International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Efficient Classification of ECG Signals Using Probabilistic Neural Network in the Detection of Cardiovascular Diseases

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Submitted: 22/07/2022 Accepted: 25/09/2022

Abstract: The significance of Electrocardiogram (ECG) in determining the electrical mobility of human heart is extremely high in the medical world since it assists in visualizing the anomalies of heart and diagnosing the Cardiovascular Diseases (CVDs) in the early stages to prevent the disease complications by providing timely medical interventions without any complexities. The present study introduces an effective signal processing approach for efficiently assessing the ECG signals, in which the Adaptive Median Filter is employed for denoising the input signals without damaging the edge informations and the Hilbert Transform (HT) is implemented for segmenting the noise free signals into multiple regions to improve the feasibility of disease diagnosis in an optimal manner. For extracting the optimal features of the segmented signals, a Crow Search Algorithm (CSA) based approach is employed, which involves in maximizing reliability of detecting the existence of CVD in a wider range whereas the Probabilistic Neural Network (PNN) is used for classifying the extracted features to distinguish the types of cardiac diseases with maximum accuracy. The performance of the overall methodology is evaluated by implementing MATLAB simulink in an efficient manner. Eventually, a comparative analysis is carried out between different classifiers and the obtained outcomes have proved that the Proposed Classifier delivers optimal results with maximum accuracy of 98.9%, which is comparatively better than the other existing classifiers.

***Keywords*:** *ECG; CVD; Adaptive Median Filter; Hilbert Transform; CSA; PNN.*

1. Introduction

The necessity of detecting the Cardiovascular Diseases (CVD) is extremely mandatory in the recent days as it has multiple life threatening issues like heart failure, stroke and death, which in turn results in severely affecting the livelihood of the people by lessening the survival rate. Moreover, it has high mortality rate among other diseases since it occupies 31% of the overall global death rate and so multiple medical interventions are introduced to prevent the deaths caused by CVD, among which the Electrocardiogram (ECG) signal monitoring is highly preferred by the clinicians for performing early- stage diagnosis of CVD and minimizing the death rate [1-3]. Though it is advantageous enough in diagnosing the cardiac diseases in the initial stage, it is highly sensitive to the inevitable noises that are initiated by the environment during the collection and transmission of signals but it is highly essential to transmit the noise free signals for accurately predicting the disease occurrence. Therefore, various approaches are employed to generate the noise free signals for attaining reliable ECG measurement but all these approaches have failed to provide accurate prediction results in false alarm rate [4-5]

The signal is processed through four different phases like pre-processing, segmentation, feature extraction and classification for accurately diagnosing the occurrence of any cardiac diseases in the early stage with optimal outcomes [6]. The input signals are initially involved in the process of denoising for eliminating the unwanted inherent noises to enhance the signal quality and hence various filters are used in this process for filtering the input signals, among which the usage of Linear filter is preferred in the initial period since it effectively eliminates the noise content in the signals. However the usage of this filter is limited because of having the disadvantage of blurring the edge and contrast of the signals [7]. Thus, the preference of mean and median filters is taken place to mitigate the limitations of linear filter because these filters are capable enough in eliminating the noise content in the signals along with the preservation of edge informations but the application of

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these filters is limited because of having the demerit of minimal accuracy [8-9]. Therefore, the present study suggests the usage of an Adaptive Median filter for obtaining optimal pre-processing outputs.

After the completion of noise elimination, the noises are segmented into multiple sections in the second stage known as segmentation to improve the simplicity of disease identification with optimal accuracy and so different methodologies are employed to segment the images, among which, the implementation of Otsu approach is preferred by various researchers as it is capable enough in delivering optimal outcomes with maximum accuracy [10]. However, the inability in identifying the global threshold in certain conditions makes it unsuitable for many applications and so it is replaced with the K-means clustering algorithm that owns the beneficial impacts like maximum reliability and fast convergence in the segmentation process but the complexity in converging procedure limits the preference of this algorithm in a wider range [11]. To limit all these disadvantages in an optimal way, the segmentation using Hilbert Transform is introduced in this present work.

In the third stage, the optimal features in the segmented signals are extracted with the assistance of an applicable methodologies for improving the reliability of detecting the existence of disease in a wider range. The implementation of Gray Level Co-occurrence Matrix (GLCM) is considered as an optimal approach among different algorithms in the early period because it is capable enough in extracting the optimum features without eliminating the edge informations of the signal but the disadvantage of having less accuracy restricts its usage in a huge range [12]. Hence, the Genetic Algorithms based approach is preferred in the segmentation of ECG signals as it is wrapped with multiple beneficial impacts like constant operation, multi-objective solutions and discrete operation but the complexity or difficulty in using this approach is extremely disadvantageous [13]. The drawbacks of these aforementioned approaches are effectively overcome in this study by employing the Crow Search based approach in the process of feature extraction.

Finally, the classification of ECG signals is carried out for classifying the types and stages of CVD in an efficient manner and different classifiers like Random Forest (RF) and Decision Tree (DT) are employed in the early days to classify the signals since the classification accuracy of these approaches is optimal but the computational complexity turns as a barrier of using these approaches. Hence, the Artificial Neural Network (ANN) classifier is introduced for classifying the signals without any complexities but the unknown duration becomes a drawback of using this classifier [15] and hence the present study employs the PNN classifier in the classification process for obtaining optimal results without any hurdles.

The overall study consists of five sections, in which the detailed explanation of present study is significantly provided in section II, the modelling procedures of the implemented approaches are explained in Section III, the result analysis is given in Section IV and the summation is provided in Section V in an efficient manner.

2. Proposed System

The implementation of PNN based signal processing approach in diagnosing the CVD at early stage is significantly explained in this present study to accomplish the ultimate objective of identifying the occurrence of cardiac diseases without any complications since this approach is capable enough in predicting the disease with maximum accuracy. As this approach effectively involves in classifying the signals for predicting the CVD, it assists in providing required medical interventions without any delay and hence the performance efficiency of this approach is remarkably high. The block diagram representing the flow of proposed approach is significantly provided in Fig.1.

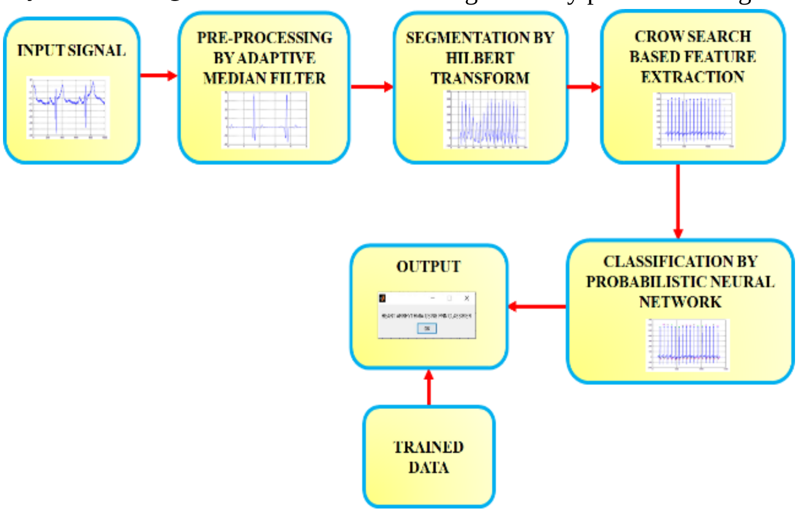

Fig. 1. Block diagram of proposed methodology

After completing the primary task of data acquisition, the input signal is processed through four different stages to deliver accurate outcomes and the input signal is fed to the initial stage known as pre-processing, in which the inevitable or unwanted noises in the signals are effectively eliminated with the aid of Adaptive Median Filter that helps in enhancing the signals in an optimal manner whereas the denoised signal is then segmented into multiple sections in the second stage with the assistance of Hilbert Transform for maximizing the reliability of disease detection. When the task of segmentation is completed, the features in the segmented signals are efficiently extracted in the next stage through the implementation of Crow search based approach, which significantly lessens the complexity in identifying the existence of CVD whereas the segmented features are effectively classified in the final stage with the aid of using PNN classifier that contributes well in diagnosing the types and stages of the disease in an optimal manner. Therefore, the proposed methodology is highly capable to be employed in the process of detecting CVD through ECG signals as it delivers optimal outcomes with maximum accuracy, less delay, fast convergence and less complexity. The modelling and structural designing of the constituent methodologies used in this study are evidently described in the subsequent section.

3. System Modeling

The detailed description and the modelling procedures of the four different stages involved in the introduced signal processing approach are significantly provided in the following subsections for highlighting the performance measures of this approach in an efficient manner.

3.1. Pre-Processing

As the ECG signal is highly sensitive to the inevitable noises, it is extremely mandatory to denoise the input signal through the implementation of applicable filters and hence the Adaptive Median Filter is introduced in this study to eliminate the noises since it involves in preserving the details of the signals while eliminating the impulse noises without any disruptions. The process of denoising the signal is remarkably described in Fig.2 in an efficient manner.

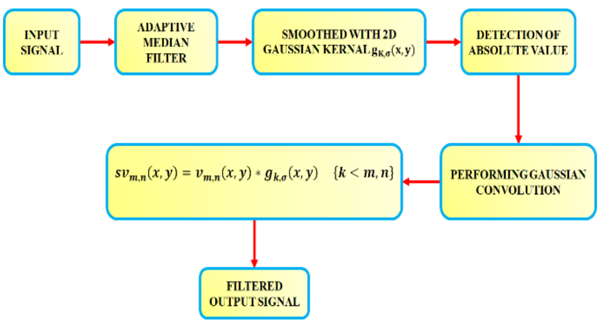

Fig. 2. Pre-Processing Using Adaptive Median Filter

The difference between the filtered signal and the original signal is assessed after median filtering the input signal, which is expressed as,

$$d_{m,n}(x,y) = f_{m,n}(x,y) - med_N[f_{m,n}(x,y)] \tag{1}$$

The 2D Gaussian kernel, $g_{k,\sigma}(x,y)$ is convoluted with the original signal in order to smoothen the input signal, which is thus expressed as,

$$s_{m,n}(x,y) = f_{m,n}(x,y) * g_{k,\sigma}(x,y) \quad \{k < m,n\} \tag{2}$$

Here, the value of σ and the smoothing degree are proportional to each other.

Then the absolute value of the variation between the smoothed signal and original signal is taken as,

$$v_{m,n}(x,y) = |f_{m,n}(x,y) - s_{m,n}(x,y)| \tag{3}$$

To attain smoothed form of the difference, the function of Gaussian convolution is carried out on $v_{m,n}(x,y)$ as,

$$sv_{m,n}(x,y) = v_{m,n}(x,y) * g_{k,\sigma}(x,y) \quad \{k < m,n\} \tag{4}$$

For attaining the ratio, the smoothed variability divides the difference in equation 1 as,

$$r_{m,n}(x,y) = \frac{d_{m,n}(x,y)}{sv_{m,n}(x,y)} \tag{5}$$

Thus, the enhanced output signal is attained after completing all the aforementioned steps and the filtered signal is then fed to the second stage known as segmentation.

3.2. Segmentation

In this stage, the pre-processed signals are segmented into multiple sections with same statistical features like amplitude and frequency for maximizing the detection accuracy in a wider range. The implementation of HT in the process of segmenting the ECG signal is discussed in this section and the analytic representation of this process is significantly illustrated in Fig. 3 in an optimal manner.

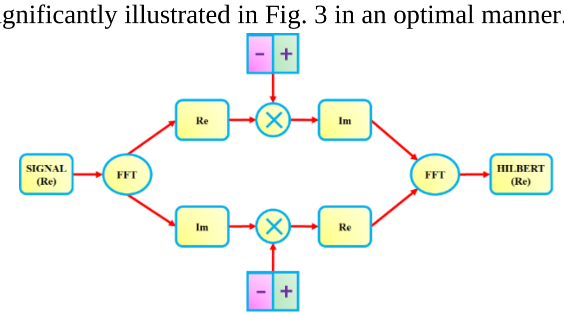

Fig. 3. Hilbert Transform

The differential output's Hilbert Transform is specified as,

$$S(t) = H[l(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty} l(\tau)\frac{1}{t-\tau}d\tau \tag{6}$$

Here, the differentiated signal output is specified as $l(t)$.

$$S(t) = \frac{1}{\pi\tau} * l(t) \quad (7)$$

$$F[S(t)] = \frac{1}{\pi} F\left\{\frac{1}{t}\right\} F\{l(t)\} \quad (8)$$

Where,

$$F\left\{\frac{1}{t}\right\} = -j\pi sgn\, f \quad (9)$$

$$F\{S(t)\} = -jsgnfF\{l(t)\} \quad (10)$$

Therefore, the original signal's HT output is derived as,

$$M(t) = l(t) + js(t) \quad (11)$$

The envelop $S(t)$ of $r(t)$ is thus specified as,

$$P(t) = sqrt\left(l^2(t) + S^2(t)\right) \quad (12)$$

Its instantaneous phase angle is expressed as,

$$\varphi(t) = arctan\left(\frac{S(t)}{l(t)}\right) \quad (13)$$

The significance of this Hilbert Transform is remarkably high in segmenting the signals in an optimal manner since it aids in maximizing the reliability of the entire system in identifying the CVDs. After completing this process of segmentation, the segmented signal are then fed to the next stage for extracting the optimal features.

3.3. Feature extraction

The process of extracting the feature from the segmented signal is regarded as one of the significant stages of the overall operation of this approach since it involves in effectively selecting and keeping the appropriate diagnostic data from the original signal for enhancing the probability of disease detection in a wider range. The present study uses one of the optimal metaheuristic algorithms known as CSA in the process of feature extraction, which significantly contributes in extracting the features like T wave, QRS complex and P wave on the basis of the clever communication behaviour of crows in an optimal manner. The structural depiction of these features is remarkably illustrated in Fig. 4.

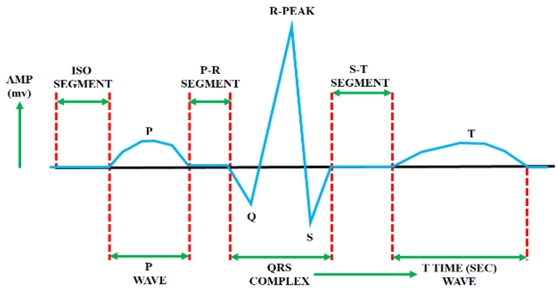

Fig. 4. Features of ECG signal

In the first stage, the hiding place of crow k is discovered by crow j without its knowledge and the cwow j achieved it new location as,

$$\mathrm{Y}^{j,rept+1} = \mathrm{Y}^{j,rept} + s_j \times flen^{j,rept} \times (n^{k,rept} - \mathrm{Y}^{j,rept}) \quad (14)$$

Here, the flight length of crow j at repetition is specified as $flen^{j,rept}$ whereas the uniform distribution of random number among 1 and 0 is specified as s_j.

In the second stage, the crow j goes to different search space to fool the crow j for preserving its cache from being stolen. Thus, these two state are expressed as

$$\mathrm{Y}^{j,rept+1} = \begin{cases} \mathrm{Y}^{i,rept} + s_j \times flen^{j,rept} \times (n^{k,rept} - \mathrm{Y}^{j,rept}) & s_k \geq KP^{k,rept} \\ a\ random\ position & otherwise \end{cases} \quad (15)$$

The steps involved in this algorithm are explained in the subsequent section in an efficient manner.

- The parameters like Knowledge Property (KP), Maximum Repetition number (reptmax), size of flock (N) and fight length (flen) are assessed in the initial stage.
- N crows are randomly placed as flock members in a-dimensional search space, in which 'a' is the number of decision variable. Each crow indicates the feasible solution as,

$$Crows = \begin{bmatrix} Y_1^1 & Y_2^1 & \cdots & Y_a^1 \\ Y_1^2 & Y_2^2 & \cdots & Y_a^2 \\ \vdots & \vdots & \vdots & \vdots \\ Y_1^N & Y_2^N & \cdots & Y_a^N \end{bmatrix} \quad (16)$$

The crows' memory is initialized in this stage and the food at the initial location is vanished since the crows have no experience in the initial iteration.

$$Crows = \begin{bmatrix} mr_1^1 & mr_2^1 & \cdots & mr_a^1 \\ mr_1^2 & mr_2^2 & \cdots & mr_a^2 \\ \vdots & \vdots & \vdots & \vdots \\ mr_1^N & mr_2^N & \cdots & mr_a^N \end{bmatrix} \quad (17)$$

- By adding the position of crow with the decision variable value's objective function, each crow's standard of location is assessed.
- The novel locations of the crows are attained.
- When the novel location is stable, the crow update the location whereas it remains in the same location when the novel location is not stable.
- The determination of fitness value for all crows is performed.
- Every crow's memory is updated as,

$$mr^{i,rept+1} = \begin{cases} Y^{j,rept+1} & flen\,(Y^{j,rept+1}) \geq flen(mr^{j,rept}) \\ mr^{j,rept} & 0.W. \end{cases} \quad (18)$$

Here, the objective functions' value is specified as $flen$.

When the fitness of the novel location is optimal then the remembered position's fitness value, the crow's memory is updated with the novel locations.

- Until $rept_{max}$ is attained, steps 4-7 are repeated. When the transmission criterion is met, the objective function of updating the memory with novel location is attained.

The flowchart representing the steps of this CSA approach is significantly illustrated in Fig.5.

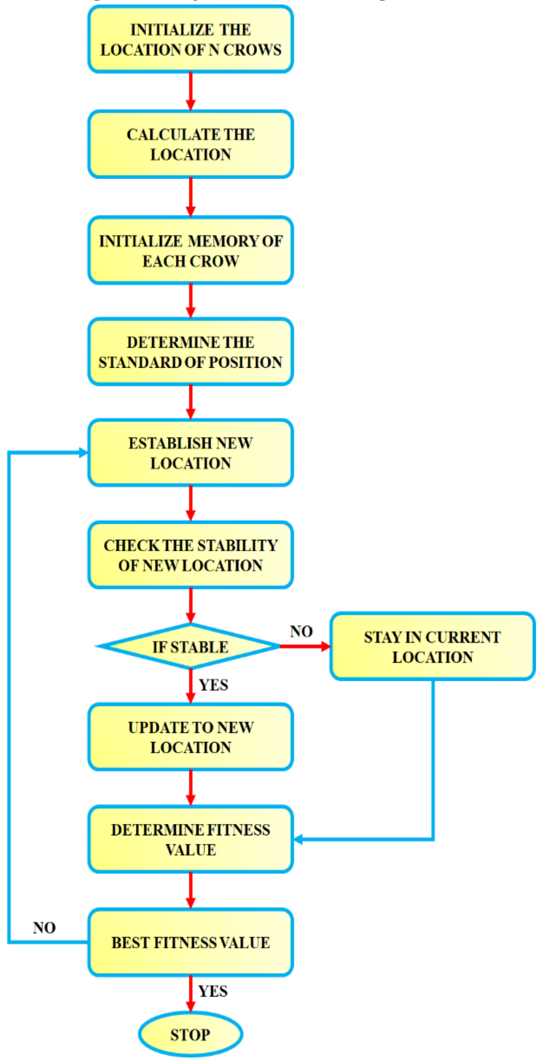

Fig. 5. Flow chart of CSA

Thus, CSA based approach performs well in extracting the optimal features and the extracted feature are then given to the final stage for classifying the signals in an optimal manner.

3.4. Classification

The classification of the extracted signals is performed in the final stage by using PNN classifier that is considered as a frequently used neural network in the classification process since it capable enough to deliver optimal outcomes with maximum accuracy and fast convergence. The layers of PNN is categorized into four kinds like input, pattern, summation and output layers, which are clearly illustrated through the architecture diagram in Fig.6 for enhancing the conception of this approach.

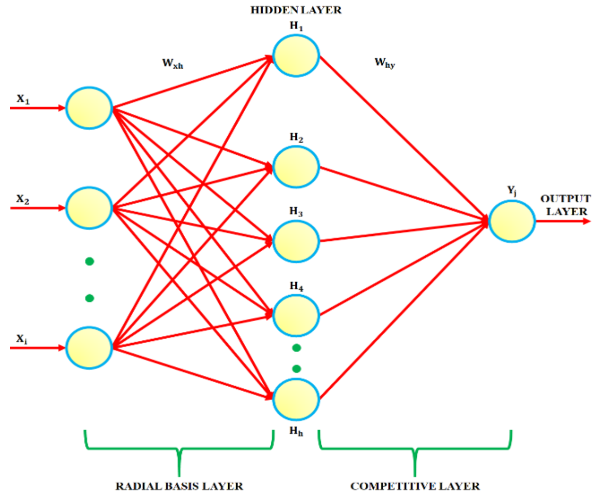

Fig. 6. Architecture of PNN

The Bayes formulation of PNN is significantly expressed as,

$$p(x|y) = \frac{p(y|x) \cdot p(x)}{p(y)} \quad (19)$$

Here, the probability of event y when event x is provided is specified as $p(y|x)$ whereas the probability of event x when event y is provided is specified as$p(x|y)$. The overall probability of all y is specified as $p(y)$ and the probability of x is specified as $p(x)$.

The input and pattern layers are fully connected with each other. Each pattern is linked with one neuron whereas the neurons involves in executing the weight sum of signals that are received from the input layer and this weight sum is given to the nonlinear activation operation for attaining the neuron output, which is expressed as,

$$\phi(\|x_{wi} - 1\|_2) = e^{(\|x_{wi}-1\|^2/\sigma_i^2)} \quad (20)$$

Here, the smoothing parameter is specified as σ and the weight input of x_i is specified as x_{wi}.

The neurons in the pattern layer transmits the output to the neurons in the summation layer, which is thus expressed as,

$$R_k(x) = \sum_{i=1}^{k} \varphi(\|x_{wi} - 1\|_2)\,, k = 2,3,4 \quad (21)$$

Only two inputs are received by the output layer neurons from two summation units. The two weights are variable and strength of unity, which are expressed as,

$$w' = [h_B/h_A][I_B/I_A][n_B/n_A] \quad (22)$$

Here, the number of A or B patterns is specified as n, the loss related to the pattern identification is specified as l and the priori probability of patterns is specified as h.

By setting the weight of a neuron in patter layer with the magnitude of elements in the training patterns, the output is computed as,

$$y_k(x) = arg(max\{R_k(x)\}) \tag{23}$$

The obtained output has validated that the Significance of PNN in the classification process of identifying the CVD is remarkably higher than the other classifiers.

4. Result and Discussion

The implementation of PNN classifier in the accurate detection of CVD using Crow Search based feature extraction is significantly explained in this work and the obtained outcomes of this approach are evidently provided in the subsequent section. The signals of 1 minute are collected from the database known as MIT-BIH Arrhythmia, which are then categorised as abnormal and normal based on the rhythmic feature of the signal. The MATLAB simulink is used to validate the present work in an optimal manner.

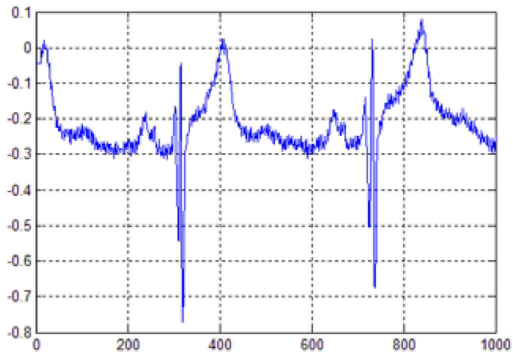

Fig. 7. Input signal

The waveform representing the input signal is significantly illustrated in Fig. 7 that exhibits multiple distortions or noises, which lessens the detection capability in a wider range and so it is highly mandatory to eliminate the noise content in the input signal for attaining optimal outcomes in the detection of CVD.

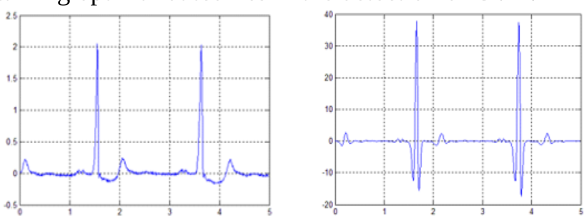

Fig. 8. Pre-processing output

The process of eliminating the noises in the input signals is efficiently carried out by using the Adaptive Median Filter and the obtained output of the pre-processed signal is evidently illustrated in Fig. 8 in an efficient manner, which proves that the performance capability of the proposed filter in denoising the input signals is extremely high.

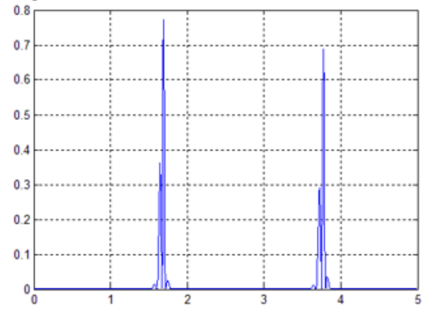

Fig. 9. Normalisation output

The normalisation of the input signal is performed for minimizing the noises in the signals without making any vast variation in the signal and the obtained output of this normalisation process is clearly depicted through the waveform in Fig. 9, which shows that the noise contents are eliminated without varying the signal informations.

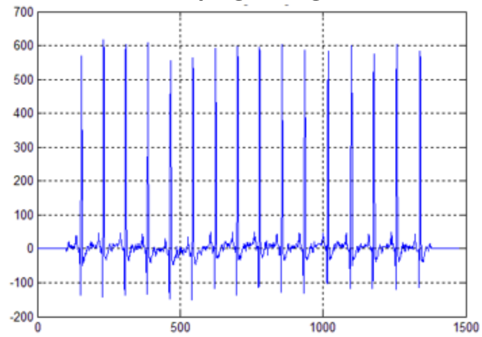

Fig. 10. Full cycle of ECG signal

The waveform illustrating the full cycle operation of EGC signal is provided in Fig. 10 in an efficient manner and it is noted from the waveform that the heart rate acquisition is remarkable evaluated through the cardiac cycles with optimal accuracy.

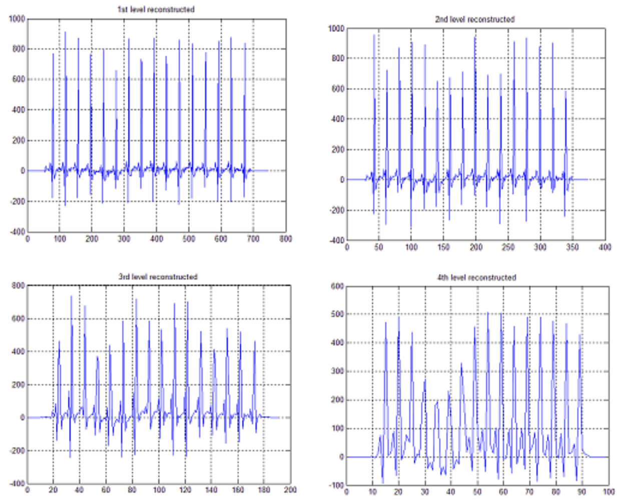

Fig. 11. Reconstructed output signals

The temporal and special features of the ECG signals are extracted through the process of reconstructing the signals for enhancing the reliability of disease identification in a wider range and the reconstructed waveforms of four levels are efficiently illustrated in Fig. 11, which validates that the signals are efficiently reconstructed with optimal accuracy by the employed methodologies.

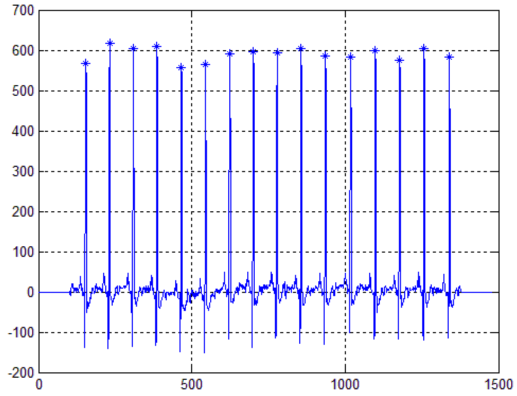

Fig. 12. R peak detection by PNN classifier

The significance of PNN classifier in the R peak detection is highly optimal since it delivers maximum reliability along with less delay in identifying the peak occurrence and the obtained waveform of R peak detection is significantly depicted in Fig.12 with prior analysis, which shows that the scalability of detecting the R peak using PNN is highly optimal.

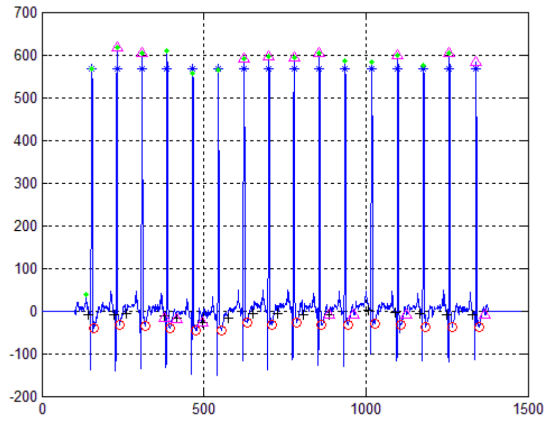

Fig. 13. QRS detection by PNN classifier

The process of QRS detection is a major part of this signal processing approach since the performance efficiency of the proposed approach is evaluated through the reliability of this QRS detection and the PNN classifier delivers optimal outcomes in the detection of QRS complex, which is significantly validated through the obtained waveforms in Fig. 13 in an efficient manner.

Fig. 14. Classification output

Table. 1. Comparative analysis of performance metrics

Methods	Accuracy	Specificity	Sensitivity
Random Forest (RF)	89.9	90.4	89.7
Support Vector Machine (SVM)	91.2	91.8	90.2
ANN	93.6	95.6	94.1
PNN	98.9	98.1	97.2

The obtained output of the clarification process is evidently illustrated in Fig. 14 and the classified signals have diagnosed one of the cardiovascular diseases known as Arrhythmia, which is evidently portrayed through the obtained output in Fig. 14. Thus, it is validated that the proposed approach contributes well in the detection of CVD in the initial stage.

The comparative analysis is carried out between various classifiers in terms of sensitivity, specificity and accuracy, which is remarkably listed out in Tab. 1.

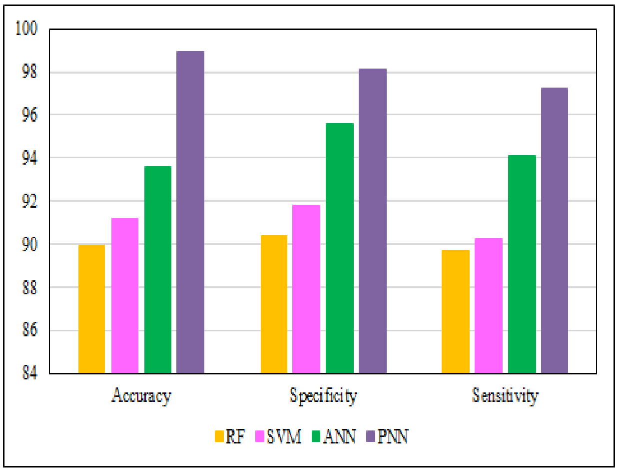

Fig. 15. Comparative Analysis

The outcome of the comparative analysis of different classifiers with respect to the performance metrics is evidently illustrated in Fig. 15 that exhibits that the proposed PNN classifier delivers optimal results with the accuracy of 98.7%, specificity of 98.1% and sensitivity of 97.2%, which are comparatively better than the other existing classifiers.

5. Conclusion

The present study analyses the contribution of signal processing approach in the process of diagnosing the cardiac diseases on time through the determination of variations in the ECG signals. It describes that the ECG signals are efficiently processed through four different stages with the assistance of suitable approaches, in which the usage of Adaptive Median Filter contributes well in eliminating the unwanted noises in the input signals whereas the Hilbert Transform involves in effectively segmenting the denoised signals into multiple sections for significantly improving the detection accuracy without any interruptions. With the assistance of CSA based approach, the ideal features in the segmented signals are extracted in an optimal manner and the features are eventually classified in the final stage with the aid of PNN classifier, which in turn involves in maximizing the overall performance of the system in a wider range. The entire working system is validated through MATLAB simulink and the attained outcomes validate that the proposed classifier delivers better performance with optimal accuracy of 98.9%.

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