A ROBUST ECG SIGNAL PROCESSING AND CLASSIFICATION METHODOLOGY FOR THE DIAGNOSIS OF CARDIAC HEALTH

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Abstract-The electrical mobility of the human heart is described by electrocardiogram (ECG) signals. Nowadays, computerized equipments assisted the physicians for identifying, classifying as well as diagnosing ECG. In this article an efficient processing of ECG signals is proposed in which the input image is preprocessed by Gaussian filter making it noise-free. Subsequently, the image is segmented by adopting Hilbert transform generating a peak value with the analysis of amplitude and frequency. Further, the features are extracted by SIFT which converts the input signal into a group of feature vectors. Finally the signal undergoes classification through ANN which classifies the signal as normal or abnormal. The dataset utilized in this approach is MIT-BIH arrhythmia with 45 recordings of 1 minute duration is considered. With ANN, the accuracy obtained is 98.7% and the efficient classification is performed.

Keywords: ECG, Hilbert transform, SIFT, QRS complex, ANN.

1 INTRODUCTION

Many applications use electrocardiogram (ECG) signals for the diagnosis of cardiovascular problems, prediction of arrhythmia, physiological input, detection of sleep apnea, monitoring of chronic patient, fatal heart arrest prediction and mental, biometric, as well as physical activities [1-3]. The use of ECG signals for diagnosing cardiovascular disease is currently emerging. The majority of research, on the other hand, have only concentrated on classifying as well as identification of heartrates. This led to greater rate of recognition, yet they are inappropriate to clinical usage [4].For more precise and reliable ECG measurements, majority of the systems for the analysis of ECG need distortion less inputs [5]. In practise, ECG signals usually get contaminated with electrode touch noise as well as motion artefacts, interference of power line, electromyogram noise, as well as noise due to instrumentation, rendering morphological analysis of these tainted ECG beats nearly impossible [6]. The majority of current systems for ECG analysis were developed to deal ECG signals which are free from noise. Current systems generate incorrect and ineffective measurements in such situations, resulting in increased rates of false alarm for ECG signals with noise [7]. As a result, automated ECG signal processing is in high demand in order to reduce false alarms caused by excessive noise levels.

In the processing of signals, four tasks have to be performed given by: preprocessing, segmentation, feature extraction and classification. The first step in preprocessing is to remove speckle noise, which avoids the loss of edge information as well as critical attributes. Several studies on speckle noise reduction have been carried out. One of the most effective preprocessing techniques is linear filters, which are commonly known. However, they ignore the noise and characteristics dispersed throughout the input signal, which obscures the contrast and also the edge region [8]. For single polarisation Synthetic Aperture Radar (SAR) despeckling, another filter called the Lee filter was designed depending on linear minimum mean squared error (LMMSE) estimator. The problem with these methods is that they demand that similar pixels be chosen to ensure scene stationarity [9]. Preprocessing is often accomplished by using an effective hashing algorithm to apply a series of pre-learned locally adaptive filters to image patches. These filters are trained and developed by analysing the statistics of local gradients. However, by regularising preparation and introducing appropriate practises, performance can be improved even further [10]. Following that, a mean filter is used for preprocessing, which reduces the amount of intensity difference between one pixel and the next. The average value of neighbours replaces the parameter value, and parameters that are not identical to the neighbours are ignored. The key drawback of mean filters is that due to edge breakup, they can produce pseudo noise edges [11]. To tackle this, Gaussian filter is utilized which implements based on derivative generating enhanced accuracy for estimation as well as decreased computational cost.

The signal must be segmented after preprocessing, which is an important phase in both medical research and clinical practise. A variety of methods for segmentation were used, with region-based segmentation being one of the most prominent. This technique creates closed contour regions, but might ignore resolution as well as attributes [12].Supervised techniques like thresholding and histogram-based segmentation suffer from performance degradation due to discrepancies in training and test results [13]. Another type of segmentation approach is edge detection segmentation, which generates substantial visual information because it relates to the key physical, photometrical, and geometrical changes. In any case, applying them to real-world signals is difficult [14]. Hence, the segmentation of ECG signals is performed by Hilbert transform in this approach which generates instant frequency which is meaningful.

Following segmentation, features must be removed from the image thus reducing the amount of redundant data in the dataset. Principal Component Analysis (PCA) is a feature extraction method for determining orthogonal transformations to increase the complete variance of predicted results. However, since spectral features have different properties, feature extraction using a single projection is not possible [15]. Independent Component Analysis (ICA) is a feature extraction technique that segregates signals which are independent from a vector group made up of linear combinations of signals. It also defines independent image characteristics, but this method is influenced by light movement and changes [16]. Another feature extraction approach is linear discriminant analysis (LDA), which aims to narrow the distance between each class's mean and minimise class spread. Additional capability improvements, such as restricted side specifics and rigidity against rotation and content loss attacks, were required [17]. Therefore, Scale-Invariant Feature Transform (SIFT) is employed which is robust in the extraction of signal features.

Finally, signal classification is used to sort the extracted features into different groups. By increasing the duration within samples which are positive as well as negative in the training set, SVM is used to classify the features. It improves classification and prediction capabilities, but it is inefficient [18]. Another classification method for deciding the most successful attribute variable of classification capability is a decision tree (DT). Using the best attribute variables, the data is be partitioned into different subsets. Although the precision of integrated and sub-classifiers is highly correlated, developing classifiers with improved classification accuracy is important [19]. The Random Forest (RF) algorithm, which uses a cascade scheme in which feature information is provided to each layer, is another method for image classification. It accounts for the risk of overfitting, improves accuracy, and can be used to solve classification and regression problems. On the other hand, the demand for computing resources and training time is extremely strong [20]. Hence, the proposed approach uses an Artificial Neural Network (ANN) to classify the inputs according to the target class.

Henceforth, an efficient signal processing for ECG is proposed in this approach with the contributions given as,

- Utilization of Gaussian filter for the preprocessing of signals.
- Segmentation of input signal by Hilbert transform.
- Extraction of features by SIFT algorithm.
- Classification of signal features with the help of ANN.

The arrangement of paper is: Section 2 elucidates the related works. Proposed framework is presented in section 3. Outputs as well as discussion are explained in section 4. Finally, work conclusion is illustrated in section 5.

2 RELATED WORKS

Shing et al [21] presented a system which was practically designed for the authentication of biometrics depending on ECG signals accumulated from wearable equipments. A crosscorrelation related to extracted templates while registering and authenticating was utilized. The presented approach minimized the computation time with efficacious authentication.

Antoni et al [22] introduced a rapid approach for detecting QRS complex depending on ECG analysis. The processing of ECG involved removal of noise, detection of features and its analysis. The resultant set of features held majority of the information about ECG emphasizing the merits. It offered an efficient computation without parameters with improved detection as well as lossy compression.

Carlos et al [23] solved the issue in discrete time state space adopting the shape of ECG signal through the horizon which is optimally averaging and varies accordingly with time. The introduced methodology performed improvingly comparing to prevailing concepts.

Fernando et al [24] introduced methodology for dynamically accessing the ECG sgnal quality for improving the estimation of heart rate. The suggested concept for classification generated improved accuracy to determining the complete quality. It reflected the variations in the quality of signals in a reliable manner.

Darren et al [25] proposed a reconstruction strategy for improving ECG performance utilizing various dictionaries. It is a framework of double-stage leveraging information regarding the ECG signal and the reconstruction of signal is performed. With the selection of accurate dictionary, an improvingly refined reconstruction of signal is obtained.

Sean et al [26] developed deep learning approaches along with alignment of signals facilitating ECG signal classification. The sample points based on time domain are obtained from ECG signals as well as extraction of consecutive signals is performed. The developed approach performs leveraging of deep neural network for the extraction of features as well as its classification.

3 PROPOSED METHODOLOGY

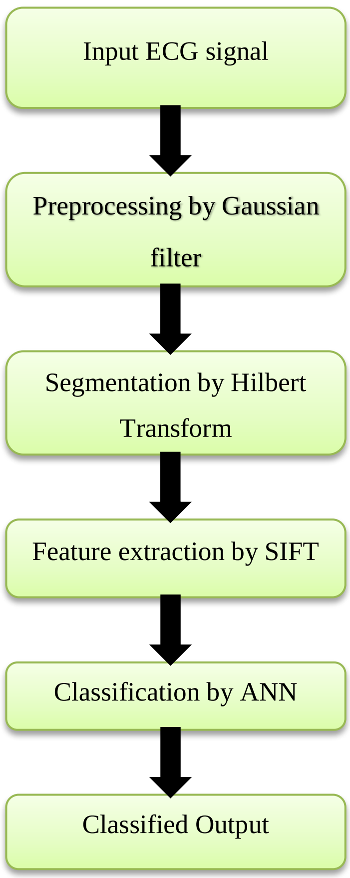


Figure 1 Process flow of the proposed method

Cardiovascular diseases have been one of the main diseases affecting human life in recent years. As a result, detecting heart signal waves like the QRS complex is important. The electrical activities of the heart are seen as a signal on an electrocardiogram, which is used to diagnose the majority of heart disorders. ECG signals provide a wealth of knowledge about heart conditions. One of the basic topics is the identification of special points and various parameters such as the QRS complex, which is very important because it leads to the diagnosis of heart diseases. Hence the processing of ECG signals is considered to be mandatory and the corresponding process flow is given in figure 1.

Initially, the input ECG signal is pre-processed by the Gaussian filter which eliminates unnecessary signals merged with the input signal. The pre-processed signal is further segmented by Hilbert transform approach that analyses the instant amplitude as well as frequency of the signal. Consequently, the extraction of features is done by Scale Invariant Feature Transform (SIFT) which converts the input signal into group of vectors. Finally, the image is classified by Artificial Neural Networks (ANN) by which classification of ECG signal into normal and abnormal occurs.

3.1 Input Signal Pre-Processing

Each sample of the signal is applied with the Gaussian filter performing convolution of the signal with the Gaussian function which is truncated and is given in equation (1).

$$q_i = A_i f \sum_{i=-N}^{N} p_{j+if} e^{-W_i(if)^2} \qquad (1)$$

Here, p and q → noisy and smoothed edges respectively.

W_i → Gaussian filter width
f → Sampling frequency
N → Constant value
A_i → Normalization factor

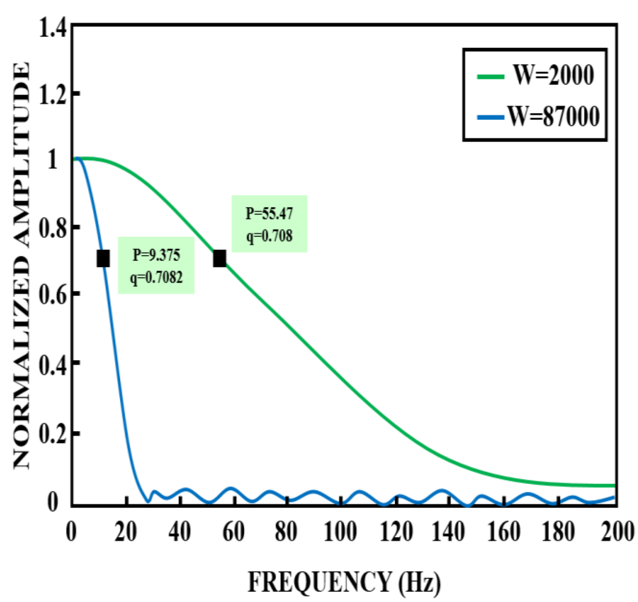


Figure 2 Cutoff frequency variation

The cutoff frequency variation as well as width and amplitude of Gaussian filter is indicated in figure 2 and figure 3 respectively. The cutoff frequency of the

Gaussian filter show variation between 10 and 55 Hz. The slope of the signal is utilized for tuning the Gaussian filter width such that the minimal cutoff frequency is applied to the segments with minimal slope.

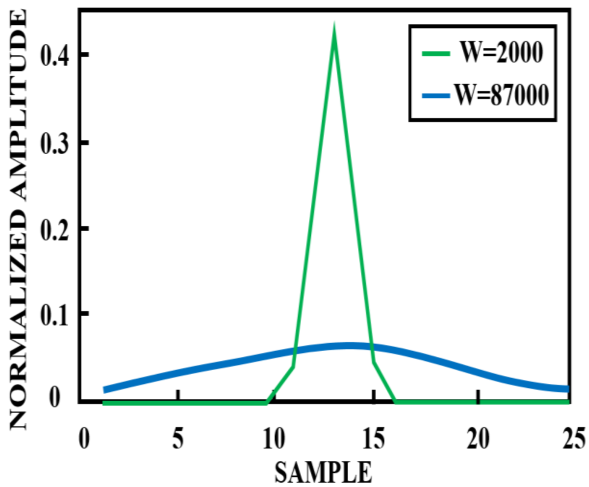


Figure 3 Width and amplitude of Gaussian filter

The normalization factor is given by,

$$A_i = \frac{1}{f\sum_{j=-n}^{n} e^{-W_i(if)^2}} \quad (2)$$

$$If\ SS < minthr, W = Wmin \quad (3)$$
$$elseif\ SS > maxthr, W = Wmax \quad (4)$$
$$else\ W = Wramp \times ((SS - minthr) + Wmin) \quad (5)$$

3.2 Segmentation

The Hilbert transform is adopted to analyse instant amplitude as well as the frequency of the signal. It is expressed mathematically as,

$$\hat{y}(t) = H[y(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{y(\tau)}{t-\tau}d\tau \quad (6)$$

The signal's Hilbert transform is generated by convoluting the signal as well as $1/(\pi t)$. For the frequency domain, the Hilbert transform is defined mathematically as,

$$\hat{Y}(f) = F\left[\frac{1}{\pi t}\right]F[y(t)] = -jsgn(f)Y(f) \quad (7)$$

$$\hat{y}(t) = IFT\left[\hat{Y}(f)\right]\ in\ which\ \hat{Y}(f) = jY(f), f < 0$$
$$-jY(f), f > 0 \quad (8)$$

Where, $Y(f)$→ Signal's fourier transform
IFT→ Inverse fourier transform

Hilbert transform is also applied for detecting the peak value of the signal. It generates positive zero that crosses in the signal transformed related to the peak of the actual signal. With the detection of the crossing points of positive zero, the maximum peaks are estimated which avoids the need of amplitude threshold value.

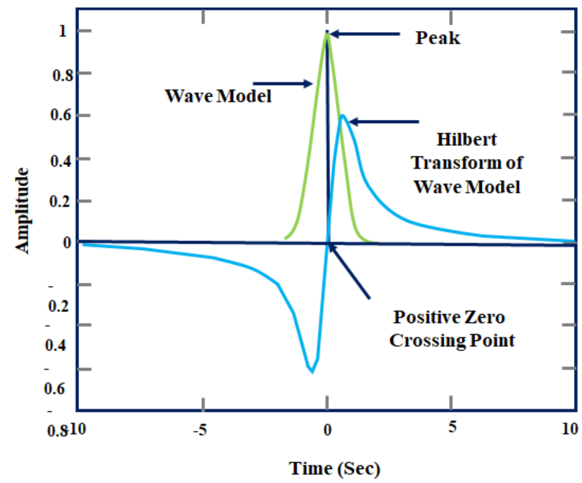


Figure 4 Logic for peak detection utilizing Hilbert transform

Figure 4 shows the detection of peak value utilizing Hilbert transform. The detected peak position in the ECG signal which is processed exhibit marginal variations of the peak values. Generally, the peak values in ECG signals are denoted by the maximal amplitude values. The maximal peak amplitude is considered for the normal wave and the absolute maximal amplitude is taken for the inverted wave. With the consideration of the maximal peak amplitude, the peak value location closer to the original position is detected.

3.3 Extraction of Features

SIFT represents the technique of transforming a signal to a group of feature vectors which do not vary with general geometrical transformations. This technique is adopted for the extraction of distinct features that are invariant from the signals for serving reliable similarity among various views.

Two main steps take place for the extraction of features by SIFT. Initially, the characteristics of the signal are extracted for calculating the corresponding descriptors. The characteristics which generally denote the signal are detected and further defined as well as discriminated with the comparison of other characteristics. The next step is setting a procedure for matching.

3.3.1 Detection of Scale-Space Extrema

A Gaussian difference function is utilized for identifying the potential points of interest which exhibit invariance as well as orientation. The candidate keypoints are attained with the location of extrema from Difference of Gaussian (DoG) pyramid.

3.3.2 Localization of Keypoint

For obtaining the stable keypoints, the accurate location of keypoints has to be identifiedand the keypoints with minimal efficiency is neglected. Finally, the keypoints present at the edge are removed utilizing principal curvature.

3.3.3 Assignment of Orientation

The orientation histograms' estimation related to the neighbourhood is utilized for justifying the descriptor invariance regarding the rotation.

3.3.4 Descriptor Calculation

The keypoint descriptor of each point is estimated for the descriptor vector generation related to every point of interest. For every sub region depending on gradient magnitude an orientation histogram is calculated.

3.4 Classification

ANN is exploited in various fields like classification, recognition of patterns etc. Depending on the input pattern features, the ANN's decision making is appropriate for the biomedical data classification. It is performed by back propogation algorithm for reducing the error.The ANN classifies the ECG signals as normal or abnormal by assigning the weights in a random manner.

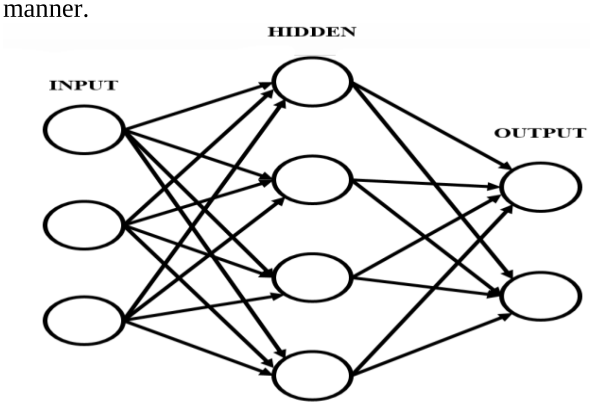


Figure 5 Three layered ANN

The ANN is usually denoted as neural network and comprises of interlinked set of artificial neurons. Figure 5 indicates a neural network of three layer encompassing of output, input as well as hidden layers interlinked with variable weights. The input unit denotes the feature vector as well as the output unit denotes the pattern class to be classified. As shown in figure 6, every feature vector is fed to the input layer and every unit's result is related vector component. Every hidden unit estimates the weighted input total for net activation. It is the multiplication between the input as well as weight vector. Consider A_i as the input vector function where input vector $A = [A_1.A_2 - \cdots A_n]^T$ and B_i as the elements of the weight $B = [B_1.B_2 - \cdots B_n]^T$. Hence, net function is given by,

$$Net_j = \sum_{i=1}^{d} A_i \, B_{ij} \qquad (9)$$

ANN is composed of parallel functioning simple elements. Generally, these networks face adjusing, training such that specific units of input to particular result and network adjustment of takes place depending on the output and target assessment. Generally, various pairs are required for training the network. The input selection of ANN is more significant for the neural network designing to generate accurate outputs. Subsequently, the details computed as well as approximated coefficients of ECG waveforms are considered as feature vectors to represent the signals.

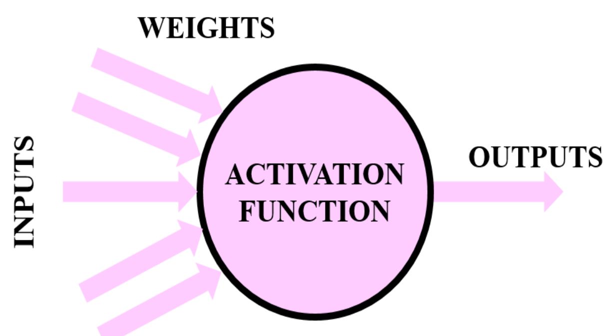


Figure 6 ANN utilizing activation function

4 RESULTS AND DISCUSSION

The inputs are obtained from MIT-BIH arrhythmia database with 45 recordings of 1 minute duration is considered and is partitioned into two distinct classes which are normal as well as abnormal. Every file is recorded for a minute as well as for normal class, maximal count of normal sinus rhythm is choosen and for abnormal class rest of the beats are regarded.

4.1 Performance Metrics

The performance of the utilized ANN classifier is enumerated by, specificity, accuracy, sensitivity.

Accuracy is defined as the ratio of samples which are accurately classified the samples of total count.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

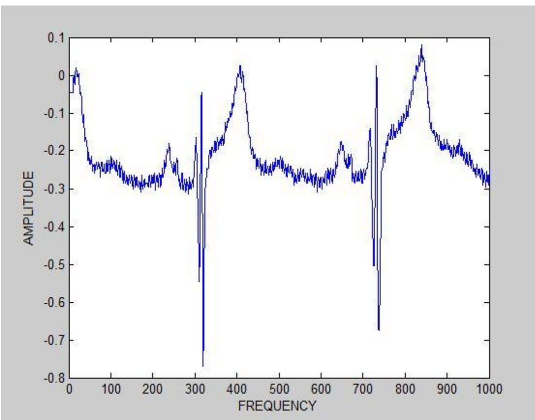
Specificity points to the negatives that are classified accurately.

$$\text{Specificity} = \frac{TN}{TN+FP}$$

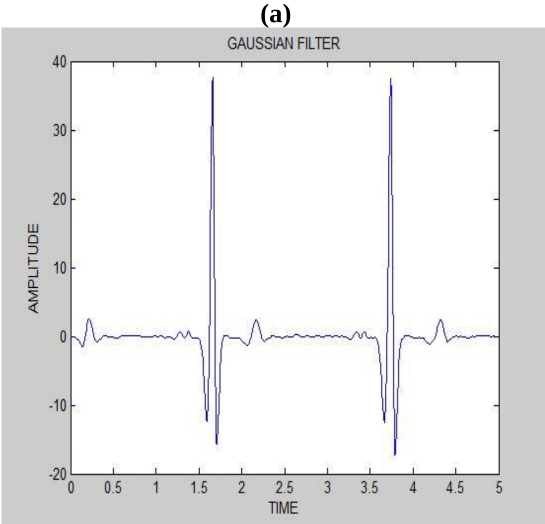
Sensitivity denotes the positives that are classified accurately.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

Figure 7 a & b indicates an ECG signal with noise as well as the resultant Gaussian functions.



(a)



(b)

Figure 7 ECG signal with noise and Gaussian function estimated

Figure 8 indicates the output of Hilbert transform in which the instant amplitude as well as the frequency is analyzed.

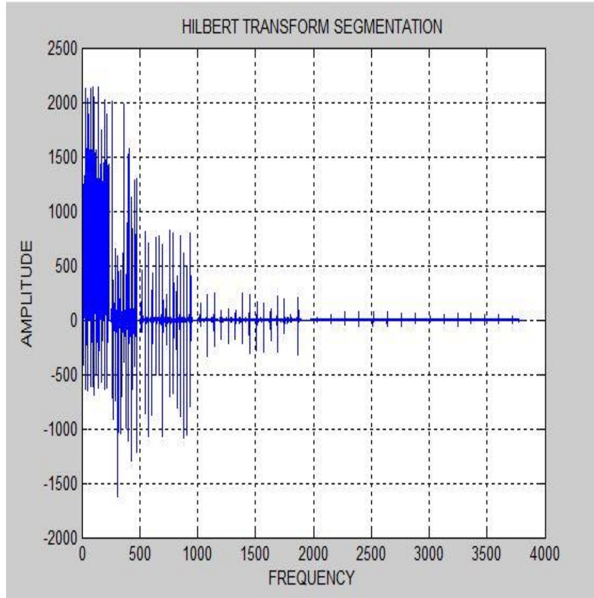


Figure 8 Output of Hilbert transform

Figure 9 indicates the first level feature extraction using SIFT approach.

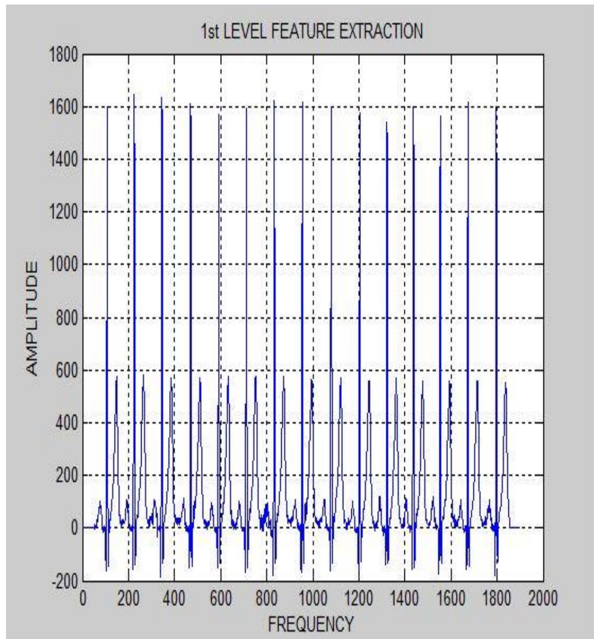


Figure 9 First level feature extraction

Figure 10 indicates the second level feature extraction using SIFT approach.

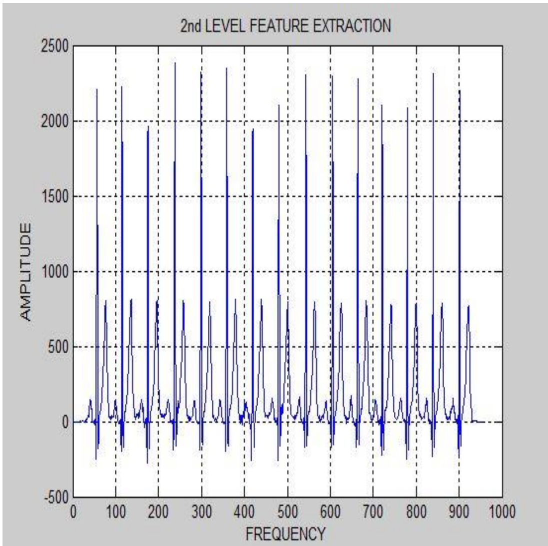


Figure 10 Second level feature extraction

Figure 11 indicates the third level feature extraction using SIFT approach.

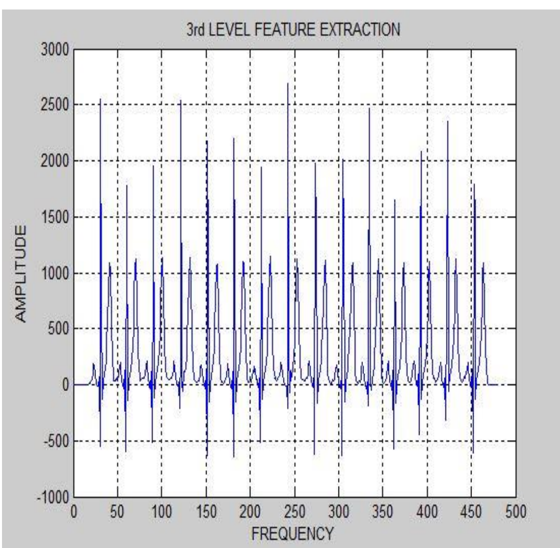


Figure 11 Third level feature extraction

Figure 12 indicates the third level feature extraction using SIFT approach.

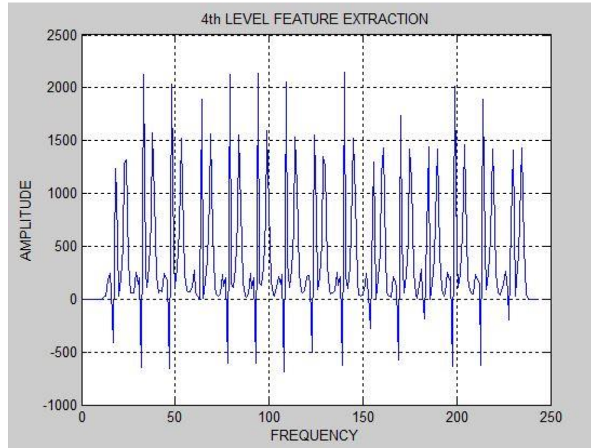


Figure 12 Fourth level feature extraction

Figure 13 indicates the detection of maximal peak values in ECG signals. This peak value is obtained in the points of maximal amplitude.

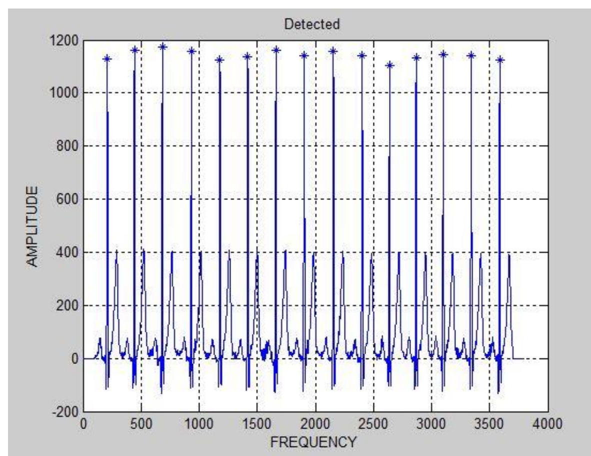


Figure 13 ECG signal with peak detection

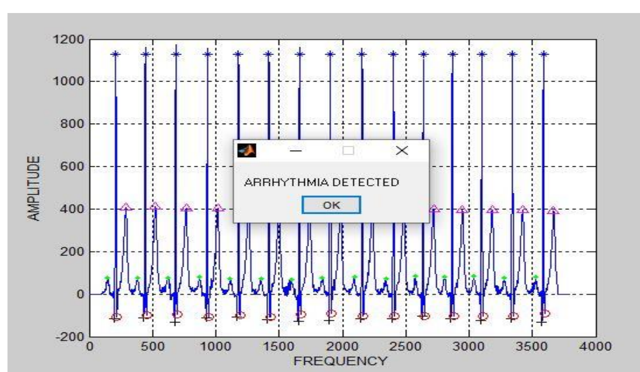


Figure 14 Detected output

Figure 14 indicates the final output with the detection of irregular heart beats.

Table 1 Comparison of performance metrics

Methods	Accuracy (%)	Specificity (%)	Sensitivity (%)
Multi SVM	98.4	96.5	80.53
KNN	95.8	97.5	87.6
NB	88.4	93.0	65.4
ANFIS	89.7	93.8	69.1
ANN	98.7	98.0	95.0

Table 1 illustrates the comparison of performance metrics like accuracy, specificity and sensitivity of Multi SVM [27],KNN [28], NB [29], ANFIS [30] and the utilized ANN classifier showed improved results.

5 CONCLUSION

The processing of ECG signals is addressed in this article utilizing Gaussian filter for pre-processing as well as Hilbert transform for the analysis of parameters. The features are extracted by SIFT and efficacious classification of signal is performed by ANN. The proposed framework is experimented on MIT-BIH arrhythmia database with 45 recordings of 1 minute duration. With the help of ANN, the accuracy obtained is 98.7 %.

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