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ECG Analysis-Based Cardiac Disease Prediction Using Signal Feature Selection with Extraction Based on AI Techniques

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Abstract

ECG (Electrocardiogram) performs classification using a machine learning model for processing different features in the ECG signal. The electrical activity of the heart is computed with the ECG signal with machine learning library. The key issue in the handling of ECG signals is an estimation of irregularities to evaluate the health status of patients. The ECG signal evaluate the impulse waveform for the specialized tissues in the cardiac heart diseases. However, the ECG signal comprises of the different difficulties associated with waveform estimation to derive certain features. Through machine learning (ML) model the input features are computed with input ECG signals. In this paper, proposed a Noise QRS Feature to evaluate the features in the ECG signals for the effective classification. The Noise QRS Feature model computes the ECG signal features of the waveform sequences. Initially, the signal is pre-processed with the Finite Impulse response (FIR) filter for the analysis of ECG signal. The features in the ECG signal are processed and computed with the QRS signal responses in the ECG signal. The Noise QRS Feature evaluate the ECG signal with the kNN for the estimation and classification of features in the ECG signals. The performance of the proposed Noise QRS Feature features are comparatively examined with the Discrete Wavelet Transform (DWT), Dual-Tree Complex Wavelet Transforms (DTCWT) and Discrete Orthonormal Stockwell Transform (DOST) and the machine learning model Cascade Feed Forward Neural Network (CFNN), Feed Forward Neural Network (FFNN). Simulation analysis expressed that the proposed Noise QRS Feature exhibits a higher classification accuracy of 99% which is ~6 – 7% higher than the conventional classifier model.

Keywords: ECG, Feature Extraction, kNN, Neural Network, Machine Learning, QRS

1. Introduction

Electrocardiogram (ECG) is the best tool to collect cardiac signals. The cardiac signals which originate from the heart muscles are very weak and carry all the information related to the heart. So, they can be easily disrupted by the noise signals [1]. The features present in the ECG signals may get buried in a noisy environment. Several factors are responsible for the interpretation of noise in the ECG signal. Some of them are the fluctuations in the power supply in which the ECG works the improper positioning of the electrodes, the movements in the human body while retrieving the signals, the interference of signal from the other parts of the body and so on. The experts may find it difficult in analysing cardiac diseases due to these noises [2].

The differential signal captured from the electrodes is received by the instrumentation amplifier. The output of the instrumentation signal is given into preamplifier which amplifies at a lower level and passed to the high pass filter. This signal is further amplified to a higher level by another amplifier [3]. Then it is given to a low pass filter to remove the high frequency noises. Finally, Analog ECG signal is converted into a digital signal for further processing. Numerous equipment is available for in-the-person and is placed inside the human body. The equipment is kept inside the human body through a surgical form or injected in the form of pills. It is very less expensive but it is not applicable [4]. Off-the-person is used to measure the ECG signal without any contact to the skin surface. This type of category is more suitable for future trends.

The ECG wave consists of PQRST wave where P is the starting wave, QRS wave is followed by P wave and is the main wave in the ECG signal and then a trailing T-wave [5].

P wave: The activation of the atria is shown by this P wave. The P wave is small because of the contraction of atria is not powerful and it ranges from 60 ms to 120 ms. It indicates the time taken by the pulse to propagate in both atria, being useful to precisely detect heart diseases such as atrial flutter etc.

PQ stretch: The PQ interval ranges are from 12ms to 20ms and look flat and free of waves. The PQ stretch measures the time taken from activated atrial to activated ventricle.

QRS complex: It is the collection of the Q, R and S waves and its duration is from 60ms to 90ms. The first, second and third wave of the QRS complex represents the depolarization of the septum, depolarization of the left ventricle apex, depolarization of the basal and rear regions of the left ventricle. The modification in the QRS complex implies the existence of heart diseases, such as arrhythmia, fibrillation, and heart attack

ST stretch: The ST stretch begins from S wave and ends with T wave. Its duration ranges from 230ms to 460ms. It provides the ischemic problem in the ECG heartbeat. It provides the time interval from ventricles contraction and rests to the baseline [6].

QT interval: The electrical systole information is indicated by the QT interval. It represents the depolarization and repolarization of ventricles. The length of QT interval changes based on heart rate and its duration range from 350 ms to 440 ms. U wave: U wave represents the ventricular repolarization and is followed by T-wave in the ECG signal. Its duration ranges from 185 ms to 228 ms.

Cardiovascular diseases contribute to the major cause of the death rate in modern days. However, those cardiac diseases do not exhibit the specific symptoms [7]. In later stage cardiac diseases exhibit the symptoms of shortness of breath or pain in chest. The prediction of diseases in the early stage provides proper medication reduces the heart diseases. The rhythm of heartbeat affected with the normal heartbeat disturbance leads to Cardiac Arrhythmia [8]. Most heart diseases affect the pattern of heartbeat, where the bradycardia exhibits the subnormal slower heart rate. The faster rate of heart is stated as tachycardia to perform the electrical activity of the signal in ECG [9]. The ECG uses the 12 electrodes located at the surface of chest patient limbs based on the Einthoven‟s triangle. The ECG signal affected by the noises from the external sources, interference in line, muscular artifacts wandering and electrode artifacts. The presence of noises in the misclassification subjected to false results to increases the elimination of artifacts to perform prediction of cardiac diseases [10]. To eliminate the noises in the ECG signal pre-processing is performed with filtering at the high-frequency signal and low-frequency signal processing.

1.1 Contribution

In this paper proposed a Noise QRS Feature to extract the features in the ECG signal for the classifications, the proposed model uses the feature extraction in the ECG signal. Initially, the proposed model Noise QRS focus on the feature extraction in the ECG signal. The model uses the noise estimation in ECG signal for the computation of features in the ECG signal. The proposed Noise

QRS Feature estimates the classes in the ECG model with the feature classification. The proposed model uses the ELM based classifier model for the classification of signal in the ECG signal. The comparative simulation analysis expressed that Noise QRS Feature model achieves the improved model for the disease's classification. With Noise QRS Feature evaluation the classification is effectively improved for the disease's classification for the cardiac diseases.

2. Related Works

In [11] proposed the standard meander disposal from ECG signal utilizing consolidated work of EMD and versatile channel methods. In this strategy, decay the ECG signal as a progression of IMFs. The disposal of pattern deterrent involved in exceptional lower recurrence IMFs to raise the sign qualities. This is the principal fundamental pre-processing step attracted this technique.

In [12] carried out ECG signal improvement utilizing the Observational Mode Disintegration (EMD). The ECG signal is exposed to different low and high-recurrence commotions. These commotions are the impacts of powerline impedance and standard meander. On account of these elements, the blunder is created in QRS highlights. To conquer this issue, EMD is carried out where it makes the Characteristic Mode Capability (IMF) as a disintegration yield. The benchmark meander is revised from Slant minimization procedure of IMF and high-recurrence commotion from the ECG signal is wiped out utilizing a boisterous arrangement of lower request IMFs with a factual pinnacle remedy. The order precision of the ECG signal is worked on by a bunch of IMF.

In [13] presented the coordination of a Sanctioned Connection Examination (CCA) and Blind Source Partition (BSS) procedure known as BSS-CCA. This strategy is utilized for the evacuation of antiquities in the ECG signal alongside the wavelet separating technique. This method is applied for muscle and visual antiquities. The arrangement result is worked on by the standardized RR-span. The got results from the standardized RR-span strategy are contrasted and different procedures.

The SVM [14] strategy distinguish the P and T waves in 12-lead ECG. Before the discovery interaction, pre-processing was finished on ECG sign to eliminate the commotion utilizing computerized separating strategies; it wipes out powerline obstruction and gauge meander. In the location cycle, P and T waves in the ECG signal is distinguished utilizing the SVM calculation with the assistance of LIBSVM programming. The outcome uncovers that the location pace of P-wave is 95.43% and recognition pace of T-wave is 96.89%.

In [15] examined out the location of QRS complex and extraction of ECG signals for various kinds of arrhythmias. In this methodology, the first bandpass channel is applied on the ECG sign to wipe out the clamour from the ECG signal. Second, QRS complex recognition is occurred by a blend of Hilbert change and the versatile limit method. The elements are separated from the ECG signal utilizing the PCA calculation. The exhibition of this approach is assessed utilizing the MIT-BIH arrhythmia data set. This technique gets the responsiveness of 96.28% is displayed in exploratory outcomes.

The joined component extraction strategy is introduced in [16] technique for the arrangement of heart arrhythmias. The consolidated component extraction techniques are; RR span, HOS and GMM include extraction. In this strategy, choice tree classifier is utilized to order the ECG signal considering the acquired element vector from mix highlights. The classifier groups the ECG signal into ordinary and unusual ECG beat. The Exploratory outcomes show that consolidated elements give better order exactness contrasted with Wavelet with ICA and Wavelet with RR.

In [17] examined toward the wavelet-based strategy and PCA technique for the extraction of elements from the ECG signal. The tops in the ECG signal are recognized utilizing the Skillet Tompkins calculation. At long last, the acquired highlights are taken care of into the classifier of PSO with SVM to arrange the ECG signal into typical and unusual. The identification and arrangement of ECG signal were proposed by Sakuntala et al. (2016). In this methodology, the versatile channel is applied on the ECG sign to dispense with the commotion, for example, power line obstruction and gauge meander from the ECG signal. In the wake of pre-processing, the Wavelet Parcel Tree (WPT) strategy is applied on denoised ECG sign to extricate the QRS complex elements from the ECG signal. At last, Neuro-fluffy classifier is utilized to arrange the ECG sign and tracks down the irregularity.

From the related works, it is seen that exploration is being done in the element extraction of the ECG signals. The significant goal of the extraction of ECG signals is to order the ECG signals into different classes of heart illnesses. Likewise found explores are being completed utilizing crossover methods, even subsequent to getting a sensible result in the above regions. This demonstrates that there exists a hole in getting a more precise result. The current strategies of ECG examination have the accompanying downsides. I. ECG signal is impacted by commotion and antiquities. ii. A portion of the element extraction strategies are computationally mind boggling. iii. The extraction of highlights is not great with the goal that the most extreme exactness gets impacted. Sound decrease technique and mix of elements would act as a phenomenal answer for defeating these disadvantages. ECG is generally utilized as an instrument to break down or decide the irregularities of the human heart. The location of arrhythmia is a difficult errand when the ECG signal is impacted by any variety and it is likewise not seen by natural eyes. The cardiologist finds the arrhythmias illnesses with the morphological shape and boundaries, for example, RR span and a few different time periods signal, however it requires greater investment to figure the infections through this boundary. Thus, PC Supported Finding (computer aided design) framework is expected to determine the arrhythmia illnesses to have exceptionally less time and higher precision in the identification of cardiovascular sicknesses through 39 unique stages, for example, pre-processing, top division, highlight extraction and order. Considering these variables DWT, DTCWT and DOST procedures are carried out in the extraction of the sign and the characterization of these signs is finished by utilizing ELM, CFNN, FFNN, multiclass SVM, KNN and fluffy KNN techniques.

2.1 ECG signal Feature Extraction with NQRSF

To extract the feature in the ECG signal Noise QRS Feature Extraction model is implemented over the ECG signal for the extraction of signal feature with the automated AI learning scheme.

2.2 Pre-processing

The functioning of the heart is reflected in the form of bioelectric signals. Electrocardiogram (ECG) is a tool used to measure these bioelectric signals. The ECG comprises of series of waves such as P wave, QRS complex and ST-segment. In clinics, the experts identify the cardiac diseases in analysing these waves. Hence it should be properly measured. The power supply and the surface electrodes are used to acquire the ECG signals. The electrodes are placed in certain parts of the body to gather the waveforms. The ECG signal is subjected to noises such as interference in power line, baseline, electro-myographic, electrode artifacts and so on. These noises may interpret wrong information and may lead to false diagnosis. Hence pre-processing is essential to eliminate the noises and for correct analysis of cardiac diseases. The proper positioning of the electrodes may help to minimize some of the noises. The figure 1 provides the segmentation model for the Noise QRS Feature.

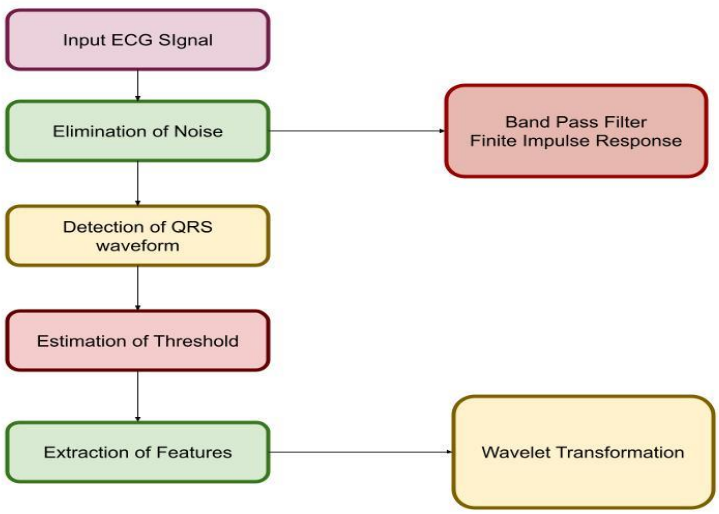


Figure 1. Segmentation with Noise QRS Feature

In figure 1 presented a block diagram of peak signal segmentation processing based on the consideration of two filters for the elimination of ECG signal. The filter-based model is employed for the estimation of different patients for the efficient filtering in ECG signal. The signal is denoised with the decomposition of arrhythmia database artifacts with noise baseline. The filtering model uses the 30 ECG signal with the FIR filter for the elimination of baseline and power interface in the ECG signal. The baseline signal is composed and varied with the electrode impedance. The QRS signal is segmented based on threshold segmentation features for the complex ECG signal.

2.3 Window-Based FIR Filter

The signal unit response sample is denoted as $f_d(n)$ with the desire frequency response of $F_d(w)$ through inverse Fourier Transform. The relationship between $F_d(w)$ and $f_d(n)$ are computed using the equation (1)

$$F_d(w) = \sum_{i=0}^{\infty} f_d(n) e^{-jwn} \tag{1}$$

Where

$$f_d(n) = \int_{-\pi}^{\pi} F_d(w)\, e^{-jwn} dw$$

In above equation (1) the impulse response $f_d(n)$ for the infinite duration with the range of n=M-1 with the FIR length of M (i.e. 0 to M-1). The truncation in $f_d(n)$ for length M-1 is evaluated with the $f_d(n)$ with window value. The process is computed with "rectangular window "with consideration of equation (2)

$$w(n) = \begin{cases} 1 & n = 0,1,2,\dots,M-1 \\ 0 & otherwise \end{cases} \tag{2}$$

Thus, the FIR filter impulse response is presented in equation (3)

$$f(n) = f_d(n) w(n) \tag{3}$$

Where,

$$= \begin{cases} f_d(n) & n = 0,1,2,\dots,M-1 \\ 0 & otherwise \end{cases}$$

The window function multiplication equivalent features are represented $F_d(w)$ and $w(n)$ window function in frequency domain function is computed as in equation (4)

$$W(\omega) = \sum_{i=0}^{\infty} w(n) e^{-jwn} \tag{4}$$

The frequency response convolution model features are represented as $W(\omega)$ and $f_d(n)$ for the truncated filter H(ω).

2.4 Peak Variation Segmentation

The QRS signal is evaluated for the identification of cardiac diseases through consideration of QRS features for computation of information about heart rate. The QRS complex depends on the difference approximation with the ECG signal with inversion and thresholding. The difference elements in the adjacent value is segmented with the 1D vector X of the ECG signal to estimate the approximation difference with the filtered ECG signal as presented in equation (5)

$$Y1 = [X(2) - X(1)\ X(3) - X(2) \dots \dots .X(n) - X(n-1)] \tag{5}$$

With assigned approximation the derivations are computed as in equation (6)

$$Y2 = [X1(2) - X(1)\ X1(3) - X(2) \dots \dots .X1(n) - X1(n-1)] \tag{6}$$

The ECG signal output peak with NQRSF to derive the output Y1 and Y2 based on R-Peak signal represented as in equation (7)

$$Y = 1.3 * B1(1{:}fs * 2) + 1.1 * (1{:}fs * 2) \tag{7}$$

Where fs denoted as the sampling frequency

The cumulative signal B of the S-peak signal is estimated for the local minimal value denoted as in equation (8)

$$S_{wave}peak = inverted\ (Y) \tag{8}$$

The threshold value of the Q-wave peak signal is computed as in condition (9)

$$if\ Y(m) > THV \&\ Y(m) < THV \rightarrow QRS\ complex$$

$$otherwise \rightarrow None \tag{9}$$

The Q-wave threshold value with the THV is estimated with peak signal value of 0.2mV and 0.5mv for the computation of the amplitude signal Y.

Algorithm 1: NQRSF Feature Selection
Input: Acquired ECG Signal Output: Feature Selection with QRS Complex Initialize Count=0 Y=Eliminate Noise in ECG Signal Y1=Differentiation the signal Y Y2= Differentiation the signal Y1 Y3= Cumulate the signal Y1 and Y2 Compute QRS complex signal based on threshold value Threshold= abs (maximum value of signal (Y3)) Threshold Value = Threshold Value/2; for i=1: length (Y3) if Y3(i)>Threshold Value QRS (i) = 1 Increment the value count i else QRS (i) = 0 End

2.5 Machine Learning Noise QRS Feature

Machine learning model is categorized as the supervised and unsupervised model. The algorithm for supervised model performs training and testing of data to derive results through unsupervised classifier those does not require training and testing. Supervised classifier model achieves the significant results compared with the unsupervised learning classifier model. The NQRSF exhibits effective model to reduce misclassification error to minimize the larger training dataset. The advantages of the AI model use the supervised method with SVM based classification through decision tree, neural network and SVM classifier. Let $X_1 = (x_{11}, x_{12,\ldots\ldots,} x_{in})$ and $X_2 = (x_{21}, x_{22,\ldots\ldots,} x_{2n})$computed as the Euclidean distance model measured as in equation (10):

$$\boldsymbol{Euclidean\ Distance}\ (\boldsymbol{X_1}, \boldsymbol{X_2}) = \sqrt{\sum_{i=1}^{n} (\boldsymbol{x_{1l}} - \boldsymbol{x_{2l}})^2} \tag{10}$$

The learning process in the Noise QRS Feature is illustrated in figure 2.

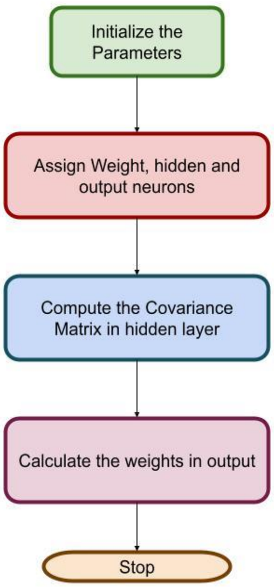


Figure 2. Structure and Learning Process

The hidden layer matrix in the output form is represented as in equation (11)

$$H = \begin{bmatrix} h_1(x_1) \dots\dots & h_L(x_1) \\ h_1(x_N) \dots\dots. & h_L(x_N) \end{bmatrix} \tag{11}$$

The linear system solution norm least-square value is estimated as in equation (12)

$$\hat{\beta} = H + T \tag{12}$$

Where, $T = [t_1, t_2, \dots., t_N]^T$

In above equation (12) the inverse matrix is computed with Moore–Penrose matrix function H. The ELM based training model exhibits the improved performance.

Algorithm 2: ELM for the Classification
Input : Training Set, hidden node and activation function Output: Weighted vector Step 1: Generate the parameters randomly Step 2: for i-1: L do $aibi$assigned in random manner Step 3: end Step 4: Evaluate the Hidden matrix value H Step 5:$fori$ = 1 :Ldo $forj$ = 1 :N do $H(ij) = G(aibixj)$ end end Step 6: Calculate the weighted matrix β Step 7:$\beta = H$ +T

3. Results and Discussion

The classification is done by three types of classifiers which belongs to machine learning approach are ELM, MSVM and KNN – Noise QRS Feature. The Sensitivity, Specificity and Accuracy is used to evaluate the performance of the system. For the APC and LBBB, DOST with ELM gives the maximum value of 100% and for the other classes it is having the maximum sensitivity. The DWT and DTCWT have an improvement in the percentage of sensitivity when compared with the neural network results. An average value of 80.5%, 83.8% and 96.6% sensitivity is obtained by DWT with ELM, DTCWT with ELM and Noise QRS Feature respectively. The table 1 presented the comparative examination of Sensitivity analysis for the cardiac signal classification. The sensitivity of the proposed method is found to be greater except for the Deep BT method. DTCWT with ELM has more sensitivity when compared DWT and ELM model.

Table 1. Comparison of Sensitivity

Events	DWT	DTC WT	Noise QRS Feature
APC	78	80	98
LBBB	67	83	97
PACED	72	79	99
PVC	74	84	98
RBBB	69	87	99
Normal	73	89	98

The specificity of ELM with DWT produces an average value of 67.2%. DTCWT with ELM produces 70.5% and DNoise QRS Feature with ELM produce 100% of specificity except for APC. The value of DWT with ELM got improved in its value in the case of PACED and RBBB. From the Table 2, it is observed that Noise QRS Feature produces good result for PACED and Noise QRS Feature produces the highest value when compared with the other methods.

Table 2. Comparison of Specificity

Events	DWT	DTC WT	Noise QRS Feature
APC	67	73	97
LBBB	71	77	99
PACED	69	71	98
PVC	74	68	99
RBBB	72	75	98
Normal	76	78	99

The proposed Noise QRS Feature value specificity and sensitivity are presented in figure 3 and figure 4 respectively.

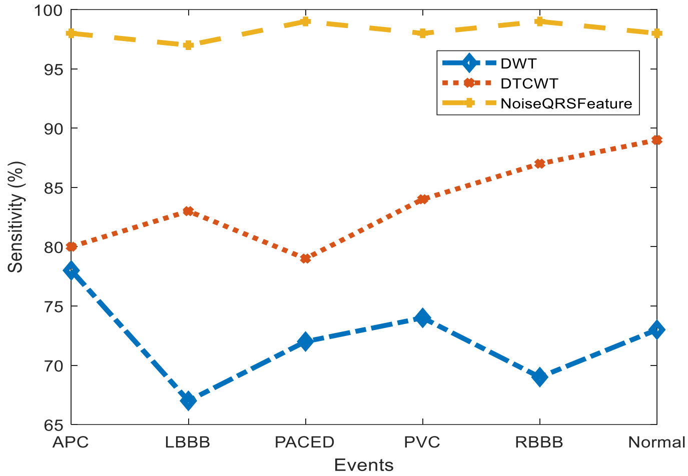


Figure 3. Comparison of Sensitivity

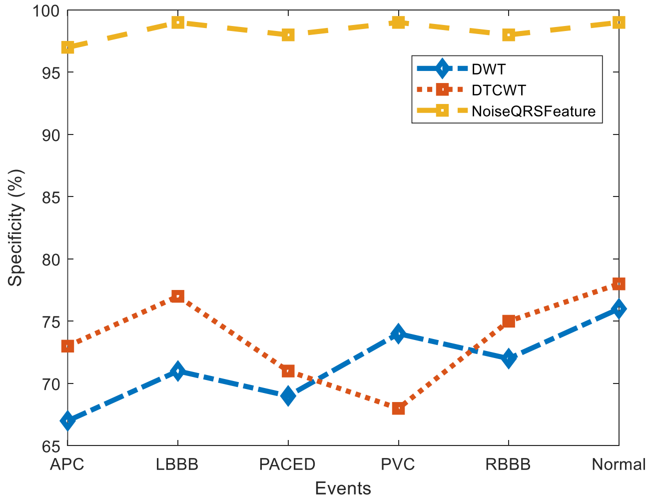


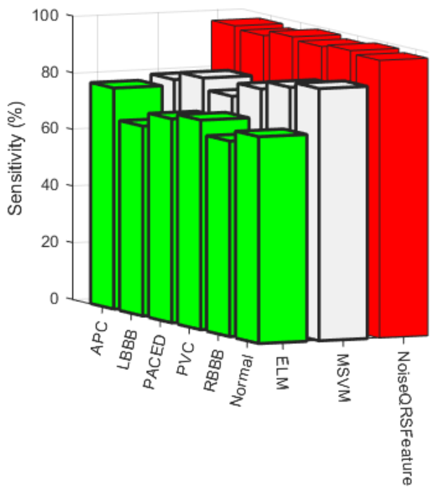
Figure 4. Comparison of Specificity

Figure 5 depicts the comparison of sensitivity, specificity and accuracy between DWT, DTCWT and Noise QRS Feature features using machine learning approach of ELM classifier method. From the above comparison observed that ELM classifier classifies the PVC classes better compared to other classes. All the three features give their maximum value for PACED class.

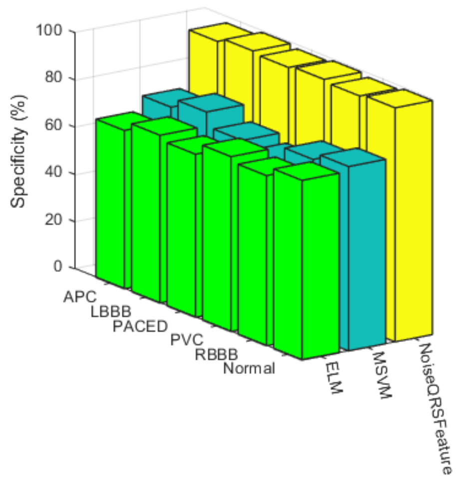
Table 3. Comparison of Parameters

	Sensitivity			Specificity			Accuracy		
	ELM	**MSVM**	**KNN – Noise QRS Feature**	**ELM**	**MSVM**	**KNN – Noise QRS Feature**	**ELM**	**MSVM**	**KNN – Noise QRS Feature**
APC	78	80	98	67	73	97	72	84	99
LBBB	67	83	97	71	77	99	78	88	100
PACED	72	79	99	69	71	98	82	89	99
PVC	74	84	98	74	68	99	84	87	99
RBBB	69	87	99	72	75	98	83	89	99
Normal	73	89	98	76	78	99	87	89	100

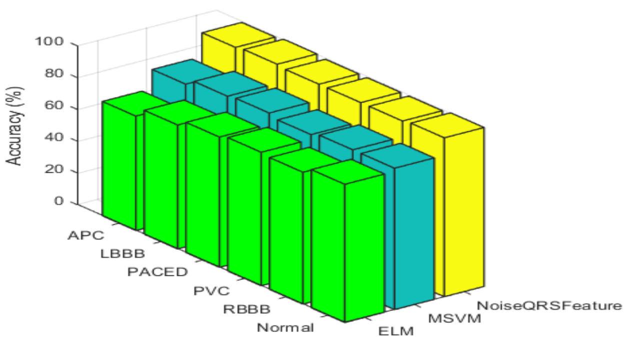
The performance of proposed Noise QRS Feature is examined with the ELM and MSVM model. The comparative analysis expressed that proposed Noise QRS Feature exhibits the improved performance compared with conventional techniques. The figure 5 (a), 5(b) and 5(c) provides the comparative illustration of sensitivity, specificity and accuracy.



(a)



(b)



(c)

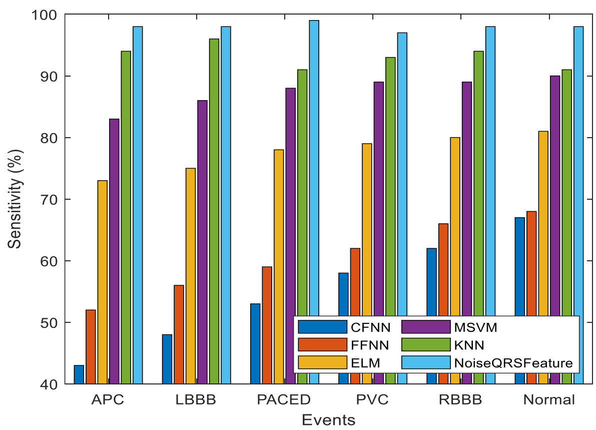
Figure 5. Comparison of (a) Sensitivity (b) Specificity (c) Accuracy

Figure 6 depicts the comparison of the accuracy of the three features with Fuzzy k-NN Noise QRS Feature classifier. It is observed that DOST with fuzzy kNN have the highest accuracy of 100% for the three types of ECG classes. DTCWT with fuzzy kNN Noise QRS Feature classifier shows 100% of accuracy for the PVC, PACED and normal classes. DWT with fuzzy kNN has greater than 90% for PACED, PVC and normal but has comparatively less accuracy for APC. The comparison of fuzzy kNN classifier in terms of accuracy with the literature work is shown in Table 5. It is found that fuzzy kNN Noise QRS Feature classifier produces 100% accuracy for normal and better than the other methods in the literature.

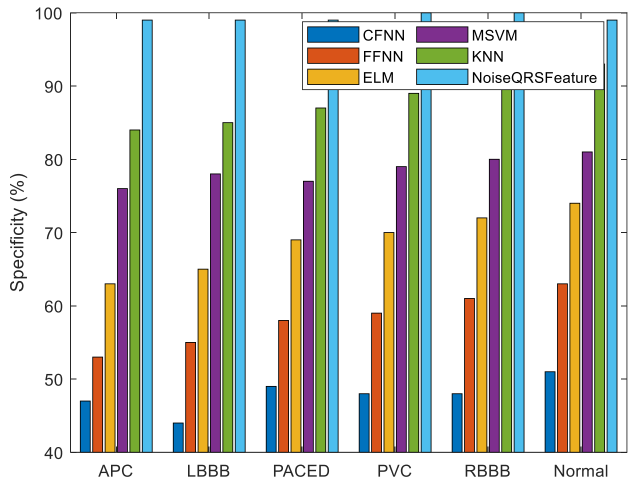
Table 5. Comparison of Parameter

			Sensitivity			
	CFNN	**FFNN**	**ELM**	**MSVM**	**KNN**	**Noise QRS Feature**
APC	43	52	73	83	94	98
LBBB	48	56	75	86	96	98
PACED	53	59	78	88	91	99
PVC	58	62	79	89	93	97
RBBB	62	66	80	89	94	98
Normal	67	68	81	90	91	98
			Specificity			
	CFNN	**FFNN**	**ELM**	**MSVM**	**KNN**	**Noise QRS Feature**
APC	47	53	63	76	84	99
LBBB	44	55	65	78	85	99
PACED	49	58	69	77	87	99
PVC	48	59	70	79	89	100
RBBB	48	61	72	80	92	100
Normal	51	63	74	81	93	99
			Accuracy			
	CFNN	**FFNN**	**ELM**	**MSVM**	**KNN**	**Noise QRS Feature**
APC	43	57	74	77	88	99
LBBB	48	59	77	79	91	100
PACED	51	63	78	83	94	100
PVC	53	66	82	86	93	100
RBBB	58	69	85	89	92	100
Normal	63	72	87	92	95	100

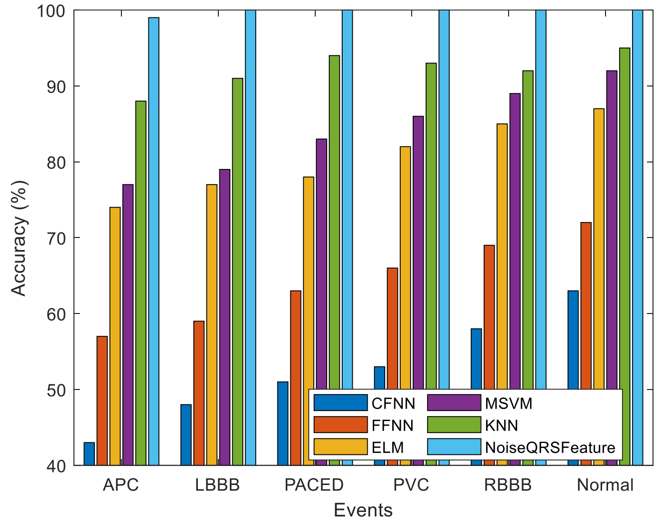
The performance of the proposed Noise QRS Features model performance is presented in figure 6 (a), 6(b) and 6(c). The illustrated model estimated for the sensitivity, specificity, and accuracy. The measured accuracy model achieves the value of 100% for the disease's classification.



(a)



(b)



(c)

Figure 6. Comparison of (a) Sensitivity (b) Specificity (c) Accuracy

The fuzzy k-NN classifier with all the three types of features i.e., DWT, DTCWT and Noise QRS Feature is used to classify the different type arrhythmias. In this approach, Noise QRS Feature with fuzzy k-NN provides better performance compared to other approaches.

4. Conclusion

ECG signal are utilized for the cardiac disease's classification with the kNN based classification model. The proposed Noise QRS Feature estimates the features in the ECG signal based on pre-processing in the ECG signal. The Noise QRS Feature model computes the ECG signal features of the waveform sequences. Initially, the signal is pre-processed with the Finite Impulse response (FIR) filter for the analysis of ECG signal. The features in the ECG signal are processed and computed with the QRS signal responses in the ECG signal. The proposed Noise QRS Feature computes the features in the ECG signal through estimation of features and classification. Simulation analysis expressed that the proposed Noise QRS Feature exhibits a higher classification accuracy of 99% which is ~6 – 7% higher than the conventional classifier model.

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