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A Review on Cardiac Abnormalities Classification using Electrocardiogram with Machine Learning and Deep Learning Classification Techniques

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***Abstract*—** Our heart works nonstop throughout our life. Its failure means the death of the person. Diseases regarding cardiac system are the main cause of death in the whole world. Therefore it is compulsory to diagnose these types of abnormalities before the failure of the heart. For showing all the electrical actions of the cardiac system, the Electrocardiogram (ECG) signal is an easy and highly recommendable mean. Normally the physicians manually examine the ECG heartbeat to analyze the different types of Arrhythmia. But manually working on ECG graphs is not a satisfactory solution due to its non-stationary nature of ECG. Therefore, there is always a need of computer based systems to examine the ECG signals, which is helpful for physicians. For classification of ECG data, there are many techniques which are implemented by different researchers. This survey is focusing on the latest research papers in which machine learning and deep learning classification techniques are applied in different manners. The implemented machine learning techniques are Support Vector Machine, k-NN, Decision Tree, Neural Network, and Extreme Learning Machine. Convolutional Neural Network (CNN) is implemented in various researches, which is a deep learning technique. A CNN is defined as a deep feed-forward artificial neural network that can mine deep features from database automatically. Mostly works were evaluated on MIT-BIH arrhythmia database which is available publically. In this survey, the existing methods are compared according to qualitative factors like purpose of the work, implemented algorithms and results achieved.

***Keywords*—** Arrhythmia classification, Convolutional Neural Network, Electrocardiogram, Extreme Learning Machine, Support Vector Machine

I. INTRODUCTION

Cardiovascular diseases are the main reason of death around the world. In human body there may be many kinds of cardiac diseases like heart attack, stroke, and ischemia. The main focus in different researches is on two diseases; first one is Myocardial Infarction i.e. Heart Attack and second one Arrhythmia. Myocardial Infarction is because of blockade in blood vessels and Arrhythmia is related to irregular heartbeats [1]. The biomedical signal which is generally used in the field of medical science is, Electrocardiogram (ECG). It is a periodic signal by this the doctor can see the electrical activities of the heart [2]. The doctors can identify the risk by analysing ECG of particular patient and give important treatment regarding that risk [3].The main target of studying ECG data is to classify the ECG into different categories like normal ECG or abnormal ECG and stage of risk in patient but for classifying ECG data is a tedious task due to its non-stationary nature.

For ECG classification, there are many basic steps; like pre-processing, feature extraction, feature selection, and finally classification. Removing noise and artifacts from ECG is the first step of cleaning the ECG signal i.e. the pre-processing of the ECG signal. Pre-processing step is followed by feature extraction and selection. After then, ECG classification is done by using some Machine Learning techniques like Support Vector Machine, Genetic Algorithm, Artificial Neural Networks, etc. We reviewed many currently published research papers. Most of the researches are based on artificial neural network or convolutional neural network. They worked on the different types of layers in neural network for feature extraction and classification of ECG dataset. Some authors applied Genetic Algorithm (GA) and Differential Evolution Algorithm (DEA) for optimization of existing techniques. Mostly researchers worked with MIT-BIH arrhythmia database for detection of arrhythmia and other cardiac abnormalities.

II. RELATED WORK

Support Vector Machine (SVM) is a popular machine learning technique for classification. Many researchers implemented this technique with some other techniques for comparison. S. Celin and K. Vasanth (2018) proposed a method in which they applied filtering algorithms like low pass, high pass, and butter worth filter for eliminating the high frequency noise i.e. preprocessing of ECG signals. After extracting the features they applied classification techniques like SVM, Adaboost, Artificial Neural

Networks (ANN), and Naive Bayes classifier. They found that Naive Bayes classifier was the most successful classifier with highest accuracy 99.7% [2]. In the same manner, Y. Kaya et al. (2017) used SVM with some other classifiers. They classified arrhythmia cardiac abnormality in a three-step process. The first step included the calculation of statistical and temporal features of the heart-beat. Next step was for minimizing the size of features by using Genetic Algorithm (GA), Principal Component Analysis (PCA), and Independent Component Analysis (ICA). The third or final step was classification process which included SVM, Decision Tree (DT), k- Nearest Neighbor (k-NN), and Neural Network (NN) for classifying the nine types of ECG beats. They found highest accuracy rate 99.3% by using k-NN classification by feeding genetic algorithm features [4]. According to A. Turnip et al. (2018), QRS recognition with zero crossing calculation is a technique by which R peak from QRS complex can be extracted specifically for identifying the arrhythmia abnormality. They recorded ECG signals in two different situations (relaxed mode and typing mode). They implemented Support Vector Machine (SVM) technique on the WEKA software for classification and they utilized MIT-BIH arrhythmia database. During classification they found accuracy rate of 88.49% [5].

According to B. Pyakillya et al. (2017) there were many problems in machine learning algorithms’ solutions for classification of ECG data, regarding choosing the correct features for achieving better accuracy. They suggested a method which was based on deep learning architectures. In this method, feature extractors role was given to the initial layers of convolutional neurons and for the final classification of ECG data a number of fully-connected (FCN) layers were used. The accuracy of this proposed method was 86% approximately [6]. A. Isin and S. Ozdalili (2018) suggested a method for diagnosing the ECG arrhythmia. The method could classify the ECG of a patient into related cardiac symptoms. For feature extraction they used transferred deep convolutional neural network (i.e. AlexNet) and for concluding classification they used standard back propagation neural network. For this research they worked on only three types of cardiac symptoms. They also used MIT-BIH arrhythmia database for this classification. As a result accurate recognition rate was 98.51% and testing accuracy was 92% [7]. H. Lassoued and R. Ketata (2018) suggested a Clinical Decision Support System (CDSS). They used this system for a multi-class classification of ECG signals into certain cardiac diseases. This CDSS was based on machine learning classifier Artificial Neural Network (ANN) and for input feature they used time scale. They used MIT-BIH arrhythmia database in which they used only 48 ECG signals, of one minute recording. They achieved 93.8% accuracy in this classification [8].

M. Kachuee et al. (2018) suggested deep convolutional neural networks based algorithm for classifying the heartbeats. The algorithm was suitable for classifying five different arrhythmias which is based on AAMI EC57 standard. They also proposed a method for classifying the myocardial infarction (MI). The effectiveness of these methods for classification of arrhythmia and MI are 93.4% and 95.9 respectively [9]. According to J. Li et al. (2018) Convolutional Neural Networks (CNNs) were suitable for multi-dimensional data but ECG was generally treated as one-dimensional signal. For this reason they converted ECG data into two-dimensional data and then applied CNN. The method that they used was involved with adaptive learning rate and biased dropout methods. This method was applied for identifying the arrhythmia from MIT-BIH arrhythmia database. The accuracy rate was 99.1% and 97% for five and eight heartbeat classes respectively [10].

For classifying ECG data effectively, Y. Ji et al. (2019) suggested a method which is based on algorithm of Convolutional Neural Network. It can be considered as Faster R-CNN. They applied this algorithm on MIT-BIH database. For training and testing sets, they transformed one dimensional ECG signals to two-dimensional image and classified the ECG data into five classes with 99.21% average accuracy [11]. J.H. Kim et al. (2019) worked for designing GoogleNet deep neural network architecture. They extended the size of kernel of the beginning layer and joined the convolution layers for ECG classification. They classified ECG beats into normal sinus rhythm, atrial pre-mature contraction, pre-mature ventricular contraction, and left/right bundle branch block arrhythmia. They achieved accuracy rate maximum 98.31% for this classification [12]. A. Rajkumar et al. (2019) proposed method for classification of ECG related to Arrhythmia. The method was based on deep learning algorithm Convolutional Neural Network (CNN). They used MIT-BIH database for their research and classified seven types of arrhythmia. They used CNN for automatically learning of features from the time domain ECG signals. The adoption of features specifically switched the extraction of features manually and this approach could help in examining the cardiac patient efficiently by the doctors. As a result the accuracy rate was 93.6% approximately [13].

S. Nurmaini et al. (2019) suggested a method depends on Deep Learning (DL) algorithm. Their DL architecture is based on Deep Auto-Encoders (DAEs) for extraction the features and Deep Neural Networks (DNNs) as a classification method. For selecting the robust features their method did not demand for human interference and expertise. By this they reduced the time in the labelling and data processing phases. For feature extraction and selection their method processed directly from raw data. They worked on 10 categories of ECG imbalanced data. The accuracy was 99.73% for the classification of ECG data [14]. According to Q. Yao et al. (2020) convolutional neural network could not work for varied-length ECG signal and gave inadequate result in identifying paroxysmal arrhythmias. For removing these limitations, they proposed attention-based time-incremental convolutional neural network (ATI-CNN). By assimilating CNN, recurrent cells and attention module, this deep neural network model could receive both spatial and temporal fusion of data from ECG dataset. They found 81.2% accuracy by this model [3]. For classification of ECG, A. Ullah et al. (2020) worked with two-dimensional convolutional neural network model. They classified ECG beats into 8 categories; normal, premature ventricular contraction, paced, left bundle branch block, right bundle branch block, atrial premature contraction, ventricular escape, and ventricular flutter wave beat. They also worked with MIT-BIH arrhythmia database. They found 99.11% accuracy for this classification process [15].

F.Y.O. Abdalla et al. (2020) suggested convolutional neural network approach with 11 layers. The four layers out of 11 layers were exchanged with other four layers of max pooling and lastly three effectively connected layers. They worked with dataset of Physionet in the Massachusetts Institute of Technology-Beth Israel Hospital. They found 99.84% accuracy for this classification process [16]. T.M. Chen et al. (2020) proposed convolution neural network model for classifying the ECG dataset. They tried to classify cardiac arrhythmias using a large 12-lead ECG database. The database was given by the China Physiological Signal Challenge (CPSC) 2018. Their model got first rank in the challenging competition. They received a median F1-score of 0.84 for the nine-type cardiac arrhythmia classification of CPSC 2018's hidden test set of 2954 ECG beats. They found accuracy from 94.0 to 97.6 for different types of beats [17]. A. Diker et al. (2019) used Physikalisch-Technische Bundesanstalt Diagnostic ECG Database (PTBDB) from Physionet Database for the classification of ECG signals. For extracting the main points of ECG signal (PR, ST, QT, and QRS complex) they utilized Pan-Tompkins algorithm and Discrete Wavelet Transform (DWT) techniques. After extracting the ECG waves they applied traditional Extreme Learning Machine (ELM) for classification of ECG signal. For finding the coefficients they used Genetic Algorithm Wavelet Kernel Extreme Learning Machine Algorithm. Finally after implementation, they found 95% accuracy in the classification process [18]. A. Diker et al. (2020) proposed the concept which purpose was to improve the hidden neurons number that was used in the traditional Extreme Learning Machine (ELM). For implementing this they utilized Differential Evolution Algorithm (DEA) and they achieved better accuracy rate during the ECG signals classification. For implementing this concept, they used publically available ECG dataset in Physionet. To find the ECG wave periods (PR, QT, ST, and QRS) they used methods like Pan-Tompkins Technique (PTT) and Discrete Wavelet Transform (DWT). Finally they achieved 97.5% accuracy during the classification process [19]. S. Dalal and V.P. Vishwakarma (2020) proposed a novel method in which they optimized the Kernel Extreme Learning Machine (KELM) using Genetic Algorithm. For implementation they used UCI repository arrhythmia and PTBDB dataset. They achieved 100% accuracy rate by applying the suggested method on PTBDB dataset [20].

P. Pławiak and U.R. Acharya (2020) proposed novel work that focused on 744 segments of ECG waveform and these segments were taken from the MIT-BIH Arrhythmia database. For their method they chose long duration (10 s) ECG signal segments. They used Welch's method and discrete Fourier transform methods for estimation of spectral power density which gave more power to the EGG signal features' characteristics. They focused mainly on the designing a novel three-layer (48+4+1) Deep Genetic Ensemble of Classifiers (DGEC). By implementing this method they achieved 99.37% accuracy during classification process [21]. F.I. Alarsan and M. Younes (2019) suggested the method which is applied using Machine Learning library and Scala language on Apache Spark framework. They simplified the machine learning algorithms by using the Spark-Scala tools. This tool could be used for large size of processing data. They implemented many classification techniques like Decision tree, Gradient-Boosted Trees (GDB), Random forests, etc. The suggested approach was estimated and validated on baseline MIT-BIH Arrhythmia and MIT-BIH Supraventricular Arrhythmia database. For binary classification, they found accuracy rate 96.75% when utilized GDB tree algorithm and 97.98% when used random forest. For multi categories classification, they found 98.03% accuracy using Random Forest [22].

III. BACKGROUND KNOWLEDGE OF ECG

ECG is a generally used system for analysis of any patient's cardiac abnormalities. There are many ECG beats in one ECG signal. Every beat is the combination of some waves i.e. P wave, QRS complex, and T wave. The waves contain the peaks named P, Q, R, S, T, and U. There is some time durations between every pair of peaks; these intervals are considered as PR, RR, QRS, ST, and QT. The terms PR and ST are also considered as segments. Therefore ECG features are the combination of these peaks, intervals, and segments. The features of one ECG cardiac cycle are shown in Figure-1.

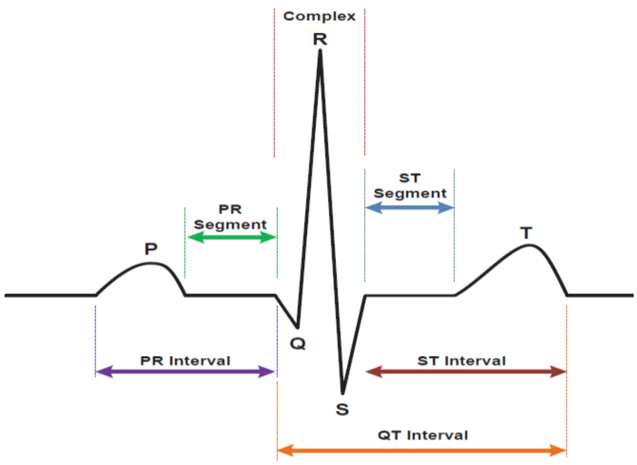

Figure 1. ECG waveform [23]

According to the figure-1, P is atrial depolarisation which duration is less than 80ms [24]; QRS is atrial repolarization which duration is less than 120 ms; and T is ventricular repolarisation with duration 160 ms. The intervals (PR, RR, ST, QT) duration are (120-200ms, 0.6-1.2s, 320ms, 420ms) respectively. The segment PR links the P wave and the QRS complex, which duration is 50-120ms; the segment ST links the QRS complex and the T wave, which duration is 80-120ms. The amplitudes of the different peaks (P, R, Q, T) are (0.25, 1.60, 25% of R, 0.1-0.5) in mV respectively.

There are several issues which are faced during the classification of the ECG signal [25]. Those issues are "there is no defined standard of ECG features", "ECG features are variable in different physiological and mental situations", "There are no standard rules for optimal classification", "For same abnormality, ECG signals of different patients may be different".

The different researches worked with ECG signal for the classification of cardiac diseases. Generally they tried to identify the Arrhythmia and Myocardial Infraction. Arrhythmia is a multi-class classification which is based on types of ECG beats. Some to those beats are shown in the table-1 [3] [14].

Table 1: Classes of Arrhythmia

Beat Description	**Label**
Normal beat	N
Atrial fibrillation	AF
Premature Atrial Contraction	PAC
Premature Ventricular Contraction	PVC
Left Bundle Branch Block	LBBB
Right Bundle Branch Block	RBBB
First-degree atrioventricular block	I-AVB
Paced	P
Ventricular Flutter Wave	VFW
Fusion of Ventricular and Normal	FVN
Fusion of Paced and Normal	FPN
Nodal Escape	NE
ST-segment depression	STD
ST-segment elevation	STE

IV. HEARTBEAT CLASSIFICATION

A number of steps are followed during the classification of heartbeats for detecting the cardiac disorders (e.g. arrhythmia classification). Figure-2 is showing the steps which generally followed by different authors.

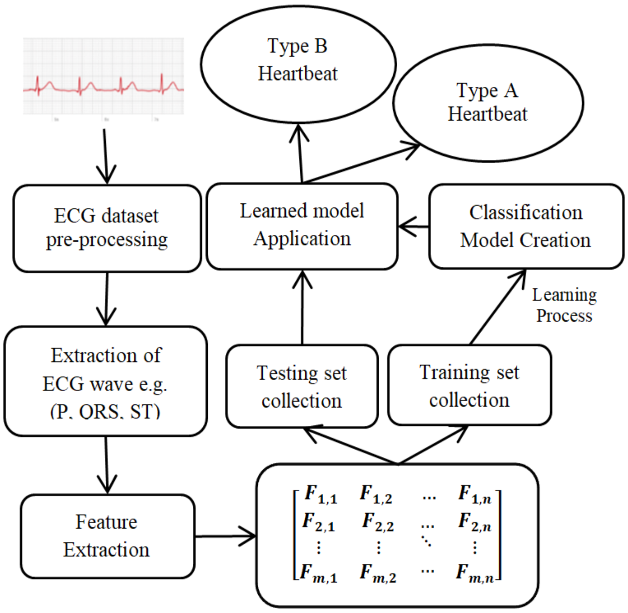

Figure 2. Steps for Arrhythmia Classification

4.1 ECG Preprocessing

ECG data are not perfect to use directly due to noise [26]. In the pre-processing step, noise and artifacts are removed from ECG signal for further process. The pre-processing may include baseline wander removal, noise removal and beat averaging.

4.2 Baseline Wanders Removal:

Due to some motion in the human-body, breathing process and fluctuations in electrode impedance ECG-signal is tampered by baseline wander [26]. Baseline wander is intervention of low-frequency i.e. 0 to 0.5 Hz. Before the analysis of the ECG signal, baseline wander should be removed otherwise it may create complications. High-pass filter is the fundamental method for removing the baseline wander. To implement filtering method is simple, needs least time and computations. Some other methods for baseline removal are cubic spline approximation, discrete wavelet transform, and empirical mode decomposition.

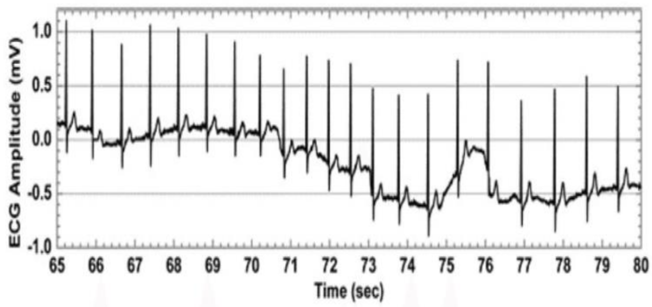

Figure 3. An ECG signal with baseline wander [27]

A derivative based filter (high-pass filter) was applied to ECG dataset by A. Isin, and S. Ozdalili, (2018) for eliminating baseline wander [7]. Median filtering algorithm was used by Y. Ji et al. (2019) for removing the baseline drift [11]. A. Diker et al. (2020) utilized the symlet scaling filter from wavelet transform and detrend operation for removing the baseline wandering [19]. Y. Kaya et al. (2017) used cascade filer for eliminating the baseline wander [4].

4.3 Noise Removal:
High frequency noise can pollute the ECG signal; this noise can be included in the ECG signal due to interfering by power line (50 or 60 Hz), electromyographic noise by movement of muscle and body motion, and radio frequency noise from extra tools. For removing the noise influence from the ECG signal, many researchers have applied different types of techniques. The most usual technique is low-pass filtering. Some other techniques are band-pass filtering, median filtering, and beat averaging.

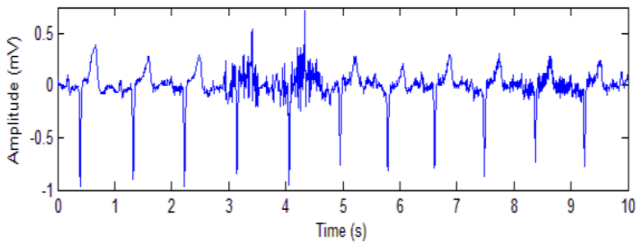

Figure 4. An ECG signal with electromyographic noise [28]

S. Celin, and K. Vasanth (2018) used Butterworth filter for eliminating the excess noises from the ECG signal. For this, the sampling frequency they used was 1000 Hz and the cut-off frequency was 256 kHz [2]. A 10- point moving average filter was applied by A. Isin, and S. Ozdalili, (2018) to remove the high-frequency noises form ECG dataset [7]. J. Li et al. (2018) [10] and A. Diker et al. (2020) [19] utilized band-pass filter for eliminating the high-frequency noise. Wavelet transform algorithm was used by Y. Ji et al. (2019) for removing the high frequency noise [11]. S. Nurmaini et al. (2019) implemented Deep Auto Encoder for cancelling the low and high frequency noises [14]. Combination of wavelet based thresholding and the reconstruction algorithm of wavelet decomposition was utilized by A. Ullah et al. (2020) for eliminating noises from ECG signals [15].

4.4 Extraction of ECG wave
The best inevitable waveform is QRS complex within the ECG [7]. The QRS shape and its existence period give important facts about the exiting state of the heart because it shows the electrical activity in the duration of the ventricular contraction of heart. As a conclusion, detecting QRS gives the basic information for all methods which are used for analysis of ECG automatically. S. Celin, and K. Vasanth, (2018) used peak detection algorithm for extracting the QRS complex of ECG signal [2]. A. Isin and S. Ozdalili (2017) [7] and A. Diker et al. (2019) [18] applied the most famous Pan-Tompkins algorithm to extract the QRS complex and they worked on RT interval.
Jiapu Pan and Willis J. Tompkins proposed the Pan-Tompkins algorithm in 1985, in the journal IEEE Transactions on Biomedical Engineering [29]. Pan and Tompkins applied their technique on annotated arrhythmia database (MIT-BIH) and found 99.3% of accuracy rate for detection of QRS complexes. In the Pan-Tompkins method, a sequence of filters is applied to focus the frequency part of rapid heart depolarization [30]. By the combination of Low-pass and High-pass filtering, the algorithm eliminates background noise from the ECG signal. The next step is derivative process, by which P and T waves that are low frequency components are suppressed and the huge gain is supplied to the high-frequency components from the QRS complex's high slopes. After derivative operation, squaring process is done, by which the output becomes positive and highlights large differences generating from QRS complexes. The moving window integrator generates a signal in which information regarding width and slope of the QRS complex are involved [29]. At last, adaptive thresholds are applied to recognize the peaks of the filtered signal.

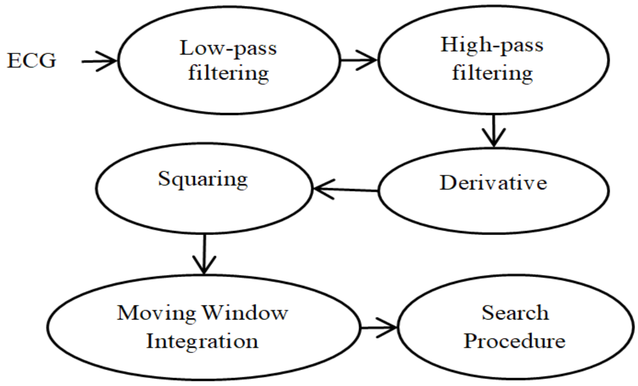

Figure 5. Steps of Pan-Tompkins Algorithm [30]

M. Kachuee et al. (2018) used beat extraction method for extracting R-R intervals from signals [9]. Y. Ji et al. (2019) used sliding window search method for extracting the ECG beat (R wave point) [11]. A. Diker et al. (2020) applied derivative method for suppressing P and T waves low-frequency segments and gained QRS wave high slopes [19]. Y. Kaya et al. (2017) used window process for extracting the R point [4].

4.5 Feature Extraction
S. Celin and K. Vasanth (2018) extracted features from QRS complex, such as mean, standard deviation, root mean square, pulse transit time, pulse rate variability [2]. A. Isin and S. Ozdalili (2018) utilized pre-trained AlexNet to extract 4096 features for every ECG signal input [7]. The features represented the R-T segment images for showing the three different cardiac disorders. A. Diker et al. (2019) [18] and A. Diker et al. (2020) [19] used different morphological features like (QRS complex amplitude, PR interval, P wave amplitude, QT interval, ST interval) and statistical features (maximum, mean, minimum, variance, skewness, kurtosis). Y. Kaya et al. (2017) calculated the features kurtosis, standard deviation, interquartile range, distribution range, average statistical features, and standard deviation [4].

Some of the formulas of statistical features are as follows. Where x_i is the i^{th} sample value, n is the total number of samples, and μ is the mean of the samples.

$$Mean\ \ \mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$Standard\ Deviation\ \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\mu)^2}{n}} \tag{2}$$

$$Skewness\ \theta = \frac{\sum_{i=1}^{n}(x_i-\mu)^3}{\left(\sum_{i=1}^{n}(x_i-\mu)\right)^3} \tag{3}$$

$$Kurtosis\ \gamma = \frac{\sum_{i=1}^{n}(x_i-\mu)^4}{\left(\sum_{i=1}^{n}(x_i-\mu)\right)^4} \tag{4}$$

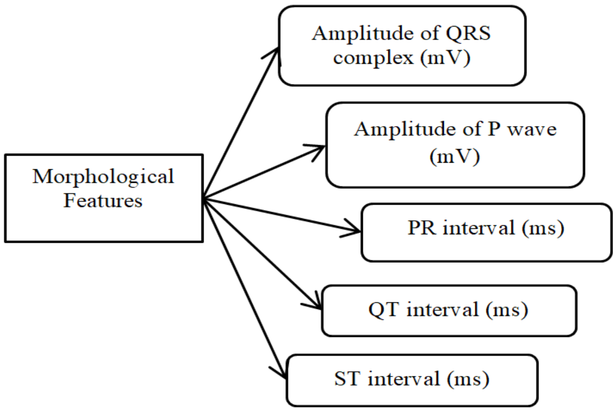

Figure 6. Morphological Features

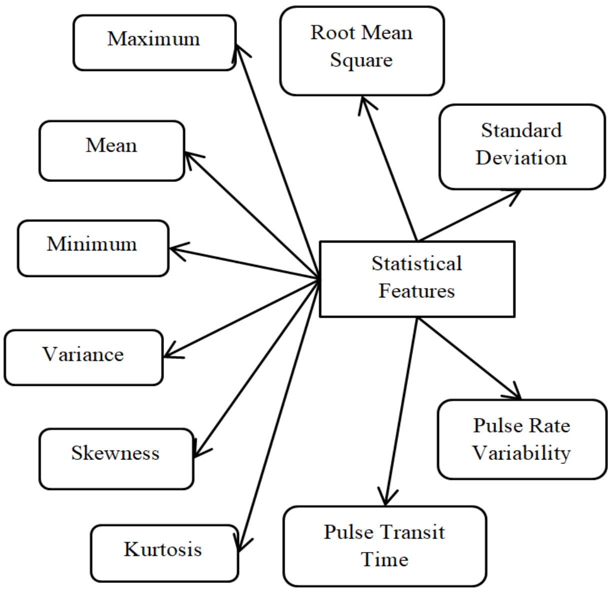

Figure 7. Statistical Features

4.6 Classification methods

There are many classification methods e.g. Support Vector Machine (SVM), Naïve Bayes classifier, k-nearest Neighbour (k-NN), Decision tree, Artificial Neural Networks, Convolutional Neural Networks (CNN), Extreme Learning Machine (ELM) etc. Different authors used different classification techniques with different manners. Some authors optimized some techniques using Genetic Algorithm and Differential Evolution. In the current years, maximum researchers worked on deep learning i.e. Convolutional Neural Networks.

4.6.1 Support Vector Machine.

SVM is a supervised learning technique which can be implemented for classification process and regression [2]. SVM uses the concept of a surface which can be considered as a hyper-plane. This hyper-plane creates a boundary between data points which are plotted in the multi-dimensional feature space. There are many applications in which SVM can be utilized such as handwriting recognition, face recognition, classifying the patterns etc. It also supports for learning of nonlinear functions effectively and by maximizing the margin higher level generalization can be found. If the SVM classifier is working as a weak classifier then the outcome of the SVM classifier is combined with adaboost classifier which considered as the final outcome because the weak classifier's error rate is decreased by the adaboost classifier [2]. For classification process, the current SVM classier can also be fixed on the WEKA algorithm [5]. The java based WEKA is open-source software for applying in the field of data mining; it is the combined form of machine learning techniques that can be utilized for generalizing or formulating from a collection of sampling data.

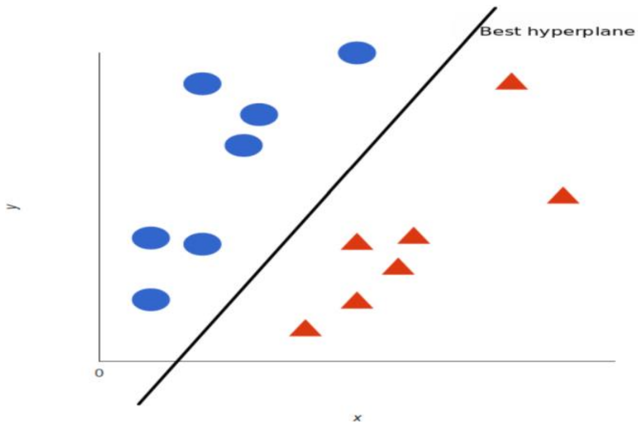

Figure 8. hyperplane for linear data points.

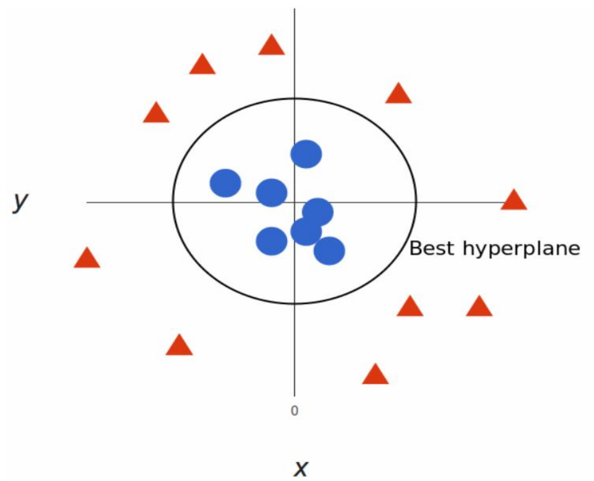

Figure 9. hyperplane for nonlinear data points.

4.6.2 Naive Bayes Classifier (NB).

For constructing classifiers, NB is the easiest method [2]. It is a model which can assign class labels to problem instances. The main concept behind the Bayes rule is that prediction of hypothesis output can be considered on the basis of some observed evidence. This classification technique can be used for classifying the ECG signal in two categories (normal or abnormal) and can be executed in rapid miner tool with high rate of accuracy. This method can be applied for large dataset. There are many application of this classifier like target marketing, fraud discovery, and analysis in medical field.

4.6.3 Artificial Neural Networks and Convolutional Neural Networks.

ANNs can be considered as the computational processing systems [31]. The working of ANNs is based on working of biological nervous systems. In ANNs there are a major number of computational nodes which are connected to each other; these nodes can be considered as neurons. In a standard ANN there are three basic layers: input layer, hidden layer, and output layer.

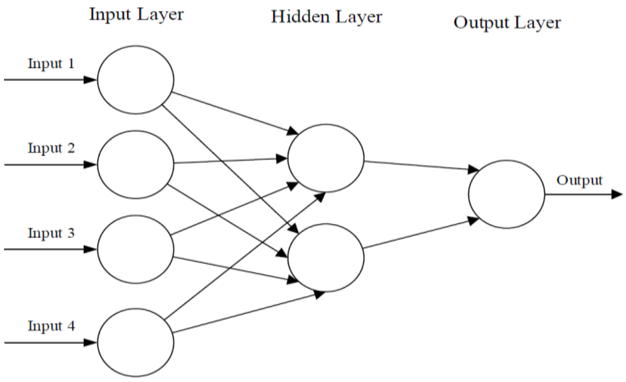

Figure 10. Basic Neural Network

An ANN with multi-layers can be considered as Deep Neural Network or Deep Learning. ANN has the ability to control a large database due to this it is one of the most effective tools and most famous in the research work over the last some decades. Convolutional Neural Network (CNN) is one of the most famous deep learning methods [32]. Convolution is a mathematical liner operation which is done between matrices; CNN got its name from this operation. There are multiple layers in the CNN. The layers which have parameters are convolutional layer and fully-connected layer; and the layers which have no parameter are non-linearity layer and pooling layer. The CNN performs outstandingly in the area of machine learning specially image processing.

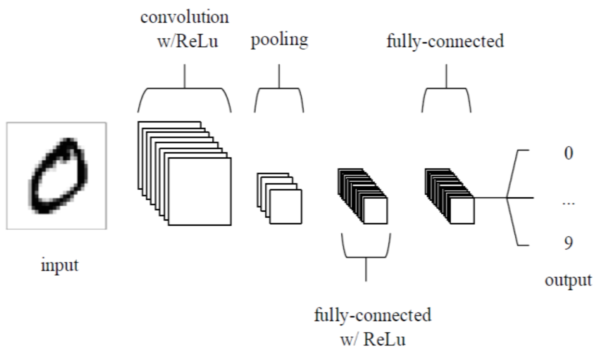

Figure 11. Architecture of Simple CNN

As an example of implementation of CNN, B. Pyakillya et al. (2017) used one dimensional CNN with following architecture: they used 7 convolutional layers in CNN, in which filter width was 5 and neurons were 128; after every layer they applied max-pooling and dropout; after this global average pooling was implemented; there were 3 fully connected layers with (256/128/64) neurons and dropout after every layer; there was softmax layer with 4 outcomes [6]. An extended version of CNN, i.e. AlexNet which is an AlexNet is a deep learning system [7]. It is trained on the 1.2 million high-resolution RGB images of the ImageNet database. There are total 8 layers in the architecture of the AlexNet CNN; 5 convolutional and 3 fully-connected layers that are trained on the generic images of the ImageNet. The AlexNet extracted a large number of features, which can increase complexity, therefore for reducing dimensions, reducing the computational load and possibility of over-fitting, PCA can be applied.

CNN are more suited for multi-dimensional data. Many researchers worked on 2-dimesionals ECG data, for that they had to transfer one dimensional data of ECG into two dimensional data. To avoid the necessity to set the learning rate manually in 2-D dataset, the ADADELTA adaptive learning rated method can be combined into the traditional CNN [10]. The ADADELTA can boost the convergence speed of learning. ECG classification can be done by using Faster Regions with a Convolutional Neural Network (i.e. Faster R-CNN) with images of ECG. ECG images are two-dimensional data which are transformed by one dimensional ECG signal [11]. By using Faster R-CNN, the rate of classification accuracy becomes higher.

For fully utilization the temporal and spatial ECG characteristics, CNN can be upgraded as Attention-based Time-incremental Convolutional Neural Network [3]. The ECG preprocessing pipeline can be divided into two steps in this model. In the first step spatial information fusion is according to CNN; and in the second step temporal information fusion is according to recurrent neural network (RNN) and attention mechanism. This model is more robust than the traditional CNN in the identification of paroxysmal arrhythmias.

4.6.4 Extreme Learning Machine (ELM).

A feed-forward network is considered as Extreme Learning Machine. It was presented by Huang [18]. In the ELM, during training process, only output weights can be altered. These weights are arbitrarily modified by radial basis functions with hidden neuron weights, parameters, and threshold voltage. ELM can be considered as a generalized single hidden layer feed forward network (SLFN) model. In the ELM, there is no need to set the hidden layer. Fig: is showing the structure of SLFN and ELM.

A. Diker et al. (2019) implemented ELM with kernel learning (Wavelet-Kernel Extreme Learning Machine). The kernel method is one of the many types of advanced methods which are used for Extreme learning machine [18]. This method is highly demanded and utilized for variety of systems. They used Genetic Algorithm also for selecting optimum value of wavelet functions. In the further research they optimized ELM by using Differential Evolution Algorithm [19].

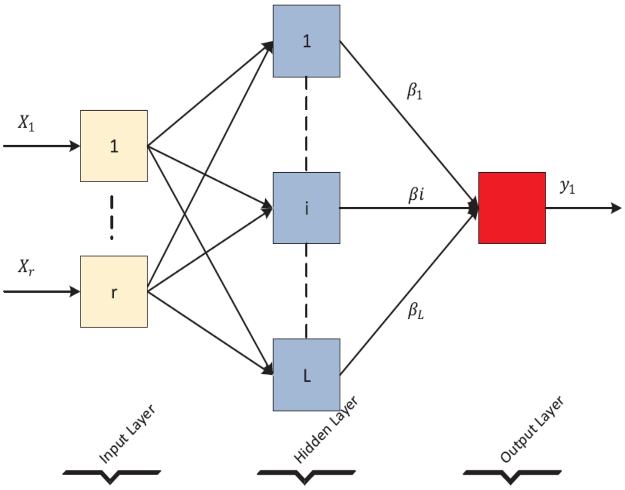

Figure 12. Structure of SLFN [18]

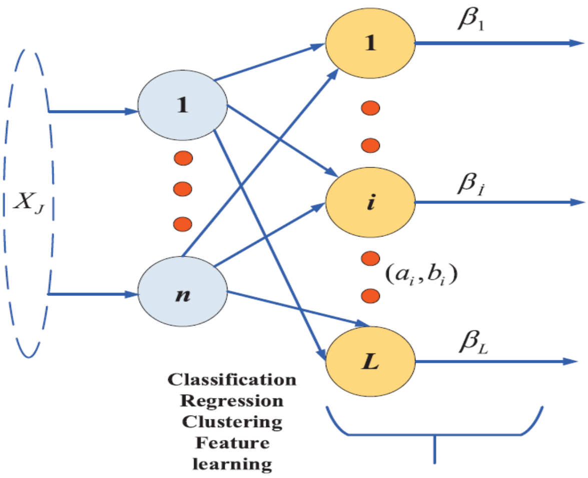

Figure 13. Structure of ELM [18]

V. COMPARISON OF DIFFERENT AUTHORS WORKS ACCORDING TO SOME PARAMETERS

The table-2 is showing that different authors worked on different ECG wave parts (e.g. whole ECG signal or some specific peaks like R peak); different ECG datasets like MIT-BIH arrhythmia and PTB Diagnostics etc.; different number of leads and different number of classes of Arrhythmia.

The table-3 is showing the performance of different classification methods developed by different authors in form of accuracy. S. Celin and K. Vasanth (2018) implemented different machine learning algorithm (SVM, Adaboost, ANN, and Naïve Bayes) and achieved maximum accuracy (99.7%) by Naïve Bayes. In the same manner, Y. Kaya et al. (2017) implemented different machine learning algorithms, but they applied optimization techniques also like GA with those algorithms and found 99.11% accuracy with KNN and GA. Due to some limitations of simple machine leaning algorithm, some other authors implemented different models with CNN or deep neural networks by using different hidden layers according to different features. S. Nurmaini et al. (2019) found the accuracy 99.73% by using deep neural network and F. Y.O. Abdalla et al. (2020) used CNN and achieved 99.84 % accuracy. A. Diker et al. (2019), A. Diker et al. (2020) and S. Dalal and V.P. Vishwakarmam (2020) worked on Extreme learning machines with GA or DDE optimization techniques and found accuracy (95%, 97.5%, 86.67%) respectively. F.I. Alarsan and M. Younes (2019) worked with Gradient-Boosted Trees and Random Forests and achieved accuracy (96.75%, 97.98%). Overall by looking the table, we can say that deep learning algorithms or models are performing well with respect to other algorithms or models.

Table 2: Details of ECG features, database and type of Cardiac abnormalities defined by different authors.

Author	ECG wave part	Database	Number of leads or type of lead in ECG dataset	Cardiac Abnormality	Number of classes of in case of Arrhythmia
S. Celin and K. Vasanth (2018)	QRS Complex	MIT-BIH arrhythmia	1	Arrhythmia	2
Q. Yao et al. (2019)	ECG signal	1st China Physiological Signal Challenge	12	Arrhythmia	8
Y. Kaya et al. (2017)	QRS complex, RR interval	MIT-BIH arrhythmia	2 (Lead II and a modified one)	Arrhythmia	9
A. Turnip et al. (2018)	QRS complex, RR interval	MIT-BIH arrhythmia	1	Arrhythmia	2
B. Pyakillya et al. (2017)	ECG signal	Not specified	1	Arrhythmia	4
A. Isin and S. Ozdalili (2018)	QRS complex, R-T interval	MIT-BIH arrhythmia	2	Arrhythmia	3
H. Lassoued and	PR, QT, PT, ST,	MIT-BIH arrhythmia	1	Arrhythmia	5

R. Ketata (2018)	QRS and RR				
M. Kachuee et al. (2018)	R peak	MIT-BIH arrhythmia PTB Diagnostics	1 (Lead-II)	Arrhythmia Myocardial Infraction	5
J. Li et al. (2018)	R peak, RR interval	MIT-BIH arrhythmia QT database	2	Arrhythmia	6 8
Y. Ji et al. (2019)	R peak	MIT-BIH arrhythmia	1	Arrhythmia	5
J. H. Kim et al. (2019)	R peak	MIT-BIH arrhythmia	1	Arrhythmia	5
A. Rajkumar et al. (2019)	ECG signal	MIT-BIH arrhythmia	1	Arrhythmia	7
S. Nurmaini et al. (2019)	R peak	MIT-BIH arrhythmia	1	Arrhythmia	10
A. Ullah et al. (2020)	ECG signal	MIT-BIH arrhythmia	1	Arrhythmia	8
F.Y.O. Abdalla et al. (2020)	QRS complex	MIT-BIH arrhythmia	1 (lead-II)	Arrhythmia	10
T.M. Chen et al. (2020)	ECG signal	China Physiological Signal Challenge (CPSC) 2018	12	Arrhythmia	9
A. Diker et al. (2019)	QRS complex, PR, ST, QT intervals, P wave amplitude	Physikalisch-Technische Bundesanstalt Diagnostic (PTBDB) ECG dataset from Physionet Database	1 (lead-II)	Myocardial infarction	None
A. Diker et al. (2020)	QRS complex, PR, ST, QT intervals, P wave amplitude	Physionet Database	1 (lead-II)	Heart disorders	None
S. Dalal and V.P. Vishwakarma (2020)	ECG signal	UCI repository arrhythmia Database, PTBDB Database	12	Arrhythmia	13
P. Pławiak and U.R. Acharya (2020)	ECG signal	MIT-BIH arrhythmia	1 (modified lead-II)	Arrhythmia	17
F.I. Alarsan and M. Younes (2019)	QRS complex, RR interval	MIT-BIH arrhythmia	1	Arrhythmia	4

Table 3: Performance Analysis of different techniques used in different research papers.

Author	Classification Methods	Number of layers in case of Neural Network	Accuracy%
S. Celin and K. Vasanth (2018)	SVM Adaboost ANN Naive Bayes	 3 	87.5% 93% 94% 99.7%
Q. Yao et al. (2019)	Attention-based time-incremental convolutional neural network	16	81.2%
Y. Kaya et al. (2017)	NN K-NN SVM DT	3	98.59% 99.11% 98.5% 91.14%
A. Turnip et al. (2018)	SVM	N/A	88.49%
B. Pyakillya et al. (2017)	Convolutional Neural Network	13	86%
A. Isin and S.Ozdalili (2018)	Transferred deep convolutional neural network	8	98.51%
H. Lassoued and R. Ketata (2018)	ANN	3	93.8%
M. Kachuee et al. (2018)	Deep Neural Network	13	93.4%, 95.9%
J. Li et al. (2018)	Convolutional Neural Network	7	99.1% (5 beats) 97% (8 beats)
Y. Ji et al. (2019)	Faster R-CNN	16	99.21%
J.H. Kim et al. (2019)	GoogLeNet Deep Neural Network Architecture	9	98.31%
A. Rajkumar et al. (2019)	Convolutional Neural Network	7	93.6%

S. Nurmaini et al. (2019)	Deep Auto Encoder, Deep Neural Networks	8	99.73%
A. Ullah et al. (2020)	2-D CNN	10	99.11%
F. Y.O. Abdalla et al. (2020)	Convolutional Neural Network	11	99.84%
T.M. Chen et al. (2020)	Deep Learning Neural Network	18	94.0% to 99%
A. Diker et al. (2019)	Genetic Algorithm Wavelet Kernel Extreme Learning Machine	N/A	95%
A. Diker et al. (2020)	Differential Evolution Algorithm-Extreme Learning Machine	N/A	97.5%
S. Dalal and V.P. Vishwakarmam (2020)	Genetic Algorithm - Kernel Extreme Learning Machine	N/A	86.67% (UCI repository arrhythmia database) 100% (PTBDB database)
P. Pławiak and U.R. Acharya (2020)	deep genetic ensemble of classifiers (DGEC)	3	99.37%
F.I. Alarsan and M. Younes (2019)	Gradient-Boosted Trees Random Forests	N/A	96.75% 97.98%

VI. CONCLUSION

The present review focused those research articles which are more recent and based on machine learning and deep learning methods. Some authors tried to optimize the existing methods by using optimization techniques and some authors gave some new or novel techniques for classification of ECG. Currently mostly researchers are working on deep learning methods (e.g. Convolution Neural Networks). This deep learning technique is very popular and effective in binary as well as multi-classification problems. Recently for ECG classification, CNN was used with some different combination of ECG features and with different hidden layers for better accuracy. For implementation, mostly authors used online available MIT-BIH arrhythmia dataset.

In the future, CNN can be implemented by changing the number of hidden layers, using some different statistical and morphological features, optimizing with different techniques, and using some other ECG database. Overall hybrid approach can be implemented for classification of ECG database.

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