

Various Networks used for ECG Signals, Heart Beats and ECG Feature's Classification

Vikas Malhotra, Mandeep Kaur Sandhu

Abstract: ECG is a graphical representation of heart's electrical activity such as electrical repolarization and depolarization of heart. It is an important non-stationary signal which contains the necessary information about the heart functioning so that it can be used to identify different abnormalities in heart beats and also to identify different diseases of human beings. Classification is an important process in ECG signal analysis and cardiac diseases diagnosis process. Different ECG signals as well as ECG parameters such as heart beats, features can be classified according to requirement. In this paper different classification networks have studied. SVM classifier with empirical mode decomposition represented the maximum accuracy of 99.54%. Any optimization technique can be used to increase the accuracy of SVM classifier with suitable decomposition method such as variational mode decomposition.

Keywords: SVM, Electrocardiogram (ECG), classifier networks, heart beats

I. INTRODUCTION

An electrocardiography (ECG) is a graphic tracing of the electric current generated by the heart muscle during a heartbeat. It provides information regarding the function of the heart. The ECG signal is characterized by six peaks and valleys, which are traditionally labelled P, Q, R, S, T and U as shown in figure 1.[1]

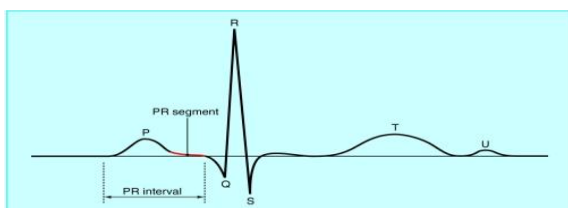


Fig.1: Normal ECG signal [1]

II. LITERATURE SURVEY

Udit et. al. [2] proposed a modified (CEEMD) complete ensemble empirical mode decomposition to remove the noise from ECG signal. Three features like local maximum peak amplitude of autocorrelation function, maximum absolute amplitude and number of zero crossing have been extracted. Decision rule based algorithm has been used to classify the processed ECG signal into six ECG categories i.e. ECG, ECG + BW, ECG+ MA, ECG+PLI, ECG+BW+PLI, ECG+BW+MA. The overall classification accuracy, positive productivity and sensitivity of classifier were achieved as 97.38%, 98.39% and 98.93% respectively.

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Kandala N. et. al. [3] proposed a method, in which the effect of class imbalance on performance of classification has been analyzed. In the proposed method, improved complete ensemble empirical mode decomposition (ICEEMD) has been used on each segment of ECG signal. The deviation from linearity and gaussianity of signal has been analyzed by higher order statics (HOS) detection from intrinsic mode function modes and similarly dynamics of heart beats have been analyzed by detecting sample entropy. AdaBoost ensemble classifier has been used for heart beat classification. The performance of the proposed method has been evaluated by overall specificity, sensitivity, accuracy and receiver operating characteristics (ROC) of 99.1%, 96.5%, 98.6% and 99.5% respectively. Class imbalance has a notable effect on heart beat classification. Adaptive beat size segment should be used because of fast and slow varying heart rhythm. Diagnosis of diseases should be workout. There is a difficulty in wavelet for selection of mother wavelet and decomposition level.

Serken Kiranyaz et. al. [4] proposed a method for ECG based heart beat classification 1D-CNN (convolution neural network) has been used for both feature extraction and as well as for heart beat classification. To improve the performance, patient specific (local) and global (common to each patient) data have been used in shallow training of 1D-CNN classifier. Four parameters (i.e. sensitivity, specificity, accuracy and positive predictivity) have been used for performance evaluation with highest value of 95.9%, 99.4%, 99% and 93.3% respectively. The drawback of CNN is that the CNN can be trained after all the parameters are properly fixed in advance. There was no guarantee to represent the anomaly beats i.e. S beats properly using both common and patient specific data.

Pengfei Li et. al. [5] used a graphic processor unit (GPU) in classification of heart beats of long term ECG signals for fast and large sample data processing. The difference operation method (DoM) has been used for feature extraction. Eight features have been extracted. Parallel general regression neural network (GRNN) has been used to classify the heart beats in five categories (i.e. N, S, V, F, Q) with on-line learning module. For evaluation of the performance, four parameters like positive predictivity, classification, accuracy (Acc), sensitivity (Sen) and specificity (Spe) have been measured. The average accuracy of GRNN was 95%. The efficiency of parallel GPU was 20-fold faster than serial programmed based CPU.

Shurouq Hijazi et. al. [6] analyzed cardiac health risk like different arrhythmia and their seriousness using ECG signal analysis. Different twenty four features of QT time and RR interval have been analyzed.



Four classifier networks (i.e. K-nearest neighbour, SVM, random forest and adaboost) with visualization and alerts as supporting decision maker have been used.

Principal component analysis has been used for lower dimension of data and chi-square tests have been used to select relevant features automatically. The highest accuracy of 70% has been achieved using RBF-SVM classifier and accuracy of RBF-SVM not effected by reduction of features. There was not any effect of beta blocker and gender on classification output. The input and parameters of classifiers should be optimized. Voting classifier should be used instead of individual classifier for better accuracy.

Sandeep Raj et. al. [7] analyzed ECG signal using discrete orthogonal stockwell transform based on Discrete cosine transform (DOST-DCT) in time frequency distribution approach. ECG signals have been collected from MIT-BIH database. Two decomposition method (i.e. EEMD and EMD) with de-noised ECG signal data have been used and compared with noisy ECG signal data by extracting features like coefficient of variation, sample entropy, band powers and singular values of intrinsic mode functions. The performance evaluation of EEMD with existing methods presented the average value of sensitivity; accuracy and specificity with 98.01%, 99.20% and 99.49% respectively whereas EMD presented the value 95.15%, 97.57% and 98.37 respectively used in heart beat segment.

Piyush Sharma et. al. [8] used empirical mode decomposition to decompose the arrhythmia beats (taken from MIT-BIH database) into four intrinsic mode functions. Hibert-Huang transform has been used to determine weight mean frequency of signal using instantaneous value of amplitude and frequency of each intrinsic mode functions. Randomness of the signal has been extracted by using kolmogorov complexity analysis. Six statistical features like standard deviation, median, kurtosis, central movement, integrated intrinsic mode function and skewness have been extracted. These features based heart beat classification using one against one multiclass support vector machine has been used to classify the heart beats into left bundle block, normal, premature ventricular contraction, right bundle branch block, paced and atrial premature beat. For performance evaluation, four parameters like sensitivity of classification accuracy, positive predictivity and specificity have been determined with value of 98.4%, 99.54%, 98.17% and 99.74% respectively

Kandala N. et. al. [9] Two decomposition method (i.e. EEMD and EMD) with de-noised ECG signal data have been used and compared with noisy ECG signal data by extracting features like coefficient of variation, sample entropy, band powers and singular values of intrinsic mode functions. The ECG signal data was taken from MIT-BIH and INCARF databases. Further, sequential minimal optimized support vector machine (SMO-SVM) classifier has been used for classification of ECG heart beats based on extracted features into five beat types (i.e. left bundle branch block, right bundle branch block, normal, premature ventricular contraction and atrial premature contraction). The performance evaluation of EEMD with existing methods presented the average value of sensitivity; accuracy and specificity with 98.01%, 99.20% and 99.49% respectively whereas EMD presented the value 95.15%,

97.57% and 98.37 respectively. In future, features can be used to identify diseases. Adaptive beat size segmentation should be used. Due to change in patient detail in testing and training, the result may be biased.

U. Iqbal et. al. [10] selected the eleven articles after filtration to study the core process of ECG analysis. These articles have been further analyzed to find, how best model driven architecture and model driven environment based terminology will be fitted in ECG feature classification so that maintainability, traceability and reusability could be possible. The dependency of features was a problem in ECG feature classification process. To remove these complexities in future, the parallel classification of ECG features using model-driven environment (MDE), regressive model and normalization of ECG signal should be used.

Taiyong Li et. al. [11] used Random forest (RF) classifier with features like wavelet packet entropy (using wavelet packet decomposition) and two RR interval to improve the performance of ECG based extracted heart beats classification into five groups (supra ventricular ectopic beat(S), normal beat(N), ventricular ectopic beat (V), unknown beat (Q) and fusion of V with N (F)). Db4 (daubechies) mother wavelet with six level decomposition has been used in wavelet packet decomposition. Inter-patient scheme (i.e. splitting testing and training data) has been used on data extracted from MIT-BIH database. For performance evaluation, four parameters like positive predictive, sensitivity, accuracy and false positive rate have been used with extracted value of 99.73% (for N), 94.67%, 94.61% and 0.71% (for V) respectively. Random forest (RF) consumes more time than KNN and DT. In random forest classifier, with increase in base learners, the time consuming also increases linearly. PCA should be used for feature selection so that performance of heart beat classification can be improved.

Gabriel Garcia et. al. [12] used temporal vectocardiogram (T-VCG) to classify the ECG heart beats in five groups using inter-patient scheme. Complex networks technique has been used for 64 features extraction including morphological features (pre RR, post RR and logical average) and heart beat interval (QRS complex duration, F wave duration and presence or absence of P wave). SVM classifier has been used for heart beat classification. Total 64 features have been selected from 178 extracted features using binary PSO technique. Optimization of SVM weights have been also done by PSO technique. For performance evaluation the accuracy, sensitivity, positive predictive and false positive rate (FPR) with value of 78%, 89.5% (for v), 96.3% (for n) and 27.0% (for n) have been determined respectively.

Honggiang Li et. al. [13] proposed a method in which wavelet packet decomposition (WPD) using db6 mother wavelet function with statistical method has been used to extract 48 features of ECG signals. The proposed method has been analyzed on MIT-BIH database and acquired ECG signals. For ECG signals classification in six categories (i.e. N, L, R, A,V,P) back propagation neural network has been used as classifier Genetic algorithm (GA) has been used for feature selection and optimization of weight,



bias of back propagation neural network .For performance evaluation four parameters i.e. sensitivity, specificity, accuracy and positive predictive value with average value of 97.86%,99.54%,97.78% and 97.8% respectively have been achieved with MIT-BIH database where as accuracy of 99.33% have been achieved with acquired ECG data.GA-BPNN classifier has higher accuracy of classification than GA-SVM.Lucie Marsanova et. al [14] evaluated comparative study of performance of four classifier (i.e. K-nearest neighbours (KNN), Radial basis function support vector machine (RBF-SVM), Linear discriminant function analysis (DFA) and Naïve bayer (NB)) to classify four types of heart beats (i.e. non- ischemic, moderate ischemic severe ischemic and ventricular premature beats (VPBs)) using different morphological features as well as using different spectral features also. For performance evaluation three parameters i.e. mean overall accuracy, sensitivity and specificity has been extracted. Radial basis function support vector machine (RBF-SVM) and K- nearest neighbours (KNN) classifiers are suitable classifiers with accuracy of 93.5% and 98.6% respectively.

Shalin Savalia et. al. [15] used artificial neural network (ANN) classifier to classify the normal and arrhythmia ECG data taken from Physionet database. Total 66 ECG signal have been used. After removing noise using FFT and IFFT, R peak QRST points have been detected using threshold filter and window size filter. Different diseases (i.e. Bradycardia Tachycardia, First degree AV block and second degree AV block) have been detected using RR interval and QRS complex duration. The accuracy of artificial neural network was 86%.

R. Castaldo et. al. [16] analyzed mental stress using ultra short term heart rate variation (HRV) features of ECG signal (i.e. duration of 5min, 2 min, 3 min, 1 min and 30 sec) of 42 healthy students in verbal examination and in rest position. The Kubios software has been used to analyze HRV. Six features (Mean NN, Standard NN, Mean HR, Standard HR, HF and SD2) have been selected from ultra HRV features and classified using different classifier networks (i.e. multilayer perception (MLP), support vector machine (SVM), IBK neighbour search, linear discriminate analysis have been used. For performance analysis mean under curve (AUC), accuracy, sensitivity and specificity have been analyzed. The IBK has the analysis mean under curve (AUC), accuracy, sensitivity and specificity of 99%, 94%, 88% and 100% respectively. Mental stress can be detected using ultra short term HRV features but not less than 1 min.

Xiaolong Zhai et. al. [17] proposed a CNN classifier with dual inputs (2D) to classify the heartbeats in N, S, V, F categories.2D matrix has been used in which morphological data of the heartbeat has been used as common part and correlated data has been used as specific part. The ECG data has been taken from MIT-BIH database. To improve the performance of classifier; systematically heartbeats have been selected for training. Four parameters i.e. sensitivity, accuracy, specificity and positive predictive rate have been used to evaluate the performance of the proposed system. However the performance of the proposed method is better than other state of arts especially in S beats but there is still

need of specific optimization for the adjacent heart beats data.

C Venkatesan et. al. [18] analyzed the performance of various classifier networks for classification of normal and abnormal subjects using MIT-BIH database. The raw ECG signals have been pre-processed to remove noises with adaptive filtering (i.e. delayed error normalized least mean square (DENLMS) filter). Coiflet wavelet has been used to extract different fourteen features in time and frequency domain. The SVM classifier with accuracy of 96% has been achieved while the overall accuracy of traditional classifier (i.e. ANN, knowledge based system, KNN and PCA) was 94.2%.

Jiayuan He et. al [19] analyzed real time acute cognitive stress using super short window (< 10 sec) by extracting six features (heart rate (HR), power ratio to low frequency to high frequency (LH), ratio of major axis to minor axis of point care plot (pQ), standard deviation of point care plot along the line of identity (SD2), standard deviation of NN interval (SDNN), combination of all features (Comb)) from twenty subjects. Three classifier networks (Linear discriminant analyses (LDA), support vector machine (SVM) and Neural network (NN) have been analyzed. For performance evaluation three parameters like false acceptance rate (FAR), error rate (ER) and false rejection rate (FRR) have been used.

Aurore Lyon et. al [20] described different computational techniques for ECG classification and clustering . The accuracy and involvements of these techniques in medical advances have been reported. The challenging in ECG data processing has been also described.

Farhana Akter Mou et. al. [21] proposed one against all support vector machine (OAA-SVM) classifier for classification of normal and abnormal ECG waveforms using fractal dimension (FD) extracted by power spectrum method (PSM). The three basis kernel functions (i.e. linear, radial basis function (RBF), Poly) have been used in SVM classification. The MIT-BIH database has been used for raw ECG data. The overall accuracy of 89.33% has been achieved by proposed method and this method can be used in ECG signal analysis.

S. Jain et. al. [22] proposed an artificial bee colony optimize technique based least squares support vector machines classifier (ABS-LSSVM) using radial basis function (RBF) to classify the normal and abnormal ECG beats. Band width features have been extracted after empirical mode decomposition of ECG data taken from MIT-BIH database. For performance evaluation, six parameters i.e. positive predictive value, negative predictive value accuracy, sensitivity, specificity and Matthews correlation coefficient have been calculated. Bandwidth features extracted from second intrinsic mode function (IMF) presented best result.

Hadeer El-Saadawy et. al. [23] used two stage hybrid hierarchical methods to classify the heart beats in normal beat (N), super ventricular ectopic (S), ventricular ectopic beat (V), fusion beat (F) and unknown beat (Q) classes.

These beat classes have been further divided in different categories.

Discrete wavelet transform (DWT) with principal component analysis (PCA) method has been used to extract morphological features along with four dynamic RR features (i.e. post RR, average RR and local RR interval). SVM classifier has been used in one versus one and one versus all strategies along with probabilistic neural network (PNN). The proposed method has been examined using lead I and lead II individually as well as using two fusion methods (i.e. stacked generalization algorithm and rejection method). For performance evaluation, four parameters i.e. positive productivity, sensitivity overall accuracy and average accuracy have been evaluated. The best average accuracy and overall accuracy of proposed method have been achieved as 95.70% and 98.40% respectively for first stage.

Similarly, for second stage best average accuracy and overall accuracy of 93.19% and 94.94% respectively have been achieved. SVM with one to one strategy has the best result for the both stages. However manual classification is still needed for rejection method, which is the drawback of proposed method.

Yufa Xia et. al. [24] used supervised learning (1D-CNN) convolutional neural network classifier with active learning to improve the performance of classifier. The breaking ties (BT) and modified breaking ties (MBT) algorithms have been used in active learning to classify the ECG signal in five heart beat categories (i.e. ventricular (V), normal (N), supraventricular (S), unknown heartbeat(Q) and fusion of normal as well as ventricular beats(F)). The lifted based discrete wavelet transform has been used to remove the noise in ECG signal. Morphological and temporal features have been extracted. As compared to other state of arts, the proposed method was better in performance.

Rolando Gonzalez T et. al. [25] used a low computational cost Daubechies wavelet based discrete wavelet transform, (using reference point) to classify the ECG beats in normal (N), Pre-mature (P) and unknown (Q) beats. Second order notch filter and third order Butterworth filter have been used to remove power line interface and motion artifacts noises. Pantomkins algorithm has been used for QRS detection. For performance evaluation, two parameters i.e. positive predictivity and sensitivity have been used with obtained value of 91.43% and 93.25% respectively.

Essam H Houssein et. al. [26] classify the different ECG arrhythmia data taken from MIT- BIH database using Gaussian RBF based multi class SVM with one against all strategy. Modified pan-tompkins algorithm has been used for noise removal and nine features extraction. Water wave optimization (WWO) technique has been used for feature selection and SVM parameter optimization. For performance evaluation five parameters (i.e. accuracy, specificity, recall, F measure and precision) have been extracted. The proposed method achieved 93% accuracy.

Deniz Ekiz et. al. [27] analyzed real life stress via physiological signals taken from commercial smart watch (Samsung gear series) and high end wrist band (Empatica E4) from 21 subjects. Different regression and classification networks have been analyzed by using different aggregation window length. The effect of interpolation and artefact

removal has been also analyzed. By using interpolation in some classifier networks (i.e. K-nearest neighbours (KNN), Logistic Regression (LR) and Multilayer Perception (MP)) for noise removal have better accuracy whereas classification networks i.e. Linear Discriminant Analysis with Principal Component Analysis (LDA+PCA) and Random Forest (RF) using filtration (artifacts removal) method has lower accuracy than principal component analysis with support vector machine (PCA + SVM) method, which has equal accuracy for both noise removal methods (i.e. filtration and interpolation). However improper attachment of wrist watch causes loss of data and loss in performance can occur using proposed method.

Dorien Huysmans et. al. [28] used unsupervised learning with self organizing map (SOM also known as kohonen neural network) for detection of mental stress using ECG and skin conductance signals in a laboratory. Three tasks (stroop color word, number subtraction and stress talk) have been performed by 21 subjects to induce stress. Average testing performance (i.e. average of sensitivity and specificity) of 79% has been achieved. However, small dataset has been used in proposed method.

Pravallika Pagadala et. al. [29] analyzed heart rate and morphological changes of ECG from relaxed state to stressed state of fifty MBBS students. Philips C3i ECG machine has been used to acquire ECG data. For acute stress generation different methods like mental arithmetic task, seminar and public speaking have been used. During mental stress time duration several parameters like heart rate, QT interval, PR interval and QRS duration have been reduced whereas P wave has been extended.

Aized Amin Soofi et. al. [30] discussed different classification techniques like support vector machine, K-nearest neighbour, Bayesian networks and decision tree induction networks with their benefit drawback and working procedure.

Iqbal Muhammad et. al. [31] discussed different supervised machine learning algorithms like logical based algorithm, statistical learning algorithm, deep learning, support vector machine and instance based learning

Gangadhar Shobha et. al. [32] discussed in detail of advantages, disadvantages and types of various methods in machine learning. Various applications of machine learning have been explained. Importance of machine learning in products of industries has been also discussed.

A. Alberdi et. al. [33] discussed different stress measurement methods and accuracy of these methods has been discussed. A ubiquitous stress assessment framework has also been proposed to monitor stress in office environment. ECG, especially using HRV features and EDA among all physiological methods has highest accuracy for measuring stress.

III. METHODOLOGY

According to literature survey, the basic method to analysis the ECG for the detection of various diseases involves ECG data acquisition, processing, feature extraction, classification and performance evaluation.



ECG acquisition: Source of ECG: ECG from the person, Online database (MIT-BIH), Hospitals.

ECG Processing: As acquired ECG data contains various noises within the signal. To remove different noises from this acquired raw signal, preprocessing of acquired ECG data using various time intervals decomposition can be processed.

Feature Extraction: Various ECG features can be extracted in order to derive a qualitative model for different disease estimation.

Classification: Different classifiers/techniques can be used to classify the extracted features. Classifier network also can be used for the heart beat classification and for different types of arrhythmia classification.

Performance evaluation: For evaluation of different diseases, different parameters like accuracy, specificity, sensitivity, false acceptance rate (FAR), error rate (ER) and false rejection rate (FRR).

The flow chart of basic methodology to analysis the ECG signal has been shown in flowchart as shown below in fig.2:

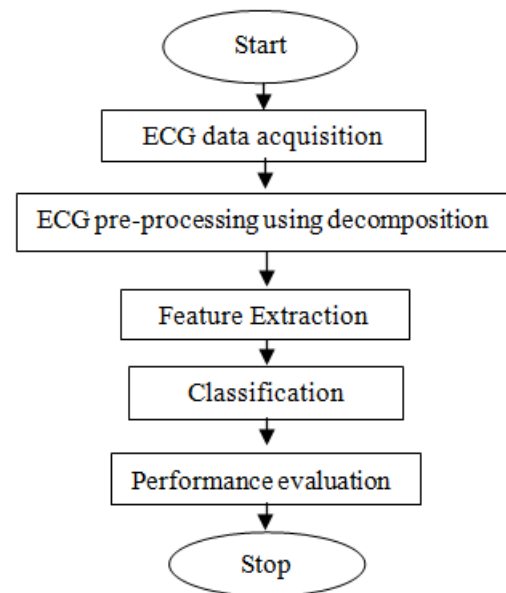


Fig. 2: Flow chart of Research methodology for ECG analysis

Table- I: Accuracy of different classifier networks with different decomposition methods

References	Method used	Classifier network	Accuracy	sensitivity	specificity	Drawback
. Udit et. al. [2]	Modified (CEEMD) complete ensemble empirical mode decomposition	Decision rule based algorithm	97.38%	98.93%	Not given	
Kandala N. et. al. [3]	Improved complete ensemble empirical mode decomposition	AdaBoost ensemble classifier	98.6%	96.50%	99.10%	Adaptive beat size segment should be used because of fast and slow varying heart rhythm
Serken Kiranyaz et. al. [4]	1D-CNN	1D-CNN	99%	95.90%	99.40%	CNN can be trained after all the parameters are properly fixed in advance.
Pengfei Li et. al. [5]	Difference operation method (DoM)	Parallel general regression neural network (GRNN)	95%	Not given	Not given -	
Sandeep Raj et. al. [7]	Discrete orthogonal stockwell transform based on Discrete cosine transform (DOST-DCT)	PSO-SVM	99.08%	99.31%	Not given	
Piyush Sharma et. al. [8]	Empirical mode decomposition	SVM	99.54%	98.40%	98.17%	
Kandala N. et. al. [9]	EEMD and EMD	sequential minimal optimized support vector machine (SMO-SVM)	99.20%	98.01% (EEMD)	99.49%	Adaptive beat size segmentation should be used. Due to change in patient detail in testing and training, the result may be biased.
Taiyong Li et. al. [11]	Db4 (daubechies) mother wavelet	Random forest (RF) classifier	94.67%	94.67%	Not given	In random forest classifier, with increase in base learners, the time consuming also increases linearly.

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Gabriel Garcia et. al. [12]	Complex networks technique	SVM	78%,	89.50%	96.30%	
Honggiang Li et. al. [13]	wavelet packet decomposition (WPD) using db6 mother wavelet function	back propagation neural network	97.78%	97.86%	99.54%	
Shalin Savalia et. al. [15]	FFT and IFFT	Artificial neural network	86%.	Not given	Not given	
C Venkatesan et. al. [18]	delayed error normalized least mean square (DENLMS) algorithm	SVM	96%	Not given	Not given	
Farhana Akter Mou et. al. [21]	power spectrum method (PSM)	one against all support vector machine (OAA-SVM)	89.33%	Not given	Not given	
S. Jain et. al. [22]	empirical mode decomposition	least squares support vector machines classifier (ABS-LSSVM)	Not given	Not given	Not given	
Hadeer El-Saadawy et. al. [23]	Discrete wavelet transform (DWT)	SVM with probabilistic neural network (PNN)	95.70%	Not given	Not given	
Yufa Xia et. al. [24]	lifted based discrete wavelet transform	(1D-CNN) convolutional neural network classifier has been used with active learning	Not given	Not given	Not given	Computational complexity has been increased with the use of active learning method.
Essam H Houssein et. al. [26]	Modified pan-tompkins algorithm	Gaussian RBF based multi class SVM with one against all strategy	93%	Not given	Not given	

IV. RESULTS AND DISCUSSION

Different classifier networks like Decision rule based algorithm, [2] general regression neural network (GRNN), [5] Support Vector Machine (SVM), [8, 9, 12, 18, 21-23, 26] Random forest, [11] back propagation, [13] K-nearest neighbour (KNN), [14] artificial neural network (ANN), [15] Neighbor Search (IBK), [16] convolution neural network-dual input CNN-2D [17] have been used by the researchers. For performance evaluation different parameters such as sensitivity, specificity, accuracy, positive predictivity, receiver operating characteristics (ROC), false positive rate, mean under curve (AUC), false acceptance rate, false rejection rate, negative predictive value and Matthews correlation coefficient. Various optimization techniques such as particle swarm optimization (PSO), [12] sequential minimal optimization, [9] an artificial bee colony optimization, [22] Water wave optimization (WWO) [26] techniques have been used. Researchers used classification networks for classifications of ECG heart beats, normal and arrhythmia (abnormal) ECG signals and feature classification.

The highest value of sensitivity of 98.93% has been achieved using Decision rule based algorithm classifier. The highest value of specificity of 99.5% has been achieved using back propagation. Highest value of accuracy and positive predictivity of 99.54% and 99.74% have been

achieved respectively using SVM classifier with Empirical mode decomposition method.

Some optimization technique out of particle swarm optimization (PSO), sequential minimal optimization, an artificial bee colony optimization, Water wave optimization (WWO) technique can be used to increase the accuracy of SVM classifier. However empirical mode decomposition has a limitation of mode mixing. Instead of empirical mode decomposition, variational mode decomposition can be used because variational mode decomposition is better than empirical mode decomposition.

V. CONCLUSION

SVM classifier can be used to analyze ECG signal for diagnosis of cardiac diseases and arrhythmia detection. Other methods instead of empirical mode decomposition can be used with optimized SVM classifier to improve the accuracy.

REFERENCES

1. Steve Meek and Francis Morris, "ABC of clinical electrocardiography Introduction II— Basic terminology," BMJ publishing group, vol. 32423, 2002.

2. Udit Satija, Barathram Ramkumar and M. Sabarimalai Manikandan, "Automated ECG noise detection and classification system for unsupervised healthcare monitoring," IEEE journal of biomedical and health informatics, vol. 22, no.3, 2018.
3. Kandala N. V .P. S Rajesh and Ravindra Dhuli, "Classification of imbalanced ECG beats using re-sampling techniques and AdaBoost ensemble classifier," Biomedical signal processing and control, 2018.
4. Serken Kiranyaz, Turker Ince and Moncef Gabbouj, "Real-time patient specific ECG classification by 1-D convolutional neural networks," IEEE transaction on biomedical engineering, vol. 63, no. 3, 2016.
5. Pengfei Li, Yu Wang, Jiangchun He, Lihua Wang, Yu Tian, Tian-shu Zhou, Tianchang Li and Jing-song Li, " High-performance personalized heartbeat classification model for long-term ECG signal," IEEE transaction on biomedical engineering, vol. 64, no. 1, 2017.
6. Shrouq Hijazi, Alex Page, Burak Kantarci, Tolga Soyata, "Machine learning in cardiac health monitoring and decision support," IEEE computer society, 2016.
7. Sandeep Raj and Kailash Chandra Ray, "ECG signal analysis using DCT- based DOST and PSO optimized SVM," IEEE Transaction on instrumentation and measurement, vol. 66, no. 3, 2017.
Piyush Sharma and Kailash Chandra Ray, "Efficient methodology for electrocardiogram beat classification," IET signal process, vol. 10, no. 7, 2016.
8. Kandala N. V. P. S. Rajesh and Ravindra Dhuli, "Classification of ECG heart beats using non linear decomposition methods and support vector machine," Elsevier, computers in biology and medicine, 2017, pp. 271-284.
9. U. Iqbal, T. Ying Wah, M. Habib Ur Rehman and Q. Mastoi, "Usage of Model Driven Environment for the Classification of ECG features: A Systematic Review," IEEE Access, vol. 6, 2018, pp. 23120-23136.
10. Taiyong Li and Min Zhou, "ECG classification using wavelet packet entropy and random forests," Entropy, vol. 18, no. 8, 2016.
11. Gabriel Garcia, Gladston Moreira, David enotti and Eduardo Luz, " Inter-Patient ECG Heartbeat Classification with Temporal VCG Optimized by PSO," nature, Scientific Reports, volume 7, article no.10543, 2017.
13. Honggang Li, Danyang Yuan, Xiangdong Ma, Dianyin Cui and Lu Cao "genetic algorithm for the optimization of features and neural networks in ecg signals classification," Nature, Scientific reports 7, article no. 41011, 2017.
14. Lucie Marsanova, Marina Ronzhina, Radovan Smisek, Martin Vitek, Andrea Nemcova, Lukas Smital and Marie Novakova, "ECG features and methods for automatic classification of ventricular premature and ischemic heartbeats: A comprehensive experimental study," Nature, Scientific reports 7, article no. 11239, 2017.
15. Shalin Savalia, Eder Acosta and Vahid Emamian "Classification of cardiovascular disease using feature extraction and artificial neural networks," Scientific Research, Journal of biosciences and medicines, vol. 5, no. 11, 2017.
16. R. Castaldo, L.Montesinos, P. Melillo, C. James and L. Pecchia, "Ultra short term HRV features as surrogates of short term HRV: a case study on mental stress detection in real life," BMC Medical informatics and decision making, vol. 19, no. 12, 2019.
17. Xiaolong Zhai and Chung Tin, "Automated ECG classification using dual heart beat coupling based on convolutional neural network," IEEE access, vol. 6, 2018, pp. 27465-27472.
18. C. Venkatesan, P. Karthigai Kumar, Anand Paul and S. Satheeskumaran, "ECG signal pre-processing and SVM classifier based abnormality detection in remote health care applications," IEEE access, vol. 6, 2018, pp. 9767-9773.
19. Jiayuan He, Ke Li, Xiaoli Liao, Ping Zhang and Ning Jiang, "Real time detection of acute cognitive stress using a convolutional neural network from electrocardiographic signal," IEEE access, Special section on advanced information sensing and learning technologies for data centric smart health applications, vol. 7, 2019, pp. 42710-42717.
20. Aurere Lyon, Ana Minchole, Juan Pablo Martinez, Pablo Laguna and Blanca Rodriguez, "Computational techniques for ECG analysis and interpretation in light of their contribution to medical advances," Journal of royal society interface, vol. 15, no. 138, 2018.
21. Farhana Akter Mou, Muhammed Abdillahi Al Mahmud, A. H. M Zaidul Karim, Salma Nazia Rahman, Shaikh Rashedur Rahman, "Classification of electrocardiogram signal using support vector machine based on fractal extraction by FD," American journal of circuits, systems and signal processing, vol. 3, no. 3, 2017, pp 12-22.
22. S. Jain, V. Bajaj, A. Kumar, "Efficient algorithm for classification of electrocardiogram beats on artificial bee colony based least squares support vector machines classifier," electronics letters vol. 52, no. 14, 2016, pp 1198-1200.
23. Hadeer El-Saadawy, Manal Tantawi, Howida A Ahedeed, Mohamed F. Tolba, "Hybrid hierarchical method for electrocardiogram heart beat classification," research article , IET signal processing journal, vol.12, no. 4, 2018, pp. 506-513.
24. Yufa Xia and Yaoqin Xie, "A novel wearable electrocardiogram classification system using convolutional neural networks and active learning," IEEE access, vol.7, 2019, pp. 7989-8001.
25. Rolando Gonzalez T and Maite Canizares F, "Optimization of algorithm for real time ECG beats classification," Research article, Open journal of cardiology and heart diseases, vol. 2, no. 5, 2018.
26. Essam H Houssein, Moataz Kilany and Aboul Ella Hassanien, "ECG signals classification: a review," international journal of medical engineering and informatics, vol. 5, no. 4, 2017, pp. 376-396.
27. Deniz Ekiz, "Stress reorganization in everyday life," Thesis, Researchgate, 2019.
28. Dorien Huysmans, Elena Smets, Walter De Raedt, Chris Van Hoot, Katlen Bogarts, Ilse Van Diest and Denis Helic, "Unsupervised learning for mental stress detection," international conference on bio-inspired systems and signal processing, Bio signals , vol.4, 2018, pp. 26-35.
29. Pravallika Pagadala "Heart rate variability and electrocardiographic changes during acute mental stress in first MBBS students: an analytical study," Research article, National journal of physiology pharmacy and pharmacology, vol. 9, No. 2, 2019.
30. Aized Amin Soofi and Arshad Awan, "Classification techniques in machine learning: applications and issues," Journal of basics and applied sciences, vol. 13, 2017, pp.459-465.
Iqbal Muhammad and Zhu Yan, "Supervised machine learning approaches: A survey," ICTACT journal of soft computing, vol.5, iss. 3, 2015.
31. Gangadhar Shobha and Shanta Rangaswamy, "Machine learning," Journal of statistics, Elsevier, vol. 38, 2018, pages 197-228.
32. A. Alberdi, A. Aztiria, A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review" Elsevier, Journal of Biomedical Informatics vol. 59, February 2016, pp. 49-75.

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