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Normalized Higher Order Statistics based Automated Cardiovascular Disease Detection using ECG

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Abstract

Since from last decade, several recent Computer Aided Diagnosis (CAD) tools introduced to assist medical professionals due to accuracy, simplicity & inexpensive approach. The Electrocardiogram (ECG) signals are used with such methods for the detection of Cardiovascular Disease (CVD) detection. The efficiency of CVD detection using ECG suffered from the many research problems such as artefacts, efficient features extraction, QRS beats extraction etc. This paper presents the novel framework for CVD using the raw ECG signals. After the signal procurement, we connected the half breed pre-preparing calculation to expel the curios &clamour from the crude ECG signal. In next stage, the calculation intended to extricate the QRS & ST sections dependent on the dynamic thresh holding approach. This technique first gauge the Q, R, S, & ST fragment from the pre-preparing ECG signal. To limit the overhead of calculation, this strategy straightforwardly connected in time-area signal with the goal that no time squanders in playing out any morphological activity. At long last, the component extraction strategy structured called Normalized Higher Order Statistics (NHOS) to separate the highlights from the combination of QRS & ST divisions. The Artificial Neural Network (ANN) used to play out the characterization. The reproduction results demonstrates that proposed strategy conveyed better execution as analyzed than existing strategies.

***Keywords**: Computer aided diagnosis, cardiovascular disease, electrocardiogram, QRS segment, ST segment, & hybrid filtering*

I. Introduction

The heart diseases like CVD are at a high rate leading to the death of men & women. Even in young aged people, who are under 15, congenital heart disease is important which is responsible for 1% of mortality [1]. A proper clinical decision support system is required to predict the heart disease in the early stage. Lot of information about heart disease is available in the medical industry but there are no efficient tools to detect the diseases with higher accuracy & lower computation efforts. It is mandatory to have an accurate clinical decision support system because the medical diagnosis is very much important & required for the mankind [2]. It is also very much essential to have a precise & accurate system. A huge variety of heart disease occurs in the mankind worldwide. The Echocardiography (ECG) is one of the methods used for diagnosing & best ways to diagnose a heart disease with minimum cost [3]. It will also inform the clinician about the working condition of the heart chambers & the heart valves. Another best method to detect the heart disease is through Electrocardiogram (ECG) which efficient & simple way to detect the CVD.The key characteristics of human ECG signal are shows in figure 1. As observed in figure 1, the key waves called P, Q, S, R, & T etc. constitutes the important segments of ECG signal called ST segment, QRS complex, & PR interval [4].

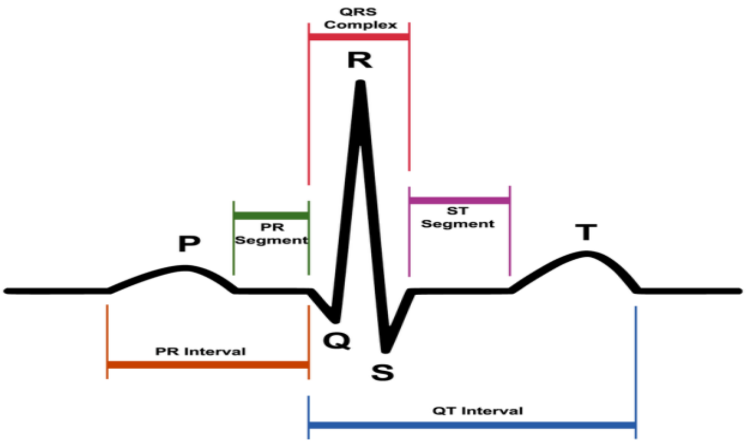

Fig.1. ECG signals characteristics [5]

The ECG signal has been extraordinary & understand the improvement of precision estimation & reproducibility. The inappropriate ECG signal while examination the signal is spoiled by disturbance during acquiring. The challenging task in ECG based processing is the estimation of important parameters from the ECG signal to outline uproarious medical signal. By included substance high repeat noise, development & measure wander increased signal in time & repeat ECG signal is spoiled. The problems are knick-knacks leads to the unwanted data presence in signal. Straightforward methods can deal with such problems;however those methods may leads to nonlinear stage shifts as well as signal winding. Propelled channels are dynamically definite. The ECG signal can be hurt by different sorts of clatter. Thusly is required to have the pre-taking care of strategies to denoise the input ECG data to perform accurate assessment & assurance using the CAD systems. Several of isolating techniques expected to remove the noises from different ECG signals proposed during last 10 years [6]-[11], however the key worries for ECG signal preparing is the multifaceted nature & proficiency.

Apart from the ECG signal pre-processing, the key challenges of ECG based CVD detection is the features extraction in which the extraction of ECG beats like P, Q, R, S, T & complex such as QRS &ST segments efficiently required to estimate the unique features of each ECG signal. There are several conventional & recent methods designed for the ECG features extraction [12]-[21]; however the challenge of accurate ECG wave's extraction within the less computation time is still the research problem. The fiducial focuses, for example, P, Q, R, & S in the ECG are found at first by the doctors. From those fiducial focuses the rest of the waves like QRS complex, P waves, T waves & U waves are found. Utilizing this fiducial focuses & the waves numerous heart anomalies estimation like pulse varieties, blood vessel/ventricular arrhythmias & ST-fragment deviations are directed. So as to analyze the ECG information precisely the clinician requires a programmed choice emotionally supportive network in light of the fact that ordinarily more than100, 000 heart cycles has been counted per quiet in multi day along with ECG gadget. It is a tremendous assignment for the doctors to decipher any heart issue from this huge measure of ECG. In this manner, it is required to mechanize approach that concentrates the floods of ECG flag proficiently & precisely.

This article proposed arobustandreliable method of cardiac disease prediction using the pre-processing technique & novel feature extraction technique. The contributions of this paper are threefold: (1) first introduce the need of efficient pre-processing algorithm to improve the prediction accuracy. The hybrid filtering algorithm proposed in which two filtering methods effectively exploited. (2) The waves extraction phase designed in which the extraction of two important segments of QRS & ST segments of each ECG signals using the dynamic thresh holding algorithm, (3) From the extracted ECG waves the efficient features extraction algorithm required to estimate the reach set of features accurate & reliable prediction. The NHOS technique used to estimate the in-depth features rather than using the conventional statistical features using the wavelet packet decomposition approach upto level 4 on each ECG fused segments (QRS & ST) followed by the normalization. Finally in classification phase, the ANN applied. In section II, brief review of various pre-processing methods of ECG signal & recent CVD detection methods presented. In section III, the algorithms for CVD detection described. In section IV, simulation results & analysis described. In section V, conclusion & future work described.

II. Related Works

The heart disease detection & classification is widely studied research problem since from the last two decades using the ECG signals.

The WHO revealed Cardiovascular Diseases is important source of death all around in [22]. A greater number of individuals bite the dust every year from CVDs than from some other reason. As the necessity increments, at a quicker rate, successful & precise ID technique is basic to diminish mortality from heart sicknesses. Information mining procedures are demonstrated to be an advantageous apparatus to help doctors in the distinguishing proof of ailment by acquiring learning & data in regards to the ailment from patient's information. In [23], creator proposed a model of anticipating the coronary illness utilizing information mining systems. In [24], creator showed the use of information mining systems in the expectation of coronary illness utilizing ECG information examination. They proposed a gradual choice trees acceptance strategy which uses outfit technique for digging evolutional indicative standards for cardiovascular arrhythmia arrangement. The work advocated that the proposed technique works superior to the conventional calculations. In [25], creator proposed a technique for ECG signal investigation & arrangement utilizing data mining& fake neural systems. The work concentrated on 4 parts of heart pulsates which is initial: branch Bundle Block Beat, Normal, Atrial Premature Contraction & Left Premature Ventricular Contraction. These heart thumps show various varieties &nonlinear in nature. Fake neural systems have beenvaluable in nonlinear issues & giving entirely able outcomes. In [26], creator explained the utilization of information mining methods in the expectation of coronary illness utilizing ECG information examination utilizing the ANN utilizing streamlining procedures. A gradual choice tree acceptance strategy is utilized which uses troupe technique for digging evolutional demonstrative guidelines for cardiovascular arrhythmia characterization. In any case, such method does not evaluate the ECG waves for the characterization.

Some ongoing works gave an account of QRS location from the ECG signal [27]-[32]. In [27], ECG signal examination & arrangement technique utilizing wavelet vitality histogram strategy & bolster vector machine (SVM) proposed. They planned the cardiovascular arrhythmia location in the ECG signal dependent on three phases including ECG signal pre-preparing, highlight extraction utilizing QRS recognition & pulses characterization. In [28], an effective & simple to-decipher methodology of cardiovascular ailment order proposed dependent on novel component extraction techniques & correlation of classifiers. Creators described the disseminations by test quintiles which outflank test imply. Creator researched the highlights extraction strategy utilizing three classifiers utilizing measurement decreased highlights by PCA: stepwise discriminate investigation (SDA), SVM, & LASSO calculated relapse.

In [29], the ongoing work on CVD location utilizing ECG signal revealed. Creators utilized signal preparing & neural systems methods for handling ECG signal comprising of removing highlights from ECG signal so as to distinguish the sorts of CVD's.

In [30], the dynamical ECG acknowledgment system proposed for CVD's & human identification utilizing the dynamical neural learning instrument. Technique of proposed system comprises of 2 stages: a preparation stage & test stage. In preparation stage, cardiovascular elements inside ECG signal are extricated (approximated) precisely by utilizing spiral premise work (RBF) neural systems through deterministic learning instrument. Acquired heart framework elements is spoken to & put away in consistent RBF systems.

In [31], late technique proposed for the QRS Complex discovery from the ECG signal utilizing 1-D convolution neural system (CNN. The CNN comprises of article level & part level CNNs for extricating diverse grained ECG morphological highlights consequently. Every extricated morphological highlight has been utilized through multi layerperception (MLP) for the QRS complex recognition. Also, creator received the ECG signal pre-preparing technique which just contains contrast activity in worldly area. Anyway such techniques neglected to accomplish the exchange off between calculation overhead & forecast precision. The work announced in this paper is diverse in which the lightweight QRS & ST fragments extraction planned pursued by the NHOS highlights to improve the exactness of discovery.

III. Methodology

As observed in figure 2, the functionality of proposed ECG based CVD detection framework using two different approaches of features extraction like statistical features & NHOS features. Input ECG signal is first processed through the hybrid pre-processing algorithm in which the noises & artefacts are removed from the raw ECG signal. Main motto of pre-processing algorithm used to decrease error rates in ECG signal with minimum computation efforts. After the pre-processing, we applied the proposed wave extraction technique in which we build the QRS & ST complex from the ECG signal for the features extraction purpose. The two types of features individually extracted &

evaluated in this work. In first case, the statistical features extracted from each QRS & ST & then fused them. The statistical features like mean &standard deviation, variance, entropy & smoothness computed for each ECG wave. In second case, the one mode designed called NHOS in which the fused of ECG waves performed first & then higher order statistic features extracted. To normalize them, the min-max approach used to form the NHOS features vector. For the classification, we used the ANN in each case discussed above.

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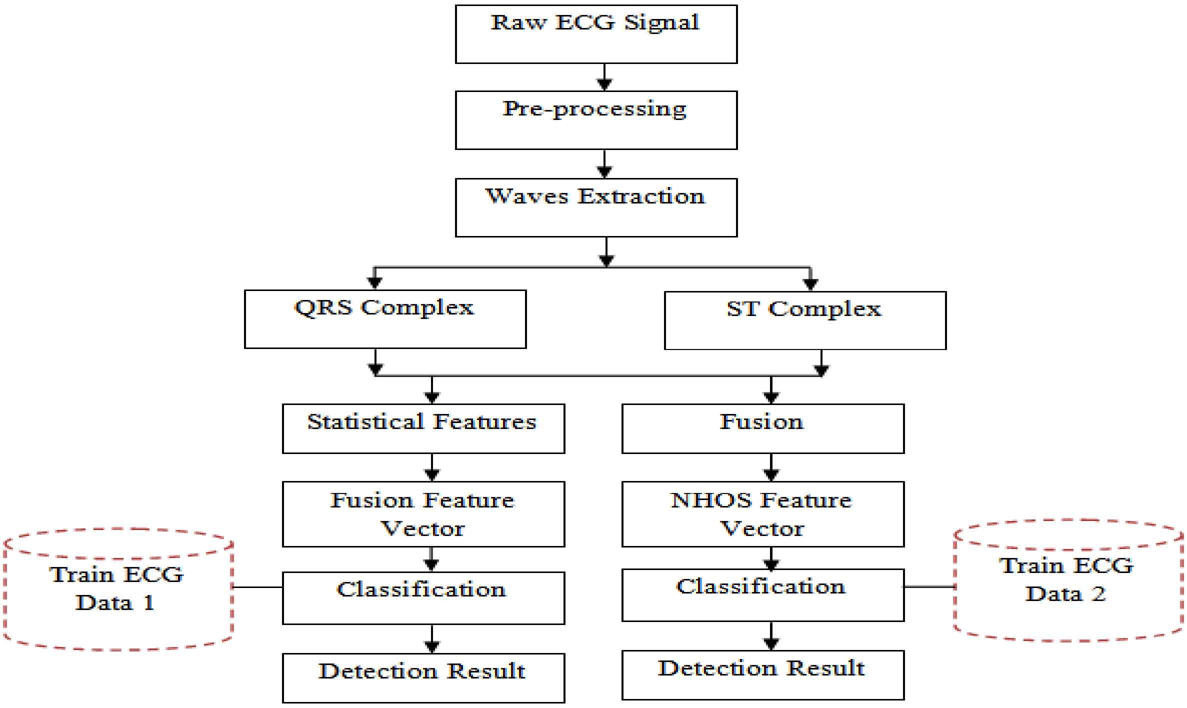

Figure 2: Proposed CVD detection framework

A. ECG Pre-processing

The hybrid filtering method for the ECG signal pre-processing designed using two filtering methods together. Butterworth filter has been built to extract baseline wandering. Further the notch filtering method (Second order) has been applied using 60 Hz frequency band, based on condition that signals connecting from US or European recordings to mitigate the effects of power-line interference. The use of both filtering methods assures that the artefacts available in raw ECG signal also suppressed. After successful removal of unwanted information from the ECG signal, we applied the process of wave's extraction & features formation process.

B. Waves Extraction

This section presents the methodology to build the QRS & ST segmentation from the pre-processing ECG signal. The extraction of beats such as Q, R, S, P, & T performed first & then form the QRS complex & ST segment for the features extraction process. Along with efficiency of wave's detection & extraction, the main objective is that wave's extraction algorithm should take minimum computation efforts. The previous adaptive thresh holding methods applied in morphological domain which takes longer computation time, however here we directly applied in time-domain signal so that no time waste in performing any morphological operation. The technique of thresh holding is dynamic in which the threshold value is fixed & computed as per the input ECG signal. This method is start from the signal normalization to QRS complex & ST segment extraction as demonstrated in algorithm 1.

Algorithm 1: Waves Extraction
Inputs *P*: Pre-processed ECG signal **Output** *QRS* *ST*
1. Compute length *N* of *P* 2. *A*: Signal Normalization using Eq. (1) 3. *AS*: Average signalling using Eq. (5) 4. α: Mean of Signal AS 5. AS: Apply the threshold on *AS* using Eq. (6) 6. [L, R]: Estimate the left & right waves 7. *Rwave*: Extract *R* wave using Eq. (7) 8. *Qwave*: Extract *Q* wave using Eq. (8) 9. *Swave*: Extract *S* wave using Eq. (9) 10. *Pwave*: Extract *T* wave using Eq. (10) 11. *Twave*: Extract *P* wave using Eq. (11) 12. *QRS*: [*Qwave, Rwave, Swave*]

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13. *ST*: [*Swave, Twave*]
14. Return (*QRS, ST*)
15. Stop

As observed in algorithm 1, the first step is to perform the normalization of pre-processed signal as:

$$A = \frac{P^2}{\max(|P^2|)} \quad \ldots (1)$$

Where, P is the pre-processing ECG signal. The normalized signal further used for the computation of average signalling using the convolution operations as:

$$B = \frac{\text{Ones}\ (1,31)}{31} \quad \ldots (2)$$

The temporary array of matrix 1's of size 1*31 which is used to perform the convolution with normalized signal *A* as*:*

$$\text{C}= conv\ (A, B) \quad \ldots (3)$$

$$\text{C}= C\ (15 + [1{:}N]) \quad \ldots (4)$$

The convolution output used to compute the average signal as:

$$AS = \frac{\text{C}}{\max(|\text{C}|)} \quad \ldots (5)$$

The normalization & average signalling of original pre-processed signal helps to minimize the overhead of computation burden while estimating the waves, also improves the accuracy of waves extraction. The dynamic threshold value is computed by taking the mean of *AS* signal. The computed threshold value applied to select the waves those satisfies the threshold value as:

$$AS = \text{AS} > \alpha \quad \ldots (6)$$

The left & right waves computed using Differences & Approximate Derivatives (DAD) operator. The DAD computes the differences between adjacent elements of AS along the first array dimension whose size does not equal. This returns the signals of matrix starting from -1 (left) to 1(right). Thus we got the left wave & right wave for the signal. From the left & right waves we perform the subtract delay operations to suppress the low pass &

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high pass filtering. After localization of left & right waves, we extract the P, Q, R, S,&T waves as using min& max operations on L (left) &R (right) waves detected.

$$Rwave = \max(\mathrm{P}(\mathrm{L}:\mathrm{R})) \qquad \ldots (7)$$

$$Qwave = \min(\mathrm{P}(\mathrm{L}: Rwave)) \qquad \ldots (8)$$

$$Swave = \min(\mathrm{P}(\mathrm{L}:\mathrm{R})) \qquad \ldots (9)$$

$$Pwave = \max(\mathrm{P}(\mathrm{L}: Qwave\mathrm{QT})) \qquad \ldots (10)$$

$$Twave = \max(\mathrm{P}(\mathrm{Swave}: R)) \qquad \ldots (11)$$

The QRS complex & ST segments formed using the extracted waves.

C. Features Extraction

In features extraction, two different approaches we consider as discussed & seen in figure 2.

1. Statistical Features: We extracted total 5 features like mean, entropy, standard deviation, smoothness & variance from the QRS & ST complex.

- **Mean:** This featuremeasure the mean valueof QRS/ST signal where the central clustering happened. Mean can be measuredwith the use of formula:

$$\mu = \frac{1}{QR}\sum_{x=1}^{Q}\sum_{y=1}^{R} I(x,y) \qquad \ldots (12)$$

Where $I\ (x,y)$ is ECG data value at location (x,y) of QRS/ST signal size $Q\ \times\ R$. I represents the input ECG segments i.e. QRS/ST.

- **Standard Deviation:** This measure estimate of mean square deviation of QRS/ST data at $I\ (x,y)$using the mean value. It is computed by:

$$\sigma = \sqrt{\frac{1}{\mathrm{QR}}\sum_{x=1}^{Q}\sum_{y=1}^{R}(I\ (x,y)-\mu)^2} \qquad \ldots (13)$$

- **Smoothness:** Relative smoothness, R is count of smoothness of QRS/ST signal which is utilized to create descriptors of relative smoothness using the outcome of standard deviation metrics σ. Smoothness explained using formula:

$$R = 1 - \frac{1}{1+\sigma^2} \qquad \ldots (14)$$

- **Entropy:** It is defined as statistical measure of randomness which is utilizing to characterize texture of input QRS/ST signal. It is computed as:

$$h = \sum_{x=0,y=0}^{x=M-1,y=N-1} I(x,y)\,(log_2(I(x,y)) \quad \ldots (15)$$

- **Variance:** It is measured as the square root of metrics standard deviation. Thus the variance metrics is computed as:

$$Var = \sqrt{\sigma} \quad \ldots (16)$$

2. NHOS Features: In this paper, the NHOS features extraction proposed which is based on HOS approach. In general terms the HOS technique is nothing but the second order measures expansion to the higher orders like power range and autocorrelation capacity. The estimation of second order measures effectively performed if the ECG signal has normal likelihood thickness work, yet as referenced above, some genuine signalsare not Gaussian. The most straightforward approach for designing the HOS techniqueis justified by their definitions. Below sections we present some common definitions of HOS technique in time-area & third-order HOS features, discrete signal, and accepting a zero-mean of $s\ (q)$.

Time domain measures: The measure is autocorrelation function in time domain as:

$$R\ (r)\ = < s\ (q)\ x\ (q\ +\ r) > \quad \ldots (17)$$

The third order measure defined as third order moment

$$T\ (t1, t2)\ = < s\ (q)\ x\ (q + m1)\ x\ (q + m2) > \quad \ldots (18)$$

Where $<>$ is expectation operator.

Note that the third request minute relies upon two autonomous slacks $t1$ & $t2$. Higher request minutes can be framed along these lines by adding slack terms to the above condition. The signal cumulates can be effectively gotten from the occasions.

Frequency domain: The second-order measure in frequency domain is computed as power spectrum $A\ (w)$ and it is measured in two ways:

Apply the Discrete Fourier Transform (DFT) on the autocorrelation function:

$$A\ (w)\ =\ DFT[R\ (r)] \quad \ldots (19)$$

Second one approach is multiplication of Fourier Transform $F\ (w)$ signals in addition of complex conjugate:

$$A\ (w)\ =\ F\ (w)\ F*(w) \quad \ldots (20)$$

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Similarly, the third-order bispectrum$BS\ (w, l)$ is calculated like the second-order measures as below.

Apply the Double DFT on third-order measure as:

$BS\ (w, l)\ =\ DDFT\ [T\ (t1, t2)]$ … (21)

And the multiplication of Fourier Transforms at different frequencies as:

$BS\ (w, l)\ =\ F\ (w)\ F\ (l)\ F * (w + l)$ … (22)

Presently similarly as the second-request measures are identified with the signal fluctuation then third request measures (third request cumulate&bispectrum) has been identified with signal skewness, fourth request measures (fourth request cumulate&trispectrum) has been identified with signal kurtosis, & higher request measures has been identified with higher request snapshots ofsignal.

In this paper, the comparable methodology followed in which first the combination of QRS & ST fragments performed & after that the fourth-request measures extricated from the intertwined ECG waves. In this manner for the highlights extraction, we utilized both skewness & kurtosis capacities. From the melded signalS (q), complete 90 highlights extricated utilizing the HOS approach utilizing the occasions (m) &cumulates (c) which are characterized as:

$z_2(q) =\ E[S(q), S(q + i)]$ … (23)

$z_3(q, r) =\ E[S(q), S(q + i). S(q + r)]$ … (24)

$z_4(q, r) =\ E[S(q), S(q + i). S(q + r). S(q + w)]$ … (25)

Where$E$ [·] is defined as the expectation operation. These are formulas which are used in extraction of moments in HOS method of feature extraction at each level.

$c_2(q) =\ z_2(q)$ … (26)

$c_3(q, r) =\ z_3(q, r)$ … (27)

$c_4(q, r) =\ z_4(q, r, q) - z_2(q)m_2(q - q) - z_2(q)m_2(w - q) - z_2(w)z_2(q - r)$
… (28)

The second (q), third (q, r)& fourth request (q, r, q)cumulates are determined for each beat taking slack 0. To put it plainly, the HOS approach when contrasted with customary

DWT procedure separate the exceptional & less highlights. The second, third & fourth request cumulates at each level extricated (absolute four levels). The info intertwined ECG wave is disintegrated into all out 30 sub bands& from each sub band three highlights extricated which structures the 90 highlights vector. The extricated highlights are in complex structure which may lead the poor exactness at order, in this way to spare the handling time just as improve precision the highlights standardization approach utilized in this paper. The way toward changing highlights from its unique incentive into the scope of -1 & 1 is called as standardization. We utilized the min-max approach for the highlights standardization utilizing:

$$N = 2\left[\frac{F - F_{min}}{F_{max} - F_{min}}\right] \qquad \dots (29)$$

Where, F is the extracted HOS features set, & N is the normalized features set.

D. Classification

The feature vector constructed from the above both cases such as statistical features & NHOS features. On both approaches the training data 1 & 2 used respectively (as showing in figure 2). For the classification we used the ANN classifier with ratio of 70 % training, 15 % testing, & 15 % validation.

IV. Simulation Results & Analysis

The proposed CVD detection methodology is simulated in MATLAB simulation tool. In this paper, to evaluate the performance of proposed approach standard research dataset called PhysikalischTechnischeBundesanstalt (PTB) [32] used. Total 545 raw ECG signals recorded in this dataset under the different types of heart diseases and healthy classes. For this research we collected the total 468 ECG signals affected by CVD & 77 samples are normal from this dataset.

International Journal of Advanced Science and Technology
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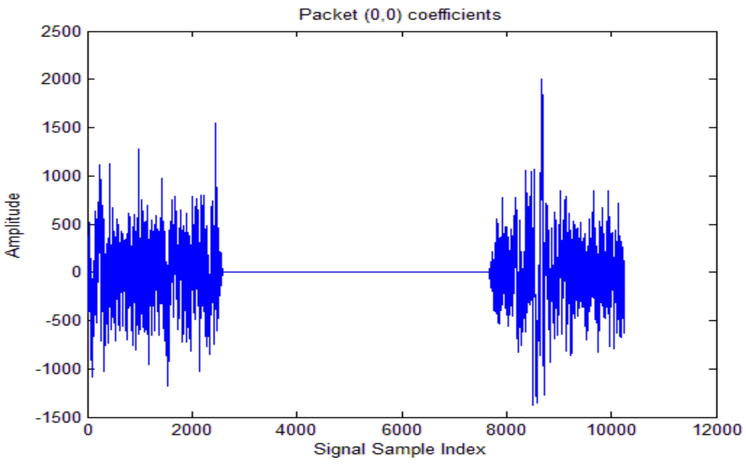

Figure 3: The input fusion signal from QRS & ST samples to NHOS

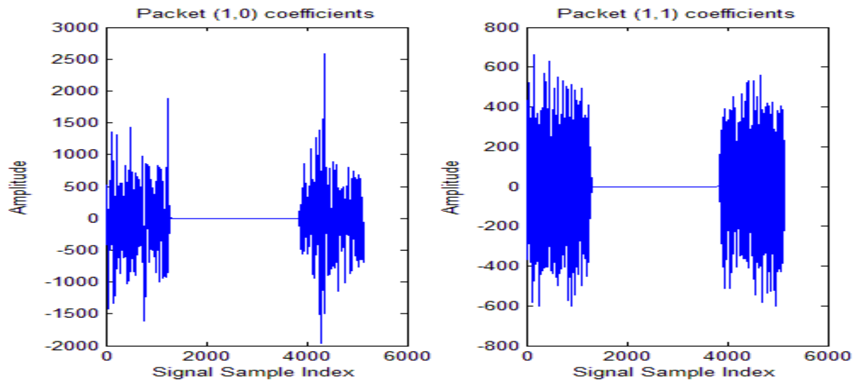

Figure 4: First level features extraction

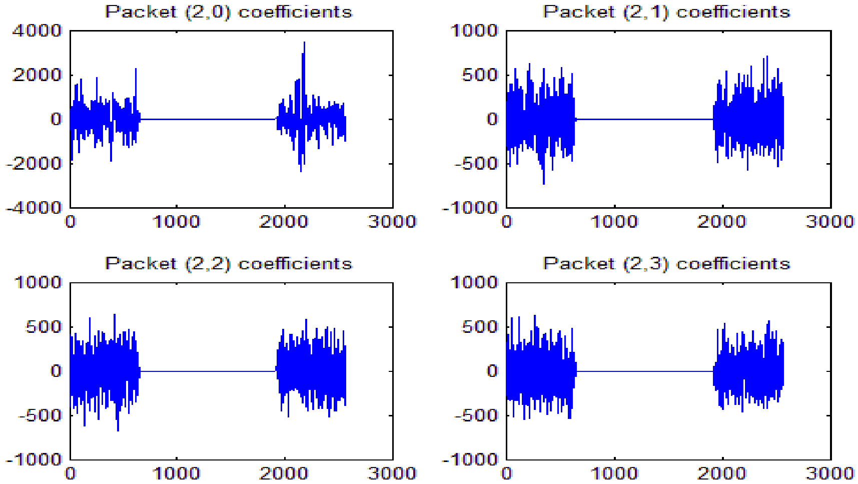

Figure 5: Second level features extraction

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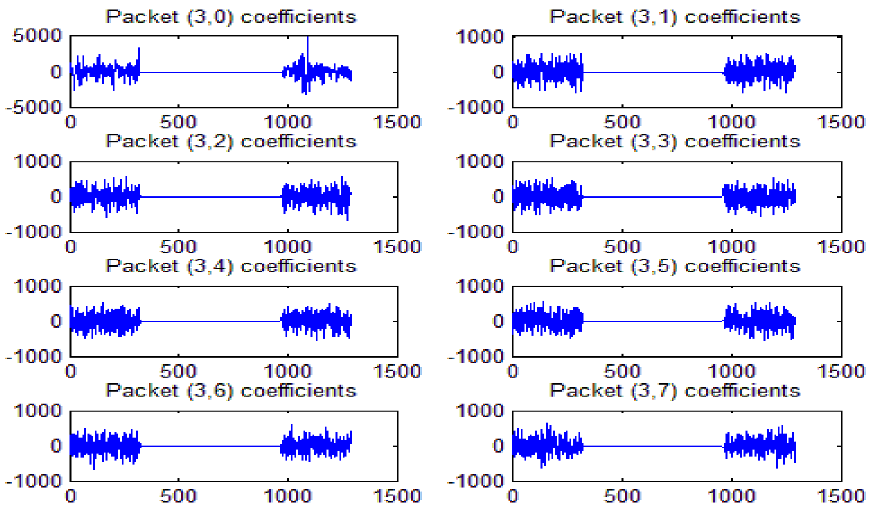

Figure 6: Third level features extraction

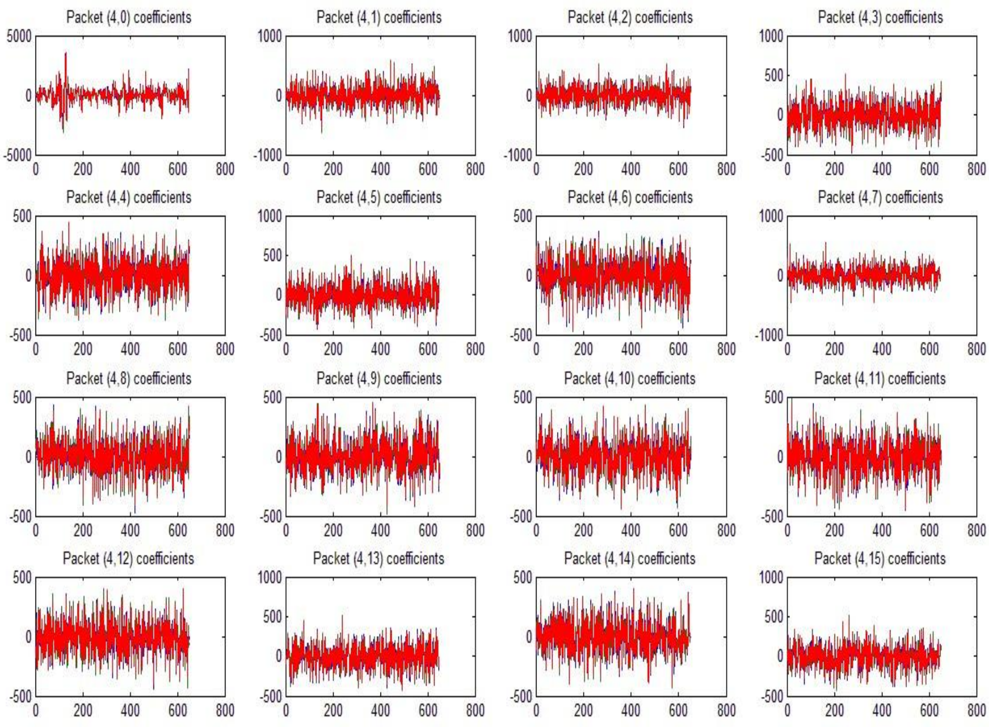

Figure 7: Fourth level features extraction

Figure 3 to 7 shows the results of wavelet parcel deterioration to extricate the highlights from each sub band up to the fourth level. The fundamental signal is disintegrated well ordered which is diminished from unique size 12000 to 750 finally level. This permits bringing the more dependable, one of a kind & less number of highlights for every ECG signal melded portion. The highlights additionally utilized in acknowledgment process where the classifier does the grouping utilizing the prepared information & their names.

The exhibition of CVD recognition is estimated regarding exactness, review, & precision. The exactness, review, & precision rates are processed as:

$$Precision = \frac{tp}{tp+fp} \quad \dots (30)$$

$$Recall = \frac{tp}{tp+fn} \quad \dots (31)$$

$$Accuracy = \frac{tp+tn}{tp+tn+fp+fn} \dots (32)$$

Where, tp, TN, fp&FN is genuine positive, genuine negative, false positive &false negative separately. The exhibition of proposed highlights extraction approach, for example, Proposed-Statistical Features (PSF) & NHOS are contrasted & the condition of-workmanship highlights extraction techniques, for example, discrete wavelet changes (DWT), Hilbert change (HT), & SVD with fluctuating number of shrouded layers (5 to 15).

Table 1: Precision rate evaluation

Layers	SVD	HT	DWT	PSF	NHOS
5	0.71	0.73	0.77	0.89	0.947
10	0.74	0.75	0.78	0.9	0.953
15	0.76	0.76	0.79	0.91	0.957

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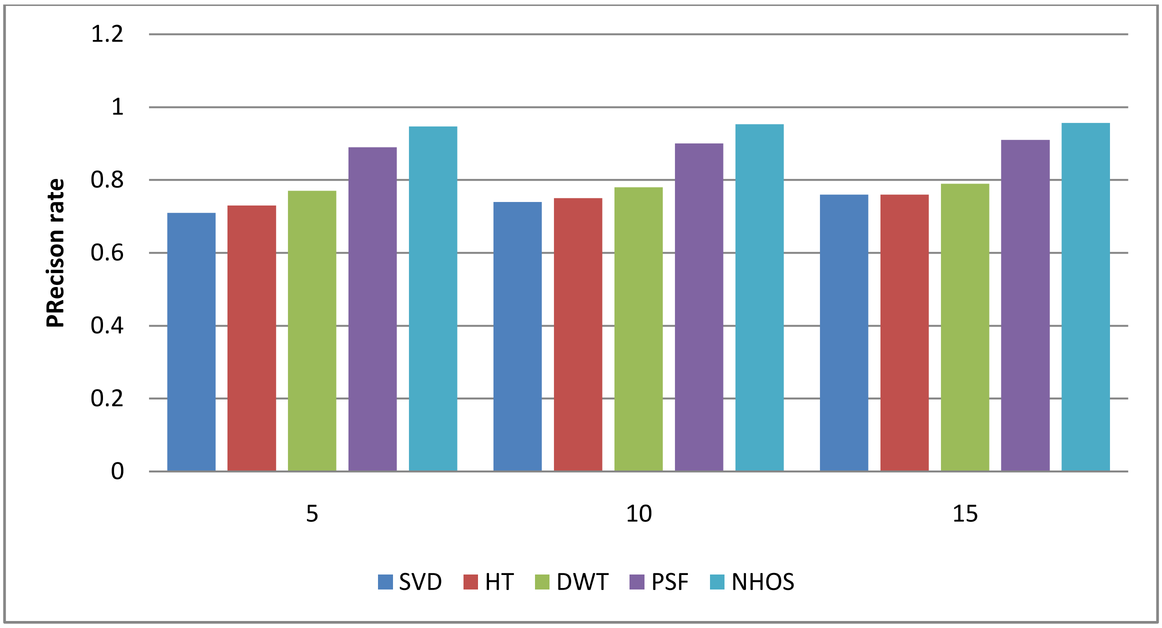

Figure 8: Performance of precision rate analysis

Table 2: Recall rate evaluation

Layers	SVD	HT	DWT	PSF	NHOS
5	0.75	0.79	0.81	0.88	0.951
10	0.75	0.77	0.82	0.89	0.952
15	0.76	0.78	0.8	0.92	0.957

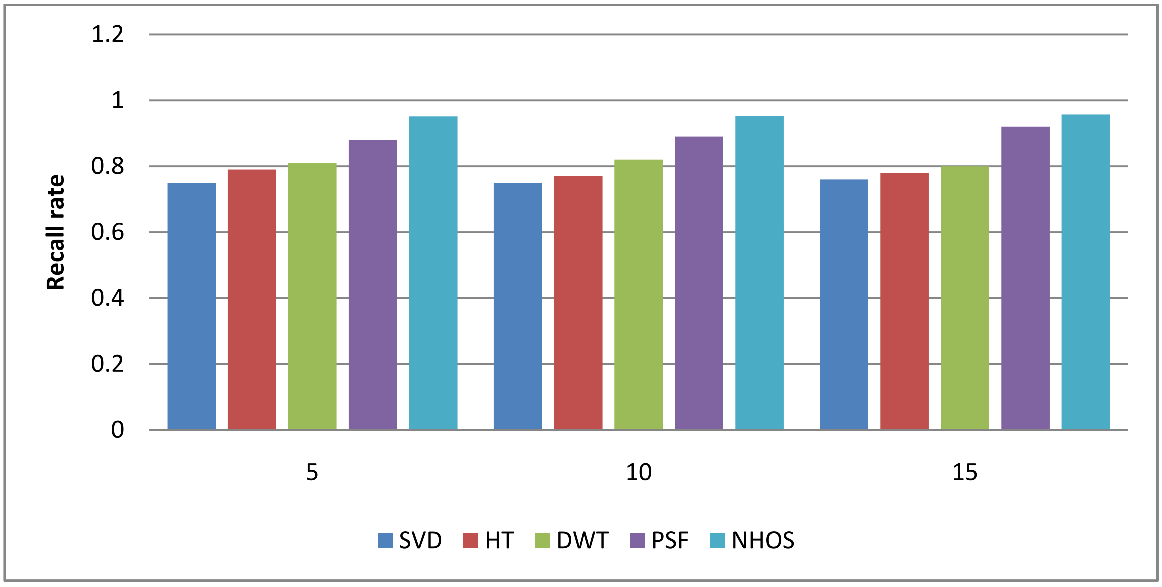

Figure 9: Performance of recall rate analysis

Table 5: Detection accuracy evaluation

Layers	SVD	HT	DWT	PSF	NHOS
5	0.745	0.775	0.805	0.893	0.947
10	0.755	0.782	0.814	0.904	0.952
15	0.774	0.789	0.82	0.915	0.958

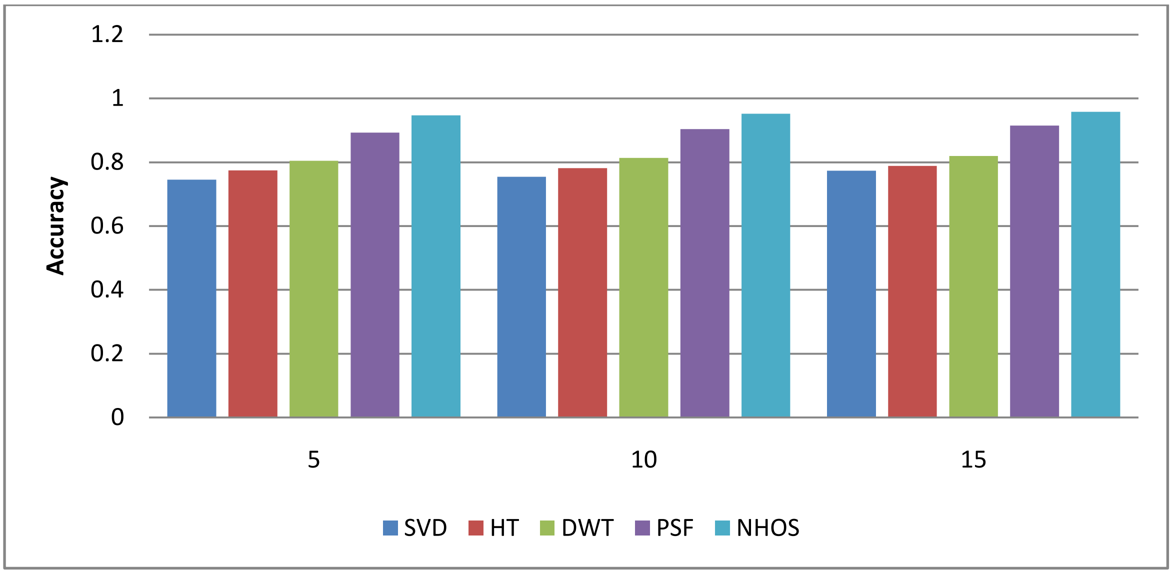

Figure 10: Performance of accuracy rate analysis

The figures 8,9,10 (table 1, 2, & 3)show the presentation of exactness, review, & precision rates for every technique with fluctuating the quantity of concealed layers individually. We saw that as the shrouded layers expands; the exhibition is expanding also for every method. Notwithstanding, expanding the shrouded layer may lead the more calculation overhead. The proposed highlights extraction technique approach demonstrates the huge improvement in exhibitions contrasted with every single other strategy. The SVD strategy demonstrates the most exceedingly awful exhibition among every one of the systems. The PSF demonstrates the improvement as the identification & extraction of QRS & ST complex performed pursued by the factual examination which conveyed the more interesting & dependable arrangement of highlights for the expectation. In any case, the utilizing NHOS beat the exhibition of utilizing the measurable highlights & conveyed the altogether improved exhibitions for CVD discovery when contrasted with every single other procedure. The reasons of expanded execution of NHOS is the less number of highlights, increasingly dependable highlights,

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one of a kind highlights, & solid highlights removed contrasted with different strategies. The methods like SVD, DWT, & HT separated the highlights with huge size which sets aside the more extended effort for acknowledgment as well as deceives the arrangement. Table 4 show the normal execution & examination with comparative strategies.

Table 6: Comparative analysis with similar methods

Method	**Accuracy (%)**	**Detection Time (seconds)**
SVD	75.8	1.23
HT	78.2	1.74
DWT	81.3	1.95
[28]	88.52	1.72
[29]	82.5	1.59
[31]	92.5	1.62
PSF	90.4	1.51
NHOS	**95.25**	**1.56**

As saw in table 6, the general exactness of NHOS based CVD location proposed in this paper is altogether higher than the past strategies just as measurable highlights based methodology. We researched the presentation of location time likewise which demonstrates that the SVD system takes less time among every one of the procedures, however its precision is poor which isn't satisfactory at pragmatist conditions. The proposed strategy demonstrates the harmony between the precision & forecast time execution as analysed every single other system.

V. Conclusion & Future Work

The research proposed framework of efficient CVD detection using the raw ECG signals consist of pre-processing, wave's extraction, features extraction & classification. The hybrid filtering technique designed to filter out different type's noises & artefacts. For wave's extraction, we proposed the lightweight & efficient dynamic threshold based algorithm. We first locate the left & right waves, &then extract the Q, R, S, T & P waves. Using extracted waves, QRS complex & ST segments extracted. To minimize the computational efforts & improve the accuracy, we applied the NHOS features extraction technique on extracted QRS complex & ST segments. The statistical features on other

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hand extracted & evaluated in comparison with NHOS technique. The performances shows that proposed method delivered the best classification results compared to existing methods as well as statistical features based techniques. In future direction, suggest investigating performance of proposed framework using different classifiers.

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