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Leveraging Machine Learning And Pre-Hospital 12-Lead ECG For Acute Coronary Syndrome Prediction

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Abstract:
Background: *Heart Failure is present in 1 out of 10 patients presenting Acute Coronary Syndrome. ECG predictors of reduced LVEF provide essential non-invasive triage capabilities, especially when echocardiography is not available instantly within reach. 12 lead ECG is easily accessible during the preliminary checkup of patient No direct comparison of the current electrocardiogram (ECG) interpretation program exists. Additional ECG training can improve accuracy. A systematic review and meta-analysis observed that across various training like pretraining and post-training and the median accuracy of ECG interpretation was 54% and 67% respectively [1].*
Method: *Here we proposed machine learning based approach to identify the highly predictive ECG Marker of Suspected Acute Coronary Syndrome i.e. the Ejection Fraction found in checkups [2]. This research proposes a modified technique for identifying cardiac abnormalities and QRS complexes, Leveraging Machine Learning and SVM (Support Vector Machine) classifiers.*
Results: *The presented technique surpasses existing methods in both sensitivity and specificity achieving accuracy of 98.4 % for cardiac irregularities for the standard 12-Lead ECG Georgia database*
Keywords: *12 Lead ECG Acute Coronary Syndrome Support Vector Machine Ejection Fraction*

1. INTRODUCTION

Acute Coronary Syndrome (ACS) is a prerequisite which describes a certain set of conditions corresponding to sudden reduction in the blood circulation of heart. The procedure of information extraction depends upon the category of the signal and sort of information convey by the signal.
The diagnosis of Acute Coronary Syndrome is crucial for emergency room care physicians. The 12-lead electrocardiogram (ECG) plays a significant role in this process. While traditional computerized ECG interpretation algorithms have limitations, machine learning (ML) models offer promise in clinical medicine. The proposed research able to diagnose and categorize the ECG beats into NSIVCB (Nonspecific Intraventricular, Ventricular Hypertrophy), AFL (Premature Atrial Fibrillation), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Incomplete Right Bundle Branch Block (IRBBB), LVH (Left Ventricular Hypertrophy), LPR (Prolonged PR interval), Sinus arrhythmia (SA) Sinus Bradycardia (SB), Sinus Tachycardia (STach), Premature Atrial Contraction (PAC), Premature Ventricular Contraction (PVC), Pacing Rhythm (PR), Left Axis Deviation (LAD), Right Axis Deviation (RAD), Low QRS voltage (LQRSV), 1st-degree AV block (IAVB), Left Anterior Fascicular Block (LAnFB), T wave inversion (Tinv), Ventricular Premature Beats (VPB). The presented technique attained an accuracy of 98.4%.
Irregularities in the ST-segment and T-wave indicates myocardial ischemia or injury which indirectly influence LVEF by affecting overall cardiac function. However, their direct predictive value for LVEF improvement remains uncertain.
The automation process of ECG signal analysing and disease diagnosing mainly divided into four steps
1. Signal Acquisition and Pre-processing: Capturing the raw ECG signal and converting it into a format suitable for further analysis.
2. Feature Extraction: Identified and extracted pre-processed relevant features of Electrocardiogram signal are the indicatives of specific cardiac conditions.
3. Heartbeat Segmentation: Dividing the ECG signal into individual heartbeats for detailed analysis.
4. Training and Testing: Developing and validating machine learning models using the extracted features and segmented heartbeats to create accurate diagnostic algorithms.

The electrical signal starts in the Sinoatrial (SA) node i.e. in right atrium and then spreads into the both atria left and right. P wave component detected in the heart's upper chamber which subsequently travels throughout the Atrioventricular (AV) node ventricles followed by atria. After passing through the atrioventricular node, Bundle of His followed by Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB) respectively [3].

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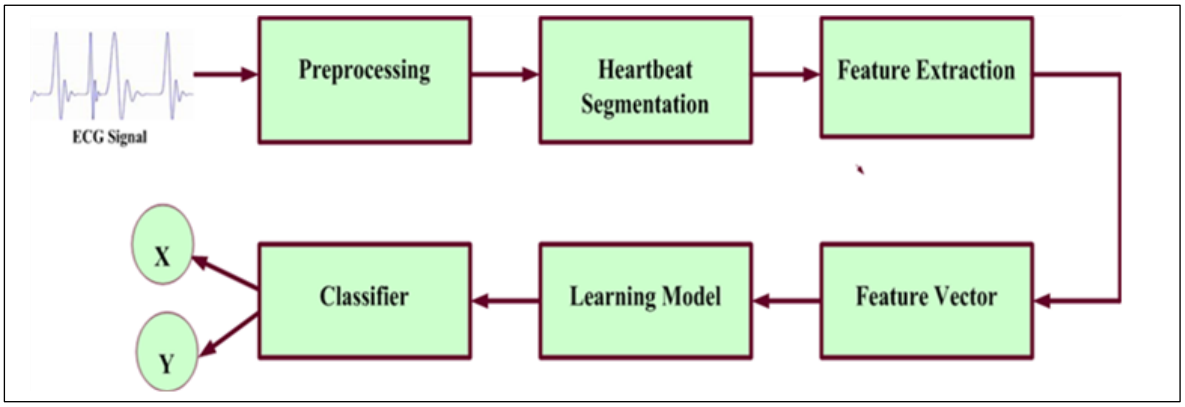

Figure 1: General Block Diagram

A systematic review compared machine learning (ML)-based ECG analysis to medical practitioners' analysis or diagnosis of acute coronary syndrome using traditional methods in emergency department (ED) or prehospital patients. The Machine Learning models are more sensitive but less precise as compare to the diagnosis of medical practitioner. Additionally, ML models demonstrated better discrimination, as evidenced by a greater area beneath the ROC i.e. Receiver operating characteristic curve, compared to medical practitioner. However, extremely through research is required to justify the superiority of ML over medical practitioners ECG diagnosis.

ML-based ECG interpretation holds promise for improving ACS diagnosis, but further research is necessary to establish its superiority over human clinicians. The algorithms have some limitations, while machine learning models offer significant potential in clinical medicine.

2. Data Acquisition and Preprocessing:

Pre-processing is a crucial data preparation technique in ECG signal analysis. It involves converting raw ECG signals into a format suitable for further processing, such as Linear filtration, Nonlinear transformations, and the application of Decision Directives.

Linear filtration and Nonlinear transformation, is essential for enhancing the quality of the ECG data and ensuring accurate and reliable analysis in subsequent steps. Linear filtration takes place by making a use of BPF (Bandpass filter), use of derivation function and integrating moving windows. Here encounters a problem in designing Band Pass Filter (BPF) directly for a 5-15 Hz passband. 3dB passband achieved by connecting a low-pass filter in series with high-pass filters. High Pass Filter designed by subtracting the output of a first-order low-pass filter [4].

Low- pass Filter

Second order transfer function of Low- Pass filter

$$H(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2}$$

i

$$|H(\omega T)| = \frac{\sin^2(3\omega T)}{\sin^2(\omega T/2)}$$

ii

The differential equation is as given as in equation no. iii [4].

$$y(nT) = 2y(nT-T) - y(nT-2T) + x(nT) - 2x(nT-6T) + x(nT-12T)$$

iii

where T indicates the sampling period, output signal represented by y(nT) and input signal represented by x(nT)

High - pass Filter

$$H(z) = \frac{(-1-32z^{-16}+z^{-32})}{(1+z^{-1})}$$ Transfer function

iv

$$|H(\omega T)| = \frac{[256+\sin^2(16\omega T)]^{1/2}}{\cos(\omega T/2)}$$ Amplitude response

v

$$y(nT) = 32x(nT-16T) - [y(nT-2T) + x(nT) - 2x(nT-32T)]$$ difference equation

vi

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Derivative of transfer functions

$$H(z) = \left(\frac{1}{8T}\right)(-z^{-2} - 2\,z^{-2} + 2z^{1} + z^{2})$$

vii

$$|H(\omega T)| = \left(\frac{1}{4T}\right)\,[\sin(2\omega T) + 2\sin(\omega T)]$$

viii

$$y(nT) = \left(\frac{1}{8T}\right)[-x\,(nT - 2T) - 2x\,(nT - T) + 2x\,(nT + T) + x(nT - 2T)]$$

ix

Integration of Moving-windows strives to record features of waveforms in detail particularly focusing on slope of the R wave.

$$y(nT) = \frac{1}{N}[x\,(nT - (N - 1)\,T) + x\,(nT - (N - 2)T) + \ \ldots\ldots\ldots + x(nT)]$$

x

Graphical representation of repolarization and depolarization of atrial and ventricular muscle tissues displayed in P, Q, R, S, T segments and ECG wave components is, as illustrated in figure 2

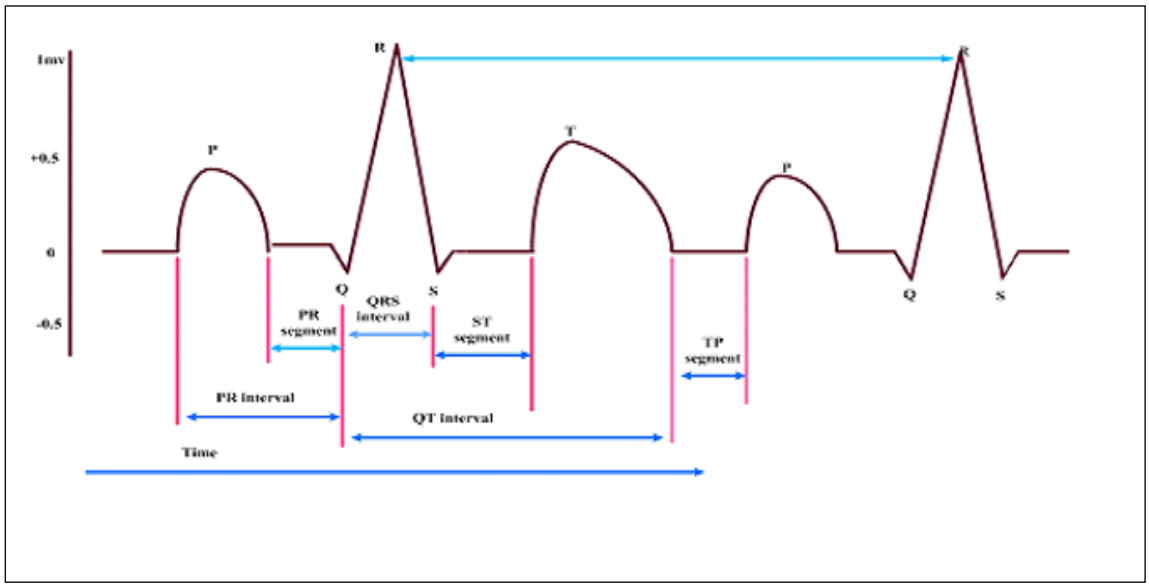


Table 1: Interpretation of Electrocardiogram signal

Sr. No	Particulars	Descriptions
1	ST Segment	ST segment connects the T waves and QRS complexes.
2	PR Segment	PR segment illustrate the electrical conduction in AV node through atria and delay.
3	ST Interval	ST interval, covers time period from beginning point of T wave to the ending point of S wave.
4	QT Interval	The process of repolarization and depolarization of signals reflects the duration of QT interval.
5	PR Interval	The AV node with delay, controls and stimulates the pulse rate.
6	QRS Interval	Time required to depolarize the ventricles which involves contraction of ventricles to expel blood from the heart

First, we have to decompress the signal into a common data format [3, 5-9] in which the ECG leads decoded as "Leads I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6 as illustrated in figure.3 and stored in columnar matrices. We can eliminate noise, artifacts, and ectopic beats at this stage.

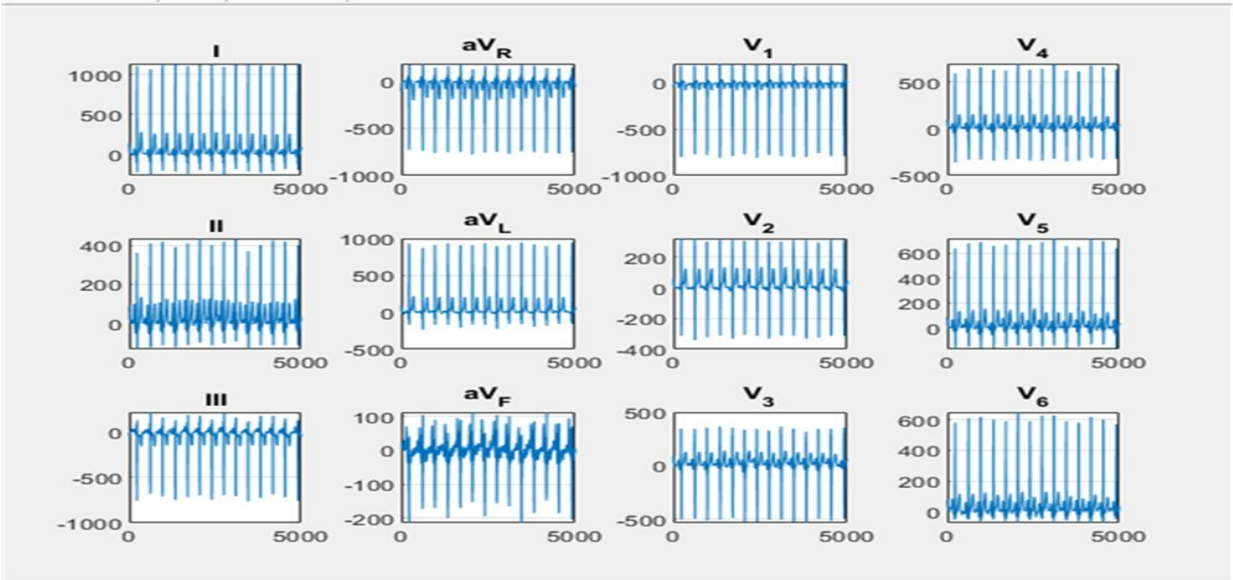


Figure 3: Decompressed Electrocardiogram Signal into 12-Leads

Median Filter is deployed to eliminate baseline wander and smooth of the signals [5] [6]. The general low pass filter used to eliminate Fourier-based, high frequency noises. removed using a low pass filter. Butterworth Filter is commonly used as Low-Pass filter [3]. FIR Band-stop filter is utilized to eliminate the 50 Hz interference produced by power lines. [6] [7]. Isoline Correction Function used to estimate and remove the offset of the electrical isoline of an ECG. Baseline noise and stable artifacts monitored by evaluating a median beat for each lead, emerging a high SNR and a consistent median signal for all 12 leads [12-13]. A nonlinear transformation will be applied to the signal. A Nonlinear transformation is implented for T wave discrimination and amplitude squaring of ECG signal e.g. square, to enhance the QRS Complex.

$$y(nT) = [x(nT)]^2 \quad \text{xi}$$

The transformation of QRS complexes into one distinct positive peak enhances their suitability for detecting peaks at the time of decision stage. The decision rules composed adaptive threshold techniques and supplementary tests employed to ensure that the data is reliable and to minimize the influence of noise or artifacts that could lead to incorrect diagnoses or misinterpretation Finally, decision rules employed to deduce whether the QRS complexes exists in the signal. Artifacts that resemble the QRS complexes might be mistaken for actual heartbeats, so distinguishing true QRS complexes from artifacts is vital. Tall T-Waves occur due to various reasons including electrolyte imbalances or as a normal variant [14]. The system needs to distinguish between pathological tall T-waves and those that are simply benign variations.

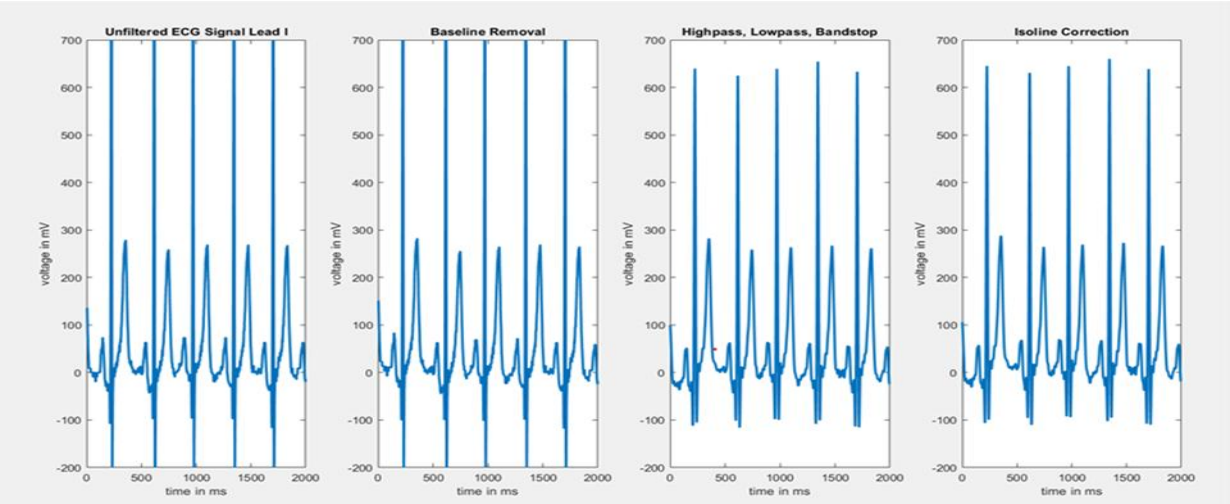


Figure 4: Filtered Electrocardiogram signal

3. Heartbeat Segmentation

Heartbeat segmentation is used to identify the QRS complex or R peak wave and to analyze the segmentation accuracy [15-16]

ECG Predictors: Features like prolonged T peak to T end interval, non-dipolar components, and visual markers provide important clues about LVEF and cardiac function [22-26]. These ECG features can serve as non-invasive tools for triaging patients, particularly in the settings when echocardiography or other imaging modalities are not easily accessible.

Shortened R Wave Progression: Shortened R Wave Progression refers to a decrease the amplitude of R wave across a precordial lead (V1 to V6), and the existence of a dominant QS pattern in +the lead V3 can indicate impaired cardiac function and is often associated with reduced LVEF. This visual marker reflects myocardial damage or significant LV dysfunction. ECG features such as repolarization dispersion, non-dipolar components, and visual markers provide valuable information about left ventricular ejection fraction (LVEF) and heart performance. Ejection fraction relates the volume of blood pumped out from each ventricle with every heartbeat. Ejection fraction is determined by dividing the Stroke Volume (SV) by the End Diastolic Volume (EDV) multiply by 100. Further research can explore interventions to optimize ventricular activation and improve LVEF. American College of Cardiology stated some standard ranges of Left Ventricular Ejection Fraction (LVEF), Depending on that standard LVEF values specified, the risk of heart failure predicted as Severe, Moderate, Mild, Normal and Hyperdynamic [58].

Table 2: Standard Range of LVEF as per American College of Cardiology

Sr. No	LVEF Range in Percentage	Category
1.	LVEF greater or equal to 70%	Hyperdynamic
2.	LVEF is equal to 50 or in between the range 50% to 70%	Normal
3.	LVEF is equal to 40 or in between the range 40 % to 49%	Mild dysfunction
4.	LVEF is equal to 30% or in between the range 30% to 39%	Moderate dysfunction
5.	LVEF less than 30%	Severe dysfunction

LVEF (%) = (SV/EDV) *100

xii [58]

As we know that Stroke Volume (SV) = End Diastolic Volume (EDV) – End Systolic Volume (ESV)

Hence LVEF (%) = (EDV – ESV) / EDV*100

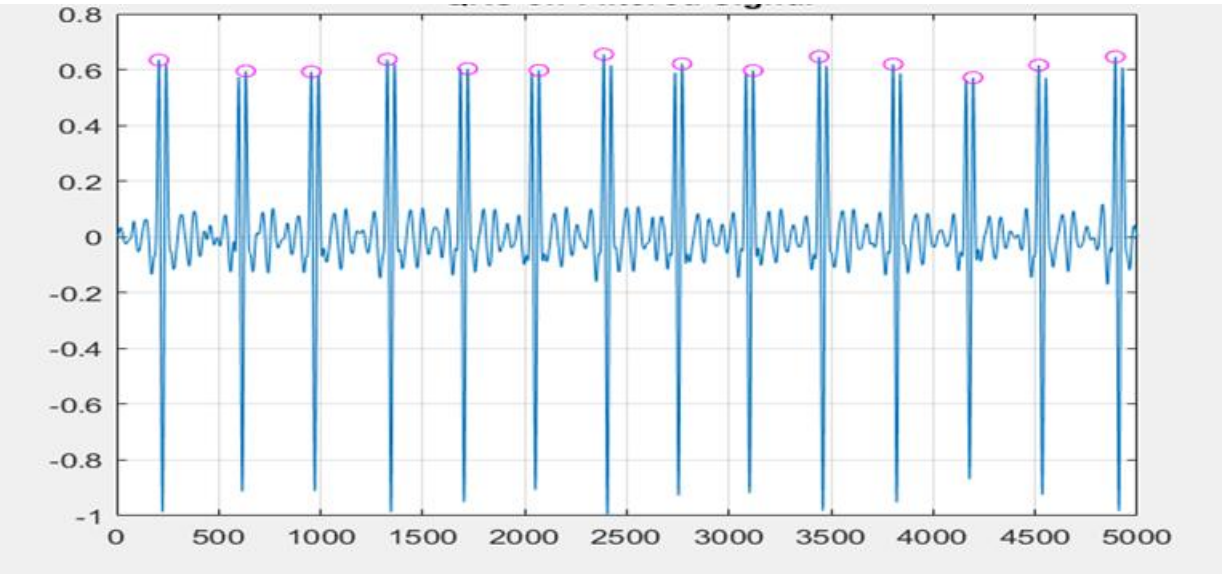


Figure 5: QRS on Filtered Signal

4. ECG Feature Extraction:

Any information retrieved from the heartbeat and utilized to determine its pattern may be termed a feature. The quality of feature extraction affects the correctness of heartbeat categorization. This stage involves transforming raw ECG signals into a set of features as it may be utilized to distinguish among various categories of heartbeats and cardiac abnormalities. Various features such as time domain features like RR intervals [21-23] and QRS Complex which detects the abnormalities in ventricular conduction. Frequency domain features by analysing frequency components of ECG signal [24-30]. Morphological features like shape. amplitude, area, inflection, and slope measured for different wave components like P-peak, Q-peak, R-peak, S- peak, and T-peak etc. computed from every single 12 lead ECG [31-32] as shown in figure 6. Statistical features duration, means, variance, skewness, standard deviation, kurtosis and amplitude modulation.

Principal Component Analysis (PCA): The ratio of eigenvalues from various intervals, such as QRS complex, ST-T Segment, J point, T subintervals, and PCA beats was calculated [40].

QRS and T Axes: Mean, earliest first 40ms, and closing final 40ms QRS axes and T axes computed in the foremost plane, parallel plane, and co-ordinate planes. Gradients and angles formed by the planes and vectors evaluated. This highlights the prominence of feature selection and classifier choice to carry out optimal interpretation in ECG analysis.

6. Performance Analysis:

Surface under ECG: Every lead in a 12-lead ECG has data that correlates to a specific spatial orientation: The limb leads I, II, and III are located on the frontal plane, while the chest leads V1 to V6 are positioned on the horizontal plane. Additionally, the augmented unipolar limb leads aVR, aVL, and aVF are also on the frontal plane.

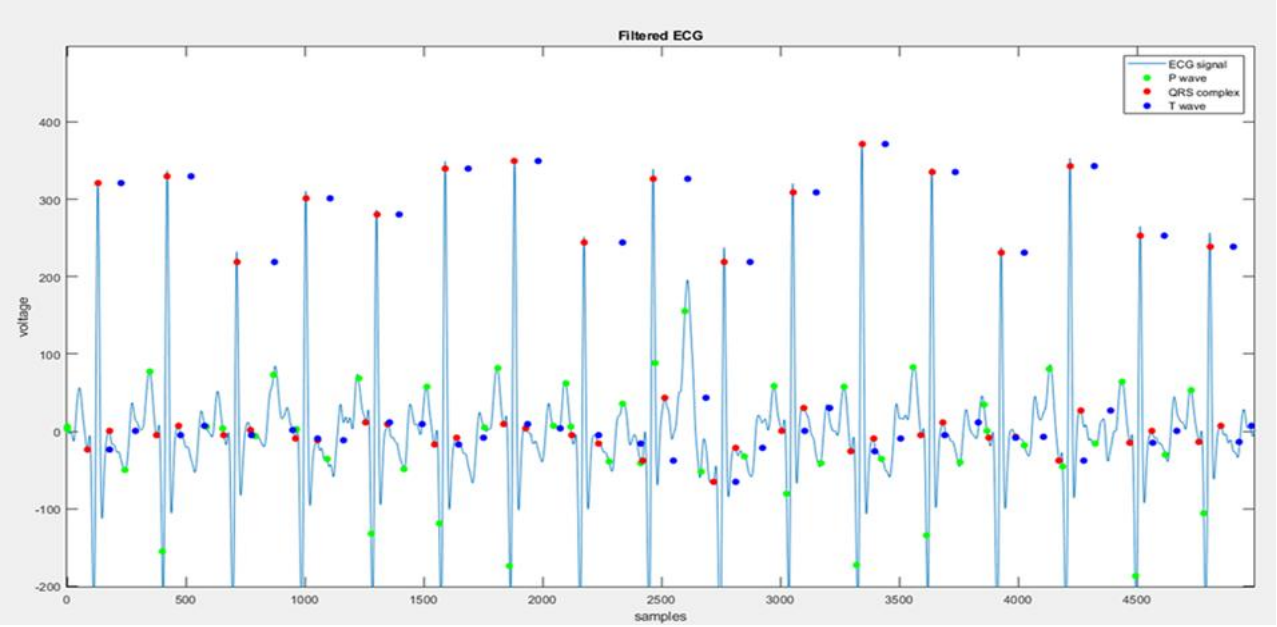


Figure 6: Filtered ECG Signal

As illustrated in figure 2, the surface under the QRS interval and ST segments were estimated using the 12-lead ECG method and the spatial information of heart's electrical activity in three orthogonal planes. The region under T-wave of ECG signal stands for the End Systolic Volume (ESV), whereas the region under the QRS segment stands for End Diastolic Volume (EDV). Trapezoidal rules were used to calculate the areas of these zones. Additionally, the volume and area were estimated using eigenvector information. Equation no. xii [56] then uses the values of End Diastolic Volume and End Systolic Volume to calculate Ejection Fraction (EF).

LVEF (%) = (SV/EDV) *100 = (EDV – ESV) / EDV*100

xiii [58]

The performance of the suggested research was assessed using a 2X2 confusion matrix for real and predicted conditions, namely True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) utilized to calculate the accuracy, sensitivity, specificity, and precision of the suggested method. Using TP, TN, FP, and FN data, the suggested algorithms accuracy, sensitivity, specificity, and precision calculated [1].

$$\text{Accuracy} = \frac{\text{True Positive(TP)+True Negative(TN)}}{\text{True Positive(TP)+True Negative(TN)+False Positive(FP)+false Negative(FN)}}$$

xiii

$$\text{Precision} = \frac{\text{True Positive(TP)}}{\text{True Positive(TP)+False Positive(FP)}}$$

xiv

Table 3: Comparison of different attributes and estimation of accuracy

Sr. No	Reference	Month and Year	Authors	Attributes	Classifier	Percentage Accuracy
1.	[3]	July 2004	Philip de Chazal, M. O'Dwyer, et.al.	Morphological, ECG Intervals	Weighted Linear Discriminant	83%
2.	[5]	January 2009	C. Li Zheng, et al.	Hybrid Beamforming and Hypothesis	Weighted Linear Discriminant	90%
3.	[6]	July 2011	M.L. Soria, J.P. Martinez,	ECG Intervals, Morphological Hypothesis, Hybrid Beamforming Coefficients	Weighted Support Vector Machine	83%
4.	[7]	April 2010	G.de Lannoy, Damien Francois, et al.	RR Intervals, Morphological, VCG, FFS (forward feature Selection),	Hierarchical Support Vector Machine	85 %
5.	[8]	September 2011	K.S. Park, et al.	Morphological features, + Temporal and Statistical features + SFFS	Weighted Linear Discriminants Multi-Layer Perceptron	89%
6.	[9]	2011	Tanis Mar, Sebastian Zaunseder, et.al.	Morphological, ECG segments, RR Intervals, Hybrid Beamforming and Hypothesis	Weighted Conditional Random Fields	85%
7.	[10]	2014	Zhancheng Z., Jun Dong	Morphological, ECG Intervals, R-R Intervals, and segments	Combined Support Vector Machine	86%
8.	[12]	March 2014	M Llamedo Soria, JP Martínez et.al.	Morphological Wavelet, RR Intervals, PCA and ICA	Support Vector Machine	86.4%
9.	[25]	14 February 2013	Can Ye, Miguel Tavares Coimbra,	Morphological features, Dynamic	Random Selection	96.5%

10.	Presented research	Time Domain features, Morphological features, R-R Intervals,	Support Vector Machine (SVM)	98.4%

$$\text{Sensitivity} = \frac{\text{True Positive(TP)}}{\text{True Positive(TP)+False Negative(FN)}}$$ xv

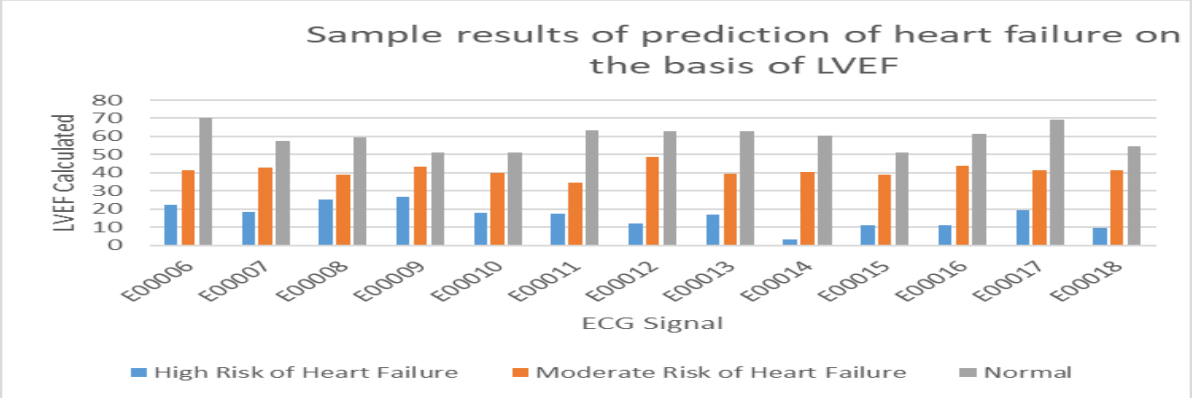
$$\text{Specificity} = \frac{\text{True Negative(TN)}}{\text{True Negative(TN)+False Postive(FP)}}$$ xvi

5. Standard Database

Standard Database: To provide an unbiased comparability of various approaches, a standard, well-annotated database is required. This helps in providing a uniform benchmark for evaluating the performance of various algorithms. For proposed research we have used PhysioNet Georgia 12 Lead ECG Database.

7. RESULTS

The performance of proposed research evaluated for the 300 number ECG signals and achieved 98.4 % accuracy, 97% Sensivity, 98.6 % specificity and 95 % Precision.



6 DISCUSSIONS

The proposed research obtained a striking accuracy 98.4%, exceeding the available low accuracy rate methodologies which employs the Weighted Linear Discriminants, Hierarchical Support Vector Machine and
Weighted Conditional Random Field
The findings highlight the significance of right feature selection improves the classification accuracy and overall performance Previous approaches utilize Hybrid Beamforming, PCA, and ICA yield strong results; however, combining morphological wavelet features which increases the model's effectiveness and stability
12 Lead ECG PhysioNet Georgia Database utilized for benchmarking, for the validation 300 ECG signals used
for evaluation which remains impartial. This method achieves a sensitivity of 97% and a specificity of 98.6%,
reinforce its reliability for real-world use. Although the model achieves remarkable accuracy, certain challenges persist. Further research is needed to enhance its adaptability across diverse datasets, address the computational demands of SVM-based classification, and mitigate its reliance on specific features.
Future advancements will focus on integrating deep learning, exploring hybrid classifier techniques, and conducting broader dataset evaluations to improve scalability and adaptability This study plays a vital role in the continuous progress of ECG classification, laying a strong groundwork for future breakthroughs in clinical diagnostics and automated signal analysis.

7. CONCLUSIONS

The proposed research developed a non-invasive method which is capable to calculate LVEF (Left Ventricular Ejection Fraction) a highly predictive marker of acute coronary syndrome in cases where electrocardiography is not readily accessible. This method is structured around analysing the area under T- wave and the region under QRS segment. The proposed technique can effectively detect and categorize ECG beats as NSVAIB, PAC, PVC, LBBB, RBBB, IRBBB, LVH, SA, SB, Stach, LAD, RAD, PR (prolonged PR interval), LQRSV (low QRS voltage), IAVB, LAnFB (Left Anterior Fascicular Block), Tinv, and VPB (Ventricular Premature Beats). The research utilized the 12 Lead ECG Georgia Database for this purpose.

The performance of proposed research evaluated for the 300 ECG signals and achieved 98.4 % accuracy and 97% Sensivity. These findings indicate that the Support Vector Machine (SVM) classifier could be valuable in examining cardiac irregularities. Additionally, the SVM classifier effectively categorizes ECG beats using discrete wavelet transform (DWT) characteristics extracted from ECG signals.

REFERENCES

[1] Shende, S. M., Shrivastava, P. C. et.al., (2024). "Detection of ECG Wave Components for the Prediction of Acute Coronary Syndrome - Brief Survey". International Journal of Intelligent Systems and Applications in Engineering, 12(17s), 151–162.
[2] Mohammad Alhamaydeh, MD et. Al., "Identifying the most important ECG predictors of reduced ejection fraction in patients with suspected acute coronary syndrome" Journal of Electrocardiology 61 (2020) 81–85
[3] P. de Chazal, et al., "Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features", IEEE Trans. Biomed. Engineering 51 (7) (2004) 1196–1206.
[4] J. Pan, et al., "A Real-Time QRS Detection Algorithm", IEEE Trans. Biomedical Engineering 32 (3) (1985) 230–236.
[5] C. Li Zheng, et al. "Detection of ECG Characteristic Points Using Wavelet Transforms", IEEE Trans. Biomedical Engineering 42 (1) (1995) 21–28.
[6] M.L. Soria, J.P. Martinez, "Analysis of Multidomain Features for ECG Classification",
[7] G. de Lannoy, et al., "Weighted SVMS and Feature Relevance Assessment in Supervised Heartbeat Classification", in Biomed. Engg. Systems and Technologies 2010, pp. 212–223.
[8] K.S. Park, et al., "Hierarchical Support Vector Machine-Based Heartbeat Classification using Higher-Order Statistics and Hermite Basis Function", in Computer Cardiology., 2008, pp.229–232
[9] T. Mar, et al., "Optimization of ECG Classification by Means of Feature Selection", IEEE Trans. Biomedical. Engineering 58 (8) (2011) 2168–2177.
[10]Z. Zhang, et al., "Heartbeat Classification Using Disease-Specific Feature Selection", Computer. Biol. Med. 46 (2014) 79–89.
[11]Z. Zhang, et al., X. Luo, "Heartbeat Classification using Decision Level Fusion", Biomedical. Engineering Letter 4 (4) (2014) 388–395.
[12]M. Llamedo, J.P. Martí Nez, "Heartbeat Classification using Feature Selection Driven by Database Generalization Criteria", IEEE Trans. Biomedical Engg. 58 (3) (2011) 616–625.
[13]C. Ye, et al., "Combining General Multi-Class and Specific Two-Class Classifiers for Improved Customized ECG Heartbeat Classification", International Conference on Pattern Recognition 2012, pp. 2428–2431.
[14]D. Zhang, "Wavelet approach for ECG Baseline Wander Correction and Noise Reduction", IEEE Engineering in Medicine and Biology Society 2005, pp. 1212–1215
[15]Y. Bazi, et al., Malek, "Domain Adaptation Methods for ECG Classification", in International Conference on Computer Medical Applications), 2013, pp. 1–4.
[16]V.X. Afonso, et al., "ECG Beat Detection Using Filter Banks", IEEE Trans. Biomedical Engineering 46 (2) (1999) 192–202.
[17]J. Pan, et al., "A Real-Time QRS Detection Algorithm", IEEE Trans. Biomedical Engineering 32 (3) (1985) 230–236.
[18]S. Kadambe, et al., "Wavelet Transform-Based QRS Complex Detector", IEEE Trans. Biomedical Engineering 46 (7) (1999) 838–848.
[19]Y. Jung, et al., "Detecting and Classifying Life-Threatening ECG Ventricular Arrhythmias using Wavelet Decomposition", in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Vol. 3, 2003, pp. 2390–2393
[20]P. Laguna, et al., "Automatic Detection of Wave Boundaries in Multi-Lead Signals Validation with the CSE Database", Computer Biomed. Res. 27 (1) (1994) 45–60.
[21]J.S. Sahambi, et al., "DSP based ST-Segment Analysis the Wavelet Approach", in Southern Biomedical Engineering Conference, 1997, pp. 455–457
[22]T.P. Exarchos, et al., "A Platform for Wide-scale Integration and Visual Representation of Medical Intelligence in Cardiology the Decision Support Framework, Computer. Cardiology (2005) 167–170
[23]T.P. Exarchos, et al., "A Methodology for the Automated Creation of Fuzzy Expert Systems for Ischemic and Arrhythmic Beat Classification Based on a Set of Rules obtained by a Decision Tree", Artificial Intelligence Med. 40 (3) (2007) 187–200.
[24]R.G. Kumar, et al., "Investigation and Classification of ECG Beat using Input-Output Additional Weighted Feed-Forward Neural Network", in International Conference on Signal Processing, Image Processing & Pattern Recognition 2013, pp. 200–205.
[25]C. Ye, et al., "Arrhythmia Detection and Classification Using Morphological and Dynamic Features of ECG Signals", in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2010, pp. 1918–1921.

[26]C.-C. Lin, et al., Heartbeat classification using normalized RR intervals and morphological features, Math. Problem Eng. 2014 (2014) 1–11.
[27]G. Doquire, et al., "Feature selection for interpatient supervised heart beat classification", Comput. Intell. Neuroscience 2011 (2011) 1–9.
[28]F. Castells, et al., Principal component analysis in ECG signal processing, EURASIP J. Appl. Signal Process. 2007 (1) (2007) 98.
[29]R. Ceylan, Y. Özbay, Comparison of FCM, PCA and WT techniques for classification ECG arrhythmias using artificial neural network, Expert Syst. Appl. 33 (2) (2007) 286–295.
[30]J. Kim et al., "Robust Algorithm for Arrhythmia Classification in ECG using extreme Learning Machine" BioMed Eng. 8(1) (2009) 1-12
[31]M. Sarfraz, A.A. Khan, F.F. Li, using independent component analysis to obtain feature space for reliable ECG arrhythmia classification, IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2014, pp. 62–67.
[32]B.M. Asl, et al., "Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal", Artificial Intell. Med. 44(1) (2008) 51–64.
[33]H. Huang, et al., "A New Hierarchical Method for Inter-Patient Heartbeat Classification using Random Projections and RR Intervals", Biomedical Engg. Online13 (2014) 1–26.
[34]I. Güler, et al., "ECG beat classifier designed by combined neural network model", Pattern Recogn. 38 (2) (2005) 199–208
[35]A.L. Goldberger, et al., Physio bank, physio toolkit, and physionet: Components of a new research resource for complex physiological signals, Circulation 101 (23) (2000) 215–220
[36]C. Ye, V. Bhagavatula, et al., "Heartbeat Classification using Morphological and Dynamic Features of ECG Signals", IEEE Trans. Biomed. Eng. 59 (10) (2012) 2930–2941.
[37]J.A. Nasiri, et al., "ECG Arrhythmia Classification with Support Vector Machines and Genetic Algorithm", IEEE European Symposium on Computer Modeling and Simulation, 2009, pp. 187–192.
[38]K. Polat, et al., "Detection of ECG Arrhythmia Using a Differential Expert System Approach based on Principal Component Analysis and Least Square Support Vector Machine", Appl. Math. Computer. 186 (1) (2007) 898–906.
[39]G. de Lannoy et al., "Feature Selection for Interpatient Supervised Heartbeat Classification", Computer. Intell. Neurosci. 2011 (2011) 1–9.
[40]V. Mahesh, et al. "ECG arrhythmia classification based on a logistic model tree", J. Biomed. Sci. Eng. 2 (6) (2009) 405–411
[41]Y.-C. Yeh, et al., "Analysing ECG for Cardia Arrhythmia using Cluster Analysis", Expert Syst. Appl. 39 (1) (2012) 1000–1010.h
[42]D.A. Coast, et al. "An approach to Cardiac Arrhythmia analysis using Hidden Markov Models", IEEE Trans. Biomed. Eng. 37 (9) (1990) 826-836
[43]P.R. Gomes, et al., "ECG Data-Acquisition and Classification system by using Wavelet-Domain Hidden Markov Models", in Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2010, pp. 4670–4673.
[44]C.M. Bishop, "Pattern Recognition and Machine Learning", 1st ed., Springer, 2006.
[45]M.A. Escalona-Moran, et al., "Electrocardiogram Classification using Reservoir with Logistic Regression", IEEE J. Biomed. Health Inform. 19 (3) (2015) 892–898
[46]M.G. Tsipouras, et al. "Arrhythmia Classification using the RR-interval Duration Signal", in Computer. Cardiology 2002, pp. 485–488
[47]ANSI/AAMI, Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms, American National Standards Institute, Association for the Advancement of Medical Instrumentation (AAMI), ANSI/AAMIISO EC57, 1998-(R)2008,
[48]M. Llamedo, J.P. Martinez, "An Automatic Patient-Adapted ECG Heartbeat Classifier Allowing Expert Assistance", IEEE Trans. Biomed. Eng. 59 (8) (2012) 2312–2320.
[49]N. M. Arzeno, et al., "Analysis of First-Derivative based QRS Detection Algorithms," IEEE Transactions on Biomedical Engineering, vol. 55, pp. 478-484, 2008.
[50]S. Rekik et al., "Enhanced and Optimal Algorithm for QRS Detection," IRBM, vol. 38, pp. 56-61, 2017.
[51]L. D. Sharma et al., "A Robust QRS Detection using Novel Pre-processing Techniques and Kurtosis based Enhanced Efficiency Measurement", vol. 87, pp. 194-204, 2016.
[52]P. Phukpattaranont, "QRS Detection Algorithm based on the Quadratic Filter", Expert Systems with Applications, vol. 42, pp. 4867-4877, 2015.
[53]Y. Li, et al., "A novel approach to phase space reconstruction of single-lead ECG for QRS complex detection", Biomedical Signal Processing and Control, vol. 39, pp.405-415, 2018.
[54]Chavate S, et, al., (2023) Hybridized Neural Network Based Approaches Used for Video Shot Boundary Detection. Indian Journal of Science and Technology. 16(33):2670-2680.
[55]Radovan Smiseket.al., "Cardiac Pathologies Detection and Classification in 12-lead ECG" Computing in Cardiology 2020; Vol 47.171
[56]Razavipour F, Nikoo MH, Abtahi F (2015) "Numerical Estimation of Ejection Fraction from 12-lead ECG". J Bioengineer & Biomedical Sci 6: 172. 1000172
[57]Mangesh Dadarao Shende et al., "RSM and ANN Modeling Techniques to Forecast How Various Parameters will Affect the Improvement of Electronics Cooling using Radial Heat Sink." Advances in Nonlinear Variational Inequalities ISSN: 1092-910X Vol 27 No. 2 (2024) 650
[59]Kosaraju A, Goyal A, Grigorova Y, et al. Left Ventricular Ejection Fraction. [Updated 2023 Apr 24]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2024 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK459131/

S. Chavate and R. Mishra, "An Efficient Approach for Shot Boundary Detection in Presence of Illumination Effects using Fusion of Transforms," Int. J. Eng. Trends Technol., vol. 70, no. 4, pp. 418–432, 2022, doi: 10.14445/22315381/IJETT-V70I4P236.

[60] S. Chavate and R. Mishra, "Efficient Detection of Abrupt Transitions Using Statistical Methods, ECS Trans., vol. 107, no. 1, pp 6541–6552, 2022, doi: 10.1149/10701.6541ecst.

[61] S. Chavate and R. Mishra, "A comparison of different procedures for hardware-based video shot boundary detection," Adv. Image Data Process. using VLSI Des. Vol. 1, vol. 1, pp. 1–15, 2021, doi: 10.1088/978-0-7503-3919-3ch14.