown. We have voltage on the y-axis and time on the x-axis. The morphology of the ECG wave consists of various components and the intervals between them ([17]). The first is the P-wave, which depicts atrial (upper heart chambers) depolarization or activation. The P-wave is the first bump on the left. The PR interval is the time interval from the beginning of the P-wave to the beginning of the QRS complex. The line from the end of the P wave to the beginning of the QRS complex is the PR segment. The next is the QRS complex which shows depolarization of the ventricles (lower heart chambers). The length of the QRS complex is the QRS duration and the peak amplitude is called the R peak, which is an important reference point for the whole signal. A short QRS duration indicates a healthy heart since it means that the ventricles have depolarized and have quickly become ready for the next cycle. A long QRS duration means the heart is sluggish. The time interval between two successive R peaks, called the R-R interval, is a very crucial factor used by most studies in ECG analysis. The next part is the ST segment which indicates the second part of the activation, followed by the T wave showing complete repolarization (recovery of ventricles). It is generally followed by a small amplitude U wave.

Each of these components measure different stages of the cardiac cycle and are subtly altered during arrhythmia. The durations of the different phases can fluctuate, or the amplitude and shape can change. While highly trained cardiologists are able to identify these changes, automated algorithms that can accurately do the same task will be of immense value for healthcare.

There are some practical challenges in analyzing ECG sig- nals. ECG signals are generally in the 0.5 - 150 Hz frequency band and are hence easily corrupted by noise which have to be filtered out ([7], [18]). Reference [12] has a thorough description of the various filtering techniques used.

While noise removal is a compulsory step in ML analysis as they rely on feature extraction, some DL studies reviewed here do not need filtering at all since they are robust enough to learn features even in the presence of noise. Another factor is the detection of ECG signal features like the QRS complex and R peak ([19]). Most of the energy of the ECG signal is in the QRS complex and variations in this part of the waveform are a key indicator of arrhythmia. Once the R-peaks are determined, the RR interval is used as a feature descriptor, among several other morphological (shape) features of the waveform. R-peak detection is also key to segment the continuous ECG signal into individual heartbeats. The R-peak is used as a reference point and an appropriate number of samples from either side of the peak are considered to be a single heartbeat. We will not elaborate much on these aspects of preprocessing since the literature has ample descriptions of the process.

B. *Types of Arrhythmia*

The association for the advancement of medical instru- mentation (AAMI) classifies non-life-threatening arrhythmias into non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q) ([20], [21]). Most of the studies listed in this review classify ECG beats into these five common classes. A few common types of arrhythmia are premature beats, supraventricular types which include atrial fibrillation, atrial flutter, paroxysmal supraventricular tachy- cardia, ventricular types which include ventricular tachycardia, ventricular fibrillation, heart blocks which include right bundle branch block and left bundle branch block. Each of these conditions has some characteristic features that manifest in the ECG signal.

IV. DATASETS

We list some databases that are used for arrhythmia clas- sification. Reference [12] has a very thorough description of all the databases and we will not repeat the information here, instead we will only briefly list them here for completion. The most commonly used one is the MIT-BIH Arrhythmia Database (MITDB). It consists of 48 half-hour excerpts of two- channel ambulatory ECG recordings, these recordings are ob- tained by studying 47 subjects at BIH Arrhythmia Laboratory from year 1975 to 1979. Randomly 23 recordings were chosen from a set of 4000 24-hour ambulatory ECG recordings which were collected from a population of inpatients and outpatients (40 %) at Boston's Beth Israel Hospital. In order to select less prevalent but medically prominent arrhythmias that would be poorly represented in a random sample, out of 48 half hour ECG recordings, remaining 25 need to be selected for representation. Two important components of the MITDB are: MIT-BIH Atrial Fibrillation database (AFDB), which has 25 long-term two-channel ECG recordings totalling 10 hours of patients with atrial fibrillation at a sampling frequency of 250 Hz; MIT-BIH Supraventricular Arrhythmia database which has 78 half hour recordings with supraventricular arrhythmia. Another prominent one is the PhysioNet/CinC Challenge 2017 database with single-channel short ECG recording and asso- ciate human annotations for 8528 and 3658 human subjects at a sampling frequency of 300 samples per second. Creighton University Ventricular Tachyarrhythmia (CUDB) has record- ings of 35 patients who suffered from sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation at a sampling frequency of 250 samples per second. The American Heart Association (AHA) constructed a database comprising of arrhythmias and electrocardiograms (ECG) contained in two series by precisely editing, beat-by-beat, ECG recordings annotated by cardiologists, available on a USB drive. The University of California, Irvine machine learning repository is a database containing a mix of different types of attributes which are 279 in number, out of which 206 are linear valued and the remaining are nominal.

A. *Performance Metrics*

We list the following metrics popular in literature to mea- sure the quality of classification. If TP, TN are the correct predictions of positive and negative class and FP, FN are the corresponding incorrect predictions then:

- Accuracy (Acc) = $TP + TN/(TP + TN + FP + FN)$
- Sensitivity (Sen) = $TP/(TP + FN)$
- Specificity (Spec) = $TN/(TN + FP)$
- Precision (Prec) = $TP/TP + FP$
- Recall = $TP/(TP + FN)$
- F score = 2. $(Prec \times Recall)/(Prec + Recall)$

V. MACHINE LEARNING TECHNIQUES FOR ECG CLASSIFICATION

In this section, we describe some studies which have used traditional machine learning (ML) techniques for arrhythmia classification. The best known ML algorithms are decision tree, support vector machine, k mean clustering, and k nearest neighbours. A common aspect among these ML algorithms is the necessity of performing feature extraction from the input ECG waveforms. These features are of various types like temporal, frequency and statistical. The magnitude of these features will differ among various arrhythmia classes and are used to train the ML algorithms. The success of ECG classification using traditional ML is critically dependent on the choice of features which have to be carefully handcrafted for different algorithms. These also depend on the dataset selected. Feature selection methods are grouped into three categories, called filter, wrapper, and embedded methods ([12]). Filter methods construct a classifying model by cal- culating feature relevancies using various scoring techniques independently. On the contrary, wrapper methods select fea- tures based on some rules and criteria of search algorithms and learning models which select subsets of features. Those methods consider feature dependencies and provide interaction between feature subset search and choice of a learning model. However, they are computationally expensive with respect to the filters. Embedded methods are designed in such a manner that there is an optimal way of integrating feature selection with the training phase. Thus they are similar to wrappers but less computationally intensive. Some studies on ECG signal analysis using feature selection methods are given in these subsections. We mention this to show that there is no unique way of selecting the best features which can be consistent across all data sets and machine learning algorithms, as each individual algorithm has its own pros and cons and it's difficult to determine one standard optimized way of feature selection which can yield higher classification accuracy. Random search algorithm (RSA) is one of the feature selection algorithms wherein, from the dataset consisting of full set of features of size N , subsets of features of features from size 1 to N - 1 are selected. After this a grid search algorithm is applied to obtain an optimized version of the random forest model.

There exist various techniques to determine the most significant features for ML training in complex datasets since choice of relevant attribute can improve the performance metrics. Before moving to specific ML algorithms, we describe some feature selection and extraction approaches followed in some studies. In [22] authors suggest a few feature selection algo- rithms such as hybrid grid, random search algorithms which can help us in choosing the best features for further classifica- tion or prediction approaches. In [23] the authors claim that as compared to previous research papers in the domain of heart disease detection using machine learning techniques with the Cleveland dataset, their technique of implementing artificial neural network outperformed other traditional approaches with an accuracy of 100 % using minimum features. The authors aimed to improve accuracy by reducing the dimensionality of features as a part of the feature selection process. Decision tree achieved accuracy of 88 % and na¨ıve Bayes of 85 %. In [24] the authors used discrete wavelet transformation, auto correlation coefficients and principal component analysis to extract features from frequency, time and morphology respectively. Reference [25] uses the random search algorithm to iteratively select a subset of features N number of times as a result of which the process of feature selection is com- putationally expensive. The dataset was initially supplied to the random search algorithm (RSA), which produced different subsets of features of sizes from 1 to N -1, where N denotes the size of full features in the dataset. For each subset of features, the optimized version of random forest model was obtained by exploiting exhaustive grid search algorithm. In [26] the authors highlight the selection of significant features based on their ranking. ML algorithms such as Random trees (RTs), decision tree of C5.0, Chi-squared automatic interaction detection (CHAID), and support vector machine (SVM) are used here to determine the significance of important features and assign the priority or rank. The authors used an updated data repository called the Z-Alizadeh Sani dataset.

Reference [11] surveys different approaches implemented in order to extract features like R-peaks, QRS complex and conclude that the Hilbert transform based methods are an effective approach in extracting discriminative features in ECG beat classification. It has the ability to distinguish dominant peaks among other peaks in ECG signal.

Reference [27] uses Empirical Mode Detection with adaptive thresholding to detect the QRS complex and R peak.

We now describe studies based on key ML algorithms for arrhythmia classification and the results are summmarized in Table I.

A. Decision tree

In [28], the authors analysed the performance of the C5.0 decision tree model with additional boosting on the ECG signal feature vector dataset. It was found that the process of boosting could remarkably improve the accuracy. The algorithm builds models in a sequential manner and the subsequent model tries to correctly classify misclassified labels by the preceding model. Multiple decisions were incorporated together to form one final choice in order to classify new labels. The boosted C5.0 DTs model performance in terms of accuracy was compared with other classifiers and the results of the experiment showed that it gained 99 % classification accuracy for ECG signals as normal or abnormal(arrhythmia). Reference [29] used the 2017 PhysioNet/CinC Challenge dataset for classifying ECG signals into normal sinus rhythm, atrial fibrillation (AF), alternative rhythm, and unclassified rhythm. They developed an approach incorporating decision tree classifier with AdaBoost.M2 algorithm for training pur- pose along with 30 extracted features from ECG recordings. The method obtained an overall F1 score of 0.84.

B. SVM

In [30] the authors used discrete wavelet transforms for the purpose of extracting features which indicate the presence of arrhythmia. A total of 190 features were extracted from the pre-processed dataset using Discrete Wavelet Transform (DWT), which was chosen as it has the ability to vary the window size depending on the frequency. Experimentally it was observed that the classification accuracy of the SVM classifier model is 95.92 %. Reference [31] used the dataset taken from University of California at Irvine Machine Learn- ing Data Repository to classify patients into one of the sixteen subclasses, wherein one class indicates non-existence of ar- rhythmia and the other fifteen classes represents ECG records of different subtypes of arrhythmia. Due to the presence of abundant data there was a need of pre-processing hence reduc- ing the dimensionality of features like wrapper based feature selection method built on random forest algorithm. For mul- ticlass classification, support vector machines based methods were employed which consisted of one-against-one (OAO), one-against-all (OAA), the output of classification indicated that OAO method of SVM outperformed all other classifiers by achieving an accuracy rate of 81.11% and 92.07 % depending upon the splitting proportion. Reference [32] proposed a pre- diction model by building two support vector machines (SVM) to predict heart disease efficiently. The first svm model, serves the purpose of removing insignificant features, and the second one is applied for prediction. In addition to this the authors have used the HGSA (hybrid gird search algorithm) to enhance the efficiency of these two methods. By using this model, they have achieved 3.3 % better accuracy than the conventional SVM models. Reference [33] proposed the design of the SVM classifier for classifying four types of arrhythmia on MIT- BIH database with an accuracy of 93 %. Optimization was achieved by integrating SVM classifier along with genetic algorithms for searching the best attributes and choosing the ones which can enhance the classification function. The authors of [34] came up with a new approach of detecting and classifying arrhythmia by combining morphological and dynamic features. Morphological features were extracted by applying wavelet transform and independent component anal- ysis to each heartbeat which further extracts corresponding coefficients. Dynamic feature were also generated due to the rhythm around the corresponding heartbeat (RR interval). Both the features were combined and fed to support vector machine for classification of heartbeats into 15 classes. Another unique feature was that this study combined information from two leads. The procedure was applied to the data generated by segmentation of two ECG leads independently and the results from two signals were merged together to give one single decision. If two results were inconsistent then the one with greater confidence was chosen. The experiment was performed on MIT-BIH Arrhythmia database which gives an accuracy of 99.66 %. The method of segmentation of ECG signals to obtain the features demands more work in detection of R peaks as it has direct implication on the dynamic features. Reference [35] uses SVM for arrhythmia classification. After denoising, segmentation was performed on the noise free filtered signal for accurate feature extraction. Peak to peak Interval (R-R Interval), BPM (Beats per minute), P wave to QRS peak were extracted. This algorithm classifies the input ECG signal with varying feature parameters to two different types of arrhythmia. This approach achieved an accuracy of 91 % and the performance regarding other criteria such as precision, recall and F1 score were high, indicating the success of the proposed method. In [36], the MIT-BIH dataset was used for arrhythmia classification using SVM monitored by optimization algorithms like PS0, GWO, MGWO. The ECG signals were filtered to remove power-line interference and baseline wander. Normalisation was done using methods like Principal component analysis and SKF, after which these normalized signals were applied to the SVM classifier. It was seen that the MGWO was the best performing optimizer. In [30], the Discrete Wavelet Transform (DWT) was used to classify signals from the MIT-BIH database. 190 features were extracted using the D and

C. *K nearest neighbors*

In [37], a model for diagnosing heart arrhythmias by extract- ing morphological features of ECG signals. The signals taken from MIT-BIH arrhythmia database were initially modelled using hermitian basis function and then optimization was done to minimize the model error. Next, the feature vector was fed as input to k-nearest neighbour (kNN), classifier. Here, classification of seven different types of arrhythmias have been done attaining the sensitivity of 99.00 % and specificity of 99.84 %. The major benefit of using hermitian model for extracting parameters and classification process using kNN is, it takes almost 0.56 seconds for each beat which is considerably lesser than a normal ECG heart beat duration. Hence this method is most suited for real- time diagnosis in medical emergency. The study [38] presented the recognition of five types of ECG beats using a three- step system. The first step is responsible for detecting peaks in ECG signals using Pan-Tompkins algorithm (PTA). Second step does the job of extracting interval features i.e. QRS time, higher order statistics (HOS), min-max and temporal features. In third step, K-Nearest Neighbour (KNN) is employed for classification of ECG beats. The signals were obtained from MIT/BIH arrhythmia database for classifying heartbeats as normal or abnormal.The results from the experiments stated that the proposed technique gained an accuracy of 98.40 %.

I. DEEP LEARNING TECHNIQUES FOR ECG CLASSIFICATION

In this section we will review the literature on deep learning (DL) techniques for ECG classification. Most DL papers related to arrhythmia classification use Convolutional Neural Networks (CNN) or Long Short Term Memory (LSTM) net-works, or a combination of these.

A. *ECG Classification using CNN*

Convolutional Neural Networks are a class of feed-forward neural networks modeled on the mammalian visual cortex ([41], [42]). These are primarily used for image processing and operate on 2D matrices, but can also work with 1D data. CNN’s have shown great success in a variety of fields like image processing, speech recognition, etc. A number of CNN’s like AlexNet ([43]), VGGNet ([44]) and GoogleNet ([45]) trained on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset have increased the popularity and usage of CNN’s. We will briefly describe the architecture of the CNN and the inspiration behind it and then describe the various studies which have used CNN’s for arrhythmia classification using ECG signals.

A study of the cat visual cortex determined that it comprises of a number of neurons, each of which responds to a small portion of its field of vision, called its receptive field ([46]). With such a structure, the visual cortex, whose basic operations are similar across the mammalian hierarchy, first learns local features like edges, corners, etc. in a given visual stimulus, with successive neurons learning higher order features. The architecture of CNN is directly inspired by this and as we shall see, confers great computational advantages compared to an ordinary fully connected ANN.

A CNN comprises of an input layer followed by a few convolutional layers, interspersed with pooling layers and a fully connected output layer. We will describe the architecture of a 2D CNN first, a 1D CNN acts in a similar way but with modifications ([47]–[50]). A convolutional layer performs a ‘convolution’ operation on the input image with a few small square matrices generally of size 3 or 5, whose elements are 1’s and 0’s in different arrangements. These filters are slid across the input and an element-wise dot product over the overlap area is taken, and the sum is written to the top-left corner, generally, of the output matrix. Each element in the output matrix represents a 'neuron' corresponding to a small region in the visual field. The value of this 'neuron' yields the local value of the particular feature corresponding to the filter being used. The filter is slid across with a an offset called a 'stride', which is one of the hyperparameters. A stride of 1 means the filter is applied to the immediate next elements, a stride of 2 means a column is skipped and so on. Larger strides lead to smaller convoluted matrices. Different filters yield outputs which differ in the quality of local information. in the input. For example, some filters might pick out edges in a particular orientation, etc. Thus the output of this layer is a set of so-called feature maps, with all neurons in a given map sharing the same filter weights. The purpose of generating this feature map is to extract small-scale information in the input, with each filter yielding a given feature. Since the filter size is small, local features like lines, corners, etc are readily picked out without averaging by the whole image space. Thus, the convolutional layer is the key component in a CNN that extracts highly local information from the input. These are then passed through an activation function, which is mostly the rectified linear unit (ReLu), since it retains positive data only and introduces non-linearity in the network. After the convolutional layer, there is a pooling layer that reduces the dimensionality of the sv

The size of the pooling layer is another hyperparameter. This is done so as to reduce noise in the input so that irrelevant data are removed, reducing the number of computations while still retaining all essential information about the input. Depending on the ap- plication, different combinations of alternating convolutional and pooling layers are used. Finally, a CNN uses a fully connected layer for final classification, where each output neuron receives input from every neuron in the previous layer. Softmax activation is used mostly for classification. Also, layers like batch normalization ([51]), dropout are used to reduce overfitting ([52]). Backpropagation is used for training. An advantage over ANN's is the reduction in computational cost for an input of a given size. This is because convolution only uses small filters and for a given feature we have only a small number of weights. Since an ANN uses all possible connections between successive layers, the number of weights increases exponentially. These advantages make CNN a very attractive technique for feature learning and classification. Thus, we will describe the results of various arrhythmia classification studies that have made use of CNN. The results

are tabulated in Table II.

1) *1D CNN:* One of the first works to use 1D CNN for arrhythmia classification was by Kiranyaz ([53]). Here the authors use 1D arrays of ECG data instead of 2D matrices, with 1D filters in the convolutional layer. After beat detection, three successive ECG beats were fed at once to learn temporal patterns, and another extended pattern with Fourier data is also used. The latter was used to check if addition of frequency information in training yields any advantage. A mix of beats were used, which consisted of beats common to all patients and beats specific to each patient, the latter being used to introduce patient-specific training. The CNN itself was shallow with 3 convolutional and 2 fully connected layers. It was determined that the base representation was the best both in terms of performance measures and computational cost, especially since the CNN had only a few layers with with 32 and 16 neurons in the convolutional part and 10 in the hidden part. The output had 5 neurons for the 5 beat classes. The accuracy was 99 % for VEB and 97.6 % for SVEB, the latter performance being poorer due to underrepresentation of beats in this class as the dataset was unbalanced. Acharya et. al, have a number of different approaches for ECG classification using CNN. In [9] the authors used the MIT BIH dataset and a 9 layer CNN, with imbalanced, noisy beats. The accuracy for imbalanced dataset was 89.07 % and 89.3 % for noisy and noise free data. The dataset was balanced by generating synthetic data such that the number of beats in S,V,F and Q classes matched those in N class, since the latter had most number of beats. On this balanced data, the accuracy rose to 93.47 % and 94.03% for noisy and noise free datasets. In [54], the authors used two different CNN's trained with

2 second and 5 second segments of ECG data to classify Atrial Fibrillation, Atrial Flutter, Ventricular Fibrillation and Normal beats. The data was taken from a variety of public databases for these different arrhythmia types. The CNN's had different architectures for the two types of input segments. The main highlight of this work is that the authors did not perform any QRS complex

detection and instead used whole segments of ECG for training. This was done to make the process comparable to a real world ECG measurement where doctors measure a segment of ECG. The accuracy was 92.5

% and 94.9 % for the 2 and 5 second data which is expected as the 5 second network had more data. However the PPV and specificity were better for the 2 second network, showing that sometimes, the nonlinear nature of ECG data can lead to better performance even with lesser data. In [10], the authors used a 11 layer CNN to classify Myocardial Infarction (MI), using data from the Physikalisch-Technische Bundesanstalt diagnostic ECG database([55]). R peak selection was done and there were only two output classes, normal and MI. With and without noise, the accuracy was 93.53 % and 95.22 % respectively. Here, the other measures were also better for denoised than noisy data.

Most studies use the morphological features of parts of the ECG signal like the QRS complex. Yildirim et al. ([56]) used 10 second fragments of the ECG signal to recognize 17 arrhythmia classes with no QRS detection, segmentation or noise filtering. 1000 signal fragments from 45 patients was used from the MIT BIH Arrhythmia database. The CNN had 16 layers and was used to classify subsets of 13 and 15 classes of beats in addition to the full 17 classes. The metrics varied among the three output numbers and for the 17 class case, the overall accuracy was 91.33 %. The network was compu- tationally cost-effective since there was no preprocessing of any kind involved, taking 0.015 seconds to classify a single 10 second fragment. However, the drawback of this method is each fragment had to contain only one class of beat. Also, a related study using genetic ensembles of classifiers for 17 arrhythmia classes ([57]) obtained a comparable accuracy of 91.4 % Nurm aim ei al. ([58]) recently have classified atrial fib- relation arrhythmia using data from three databases and an Indonesian hospital. Several novel insights have been provided with a 1D CNN where the hyperparameters were varied extensively and the whole process is described in detail, as against most other papers where the parameter tuning process is not explained in detail as the authors in those papers chose to concentrate on other factors. The raw ECG signal was first normalized and filtered with the Discrete Wavelet Transform technique with a Sym5 mother wavelet as this produced the best results. The signal was segmented into samples of different lengths. The number of convolutional layers too were varied between 7, 10 and 13 it was determined that the CNN with 13 layers and the smallest input segment length of 9 seconds (vs 60 seconds) performed best. The imbalanced dataset was balanced with 10-fold splitting. Finally for 3 classes, the CNN achieved an accuracy of 99.17 %. In addition, the authors also presented the computational cost of using 7, 10 and 13 layers using 5 different CPU-GPU combinations.

An interesting study of a very large dataset of 30000 patients was done by Rajpurkar et al. ([8]) with a CNN of 34 layers and a special block architecture, with 14 output classes. The data was collected using a wearable device called the Zio patch monitor ([59]) and is much larger than the usual MIT BIH dataset normally used in most studies of ECG classification. This CNN precision and recall scores outperformed those of committees of certified cardiologists (0.8 vs 0.723 in precision and 0.784 vs 0.724 in recall) and was the first to accomplish such a feat, hence we will describe the methodology in a bit of detail. A total of 64123 ECG records were obtained from 29163 patients using the device. Each record contains more than one rhythm was 30 seconds long and was annotated by a clinical ECG expert. For testing, 336 records from 328 patients were used and ground truth annotations were obtained by a committee of three cardiologists. Three different committees were used for different parts of the test data. In addition, six other individual cardiologists also separately annotated the data, thus forming a rigorous testing protocol. The CNN itself comprised of 16 blocks with 2 convolutional layers per block, and an increasing filter length every 4 blocks. Batch normalization and dropout were used. A similar study was repeated in [60]. We highlight this study as this shows that collecting large amounts of data for arrhythmia detection is very useful for deep learning methods.

While all these above studies focused ECG classification from a single lead, Liu et al. ([61]) used all 12 leads for MI classification into 5 types. The Physikalisch-Technische Bundesanstalt (PTB) diagnostic ECG database ([55]) was used, with 549 records from 290 patients. The dataset was imbalanced and the authors retained it that way to reflect real world recording conditions. The rationale behind the paper is that a complete picture of heart activity is obtained by combin- ing information from all 12 leads rather than focusing narrowly on just one lead. Hence, a multi-feature branch CNN (MFB- CNN) was developed where each lead information is supplied to a feature extracting convolutional part and a fully connected layer at the end combines information from all leads. Each feature branch was independent of the others and had 7 layers, which are the input layer followed by 3 convolutional and 3 pooling layers. By combining all available information fromthe ECG, a classification accuracy of 99.95 % was reported. An important point to be noted here is that most studies use a single lead since computational cost multiplies with more leads and hence, in this study, the network was rather shallow. However, with clever use of high performance computing, it should be possible to use all 12 leads with deeper networks to achieve competitive results for arrhythmias other than MI as well. This is our recommendation for future research to combine the various leads.

1) *2D CNN:* While 1D CNN's use either the filtered or raw ECG signal, there are studies of arrhythmia classification where additional information, mostly from the frequency do- main using Short Time Fourier Transforms (STFT), Discrete Wavelet Transforms (DWT) etc. are used to augment the input signal and convert it into a 2D matrix. Since CNN's are primarily used for image classification, converting a pure 1D time series like the ECG into an image allows to use some of the core strengths of CNN's for arrhythmia classification.

One of the first studies to use 2D CNN's was [62]. A spectrogram was formed from ECG data and was classified with the GoogleNet CNN. However, in that study, a 1D CNN with 16 layers and skip connections that decreased training time, performed better than the 2D version. However other studies have demonstrated good success with the 2D method. Another study is [63] where the authors coverted ECG data after filtering into a wavelet, by the Morlet method and STFT representation to train a CNN. Cardiologist annotated data was used for this purpose.

In [64], the authors used STFT and Stationary Wavelet Transform (SWT) to convert the ECG signal into a 2D matrix to classify Atrial Fibrillation using the MIT BIH database. Two different CNN architectures were used to classify the STFT and SWT versions. An STFT is a time-frequency rep- resentation of the signal which shows the dynamic evolution of frequencies through time and is expected to encode the signal morphology, showing differences between a healthy and arrhythmic heartbeat. The SWT works on a similar principle, the difference is that in an SWT, this information is encoded in the wavelet coefficients which vary with time, a total of 12 coefficients were used here. Hence the SWT input is a 2D matrix of coefficients indexed by time. The original dataset was balanced first. After extracting 5 second segments of the signal and filtering, the STFT was generated using a Hamming window of 128 samples. The SWT matrix was constructed by using a Daubechies 5 wavelet. The best architecture for STFT and SWT was determined by experimentation and was different for both types. With an RGB spectrogram for STFT, the accuracy was 98.29% and with a grayscale it was 97.74%. With SWT the accuracy was 98.63 % and the other metrics were better too, showing that the SWT was better at classification.

A 2D CNN was used in [65] which did not use any frequency domain information. The MIT BIH database was used to classify into the 5 usual classes, while focussing on V and S beats. The dataset used had a common part and a patient specific part. The heartbeats were segmented over a durationof 10 seconds around a given beat and then scaled up to the same size for all beats. Finally, the authors constructed column vectors of two adjacent beats and the input to the CNN was the outer product of two such consecutive vectors. The CNN had 3 convolutional, 2 pooling and a final connected layer. For training, the S beats from the common part were chosen carefully, since for S beats, the morphology varied from beat to beat and this was also seen in other similar studies, due to which S beats were misclassified as N beats. By randomly choosing 75 N and S beats and performing training, a final set of 75 S beats with highest accuracy were selected for training. With these changes, the final classification accuracy of V and S beats were 98.6 % and 97.5 % respectively. It was also seen that the positive prediction rate for S beats was highest when the most representative S beats were used for training (73.9 % vs 57.4 %). This highlights the fact that in most imbalanced ECG datasets, choice of the correct beat classes for training significantly improves the CNN performance.

In [66], the authors used a CNN pretrained on the ImageNet database and used a transfer learning approach to use this CNN on their input ECG data. The datasets used were MIT- BIH arrhythmia, Incart and SVDB. The raw ECG signals were filtered and the QRS complex was extracted. The signals were converted to a 2D image representation using Contin- uous Wavelet Transform (CWT). Three different wavelets, the Daubechies, Biorthogonal and Coiflet were used together. For pretraining, the authors used the VGG model with five convolutional layers. The pretraining was done on the Ima- geNet database with 1.2 million RGB images which comprised of general scenes like animals, scenery, etc. On passing the input 2D images through the CNN, a one dimensional feature vector of size 4096 was produced, which was applied to an additional layer that did the final classification. Through this unique approach, the authors obtained overall accuracies of 99.9 % and 99.8 % for VEB and SVEB respectively. This demonstrates that using a pretrained CNN can also be very effective at classification since CNN's are versatile feature learners.

In [67], the authors used the PhysioNet Challenge 2017 dataset and a novel CNN to classify arrhythmia into 4 classes for Atrial Fibrillation detection. The dataset was first balanced by resegmenting. Then discrete wavelet frames (DWF) are used to extract information at various scales, enabling a multi- scale decomposition of the ECG signals. The key feature of this paper is the construction of two CNN's of different architecture. The first is called FDResNet (Fast down-sampling residual CNN) which is composed of a fast down-sampling module, which has two convolutional layers with a stride of 3, reducing the dimension of the input. This is followed by the residual module with 3 convolutional layers of increasing width, max-pooling and a residual short circuit. The last is a fully connected classification module. The other type of CNN is called multi-scale residual CNN (MSResNet), which has three FDResNets all of the same architecture but trained at different wavelet scales. Thus each FDResNet here learns features at different scales of the input waveform. The output of this is combined together in a single vector and a fully connected neural net does the final classification. It was seen that the FDResNet with skip connections performed better than ones without any skipping and overall, the MSResNet performed the best. Although the test accuracy was 92.1 %, the CNN's used in this study are unique and deserve further attention.

B. *ECG classification with LSTM*

There are some studies on arrhythmia classification using neural nets working on different principles than CNN. One of them is Long Short Term Memory Network ([72]). They have units that introduce memory in the network, which helps in classifying temporal patterns. The temporal sequence in an ECG signal contains information about different arrhythmia and LSTM's are ideally placed in detecting these patterns.

We will describe some LSTM based studies here and list the results in Table III.

In [73], the authors tackle the problem of Atrial Fibrillation (AF) classification with a bidirectional LSTM. The occurrence of AF is unpredictable and is interspersed with a large number of normal sinus rhythms. Thus, long duration sequences have to be collected to accurately detect AF, which is possible by monitoring the patients even outside the hospital since AF rhythms, though lethal, are very intermittent in nature. This makes the use of automated analysis essential to classify the long duration signals collected. The input was MIT BIH AF dataset of 23 patients, 20 of which were used for training and 10-fold cross validation, the remaining were used for blind-fold validation. Each dataset was 10 hours long with RR annotation, from which the RR intervals were split into overlapping sequences of 100 beats. Beat sequences with one or more AF beat were classified as AF. The LSTM classifier had forward and backward LSTM cells constituting the LSTM layer, followed by a global max pooling and a fully connected layer. Tthe number of cells in forward and backward direction were twice the input length sequence and max pooling was used between the LSTM layers. Dropout layers were used to prevent overfitting. Finally the LSTM network had an accuracy of 98.51 % and a blindfold accuracy of 99.77 %. However, as the authors acknowledge, the use of a small dataset hampers the training quality and computational time is also large for this particular network, hindering a more thorough exploration of the parameter space.

In [74], the authors used four different types of LSTM networks to classify ECG from the MIT-BIH database into 5 classes. Unidirection, Bidirectional and both versions with a new input layer using wavelets were the four types. In the wavelet networks, the wavelet coefficients were used along with the main signal as inputs. DWT with a filter bank was used to decompose the ECG signals and wavelet coefficients were extracted at different levels with the Daubechies family. All four networks had two LSTM layers (uni or bi) of 64 and 32 dimensions after the wavelet layer and two terminal dense layers of dimensions 128 and 5. Dropout layers were used between the two LSTM layers and between the dens layers to prevent overfitting. It was seen that the networks without wavelets performed poorly and a correlation analysis showed that certain classes whose features were correlated, were misclassified. The best performing networks were the unidirectional LSTM with wavelets decomposed to 3 levels, with accuracy of 99.25 % and the bidirectional LSTM with 2 level wavelets with accuracy of 99.39n %. An interesting point is that with additional wavelet levels, both networks underperformed, and the given wavelet numbers were the best. This again shows that a large amount of detail can confuse highly non-linear classifiers like LSTM's.

LSTM's have been used to tackle imbalanced datasets in [75] using data from the MIT-BIH arrhythmia DB to classify into 8 classes. Over and undersampling methods have been mentioned before to address these but they involve resampling and modification of the dataset. Hence the authors use a loss function called Focal Loss ([76]) combined with LSTM, which concentrates on difficult to characterize arrhythmia beats while reducing the importance of normal ECG beats which are large in number compared to the unhealthy beats of greater interest. The focal loss function is a dynamically scaled cross-entropy, which multiplies beats which are wrongly classified by a factor close to 1 and leaves its importance un- changed. A scaling parameter is used for tuning the focal loss function. Mostly normal beats are easy to classify and are multiplied by a factor less than one, leading to a balanced classification. As for opertation, first the ECG signals were denoised with a Daubechies wavelet method and segmented into samples of length 250 with R-peak annotation. The LSTM had an input, 1 LSTM and two fully connected output layers. For network optimization, a combination of Adam and NAG methods were used. After extensive experimentation it was determined that dropout was not required and a stable value of the focal loss parameter was determined. It was determined finally that with the normal cross entropy loss function, an accuracy of 98.7 % was achieved. With the improved focal loss function, the accuracy increased to 99.26 %, whowing that the focal loss method indeed improves classification performance. This example shows a way to account for an imbalanced dataset by suitable choosing a loss function. For future work, researchers could explore different varieties of loss function taking inspiration from this approach.

I. CONCLUSION

This literature survey provides an overview of various machine learning (ML) and deep learning (DL) techniques implemented for the purpose of arrhythmia detection and classification. Through many experimental results it has been found that deep learning techniques have an edge over machine learning algorithms in various aspects. For example, ML techniques requires an essential step before classification i.e. pre-processing step mainly responsible for noise removal, data cleaning and hand-crafted feature selection. On the other hand, DL methods can perform very well even in the absence of pre-processing steps since the input i.e. raw ECG signals can be fed to the classifier directly without the need for feature extraction. However, it has to be noted that some level of preprocessing might be necessary for some of the DL methods presented here to be fully effective. With the ML approach, there is no standardized universal method for feature extraction which can be applicable for all types of datasets and arrhythmias, instead these steps depends on various factors such type and size of dataset, type of ECG signal, type of ML algorithm employed etc. In previous works, many authors have integrated feature selection algorithms with core machine learning techniques. It was found that different feature selection algorithms on same datasets and can give output of different set of selected features based on dissimilar criteria during selection process, whereas DL methods bypass the feature selection step which makes the overall process computationally less expensive and improves efficiency and other performance metrics. We have also reviewed some studies where DL methods needed significant pre-processing like R-peak detection, QRS complex detection, RR-interval estimation and noise filtering which were necessary for these DL methods to perform to their highest potential. At the same time, we have also presented studies with DL where no preprocessing and/or filtering of any kind was required and the raw ECG could be fed directly as input. Thus, we can conclude that although some DL techniques might need basic preprocessing, it is not a necessity. In contrast, ML techniques demand preprocessing and it is a must-have not a luxury. It must be noted that while DL methods appear superior, they do suffer certain disadvantages. DL techniques generally need significant amounts of data for training, which is a challenge. In addition, arrhythmia datasets are mostly imbalanced since all the datasets described here have a large proportion of normal beats as against beats with arrhythmia. With imbalanced data, DL methods can lead to incorrect classification since beats of some arrhythmia classes are very similar compared to others. When the number of samples of these classes are small, the DL method can confuse one class for the other. Techniques have been presented to reduce the impact of imbalanced data, but obtaining a balanced dataset from the source could be much better for classification which is a challenge that DL researchers must consider seriously. While writing a review, it is often difficult to compare different studies. While the various authors might use the very popular MIT BIH arrhythmia database, they employ vastly different techniques for preprocessing and/or classification, often differing in the number of target classes. Hence it is difficult to objectively rank different studies. Hence we aim at no such ranking and instead describe in an objective manner the niche aspects of various studies, summarizing their results in the tables.

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Reference	Dataset	Arrhythmia Classes	ML algorithm used	Performance Metrics
[23]	Cleveland dataset	2 - Normal and Abnormal	Decision tree and naïve Bayes	DT Acc 88 % NB Acc 85 %
[38]	MIT-BIH	2 - Normal and Abnormal	KNN	Acc 98.4 %
[24]	MIT-BIH	8 - LBBB, RBBB, PVC, FUSION, APC,PB, FLWAV, FPUS	Random Forest	Acc 99.7 % Sen 95.56 % Spec 99.83 %
[30]	MIT-BIH, BIDMC	3 - Normal Sinus Rhythm, Congestive Heart Failure and Cardiac Arrhythmia	SVM	Acc 95.92 %
[36]	MIT-BIH	Normal and Preventricular Arrhythmia	SVM classifier monitored by optimization algorithms like PS0, GWO, MGWO	SVM with MGWO Acc 100 % %
[34]	MIT-BIH	15	SVM	Acc 99.66 %
[31]	University of California at Irvine Machine Learning Data Repository	15	SVM	Acc of 81.11 % and 92.07% depending upon the splitting proportion
[33]	MIT-BIH	4	SVM	Acc 93 %
[37]	MIT-BIH	7	kNN	Acc 99.0 %
[28]	UCI	2 - Normal or Abnormal	Decision Tree	Acc 99 %
[29]	2017 Phys-ioNet/CinC Challenge	4 - normal sinus rhythm, atrial fibrillation (AF), alternative rhythm, and unclassified rhythm	Decision Tree	Normal 0.93, AF 0.86, Other 0.79 Final F1 score 0.84
[39]	MIT-BIH	5 - Normal(N), Premature Ventricular Contraction (PVC),Premature Atrial Contraction (APC), Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB)	SVM	Sensitivity:99.2 % Specificity:99.70 % Accuracy :98.60% positive predictive value (PPV) :99.90 % negative predictive value (NPV):97.60 %
[40]	MIT-BIH	5 - Normal, Premature Ventricular Complex (PVC), Atrial Premature Contraction (APC), Right Bundle Branch Block (RBBB), and Left Bundle Branch Block (LBBB)	Decision Tree	Acc 98.88 %

Reference	Dataset	Arrhythmia Classes	DL technique used	Performance Metrics
[73]	MIT-BIH	2 - Normal and AF	LSTM	Acc 98.51 % Sen 98.32 % Spec 98.67 %
[74]	MIT-BIH	5 - Normal Sinus Rhythm (NSR), Ventricular Premature Contraction (VPC), Paced Beat (PB), Left Bundle Branch Block(LBBB) and Right Bundle Branch Block (RBBB)	LSTM	Unidirectional LSTM with wavelet Acc 99.25 % Bidirectional LSTM with wavelet Acc 99.39 %
[75]	MIT-BIH	8 - N, LBBB, RBBB, APC, NESC, ABERR, NPC, AESC	LSTM	Acc 99.26 % Spec 99.14 % Recall 99.26 % Prec 99.3 % F1 Score 99.27
[77]	MIT-BIH	5 - NSR, LBBB, RBBB, Atrial Premature Beats (APB), Premature Ventricular Contraction	LSTM, CNN	Acc 98.1 % Sen 97.5 % Spec 98.7 %
[78]	MIT-BIH, MIT AF, MIT NSR	2 - Normal and AF	LSTM, CNN	Acc 97.8 % Sen 98.98 % Spec 96.95 %
[79]	MIT-BIH	5 - N, S, V, F, Q	Stacked bidirectional LSTM, 2 DCNN	Acc 99.5 % Sen 99.9 % Spec 98.2 %
[80]	CPSC	9 - N, AF, LBBB, RBBB, I-degree Atrioventricular Block, Premature Atrial Contraction, Premature Ventricular Contraction, ST segment depression, ST segment Elevation	LSTM, CNN	F1 Score 0.806

Reference	Dataset	Arrhythmia Classes	DL technique used	Performance Metrics
[53]	MIT-BIH	5 - N, S, V, F, Q	1D CNN	VEB Acc 99 %, Sen 93.9 %, Spe 98.9 %, Ppr 90.6 %. SVEB Acc 97.6, Sen 60.3 %, Spe 99.2 %, Ppr 63.5 % %
[9]	MIT-BIH	5 - N, S, V, F, Q	1D CNN	Noisy data: Acc 93.47 %, Sen: 96.01 %, spec: 91.64 %. Denoised data: Acc 94.03 %, Sen: 96.71 %, spec: 91.54 %.
[54]	Creighton University, MIT BIH Atrial Fibrillation, MIT BIH Arrhythmia	4 - AFib, AFlu, VFib, Normal	1D CNN	2 second input: Acc 92.5 % Sen 98.09 % Spec 93.13 % 5 second input: Acc 94.9 % Sen 99.13 % Spec 81.44 %
[10]	Physikalisch-Technische Bundesanstalt	2 - Normal and MI	1D CNN	Noisy data: Acc 93.53 % Sen 93.71 % Spec 92.83 % Denoised data: Acc 95.22 % Sen 95.49 % Spec 94.19 %
[56]	MIT-BIH	17	1D CNN	Acc 91.33 %, Sen: 83.91 %, Spec: 99.41 % Prec 89.52 % Rec 83.91 % F-Score 85.38
	MIT-BIH AF, PhysioNet AF, MIT-BIH Malignant Ventricular Ectopy, Indonesian	3 Normal sinus rhythm (NSR), atrial		Acc 99.17 % Sen 98.9 % Spec 99.17