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ATRIAL FIBRILLATION RISK PREDICTION FROM ELECTROCARDIOGRAM AND RELATED HEALTH DATA WITH DEEP NEURAL NETWORK

Sharmila R[1], R. Mohan Kumar[2]

[1]*P.G Scholar, Dept. of Biomedical Engineering, Udaya School of Engineering, Vellamodi, Tamil Nadu, India*
[2]*Assistant Professor, Dept. of Biomedical Engineering, Udaya School of Engineering, Vellamodi, Tamil Nadu, India*

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Abstract - Atrial fibrillation (AF) is a common cardiac arrhythmia that can increase the risk of stroke and other complications. Early detection and risk prediction of AF can aid in the prevention of its complications. ECG is an important non-invasive clinical tool for the diagnosis of heart diseases. The detection of cardiac arrhythmias is a challenging task since the small variations in ECG signals cannot be distinguished precisely by the human eye. The objective of this work is to detect cardiac arrhythmias with the highest detection accuracy. This project proposes a method for AF risk prediction using electrocardiogram (ECG) signals and deep neural networks (DNNs) combined with wavelet transformation implemented in MATLAB. The proposed method involves preprocessing the ECG signal using wavelet transformation to extract time-frequency features, followed by feature selection and classification using a DNN algorithm. The proposed model was evaluated on a dataset of ECG signals and achieved an accuracy of 96%, demonstrating its potential for clinical use in AF risk prediction. The proposed approach has the potential to assist clinicians in identifying patients at high risk of AF and providing personalized interventions to prevent its complications. The use of MATLAB makes the proposed approach readily accessible to researchers and clinicians in the field.

***Key Words*: Atrial fibrillation, electrocardiogram, wavelet transformation, deep neural networks, ada-boost classifier.**

1. INTRODUCTION

The electrocardiogram (ECG) indicates the electrical activity of the human heart. It offers cardiologists helpful information regarding the rhythm and functioning of the heart [1]. ECG signals are acquired by placing electrodes across the thorax or chest of the human body for a limited time and the electrical recordings are visualized using an external device [2]. The recording of ECG signals is performed by placing electrodes across the chest of the human body. The term lead refers to the electrical voltage difference between two electrodes. The most used lead system for recording the ECG signals is the 12-lead ECG system which includes three classes of leads.

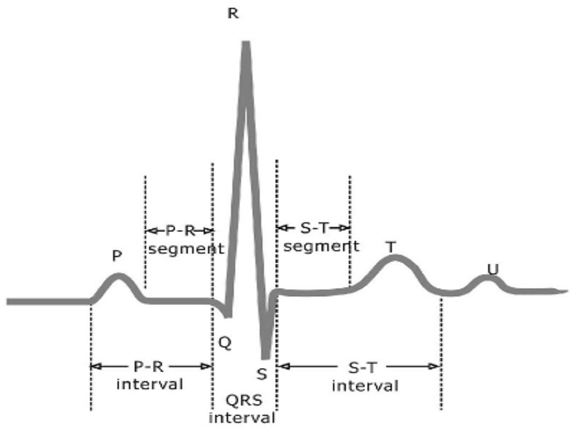

Figure 1.1: ECG signal representing one cardiac cycle

It is difficult for medical experts to analyze ECG signals embedded with noise. The noise removal technique is a challenging task due to the spectral overlap between the ECG signal and the noise signal [5]. Baseline wander results in the movement of isometric lines in upward and downward directions. It is caused by the movement of electrodes connected across the chest during breathing or due to the movement of the arm or leg [6]. The variation in temperature and bias of the instrumentation amplifier circuit can also be a cause of baseline drift. It is a low-frequency noise with a frequency range of 0 - 0.5Hz. It occurs due to the poor grounding of ECG machines connected to the power supply. The ECG machine picks up the AC signal of 50/60 Hz frequency and displays a thick-looking ECG signal [7-8]. The electrical activity of muscles causes the contraction of muscles. The resulting signals are band-limited Gaussian noise with a zero-mean distribution. The EMG interference causes fast fluctuations which are faster than the ECG signals [9]. Its frequency range is 0-10 KHz and occurs for a duration of 50 msec. A normal sinus rhythm (NSR) represents an ECG signal with no cardiac disorder and has a heart rate of 60-100 beats per minute (BPM). A heart rate beyond 100 BPM indicates sinus tachycardia while a heart rate below 60 BPM indicates sinus bradycardia which affects the vital organs [10]. The SA node of the heart is responsible for this type of arrhythmia. The distinguishing feature of this type of arrhythmia is that the morphology of the P wave of ECG signals remains normal [11]. Sinus arrhythmia, Sinus bradycardia, and Sinus arrest are different type of arrhythmias that comes under the category of sinus node arrhythmias. The use of varying window sizes in wavelet transform helps in analyzing non-stationary signals at multiple resolutions [15]. In practical situations, signals with high-frequency components exist for short duration, and low-frequency components exist for long duration. The wavelet transform can be represented in continuous and discrete forms. In literature, numerous feature extraction techniques are applied to analyze and classify ECG beats such as the particle swarm optimization technique, principle component analysis, and ECG morphological features in conjunction with timing information. In the proposed study, atrial fibrillation (AF) is a common cardiac arrhythmia that can lead to serious health problems if left untreated. Electrocardiogram (ECG) signals are commonly used to diagnose AF, as they provide valuable information about the electrical activity of the heart. The use of wavelet transforms in AF detection has gained popularity in recent years due to its ability to capture both time and frequency domain information in the ECG signal. In this approach, the ECG signal is decomposed into different frequency bands using wavelet transforms, and features related to AF are extracted from these frequency bands. The process typically involves preprocessing the ECG signal to remove noise and baseline drift, followed by wavelet decomposition to obtain the frequency bands of interest. Feature extraction is then performed on these frequency bands, and a classification algorithm is used to differentiate between AF and normal sinus rhythm. Some common features used in wavelet-based AF detection include the Shannon entropy, the energy of the high-frequency sub-bands, and the variability of the QRS complex. Different classification algorithms can be used to classify the ECG signal as AF or normal, including support vector machines (SVMs), artificial neural networks (ANNs), and decision trees.

The order of the paper is given as follows section 2 covers the literature review, section 3 narrates the proposed research methodology, section 4 has results and section 5 holds the conclusion part.

2. LITERATURE REVIEW

H. Yazdani and M. Soleymani (2016) provide a comprehensive review of various wavelet-based methods for detecting atrial fibrillation (AF) from ECG signals. The authors provide a critical analysis of these techniques and their effectiveness in detecting AF from ECG signals. Overall, the paper is a useful resource for researchers and practitioners interested in the use of wavelet transforms for AF detection in ECG signals [14].

S. V. Suresh and P. G. Gulhane (2016) provide a comprehensive review of various ECG signal processing techniques that have been used for the detection of atrial fibrillation (AF). The paper covers different techniques for ECG signal pre-processing, including filtering, baseline wander removal, and artifact removal. It also discusses the various feature extraction techniques used in AF detection, such as time-domain features, frequency-domain features, and nonlinear features. The paper also covers different classification techniques used for AF detection, including decision trees, support vector machines (SVMs), artificial neural networks (ANNs), and fuzzy logic systems [13].

M. M. Abdelghany et al. (2018) present a method for the detection of atrial fibrillation (AF) from electrocardiogram (ECG) signals using the wavelet transform and support vector machine (SVM) classification. The paper uses a support vector machine (SVM) classifier to classify the extracted features as AF or normal sinus rhythm (NSR). It provides a novel approach for the detection of AF from ECG signals using the wavelet transform and SVM classification, and it demonstrates promising results in terms of accuracy and sensitivity [3].

M. N. Baig and M. M. Idris (2019) provide a comparative study of different ECG feature extraction and classification techniques for the detection of atrial fibrillation (AF). The paper also covers different classification techniques used for AF detection, including decision trees, k-nearest neighbor (KNN) classifiers, support vector machines (SVMs), and artificial neural networks (ANNs). The authors evaluate the performance of these classifiers using various metrics, including accuracy, sensitivity, and specificity [4].

S. S. Limaye and S. A. Ladhake (2019) present a survey of various feature extraction and classification techniques used for the detection of atrial fibrillation (AF) from electrocardiogram (ECG) signals. The authors provided insights into the challenges associated with AF detection, such as noise and variability in ECG signals, and discussed potential solutions to address these challenges. Overall, this paper provides a comprehensive survey of different feature extraction and classification techniques used for AF detection, providing insights into the state-of-the-art and identifying potential areas for future research [12].

3. PROPOSED METHOD

The proposed system comprises of a pre-processing section, feature extraction section, and an ada-boost classifier. For pre-processing of ecg signal LMS filter is used after that temporal and spectral features are extracted by the feature extraction system and is given to the ada-boost classifier.

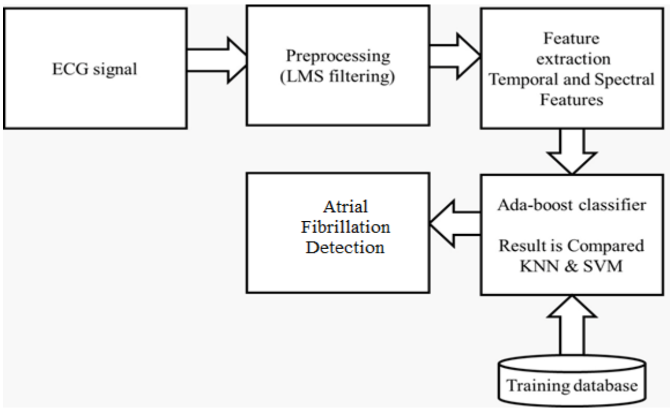

Figure. 3.1 Block diagram of Atrial Fibrillation detection

In this work, an automated pathology detection system in electrocardiogram (ECG) is addressed. In the proposed system, raw ECG signals are processed in the form of time domain specifications. The ECG signals are the input to the proposed deep learning networks. The network is trained with a huge number of data samples that include both normal and pathological signals. The data in the analysis include breath signals collected from the PhysioNet database which is a public database for various research purposes. The block diagram of the overall methodology used in this work is shown in figure 3.1. The PhysioNet database is the collection of signal recordings and the breath signals for this work is collected from the PhysioNet database. The signal records of the MIT-BIH reference PSG database that is freely available for research purposes from PhysioNet.

3.1 Least Mean Square Filter

Least Mean Square (LMS) algorithm has two inputs: an original input and a reference input. The abdominal signal was used as the original input d (n) and the thoracic signal as the reference input x (n). The coefficients of the adaptive filter were constantly adjusted with the feedback e (n) until the output y (n) was very close to the maternal ECG component of the abdominal signal. The algorithm starts by assuming a small weights (zero in most cases), and at each step the weights are updated.

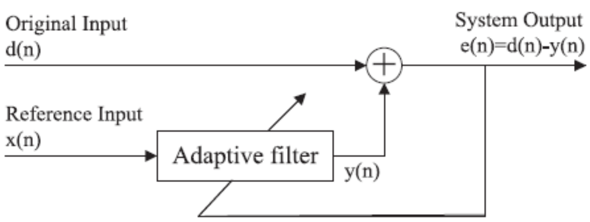

Figure 3.2 General block of LMS adaptive filter

The abdominal signal d(n) as the original input at the n^{th} moment is given by,

$$d(n) = [d(n), d(n-1), \ldots., d(n-m+1)]^2 \quad (1)$$

The thoracic signal x(n) as the original input at the n^{th} moment is given by,

$$x(n) = [x(n), x(n-1), \ldots., x(n-m+1)]^T \quad (2)$$

where m is the length of the adaptive filter.

The LMS update is given by

$$w(n+1) = (w(n)^2 \mu e(n) x(n) \quad (3)$$

The filtered output signal y(n) which is close to the maternal ECG will be

$$y(n) = w^T(n) * x(n) \quad (4)$$

Then fetal ECG can be obtained after adaptive processing as,

$$e(n) = (n) - (n) = d(n) - w^T x(n) \quad (5)$$

For the decomposition scale of 5, we get five different fetal ECGs in addition to noise at the output of least mean square algorithm.

We are using the direct spatial correlation of wavelet transform contents at several adjacent scales to accurately detect the locations of edges or other significant features.

$$Corr(m,n) = \prod_{i=0}^{l-1} W(m+i,n) \quad (6)$$

where , n = 1,2,……….N

l = no. of scales involved in the direct multiplication

W (m,n) = Wavelet transform data on each scale.

First, the power of the correlation data is re-scaled to that of the W (m,n). The most important edges are identified by comparing the absolute values of correlation and W (m,n). A peak is identified at any position n for which correlation>W (m,n).This peak position and its corresponding value(m,n) are stored. Finally, all the edges identified in this way are extracted from Correlation and W(m,n)by resetting the values of these signals to 0's at the positions identified.

3.2 Empirical Mode Decomposition

The purpose of EMD is to decompose a signal into a number of IMFs, each one of them satisfying the two basic conditions: 1) the number of extrema or zero crossings must be the same or differ by at most one; 2) at any point, the average value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

3.3 Analytic Representation of IMFs

After the extraction of IMFs from EEG signals, their analytic representation is obtained. This representation removes the DC offset from the spectral component of the signals, which is an important aspect to compensate for the non-stationarity of the signals. Given that we have an IMF $c_m(t)$, its analytic representation is given as,

$$y(t) = c_m(t) + iH\{c_m(t)\}$$

where $H\{c_m(t)\}$is the Hilbert transform of $c_m(t)$, which is the m^{th} IMF extracted from the signal $x(t)$. After performing EMD of the signal, the IMFs are used for feature extraction purposes.

3.4 Feature Extraction

The Feature Extraction stage extracts diagnostic information from the ECG signal. To detect the peaks, specific details of the signal are selected. The detection of the R peak is the first step of feature extraction. The R peak in the signal from the Modified Lead II (MLII) lead has the largest amplitude among all the waves compared to other leads. The QRS complex detection consists of determining the R point of the heartbeat, which is in general the point where the heartbeat has the highest amplitude. Most of the energy of the QRS complex lies between 3 Hz and 40 Hz. The 3-dB frequencies of the Fourier Transform of the wavelets indicate that most of the energy of the QRS complex lies between scales of 23 and 24, with the largest at 25. The energy decreases if the scale is larger than 25. In the proposed method inverse Discrete Wavelet transform is applied to reconstruct the signal approximately. This reduced the DC offset and eliminated the amplitude variance from file to file. QRS width is calculated from the onset and the offset of the QRS complex. The onset is the beginning of the Q wave and the offset is the ending of the S wave. Normally, the onset of the QRS complex contains high-frequency components, which are detected at finer scales. This work imposes two different feature extraction methodologies for the effective classification of the ECG signals.

3.4.1 Spectral Statistics features

The discrimination power of the PSD features can be visually analyzed by their respective plots for three IMFs from the normal and pathological EEG signals. The PSD can be calculated as follows:

$$P(w) = \sum_{-\infty}^{\infty} r_y[n]e^{-jwn} \qquad (7)$$

where $r_y[n]$represents the autocorrelation of $y[n]$, defined as $r_y[n] = E(y[m]y * [m])$. Visual analysis of the PSD of IMFs shows that the statistics of the PSD can be used as relevant features for feature extraction.

The researchers have shown that the centroid frequencies of the IMFs extracted from EEG signals form distinct groups when supervised clustering is applied on the EEG signals. These respective groups are indicative of the seizure and non-seizure EEG signals. The centroid frequency is therefore a distinctive feature that can be used for the characterization of EEG signals,

$$C_s = \frac{\sum_w \wp(w)}{\sum_w P(w)} \qquad (8)$$

where $P(w)$is the amplitude of w^{th} frequency bin in the spectrum.

2) Variation Coefficient: Since the spectral variation in the IMFs is different for normal and pathological EEG signals, therefore it can be used for their characterization. This variation can be calculated as follows:

$$\sigma_s^2 = \frac{\sum_w (w - C_s)^2 P(w)}{\sum_w P(w)} \qquad (9)$$

where $C_s$is the spectral centroid.

3) Spectral Skew: Skewness is the third order moment, and it measures the symmetry/asymmetry of a distribution. Visual inspection of the plot of PSD of IMFs shows that the skewness of the power of IMFs for the normal and pathological EEG signals differs thus potentially yielding a useful feature for the classification of EEG signals. Skewness of the PSD can be calculated as:

$$\beta_s = \frac{\sum_w \left(\frac{w - C_s}{\sigma_s}\right)^3 P(w)}{\sum_w P(w)} \qquad (10)$$

The feature vectors obtained from several IMFs can then be used for classification purposes.

3.5 KNN Classification

In this work, an attempt has also been made to find out the optimal value of K and distance metric using fivefold cross-validation for achieving the highest classification accuracy. After evaluating these best possible values of K and distance metric, a KNN algorithm has been used for QRS detection. The feature vectors and class labels of training samples are stored. In the classification phase, K is a user-defined constant, a query or test point (unlabeled vector) is classified by assigning a label, which is the most recur- rent among the K training samples nearest to that query point. In other words, the KNN method compares the query point or an input feature vector with a library of reference vectors, and the query point is labeled with the nearest class of library feature vector.

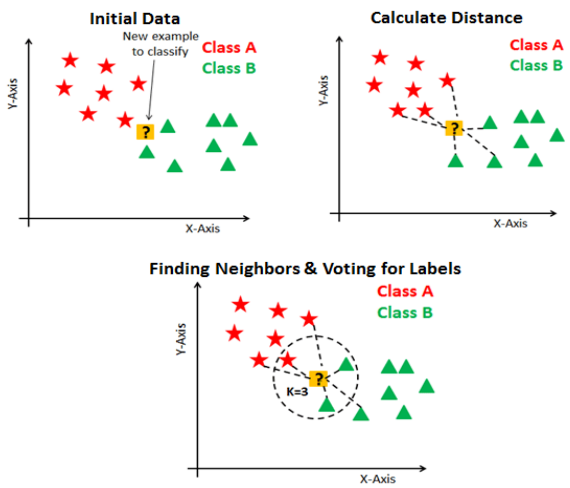

Figure 3.3 K-nearest neighbor Algorithm

3.6 Support Vector Machine Classifier

SVMs can be used to solve various real world problems like: text and hypertext categorization, Classification of images, Hand-written characters can be recognized and also it is widely applied in the biological and other sciences.

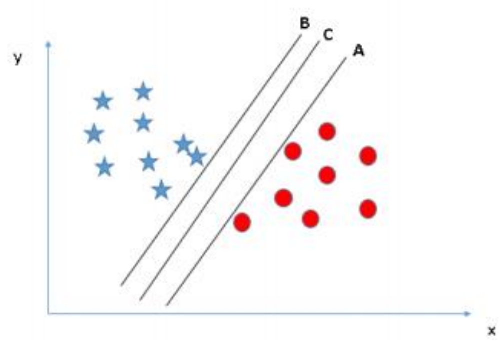

Figure 3.4 SVM classifier

Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. SVM which is mostly used in classification problems is selected for better accuracy than the other classifier. It can find optimal hyper plane as shown in Figure 3.4 to separate different group input data into higher dimensional feature space.

SVM is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes.

3.7 ADA Boost Classifier

Ada-Boost is sensitive to noisy data and outliers. In some problems it can be less susceptible to the over fitting problem than other learning algorithms. The individual learners can be weak, but as long as the performance of each one is slightly better than random guessing (e.g., their error rate is smaller than 0.5 for binary classification), the final model can be proven to converge to a strong learner.

4. RESULTS AND DISCUSSION

The designed MATLAB software was used to plot the ECG signal obtained from the physionet database. The input ECG signal has the average amplitude value of 0.5 and the sampling frequency is 100Hz. Figure 4.1 shows the input 1-minute ECG signal.

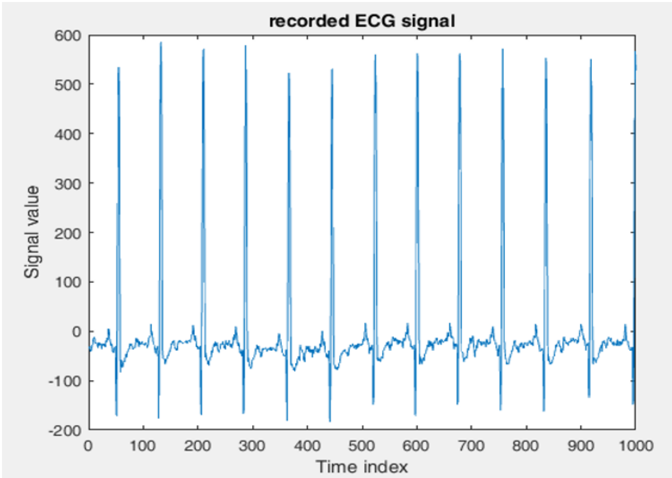

Figure.4.1. Plotted original ECG signal

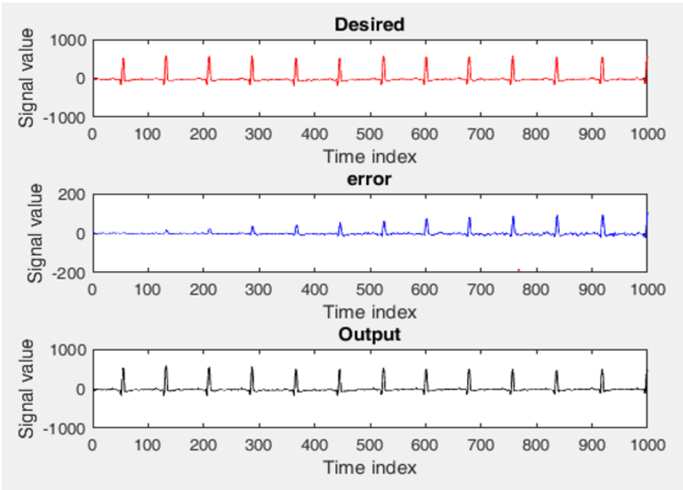

Figure.4.2. ECG signal after Drift Cancellation

Figure 4.2 shows the ECG signal after drift cancellation. It reduces noise in the ECG signal by matching the spectrum of the average QRS complex. This attenuates noise due to muscle noise, power line interference, baseline wander, T wave interference.

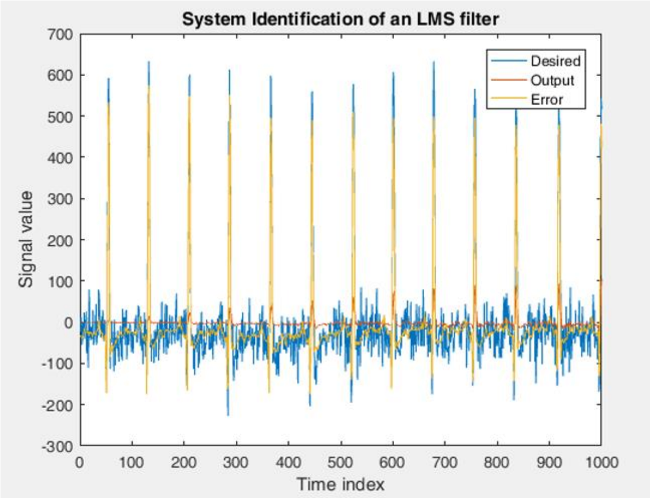

Figure 4.3 LMS filter performance

The LMS filter eliminates the noise from the given ECG signal when a pure noise signal is given as the reference and it extracts the signal of interest from the noisy signal when a noiseless ECG signal is used a reference. Figure 4.3 above demonstrates the two adaptive structures of the LMS filter.

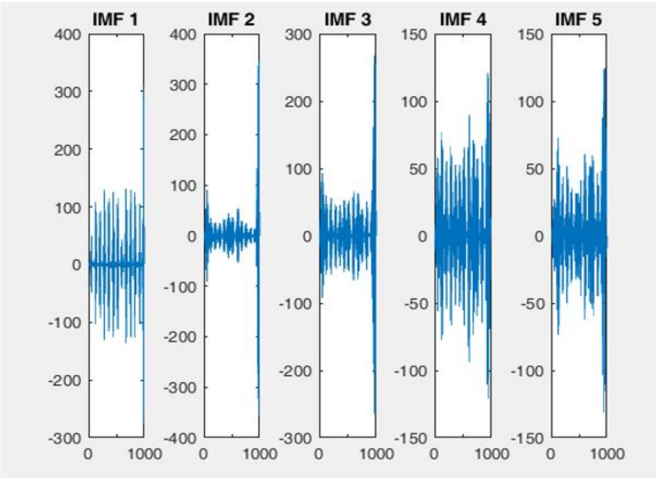

Figure.4.4. ECG signal after IMF decomposition

Empirical mode decomposition (EMD) is a powerful algorithm that decomposes signals as a set of intrinsic mode function (IMF) based on the signal complexity. Partial reconstruction of IMF acting as a filter was used for noise reduction in ECG is shown in figure 4.4.

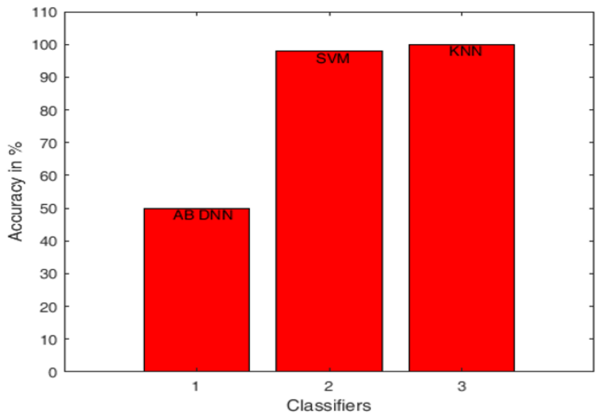

Figure.4.5 Comparison of classifiers

Using SVM, KNN, and Ada Boost classifiers using deep neural networks to detect the atrial fibrillation in ECG signal. And compare the results of each classifier for better accuracy is shown in figure 4.5.

4.1 DISCUSSION

The input ECG Signal is preprocessed using LMS filtering and feature extraction is done using temporal and spectral features. The application of the LMS filter, IMF, and Empirical Mode Decomposition (EMD) effectively reduced noise and highlighted relevant components of the ECG signal. This preprocessing step improved the quality of the input data for subsequent analysis. The Hilbert transform was applied to extract both temporal and spectral features from the preprocessed ECG signals. These features provided a comprehensive representation of the ECG signal in both time and frequency domains. HRV analysis was conducted to further characterize the ECG signals and classify them into normal, bradycardia, and tachycardia conditions. HRV features were computed, and statistical analysis was performed to differentiate between these conditions. The comparison of different classifiers, including DNN, Adaboost, SVM, and KNN, has shown that machine learning models can effectively classify ECG signals into the desired categories. These classifiers were trained on the extracted features and evaluated using a suitable performance metric.

5 CONCLUSION

Electrocardiogram (ECG) signals are widely used to diagnose AF, and feature extraction techniques based on wavelet transform have emerged as a promising approach for detecting AF from ECG signals. Two sets of temporal and spectral features were extracted using Hilbert technique from MIT-BIH database. The annotation file from MIT- BIH database is used for locating the positions of R- peaks. The combination of signal processing techniques, feature extraction, HRV analysis, and machine learning classifiers holds promise for the detection of atrial fibrillation from ECG signals. These findings have the potential to contribute to early diagnosis and improved management of atrial fibrillation, a significant cardiac condition. Future work should focus on improving robustness, real-time capabilities, and clinical validation to make these systems clinically useful and accessible to healthcare practitioners.

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