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A STUDY ON ECG SIGNALS FOR EARLY DETECTION OF HEART DISEASES USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Early detection and treatment of heart disease can significantly reduce mortality worldwide. Heart disease often leads to malfunctioning of heart, resulting in an abnormal behavior that can be captured in ECG called as arrhythmia. As few types of arrhythmia are life threatening and others are not, it is very important to detect the arrhythmia type correctly from ECG. But it is a complex process because little variation in ECG can change the arrhythmia type and also need human expertise to diagnose it correctly. So, utilization of machine learning techniques is essential. In this paper we discussed about various machine learning classifiers including variants of Artificial Neural Networks (ANN), Support Vector Machines (SVM) and others used in arrhythmia identification process along with their performance. In addition, we also discussed ECG signal preprocessing methods including noise reduction and feature extraction techniques.

Keywords: *Early Prediction, Heart Disease, Arrhythmia, ECG Signal, Machine Learning, Preprocessing, Denoising Technique, Feature Extraction, Support Vector Machine, Neural Networks*

1. INTRODUCTION

According to the WHO reports, 17.9 million of all human deaths around the globe are due to Cardiovascular diseases (CVD) in 2016 [1]. This accounts to approximately 30% of human deaths happened in that year. The WHO has also estimated that the number of deaths from CVDs will increase further and reach 23.6 million by 2030. The statistics show that heart diseases are very dangerous and number one killer disease on the globe. If the heart disease is detected in the early stage, death caused by it can be prevented by changing the person's lifestyle and taking appropriate medications. When the delay in detecting chronic diseases such as CVD increases, the disease risk also increases and may leads to death [2][3]. Therefore, detecting cardiac abnormalities at the early stage is more important.

The heart pumps oxygen and nutrient-rich blood to all parts of the human body through the blood vessels. Nutrients and oxygen are essential for keeping the body's organs healthy and functioning properly. The blood becomes impure due to the metabolic activity of the organs. The blood vessels return the impure blood to the heart for purification and again pump the purified blood back to the body parts. This pumping activity of the heart is continuous and controlled by the electrical impulses generated in it. When these impulses are interrupted or deviated, abnormal heart rhythms are produced. This abnormal behavior of heart is called as arrhythmia. The cardiac arrhythmia can be a sign of serious heart diseases such as sudden heart attack or stroke in future, which can lead to death [4]. When there is an arrhythmia, enough blood may not be pumped by heart to all the body parts [5]. Due to lack of proper blood circulation, organs in the body can be damaged. In particular, when the heart, kidneys, or brain damaged, it can lead to death. These deaths can be prevented by detecting the arrhythmia at an early stage and treating it appropriately. Arrhythmia can be classified into two categories [6]. The first category includes life-threatening arrhythmias that require immediate treatment such as ventricular fibrillation and tachycardia. The other category contains not imminently life-threatening arrhythmias but may require treatment to prevent further complications such as premature ventricular contractions (PVC).

Currently, there are many types of tests and procedures available to detect arrhythmias. Few

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of them are blood tests, electrocardiography (ECG), chest x-ray, ultrasound, etc. Out of these, the ECG is the most widely used non-invasive clinical tool for cardiologists to diagnose various heart diseases [7]. An ECG test can detect heart irregularities by evaluating the electrical signals produced by heart. The ECG signal is captured by attaching electrodes to specific locations on limbs and the chest to record the electrical activity of the heart. This recorded information is displayed as a wave on a monitor screen or on a piece of paper. The real-time identification and classification of arrhythmias can be exceptionally problematic for a human being, as sometimes heartbeats recorded by ECG needs to be analyzed over a period of hours or days [8][9]. Beside this, there is a possibility of human error when analyzing ECG data due to a slight variation in ECG can misdiagnoses the arrhythmia type [10]. So, utilization of machine learning techniques is essential. Therefore, automated tools are necessary to analyze the large amount of ECG data. The automated diagnostic tools developed by machine learning techniques in health care have become increasingly popular, since it offers benefits to Doctors, patients and healthcare organizations [3].

Initially, during the preprocessing phase of arrhythmia detection, ECG signal quality is enhanced by applying denoising techniques and latter features are extracted from it. Then, feature reduction is implemented to select a small number of features that represent a given pattern. Finally, the classification is done with machine learning algorithms such as SVM, ANN or others.

2. BIOLOGICAL BACKGROUND

2.1. ECG Signal

The main function of the heart is to pump oxygenated blood throughout the body. This pumping activity is performed by the contraction and relaxation of the myocardial muscle present in the heart. The sinoatrial (SA) node generates electric impulses that are responsible for repeated contraction and relaxation activity of heart chambers [11][12][13]. These electrical impulses can be detected and measured by placing electrodes on specific locations on our body using ECG machine. Each impulse detected by ECG machine as P-QRS-T wave having specific amplitude, duration, shape and appearance [13]. The sequence of P-QRS-T waves collected by ECG machine is translated into graphical representation and printed on a paper. These printed data can be interpreted by a doctor to find an irregular heartbeats or heart abnormalities. The ECG signal with different components is shown below.

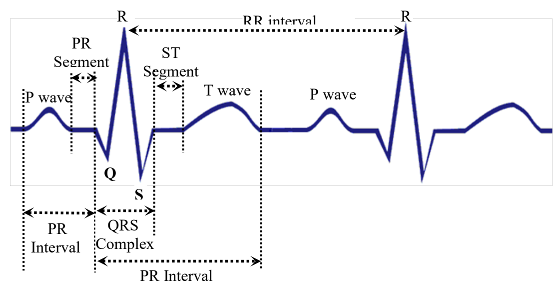

Figure 1: ECG signal and its components

- The P wave represents atrial depolarization. Due to this, the arteries contract and as a result, left atrium pushes oxygen-poor blood into the left ventricle; right atrium pushes oxygen-rich blood collected from the lungs to the left ventricle.
- The PR interval denotes the passage of electrical impulse from both arteries into AV node; the signal is slowed and paused for a short period to allow blood from the atria to fill the ventricles.
- The QRS complex indicates the ventricular depolarization. Due to this, left ventricle pump oxygen poor blood into lungs and right ventricle pump oxygenated blood into body parts.
- The ST segment represents the contraction of ventricle but no electricity is flowing through it.
- The T wave indicates the repolarization of both ventricles which makes them to relaxation and preparing for next cycle of pumping blood.

The important features of normal ECG include its inherent characteristics such as amplitude and duration is summarized in given below table-1.

Table 1: Important features of Normal ECG

ECG Feature	Description
P Wave	It represents atrial depolarization; Amplitude: 0.1–0.12 mV; Duration: 0.08 to 0.1s
QRS Complex	It represents ventricular depolarization; Amplitude: 1 mV; Duration: 0.08 to 0.12s
T Wave	It represents ventricular repolarization; Amplitude: 0.1 to 0.3 mV; Duration: 0.12 to 0.16s
P-QRS-T	It indicates one mechanical heart beat; Duration: 0.6 to 1s
PR interval	It tracks the impulse from atria through A-V node; Duration: 0.12–0.2 s
RR interval	It is the time elapsed between successive two R waves; Duration: 0.6 to 1s

QT interval	It is the time taken to complete the entire ventricular cycle; Duration: 0.36 to 0.42s
ST Segment	It represents isoelectric part of ventricular repolarisation; Duration: 0.8 to 0.12s

2.2. Types of arrhythmias

Different types of arrhythmia occur due to different combinations of abnormal heartbeat rate and abnormal rhythm [14]. Abnormally increased heartbeat rate can lead to fainting and can be fatal. Even abnormal rhythm of heart can also lead to sudden death. So, determining the correct arrhythmia type is essential to increase the survival rate. The type of arrhythmia can be determined based on heart beat rate, P-wave visibility, relationship between P-wave and QRS complex, PR interval, QRS width and other morphological characteristics of ECG [13]. The type of arrhythmia and their ECG characteristics are summarized in the table-2 given below.

Table 2: Arrhythmia And Their Characteristics

Arrhythmia Type	Rhythm	Heart Rate (bpm)	P wave	PR interval (ms)	QRS (ms)
Normal (N)	regular	60-100	one P-wave exist for each QRS complex; all P-wave have same size, shape and deflection	120-200	60-200
Bradycardia	regular	<60	one P-wave exist for each QRS complex; all P-wave have same size, shape and deflection	120-200	60-200
Tachycardia	regular	>100	one P-wave exist for each QRS complex; all P-wave have same size, shape and deflection	120-200	60-200
Atrial Fibrillation (AFib)	irregular	100-200	Absence of P wave; Mostly P wave replaced by fibrillatory wave (f-wave). More than one f-wave exist for each QRS	Not measurable	60-200
Atrial Flutter (AF)	regular	Around 150	P-wave is replaced with "Saw-tooth" pattern waves called as Flutter waves (F-wave); More than one F-wave exist for each QRS complex	Not measurable	60 to 200
Supraventricular Tachycardia (SVT)	regular	>150	P-wave not visible; one P-wave exist for each QRS complex, but it usually hidden in preceding T-wave	Not measurable	<40
Ventricular tachycardia (VT)	Regular	100 - 250	P-wave is not visible; but if present it do not have any relation to the QRS complex	None	>120
Ventricular Fibrillation (VFib)	Irregular	>250	absent	absent	>120
Ventricular Flutter (VF)	Regular	>250	No identifiable P waves, QRS complexes, or T waves	absent	>120
Sinus Arrhythmia (SA)	Irregular	60-100; sometimes<60	one P-wave exist for each QRS complex; all P-wave have same size, shape and deflection	120-200	<120
premature ventricular contraction (PVC)	Regular with ectopic beat	Varies	No P wave preceding PVC	None	>120
premature atrial contraction (PAC)	Irregular with PAC	Varies	one P-wave exist for each QRS complex; abnormal in size, shape, deflection; may be hidden in preceding T wave	120-200	<120

Some types of arrhythmias are harmful and require immediate treatment to avoid sudden death. Ventricular fibrillation (VFib), atrial flutter (AF) and atrial fibrillation (AFib) are the most recurrent life-threatening arrhythmias [15]. Among them, large number of deaths is due to ventricular fibrillation (VFib) and ventricular tachycardia (VT) [16]. As VT and VFib visualize similar in the ECG, they need human expert or machine learning models to identify them correctly[16]. Atrial flutter (AF) and atrial fibrillation (Afib) can increase the risk of stroke if they persist for more than few weeks without treatment. The A-Fib arrhythmia commonly occurs in elderly population due to various health issues [15]. It is associated with stroke, heart failure and mortality [11][17]. Bundle branch block (BBB) occur due to interruption of electrical impulses in left (LBBB) or right (RBBB) of the ventricular bundle branches [12][13]. Either LBBB or RBBB are not treated directly, instead their cause has to be treated otherwise they may leads to other serious heart diseases.

3. EARLY STAGE DETECTION PROCESS OF HEART DISEASE

The ECG serves as a primary diagnosis test to detect cardiac abnormalities called arrhythmias. Some arrhythmias are fatal, while others are not. However, if left untreated for several days, they can lead to life threatening heart diseases. For example, arrhythmias such as Right

Bundle branch block (RBBB), Left Bundle branch block (LBBB), Premature Atrial Contractions (PAC) and Premature Ventricular Contractions (PVC) are not very severe arrhythmias, but they indicate as an early signal for the development of malignant heart diseases. LBBB indicates the chance of the risk of aortic valve failure, heart attack, coronary artery disease, or cardiac arrest. RBBB may reflect the risk of blood clots, heart attack, or heart failure in the lungs. The frequent occurrence of PVC indicates the risk of stroke and death. PAC may reflect the risk of cardiomyopathy or coronary heart disease.

The survival rate can be improved with proper medical treatment based on arrhythmia type. So, detecting arrhythmia type is essential. If suddenly or frequently, when a person faces any few of the symptoms like, shortness of breath, chest pain, dizziness, lightheadedness, fainting or near fainting, and or discomfort, they should undergo ECG test to detect heart abnormalities [11][12]. Since ECG signal analysis is very difficult for humans, it is necessary to develop an automated system to diagnose and detect the presence of arrhythmia from it [15]. The following steps are used in automated arrhythmia detection process.

Step 1: Collect and store ECG signals in digital form
Step 2: Perform de-noising to filter unwanted signals
Step 3: Extract significant features that retain all important information from original signal
Step 4: Apply machine learning models on extracted features to predict arrhythmia type
Step 5: Based on arrhythmia type, test for heart diseases associated with it

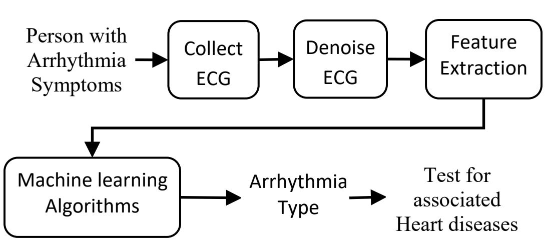

Figure-2: Early detection process of heart diseases from ECG

3.1. ECG Dataset

A good ECG database is essential to develop more accurate machine learning-based prediction methods to detect various types of heart disease, especially arrhythmia and congenital heart disease. Researchers can use the standard ECG database to conduct, compare and validate their new prediction methods on arrhythmia. In addition, databases can also be used to detect heart disease severity and associated complications before and after treatment. If the ECG database is available to the public, a large number of researchers will be able to work on it using a variety of methods to improve the accuracy of arrhythmia detection. All most all the standard ECG databases are maintained by Physionet which can be accessible freely [18]. The popular ECG database used by many researchers is the MIT-BIH Arrhythmia Database [19] provided by Massachusetts Institute of Technology and Beth Israel Hospital in Boston. It contains 10 different databases for different testing purposes and the most important of them are the Arrhythmia Database, the Atrial Fibrillation Database, the Supraventricular Arrhythmia Database, the Malignant Ventricular Arrhythmia Database and the Normal Sinus Rhythm Database. The more commonly used ECG databases by the researchers are summarized and given in the below table.

Table-3: ECG Arrhythmia Database list

Database	No. of records	Frequency sample (Hz)	ECG signal duration (hours)
MIT-BIH Arrhythmia Database (MITADB)	48	360	0.5
MIT-BIH malignant ventricular arrhythmia database (MITVFDB)	22	250	0.5
MIT-BIH Atrial Fibrillation Database (MITAFDB)	25	250	10
MIT-BIH Supraventricular Arrhythmia Database (MITSVDB)	78	128	0.5
MIT-BIH Normal Sinus Rhythm (MITNSR)	18	128	24
European ST-T Database	90	250	2
Long-Term ST Database	86	250	21-24
American Heart Association database	80	250	2.5
QT database (QTDB)	105	250	0.25
Creighton University ventricular tachyarrhythmia database (CUVTDB)	35	250	0.13 (8min)
Spontaneous Ventricular Tachyarrhythmia Database (SVTDB)	78	250	~ 0.16 (10min)

Beside these the other important ECG Dataset available to researchers is UCI Arrhythmia

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data set (UCIAD). It can be collected from UCI Machine Learning Repository [20]. It contains 452 records and each with 279 attributes. These records are classified into 16 different classes in which one of them refers to normal case and the other 15 classes refers to different types of cardiac arrhythmias.

3.2. ECG signal Denoising

ECG signal contain various types of noise like baseline wander, power-line interference, electromyography signals, high-frequency noise, etc. The baseline wander is a low frequency noise (usually less than 1 Hz) caused due to body movements, respiration, and poor electrode contact [21]. It perverts the ST segment as well as other low-frequency ECG components. The electromyography signal is high amplitude and high frequency noise caused due to muscles contraction other than heart muscles. Due to considerable overlapping of EMG frequency with ECG signals, local waves of ECG are distorted [22]. The power-line interface is a high frequency noise (usually around 48 to 50 Hz) caused due to electromagnetic field developed while capturing ECG signal. It alters the morphological features of ECG like duration, amplitude and shape of the P-wave [22]. The arrhythmia detection is influenced by all these types of noises [23]. So, de-noising techniques are applied to remove these noises from ECG signal. The type of noise to be removed purely depends on feature extraction and classification methods.

Many researchers have proposed different techniques for removing noise from ECG such as digital filter [16][21][24], wavelet transform [25], and empirical mode decomposition [9]. A digital filter is a mathematical based design that removes noise and extracts user interested information. They are broadly categorized as infinite impulse response (IIR) and finite impulse response (FIR) filters [26]. FIR filter are more powerful and flexible and IIR filters are preferred in real time noise filtering. FIR filters such as moving average filter [21] and median filter [24] are used to filter the baseline wander from ECG. The band pass filter is applied to elemenate both high and low frequency noises from ECG [27]. Due to the wide frequency range and different amplitudes of the distorted ECG signal, the de-noising effect of digital filters is very limited [22].

The other approach to remove noise is based on Wavelet transform. The wavelet transform preserves important signal characteristics represented simultaneously in frequency and time domain [28]. These methods perform level-wise signal decomposition into different frequency components from high frequency detail coefficients to low frequency approximate coefficients. Then noise is removed by applying wavelet threshold function on the detail coefficients. Finally, the ECG signal is reconstructed from the low-frequency and high-frequency coefficients. Here, selection of appropriate wavelet threshold function is the vital to get the preferred noise-filtering effect. The most commonly used wavelet threshold functions are hard and soft thresholds [29]. Better approximation can be achieved using hard threshold function, but can cause oscillation in de-noised ECG signal. The soft threshold method has superior smoothness but with large error in de-noised ECG signal. Alternatively, polynomial threshold, non-negative garrote threshold or sigmoid based threshold functions can be used which blends the advantages of soft and hard thresholds [28][29]. Discrete wavelet transform (DWT) is used specifically for filtering baseline wandering from ECG. DWT achieves better noise cancellation for high-frequency, but it loses important data at low frequencies [28].

Empirical mode decomposition (EMD) is other technique used for accurate removal of baseline wander noise from ECG [9]. EMD decomposes the non-stationary and non-linear signals like ECG into many Intrinsic Mode Functions (IMFs). The Spectral Flatness (SF) can be employed to determine IMFs with noise. These noisy IMFs are removed to filter noise components from the original signal.

3.3. ECG Feature Extraction

One heartbeat of ECG contains a P wave followed by a QRS complex and T wave. It can be divided into segments such as PR segment, ST segment and QRS complex. The duration of these segments, duration and amplitude of P, R and T wave, ST slope, time interval between successive R points, heart rate are primitive ECG features. Other features can be derived based on these primitive ones. The accuracy of arrhythmia type detection mainly depends on the effective feature extraction method. Therefore extracting appropriate features from ECG signal by selecting suitable feature extraction method is crucial for heart disease diagnosis. ECG features can be categorized mainly into different groups such as morphological, statistical, wavelet based and others [30].

Mostly, the first extracted feature is QRS complex, based on this other morphological features could be extracted. Pan and Tompkins developed the first ever automated QRS detection algorithm [31]. It used band pass filter to filter out various types of interference from ECG. Then this filtered signal is analyzed based on amplitude, slope and width to accurately detect QRS complex. An improved variation of Pan and Tompkins algorithm is a Hamilton-Tompkins algorithm [32]. It detects QRS peak based upon adaptive decision rules. This algorithm widely used for Heart rate variability (HRV) analysis in past two decades. Benitez, Ds S., et al [33] proposed the Hilbert transform based QRS detection. When this algorithm tested against MIT-BIH Arrhythmia database, it attained 99.64% of QRS detection rate (sensitivity = 99.81% and positive prediction = 99.83).

The mean, range, variance, standard deviation, Shannon entropy, etc of ECG signal are called statistical features. They are not affected by wrong identification of fiducial points in ECG. Discrete wavelet transform with Haar, Daubechies and Coiflet mother wavelet are used to extract statistical feature coefficients [8]. Frequency domain, Time domain and non-linear analysis are also used to extract statistical feature [16].

The times as well as frequency details of ECG signal component can be provided by Wavelet transform [30]. A discrete wavelet transform (DWT) is one type of wavelet transform that decomposes ECG signal into a number of segments with multiple resolutions. Each segment expressed by a polynomial and its coefficients are utilized to extract features [21]. Wavelet is especially valuable due to their ability of expressing both temporal and local spectral information of a signal in a more flexible way. Beside this, the availability of various wavelet functions allows to choose the most appropriate one for the signal under investigation. However among several wavelet families, Daubechies Wavelet has been found to give more accurate details than others.

Beside these, Independent component analysis [2], Adaptive threshold [4], Auto regression model [34], Rényi entropy [24] and Genetic algorithm [35] can also be used to extract ECG features.

3.4. Arrhythmia Detection Techniques

Artificial Neural network (ANN) is one of the most widely used techniques to detect and classify arrhythmia. ANN is inspired from the human brain functionality. It contains a series of interconnected layers with nodes called neurons that learn the complex relationship between input and output. Joo et al [16] proposed ANN model to predict ventricular tachycardia using statistically derived metrics. They achieved accuracy of 76.6%, *sensitivities of 82.9% and specificity of 71.4%.* The main limitation of their methodology is that the statistical features used by them cannot be accurately derived from a small-sized dataset. Sarkaleh et al. [21] used the moving average filter to de-noise ECG signal and then features extracted from it using DWT. These extracted features are feed to ANN with one hidden layer to recognize three classes of arrhythmia. They compared the implementation of ANN in MATLAB using three different training algorithms such as “traingdx”, “trainrp” and “trainlm” algorithms. The prediction accuracy of all the three algorithms is same and it is 96.5%. They found “trainrp” is the fastest training algorithm as compared to others, but needs more memory.

The back propagation algorithm can be used in ANN to fine tune weights and bias to improve arrhythmia prediction results. Adams et al. [12] employed ANN with back propagation to classify six types of arrhythmia including normal. The frequency characteristics of SVT and VT appear similar. But, VT is a potentially fatal arrhythmia while SVT is not. Therefore, it is essential to distinguish and identify them accurately. In such case, they emphasized that ANN is better than the fast Fourier transform. Kamath et al [36] attempted a novel approach to derive features from non-linear components of ECG using teager energy function. They classified five types of ECG beats with Feed-Forward Neural Network with back propagation as training algorithm and achieved accuracy more than 95%. The main disadvantage is that, apart from the use of two non-linear features, if they use the different combination of other features derived from AM-FM with these two features could further enhance the results.

Researchers have been tested numerous variants of Neural Networks (NN) such as Quadratic NN [4], Fuzzy NN [23][34], Probabilistic NN [2][7] etc in arrhythmia detection process.

These variations can be used to modify the natural behavior of ANN to learn much faster and predict more accurately. Rodriguez et al. [4] used Quadratic Neural Unit with back propagation algorithm to classify the arrhythmia types. They combined adaptive threshold technique with Hilbert transform to extract features and PCA is used to reduce these features. They achieved 98.16% accuracy when classifying three types of ECG beats such as Normal, APC and PVC. However, the authors did not include more types of arrhythmias that can lead to sudden cardiac death.

Fuzzy logic in combination with neural networks can produce an interpretable model that could recognize ECG beats with use of human-like reasoning knowledge. Engin et al [34] proposed the use fuzzy-hybrid neural network to classify four types of ECG beats using statistical features. This model contains two classifiers, the initial classification done by a fuzzy self-organizing layer followed by final classification done by the Multi-Layer Perceptron network. The test accuracy of this method is 93.5% and it could be further improved if the number of beats for learning increased. Shan-xiao et al.[23] used Takagi-Sugeno type Fuzzy Nueral Network (FNN) and trained it with the Cam Delta learning algorithm. Initially the wavelet transform is used to denoise cardiac signals and obtain evolution rules at different scales. When this information is passed to FNN, it produces fuzzy membership values. Based on these fuzzy values, Ventricular Premature Beats (VPB) and Atrial Premature Beat (APB) are classified. Their model is evaluated with only two types of beats which is not sufficient to confirm its performance.

Probabilistic Neural Network (PNN) work well in the presence of outliers compared to other ANN variants. S.Yu et al., [2] compared the use of Independent Component Analysis (ICA) along with PNN and back-propagation neural network (BPNN) to classify eight types of beats. They showed ICA with PNN is better than ICA with BPNN. Rai et al. [37] applied a novel multi-resolution DWT technique to extract features from ECG and used multilayer-PNN to classify three types, including Normal, RBBB and LBBB. Their model is superior to FFNN and BPNN in terms of accuracy and execution speed. Due to the fast processing time, this model could be used in big data of ECG. The main disadvantage of above method is that, despite the high accuracy, only three beats are classified excluding most of life threatening arrhythmias.

Beside above discussed variants of Neural Networks, the deep learning based models such as Convolution Neural Network (CNN) and Long-short term memory (LSTM) can also be used to detect arrhythmia. The uniqueness of the CNN model is the ability to extract features itself from raw data without the need of handcrafted features. Acharya et al [15] used Daubechies-6 wavelet to filter out the baseline noise from ECG signals. These denoised signals are given as input to eleven-layer deep CNN model to classify four classes of arrhythmias. A doctor detects arrhythmia by studying a small duration of ECG signal than a single ECG beat. So, they used short duration of ECG signals such as 2-seconds and 5-seconds separately to detect arrhythmia type. The best part about the CNN model is that it can extract and select the features used for classification on its own. The problem with this model is that it needs large ECG data for training and also takes a long time to complete the process. Hilmy Assodiky et al [27] used three hidden-layers LSTM to classify Normal, PVC and PAC arrhythmia classes. They compared the performance of the LSTM along with and without use of Adadelta. They found that using Adadelta with LSTM would give better performance. Their model failed to accurately classify few of the PAC beats that were highly similar to normal beats. The beat segmentation method used by them is only suitable for the beat that occur exactly middle in between 2 normal beats. But, a good segmentation method is needed to identify the type of arrhythmia beats that occur in any position and have a wide variety of shapes. Oh, Shu Lih, et al [10] developed a model by combining CNN with LSTM to classify variable length ECG signals. They used 10-fold cross validation is used to evaluate their model and achieved specificity of 98.70%, sensitivity of 97.50% and an accuracy of 98.10%. This model does not require any hand-crafted features. The main disadvantage of this model is that it assumed each ECG segment contain only a single arrhythmia type. But, generally each ECG segment can contain more than one arrhythmia types.

Another machine learning technique most widely used in the arrhythmia detection process is Support Vector Machine (SVM). The basic SVM is a binary classifier that classifies the input data into two classes by defining a separating hyper-plane with maximum possible width. Rizal et al. [24] used multi-order Rényi entropy to extract features from ECG. They proposed a SVM model with fine Gaussian kernel to detect two classes of beats and achieved 95.8% accuracy. This model can be used in real time applications due to less computational cost and simplicity. Since it can only detect PVC and normal beats, its use is limited in real time. SVM with radial basis function is used by Nuryani et al. [17] to detect atrial fibrillation. They used only two features such as the standard deviation and the average of RR differences in specified duration for detection of AFib. They tested this method on MITBIH arrhythmia Database by dividing the ECG data into AFib and Non-AFib arrhythmias and achieved accuracy of 97.5%.

Researchers have implemented SVM using both one-against-all (OAA) [8] [9] and one-against-one (OAO) [35][38] strategies in arrhythmia detection process. OAO perform better on ECG than OAA, but it needs more number of models to be built. Czarina Isabelle et al [8] compared different combinations of DWT mother wavelets (Haar, Discrete Meyer, 2nd order Daubechies, and 4th order Coiflet) used to extract features with ANIFS (Adaptive Neuro-Fuzzy Inference System) and also with different combinations of SVM kernels (Sigmoidal, RBF and Polynomial) to classify ECG arrhythmias. They found that Haar with ANFIS and Daubechies with SVM using RBF kernel provide better performance. They proved that DWT-SVM is the best compared with DWT-ANFIS for classifying ECG arrhythmias. Onkar Singh et al., [9] calculated statistical features from ECG signal using the Discrete Wavelet Transform (DWT) and the Double Tree Complex Wavelet Transform (DTCWT). The DTCWT was used to strengthen the DWT outcomes. The calculated statistical features are given as input to SVM to classify three ECG beat types and achieved overall sensitivity of 94.78% and overall accuracy of 93.2%. It has been observed that the use of statistical features of the ECG does not improve the ECG beat classification.

The selected features will influence the hyper-plane in SVM and in turn affect classification accuracy and computational cost. So, robust feature extraction and selection methods are important in SVM. Nasiri et al., [35] proposed SVM with genetic algorithm to classify ECGs according to cardiac arrhythmia. A genetic algorithm has been used to optimize the process to identify the best subset of features and improves the generalization function of the SVM classification. This method achieved 93% accuracy. Although genetic algorithms improve the learning process, the performance obtained with SVM is not satisfactory when compared with other existing methods. Daamouche et al [38] used particle swarm optimization technique to optimize features of ECG signal from poly-phase representation of wavelets. They validated this procedure with the SVM classifier on the MIT-BIH arrhythmia database. They compared the classification accuracy of it with two other standard wavelet families such as Daubechies and Symlet. They found that their method gave better results than the other two. The main limitation of this model is that it takes more processing time to achieve convergence, especially when considering large training sets. Sahoo et al [25] used wavelet and Hilbert transform to extract features from ECG. Then PCA is applied to select the best features from these extracted features. These features are given as input to the SVM to classify five types of arrhythmia beats and achieved average accuracy of 98.5%. Although the model performs better, it has not been tested with a variety of ECG beats for use in real time. Weiyi Yang et al. [39] extracted feature from noisy ECG signal using the CNN-based Principal Component Analysis Network. Latter, linear SVM was applied on extracted features to classify heartbeat types. They evaluated their model by experimenting on five types of unbalanced original and noiseless ECGs collected from the MIT-BIH arrhythmia database and achieved accuracy of 97.77% and 97.08%, respectively. Because their model works well on skewed and noisy heartbeats, it can be used in real time. They also noted that the use of dimensional reduction methods and synthetic minority over-sampling technique could further enhance the results.

Cheng et al [40] proposed the use of personalized features based on correlation coefficient and R-peak related features. Five correlation coefficient features are calculated by correlating patient-specific regular QRS-complex pattern with their ECG data captured in real time. Similarly, six R-peak related features calculated from each ECG segment. They evaluated different combinations of these 11 features with the previous existing 15 features using SVM and found that two feature combination of VFleak, aveCC or three feature combinations of VFleak, MEA with either aveCC or medianCC perform better. These fewer features provide better performance at faster and lower computation cost. Therefore, this model is suitable for real time detection of Ventricular arrhythmias. The main limitation is that the QRS-complex template used in this proposed method is not designed to be adaptive. In addition, the patient-specific fixed QRS-complex template needs to be further verified at different heart rates in a real time online application.

In additional to the popular variants of ANN and SVM, other machine learning techniques such as ID3 decision tree [14], logistic regression model [41], Naïve Bayesian model [42], random forest [41][43] and K-Nearest Neighbor [11][41] models are also utilized in arrhythmia detection process. The advantage of these models over ANN and SVM models is lower computational cost but poor results compared to them.

Sadiq et al. [14] proposed simple ID3 algorithm with wavelet decomposition to classify five classes of arrhythmia. They compared the use of Harr and Daubechies wavelet families along with ID3. They found Daubechies wavelet is better than Harr wavelet in terms of execution time and performance. Ganesh et al., [43] proposed the classification of ECG beats using random forest tree algorithm. The RR interval extracted from the ECG which was converted using the Discrete Cosine Transformation (DCT) used as input feature. Ten-fold cross-validation with 20 trees in the proposed method achieved an average classification accuracy of 92.16%. The performance of this method is poor compared to SVM. Shimpi et al [36] classified the ECG data collected from UCI arrhythmia dataset into one of sixteen arrhythmia types. To assist and simplify the classification process, feature reduction was done using PCA and the visual word bag approach used to perform clustering. Finally classification on this data is carried out using different machine learning algorithms like K-Nearest Neighborhood, Logistic Regression, Random Forest and SVM. SVM has outperformed the others in comparing the performance of these algorithms.

Resiandi et al [11] proposed the use of K-Nearest Neighbor classifier to detect presence of AFib using RR interval. This method classifies ECG signals into AF and non-AF, ignoring the fact that the same ECG signal may have different rhythms. The main problem with this method is that it may not detect AF patterns from ECG signal that has different types of arrhythmias. Tuncer et al. [44] used a novel and simple one-dimensional hexadecimal local configuration (1D-HLP) technique coupled with Discrete Wavelet Transform to extract the features from ECG. Latter, the size of the feature set was reduced using Neighborhood Component Analysis (NCA). Then these reduced features are given as input to 1-Nearest Neighborhood (1NN) classifier to classify 5, 13, 15 and 17-classes of arrhythmias and achieved an accuracy of 99.7%, 99.3%, 97.7% and 95.0% respectively. They concluded that their model is computationally less complex and achieved better accuracy compared to other machine learning models. However, their model was tested with a very small set of input data in some of the classes.

Table 4: Arrhythmia Detection Using Machine Learning Techniques

Reference	Database Used	Features Used	Preprocessing	Modeling Technique	Type Detected	Performance Measures
Engin [34] (2004)	MITADB	QRS complex	Butter-worth filter, Wavelet transform, Auto Regressive model	Fuzzy C-means with ANN	Normal, PVC, RBBB, non-conducted P	Sensitivity=99.6 Specificity=95.3 Accuracy =93.5
Soman et al [42] (2005)	UCIAD	279 attributes	probability based Missing value imputation	Naïve Bayes	16 classes of Arrhythmia	Train Accuracy =76.6 Test Accuracy =72.9 ± 2.1
S.Yu et al.[2] (2008)	MITADB	RR interval, ICA-based features	Independent Component Analysis (ICA)	probabilistic neural network, 3-layer back-propagation neural network	Normal, LBBB, RBBB, PVC, PAC, PB, VF, VEB	Sensitivity=98.5 Specificity=99.9 Accuracy =98.71
J.Nasiri et al. [35] (2009)	MITADB	19 temporal features, 3 morphological features	WT, Principal Component Analysis(PCA), Genetic Algorithm(GA)	Genetic-SVM	Normal, RBBB, LBBB, PB	Accuracy =93.46
S Joo et al. [16] (2010)	SVTDB	RR interval, statistical features	Pulse Frequency Modulation, High-pass filter with cubic spline interpolation	ANN	VT	Sensitivity =82.9 Specificity =71.4 Accuracy = 76.6
Shan-xiao et al.[23] (2010)	MITADB	R-R interval, QRS complex	Continuous Wavelet Transformation	Fuzzy neural network	VPC, PAC	Accuracy =92.48

A.Daamouche et al. [38](2011)	MITADB	QRS duration, RR interval, other morphological features	Discrete wavelet trans form, QRS detection using ecgpuwave software	SVM classifier	Normal, PAC, VPC, RBBB, LBBB, PB	Sensitivity=91.75 Specificity=96.14 Accuracy = 88.84
Kamath et al [36] (2011)	MITADB	Teager energy based features	Hilbert transform, Teager energy operator	Feed Forward Neural Network	Normal, LBBB, RBBB, Paced, PVC	Sensitivity=80 Specificity=100 Accuracy = 95
ER Adams et al. [12] (2012)	MITSVDB, MITADB	QRS complex	Not mentioned	Feed Forward Neural Network	BBB, SVT, VT, T and B	Accuracy = 98.6
Sarkaleh et al [21] (2012)	MITADB	wavelet coefficients based features	daubechies wavelet, moving average filter	Discrete wavelet with ANN	PB, PAC	Accuracy = 96.5
JS Wang et al. [7] (2012)	MITADB	R peak, RR interval	Z score, LDA and PCA	Probabilistic Neural Network	Normal, PVC, PB, RBBB, LBBB, PAC, VF, VEB	Sensitivity=97.9 Specificity=99.1 Accuracy = 99.7
Ganesh et al. [43] (2012)	MITADB	RR interval	Discrete Cosine Transform	Random Forest	Normal, LBBB, RBBB	accuracy =92.16
Sadiq et al. [14] (2013)	MITADB	P, R, Q, S,T peaks, average RT amplitude, max QS amplitude	Discrete Wavelet Transform	ID3 Decision tree	Normal, LBBB, RBBB, PVC, PB	accuracy =94
Nuryani, et al [17](2015)	MITADB	RR interval	Not mentioned	SVM	AFib	Sensitivity=95.81 Specificity=98.44 Accuracy = 97.50
Rodriguez et al. [4] (2015)	MITADB	R-peak, QRS segment	Hilbert transform, adaptive threshold technique, PCA	Quadratic NN	APC, PVC	Sensitivity=97.05 Specificity=97.60 Accuracy =98.16
Onkar Singh et al. [9] (2016)	MITADB	R-peak, DWT coefficients	Empirical mode Decomposition, Discrete Wavelet Transform	SVM	Normal, AFib, SVT	Sensitivity=94.78 Accuracy =93.2
Czarina Isabelle et al.[8] (2016)	MITADB	DWT based statistical features	Discrete Wavelet Transform	SVM	Normal, AFib, VT, Unclassified	Accuracy=95
Shimpi et al [41] (2017)	UCIAD	150 predefined attributes	PCA, Visual Word Bag approach, K-means	K-Nearest Neighborhood	16 classes of Arrhythmia	Accuracy =88.0
				Logistic Regression		Accuracy =84.0
				Random Forest		Accuracy =80.8
				SVM		Accuracy = 91.2
Cheng et al [40] (2017)	MITADB, CUVTDB, MITVFDB	Correlation coefficient features, R peak related features, spectral feature	Five order moving average filter, high pass filter, Butterworth low pass filter, Pan and Tompkins algorithm	SVM	Ventricular arrhythmias, Non-ventricular arrhythmias	Sensitivity = 93.87±3.80 Specificity = 95.56 ± 1.45 Accuracy = 95.46±1.36
Acharya et al. [15] (2017)	CUVTDB, MITAFDB, MITADB	Automated feature selection by CNN	Daubechies wavelet, Z-score normalization	CNN (11 conv. layers)	Normal, AFib, AF, V-Fib	Sensitivity=98.09 Specificity=93.13 Accuracy=92.5
Resiandi et al [11] (2018)	MITAFDB MITNSR	RR interval	Threshold differentiator	K-Nearest Neighbor	Normal, AFib	Accuracy =91.75
Weiyi Yang et al. [39] (2018)	MITADB	PCA filter based features	CNN-based Principal Component Analysis Network	Linear-SVM	AAMI based 5 classes	Accuracy=97.7
Rai et al [37] (2018)	MITADB	Multi-level wavelet features	Multi-resolution Discrete Wavelet Transform with Independent Component Analysis	Multilayer Probabilistic Neural Network	Normal, LBBB, RBBB	Sensitivity=99.01 Specificity=99.53 Accuracy = 99.07
Hilmy Assodiky et al.[27] (2018)	MITADB	Automated feature selection by LSTM	6th-order band pass filter	LSTM	Normal, APC, PVC	accuracy=97
Oh, Shu Lih, et al [10](2018)	MITADB	Automated feature selection by CNN	Not required	CNN+LSTM	Normal, LBBB, RBBB, PAC, PVC	Sensitivity=97.5 Specificity=98.7 Accuracy=98.1
Rizal et al. [24] (2019)	MITADB	Rényi entropy features	median filter, Rényi entropy	SVM	Normal, PVC	Accuracy =95.8
Tuncer et al. [44] (2019)	MITADB	Multi-level wavelet features	DWT, 1-dimensional hexadecimal local pattern technique,	1 nearest neighborhood (1NN) classifier	5 classes 13 classes 15 classes	Accuracy =99.7 Accuracy =99.3 Accuracy =97.7

			Neighborhood Component Analysis		17 classes	Accuracy =95.0
S. Sahoo et al [25] (2020)	MITADB	R peak, DWT, Temporal and Morphological features	Denoising: Wavelet Transform, Hilbert Transform, PCA	Cubic-SVM	Normal, LBBB, RBBB, PVC, PAC	Sensitivity=95.68 Specificity=99.18 Accuracy = 98.50

4 CONCLUSION

In this paper, we discussed about various machine learning techniques used to detect arrhythmia type. Beside this, standard ECG databases available, different preprocessing techniques available for ECG noise reduction and various feature extraction methods are also presented. It was observed that SVM models outperformed Neural Networks when number of arrhythmia types to be detected is more. But SVM models are influenced by feature selection; where as Deep learning models such as CNN can extract their own features. Recently, Convolution Neural Network and Long Short-Term Memory models from deep learning are becoming increasingly popular and showing promising results in arrhythmia detection from ECG.

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