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Support Vector Machine based Classification of the ECG Arrhythmia Disease Patterns

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Abstract: Recently, ECG signals—records of the electrical activity of the heart—was used to classify the patterns of various cardiac diseases. The goal of the study is to use SVM based machine learning (ML) and the selected QRS feature set to detect distinct ECG disease patterns. Knowledge about the recognized QRS wave peaks are used as a standard further for classification. The basic recommended method successfully locates the ECG signal peaks for said Q, R, and S peaks in circumstances involving ECG HRV variability. SVM classifiers are applied over the time domain QRS peaks. The visual results demonstrate the ECG's ability to detect QRS in the absence of artifacts. Also validated is peak detection for the ECG APB pattern.

Keywords: ECG Classification, Arrhythmia, QRS Complex, Peak Detection, Machine Learning.

I. INTRODUCTION

This study aims to compare the effectiveness of different support vector machine (SVM)-based classifiers. Classifying the ECG patterns as sinus rhythm normal rhythms (NSR), atrial premature beats (APB) complexes beats, atrial flutter (AFL), an example of arrhythmia, and indeed the MIT arrhythmia databases are the objectives. The extraction of features from the ECG data is proposed to be done using the suggested peak detection approach. The crucial step that contributes to the classification algorithms' increased accuracy is feature extraction. The process of classifying patterns proceeds sequentially. For the purpose of presenting ECG data patterns, the initial ECG peak detection is confirmed for QRS peak detection. The second section presents ECG extraction of features employing peak detection. Lastly, multiple classification techniques for ECG pattern recognition are contrasted.

Analyzing electrocardiogram (ECG) data is essential for treating variety of disorders. Heart diseases cause a variety of heart rate variations (HRV), which in turn lead to diverse ECG patterns.

Recognizing and retaining the QRS complex is one of the most important steps in the processing of ECG data [1]. The R wave is essential for determining aberrant cardiac rhythms and assessing variations in the typical heart rate (HRV). The basic peak detection approach is used to extract the temporal time-series data features.

It is suggested in this explanation to utilize machine learning (ML) for distinguishing different ECG illness patterns by using chosen feature set. The specifics of the QRS waves' identified peaks are extracted and utilized as

features for additional classification. The purpose of a QRS ECG heartbeat is described, and the showman process is described. Figure 1.

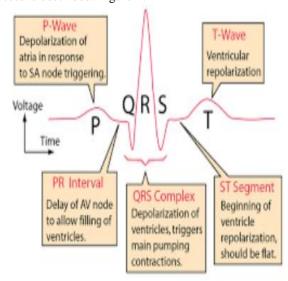


Fig.1.The function's description of the QRS ECG pulse

Although ther are many heart patterns in this paper the one specific case of the heart pattern is used for the classification this pattern is found in specially in BP pattients and is critical.

AFL: Atrial flutter (AFL) which starts inside the atrial heart chambers, is a common cause of abnormal cardiac rhythm. It is categorised as a form of supraventricular and thus is typically accompanied by a rapid heartbeat when it first manifests. Those who have AFL experience their heart beating both unusually quickly and consistently. The example of the database signals consder for the ECG of AFL data are shown in the Figure 2. Below.

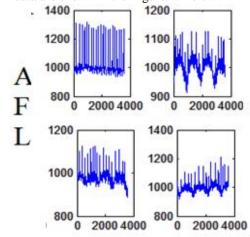


Fig.2. The representatioion of the AFL ECG data used for



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the classifcation

The normal EGG data

Figure 3 depicts the waveform characterization of normal EGG receive the results in relation to a healthy man's heart. It is evident that the ECG signal for a healthy human has a set rhythm and that all of the QRS waves occur at the same time. Yet, these waves' characteristics and pattern changed when the HRV was present. Thus, further study is necessary.

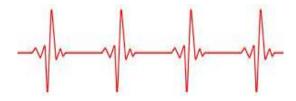


Fig.3 Examples of Normal EGG signal waves

II. LITERATURE REVIEW

The various researches in the field of ECG peak detection and classification are summarized and is s tabulated in the Table 1. The various features of ECG are mentioned in Table.

Table 1 Summary of the ECG Survey and Methodologies

S. No	Author's Name	Methodology	Evaluation Parameter	
1	S. Karpagachelvi et. al [1]	Presented various Feature extraction methodologies from ECG data. Such as SVM and ANN.	Performance is measured based on the range of Simplicity Accuracy and Productivity	
2	Sumanta Kuilar et al [3]	The proposed to perform the biometric recognition system based on feature extraction on P-QRS-T signal ECG which processes the raw ECG signal.	Accuracy achieved 95.245%, Specificity, true positive 81.361%, Recall, Precision	
3	Jeong-Hwan kim et al [4]	Propose R-peaks in ECG can be automatically detected with the high accuracy of more than 98% with the NN use of ADALINE network.	Accuracy, Specificity, true positive. True negative's	
4	Gorav Kumar Malik et al [5]	proposed detection of arrhythmias in ECG signals using feature Extradition as well as SVM learning	The clinical decision accuracy must be on as high as possible. The features are based on the PR Interval, ST Interval D,. QT Interval, TP Interval, HRV, and Energy	
5	Dr. M. Anto Bennet et al [7]	The creation of a cardiac diseases classification method and real-time portable ECG monitoring system	Using time and frequency based features set. As low frequency component (LF) index ratio LF/HF Power Spectral Density (PSD), time domain HRV	
6	Apurva Kulkarni, et al [9]	The Pan Tompkins method was used to detect R peaks.	For both pathological and normal cases, several statistical as well as morphological features were identified features used are R-R interval, HRV, mean, variance, median, skewness, and kurtosis	
7	Carlos Lastre- Dom- nguez et al [10]	Have used unbiased finite impulse response (UFIR) filter	The performance is evaluated using P-wave, QRS-complex, and T-wave; Accuracy of SVM is used as performance measure. SNR and MSE estimation is used for parameter performance	
8	Jannah N. et al [14]	The proposed work provides a useful methodology for multi-lead ECG analysis and classification of arrhythmia conditions based on CSVM classification following DFT signal pre-filtering.	The advantage of CSVM over standard SVM in simultaneously detecting different types of arrhythmias on the basis of multi-lead recordings following signal compression in the Fourier domain. Implementation of the algorithms was performed in MATLAB. The CSVM classification algorithm provided.	



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III. VALIDATION OF PEAK DETECTION

Performance of our proposed ECG QRS Peak detection algorithm is validated and this chapter presented results of peak detection for different ECG data bases. In order to compare and validate the performance the modified Pan Tomkins based statistical time domain R-R interval parameters are compared with proposed optimum filter based ECG peak detection method. The R wave peaks will be further used to measure critical statistical features as heart rate variability (HRV) parameters viz. NN50, SDNN and heart rates.

The proposed method of peak detection as already descried is findings of our proposed optimum IIR filter based on Hilbert and Wavelet transformation approaches with combination of HRV based classification. The Chapter presents results validation of statistical parameters on the four different ECG data bases.

Proposed Peak detection

Both the diagnosis of illnesses and the calculation of the variability of heart rates (HRV) depend on the QRS peak detection (HRV). The chronological recorded analysis has a substantial impact on the suggested method for HRV peak detection; The MIT-BIH validated Arrhythmia ECG measurement dataset is used to categorize the ECG cardiac arrhythmias of a aberrant ECG readings.

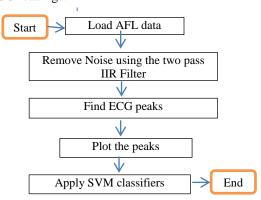


Fig.4. Flow Chart of ECG Classification

Figure 4 depicts the flow chart for the fundamental steps in the ECG categorization of AFL data. IIR filter is used for the preprocessing The absolute squared ECG signal option effectively detects the peaks.

Expected Result of EEMD Decomposition

Results for filter verification are displayed across the AFL based ECG databases four cases are labeled as shown in the Figure 5. It is evident that the suggested filter is effective for all types of ECG data. On a specific dataset of 15 cases, the IIR based filter base line pondering problem has been validated. The results of the Q R S Peak detection testing and validation for the

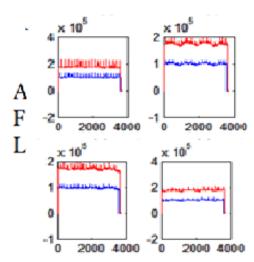


Fig.5 The results of the ECG AFL data IIR filtering

additional ECG rhythms AFL are shown in Figure 6.AFL 202 (0) (0). Mat are taken into account at random when plotting the findings.

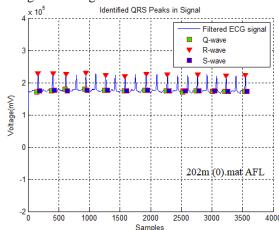


Fig.6.ECG peak detection results for AFL data

Table 2 Features extracted for AFL data

Category	True Mean mu	Filtered Mean	RR	RMSSD
AFL	916.5013	1398.572	0.494286	15.7211
AFL	925.3077	1412.662	0.525	15.09511
AFL	913.6464	1394.806	0.524714	22.91934
AFL	940.1826	1435.354	0.497286	19.69668

The SVM based classifiers are applied using the extracted features sets.

Table 3 Classification Efficiently for SVM classifiers



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IV. CONCLUSIONS AND FUTURE SCOPE

This work presents a novel approach for classifying and identifying QRS peaks in ECG signals. In this research, it is proposed to develop and assess ECG signal classification methods for the classification of cardiac problems on the basis of the arrhythmia database. The suggested technique for categorizing and identifying QRS peaks is simple and suitable for use in real-time applications.

The results of the Q R S Peak detection testing and validation for the additional ECG rhythms AFL the IIR filter is used for processing and the SVM classifier efficiency on AFL is found to be 95 %.

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Linear SVM	90.50%	
Quadratic SVM	92.50%	
Cubic SVM	95.20%	