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Designing Efficient Multi-Class ML based ECG Arrhythmia Patterns Classification and Feature Extraction Approach

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Abstract: *This study presents a novel approach for multiclass electrocardiogram (ECG) arrhythmia classification using machine learning techniques. The proposed method employs the Pan-Tompkins algorithm for preprocessing and noise removal, followed by the extraction of time-domain features such as NN50, SDNN, mean heart rate variability (HRV), and root mean square of successive differences (RMSSD). These features are then used to train and evaluate the performance of support vector machine (SVM) classifiers. The study utilizes the MIT-BIH Arrhythmia ECG measurement database to classify three types of cardiac arrhythmias: normal sinus rhythm (NSR), atrial premature beat (APB), and atrial flutter (AFL). The results demonstrate that the proposed Bayesian optimization-based SVM classifier achieves the highest accuracy of 96.8%, outperforming both cubic and quadratic SVM classifiers. The optimized SVM offers a 6.5% improvement over cubic SVM and a 3.3% improvement over quadratic SVM, with a faster training speed of approximately 630 observations per second. The class-wise precision and recall analysis reveals that the optimized SVM achieves 100% precision for all three ECG classes, with a recall of 100% for NSR and APB, and 90.3% for AFL. The proposed method's effectiveness in accurately classifying ECG arrhythmia patterns highlights its potential for enhancing clinical decision-making processes and improving patient outcomes in cardiology*

Keywords: ECG, Peak Detection, SVM, HRV, Pan-Tompkins Algorithm, Arrhythmia Classification.

I. INTRODUCTION

Electrocardiogram (ECGs) analysis is vital for diagnosing various heart conditions, especially arrhythmias, which are irregular heartbeats that can result in serious health issues. The prompt and precise identification of arrhythmias is crucial for optimal patient treatment and care. Nevertheless, interpreting ECG signals manually is time intensive, susceptible to errors, and requires considerable expertise. To overcome these obstacles, there has been an increasing focus on developing automated systems for ECG arrhythmia classification using machine-learning techniques. This study aims to create an effective multiclass machine learning system for classifying ECG arrhythmia patterns and extracting relevant features. By utilizing cutting-edge signal processing methods and machine learning algorithms, we sought to develop a dependable and precise approach for detecting and categorizing different types of arrhythmias in ECG data. This study not only advances the field of biomedical signal analysis but also has the potential to enhance clinical decision-making processes and improve outcomes for cardiology patients.

Analyzing irregular ECG patterns to categorize cardiac arrhythmias offers crucial information regarding various heart rhythm abnormalities. This technique of identifying peaks and classifying arrhythmias has the potential to facilitate early identification and management of diverse heart-related issues. Moreover, utilization of an authenticated database enhances the dependability and precision of the findings derived from this methodology. The incorporation of this HRV peak detection and arrhythmia classification system into portable devices or smartphone applications can enable ongoing cardiac monitoring. Such an implementation would allow for instantaneous identification of possible heart problems, facilitating timely medical action when required. Furthermore, the capacity of this method to differentiate

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among various arrhythmia types could assist medical professionals in developing more personalized treatment strategies for individual patients.

In recent years, substantial advancements have been made in the application of machine-learning techniques for ECG arrhythmia pattern classification. Numerous studies have explored diverse approaches to feature extraction and classification, yielding high accuracy rates. Several studies have documented successful multiclass ECG arrhythmia classification using various feature extraction methods and machine-learning algorithms. For example, groundbreaking approach utilizing multilayer feature analysis and deep learning achieved a remarkable 99.05% accuracy using a deep neural network (DNN) (Sinha et al., 2022). In another study, researchers employed the discrete orthogonal Stockwell transform (DOST) for feature extraction and an artificial bee colony (ABC) optimized twin least-squares support vector machine (LSTSVM) for classification, attaining 96.29% accuracy (Raj & Ray, 2018). Notably, some investigations have revealed that optimized traditional machine learning algorithms can surpass complex deep learning models in terms of performance. One case is a hybrid approach that combines the Manta ray foraging optimization (MRFO) algorithm with a support vector machine (SVM), achieving 98.26% accuracy (Houssein et al., 2021). Similarly, a novel feature engineering method based on deep learning and K-NNs, used in conjunction with conventional classifiers such as decision trees and SVMs, achieved 99.77% accuracy with reduced computational time (Khatibi & Rabinezhad sadatmahaleh, 2019).

Thus, it is clear that effective multiclass ECG arrhythmia classification can be accomplished through meticulous feature extraction and selection coupled with optimized machine learning algorithms. Although deep learning approaches show potential, optimized traditional machine-learning methods can also produce excellent results with lower computational demands. The selection of the method should consider factors such as the accuracy, computational efficiency, and particular characteristics of the ECG data under analysis.

II. ECG PROCESSING STEPS

The basic process involved in ECG pattern classification is illustrated in Figure 1.

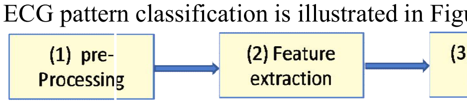

Figure 1 Basic Steps of ECG classification

At the front end, the ECG data must be preprocessed (as 1) for noise and artifact removal. \"The Pan-Tompkins algorithm plays a vital role in ECG signal processing, significantly improving the quality and reliability of electrocardiogram data. This technique is particularly important for accurately detecting QRS complexes, which are essential for evaluating heart rate variability and identifying various cardiac abnormalities. By employing digital filtering methods and dynamic threshold adjustments, the Pan-Tompkins approach effectively removes noise and artifacts from ECG signals, thereby enhancing the signal-to-noise ratio and facilitating more precise feature extraction. It is especially helpful in clinical settings because of its real-time data interpretation capabilities, which enable the quick and precise diagnosis of cardiac issues. Furthermore, the algorithm's adaptability to various ECG waveforms and its computational efficiency have made it a standard preprocessing step in many ECG analysis systems, significantly contributing to improvements in cardiac monitoring and diagnostic techniques The second step in ECG analysis is the feature extraction. Essential information regarding the morphology, duration, and amplitude of various ECG components is provided by time-domain features that are directly extracted from the raw ECG waveform.

These features include the duration and amplitude of the individual waves (P, QRS, and T), intervals between successive R-peaks (RR intervals), QT intervals, and PR intervals. These measurements are particularly important for identifying rhythm abnormalities, conduction disorders, and structural heart diseases. The computation of heart rate variability metrics, which are suggestive of autonomic nervous system function, is also made possible by time-domain analysis. Time-domain properties are particularly helpful in clinical contexts because of their ease of use and interpretability, which facilitate prompt diagnosis and evaluation. Additionally, these characteristics frequently form the basis for more intricate frequency and nonlinear domain analyses, improving the general precision and resilience of ECG classification algorithms. Heart rate variability (HRV) analysis uses time-domain features, such as NN50 and

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SDNN, to quantify variability over time. The NN50 measures the number of adjacent NN intervals differing by more than 50 ms, reflecting short-term heart rate variations. The SDNN calculates the standard deviation of all NN intervals, representing the overall HRV, including both short-term and long-term variations. These features provide insights into cardiac autonomic regulation and cardiovascular health and are defined as follows:

NN50: is number of RR peak having range > 50 ms.

SDNN: is the standard deviation of the NN50 values

Mean HRV: is defined as the average values of the heart rate variability and is defined within the range of 30 t0 90.

RMSSD: is the root mean square value of the SDNN.

$$RMSSD = \sqrt{\frac{1}{M}(diff(RR_{Region}).^{2})} \qquad (1)$$

This research has proposed to extract these ECG parameters as temporal features. The extracted features are used for the investigation of multi class ECG patterns classifications.

III. LITERATURE REVIEW

Huge research has been carried out to improve the accuracy of the ECG pattern detection. Identifying R-peaks is a vital component in analyzing ECG signals for classifying arrhythmias. Researchers have developed various techniques to accurately detect R-peaks and categorize arrhythmias. One successful approach combines wavelet multi-resolution analysis with local maximum detection and thresholding, achieving high sensitivity (99.39%) and positive productivity (99.49%) when tested on the MIT-BIH arrhythmia database (Qin et al., 2017). Another effective method employs Shannon energy envelope extraction, which demonstrated an accuracy of 99.84% and sensitivity of 99.95% using the same database (Rakshit et al., 2016). Notably, some strategies skip QRS detection altogether and instead focus on directly classifying ECG segments.

A convolutional neural network (CNN) approach attained accuracies of 92.50% and 94.9% for two and five-second ECG segments, respectively, without performing QRS detection (Acharya et al., 2017). This finding suggests that QRS detection may not always be essential for accurate arrhythmia classification. In summary, while QRS peak detection remains a crucial step in many ECG analysis techniques, researchers have developed various methods to enhance its precision and efficiency. These include wavelet-based approaches, Shannon energy envelope extraction, and even direct classification of ECG segments using deep learning techniques. The selection of a particular method depends on the specific requirements of the application, such as computational efficiency, real-time processing capabilities, and the types of arrhythmias to be identified. This section has sequentially reviewed the ECG classification based on the classification diagram given in the Figure 2.

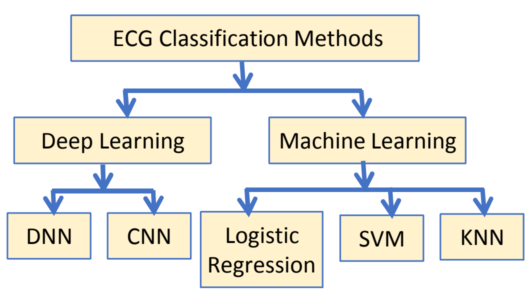

Figure 2 Method of classification of ECG patterns

For specifically address the use of K-Nearest Neighbors (KNN) for the classification of Atrial Flutter (AFL), Atrial Premature Beat (APB), and Normal Sinus Rhythm (NSR) ECG arrhythmia patterns, numerous studies have investigated various classification techniques for these arrhythmias. For instance, Kim et al. (2019) used an extended- GoogLeNet architecture to obtain 98.31% accuracy in differentiating Atrial Premature Contraction (APC) from NSR and other beats. Furthermore, utilizing a combination of Auto-Encoder and Bidirectional Long Short-Term Memory (AE-

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biLSTM), Ramkumar et al. (2022) found an overall accuracy of 97.15% for classifying AFL and NSR among other arrhythmias (Kim et al., 2019; Ramkumar et al., 2022).

Although KNN is not prominently featured for these specific arrhythmias, (Çınar & Tuncer, 2020) mentioned its use in classifying Arrhythmia (ARR), Congestive Heart Failure (CHF), and NSR signals, with an accuracy of 65.63%. This suggests that KNN, while applicable, may not be as effective as more advanced techniques like deep learning models for ECG arrhythmia classification (Çınar & Tuncer, 2020). In summary, although the papers do not directly address the classification of AFL, APB, and NSR using KNN, they indicate that more sophisticated machine learning and deep learning approaches generally yield better results for ECG arrhythmia classification compared to traditional methods. Further research could investigate the efficacy of KNN specifically for these arrhythmias and compare it with the high-performing deep learning models.

Logistic regression (LR) is a popular classification algorithm employed in ECG arrhythmia detection, known for its capacity to classify data into distinct categories by identifying patterns in labeled datasets (Zaidi & Al Luhayb, 2023). In the field of cardiac arrhythmia classification, this method has demonstrated promising outcomes across various investigations. One study revealed that logistic regression models performed optimally with unmodified ECG data, achieving high accuracy in arrhythmia classification (Seera et al., 2014). Another investigation utilizing multiple logistic regression models for predicting premature ventricular contractions (PVCs) yielded remarkable results, with 99.96% accuracy, 98.9% sensitivity, and 99.20% specificity (Mastoi et al., 2021). It is important to note, however, that ensemble-based learning models outperformed logistic regression in noisy environments (Seera et al., 2014). While logistic regression has proven effective in ECG arrhythmia classification, recent developments in deep learning techniques have shown superior performance in certain instances. For example, deep belief networks (DBN) and long short-term memory (LSTM) networks have surpassed traditional methods, including logistic regression, in classifying ECG arrhythmias (Liaqat et al., 2020; Wu et al., 2016). Nonetheless, logistic regression remains a valuable component in the array of machine learning techniques for ECG analysis, particularly in scenarios where interpretability and computational efficiency are prioritized.

The Support Vector Machine (SVM) classifier has been extensively employed in the classification of various ECG arrhythmia patterns, including Atrial Flutter (AFL), Atrial Premature Beat (APB), and Normal Sinus Rhythm (NSR). Numerous studies have showcased the efficacy of SVM in distinguishing these arrhythmias. For example, research utilizing Recurrence Quantification Analysis (RQA) features with ensemble classifiers, such as SVM-based Random Forest and Rotation Forest, attained an overall accuracy of 98.37% in categorizing NSR, AFL, and other arrhythmias (Desai et al., 2016).

An alternative method combining wavelet coefficients with multiclass SVM exhibited high classification accuracies for diverse ECG beats, encompassing NSR and atrial fibrillation (Übeyli, 2006). Notably, some investigators have delved into hybrid approaches to enhance classification accuracy. A Hybrid Alexnet-SVM algorithm applied to ECG signal spectrograms reached 96.77% accuracy in differentiating NSR from other arrhythmias (Çınar & Tuncer, 2020). Furthermore, an innovative deep learning-based algorithm integrating a long short-term memory (LSTM)-based auto-encoder network with SVM yielded remarkable results, achieving average accuracy, sensitivity, and specificity of 99.74%, 99.35%, and 99.84%, respectively, for classifying various heartbeat types including NSR and atrial premature complexes (Hou et al., 2019). The SVM-based methodologies have demonstrated promising outcomes in classifying AFL, APB, and NSR ECG arrhythmia patterns. The combination of SVM with other techniques, such as wavelet transforms, deep learning architectures, and ensemble methods, has further improved classification performance. These advancements contribute to more precise and efficient automated ECG analysis, potentially enhancing cardiac disorder management and early diagnosis.

Avilar Soni recently (2023) has presented use of SVM based classifier to classify normal and the AFL ECG patterns and have achieved maximum accuracy of 95.20 %. Hemant Amhia et al (2021) have used the optimal IIR reduced order filter for the ECG abnormality classification. They opted to QRS peaks detection/and pan Tompkins approach for their work. Sara et al (2019) have proposed detection of the atrial fibrillation (AFIB) and have used spectral features and achieved accuracy of 93.16 %.

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IV. PROPOSED ECG PROCESSING BLOCK DIAGRAM

In order to diagnose illnesses and measure heart rate variability (HRV), it is essential to detect QRS complexes. The sequential recorded analysis is a key component of the currently advised method for HRV peak detection. Researchers use the MIT-BIH verified Arrhythmia ECG measurement database to classify cardiac arrhythmias in aberrant ECG readings.

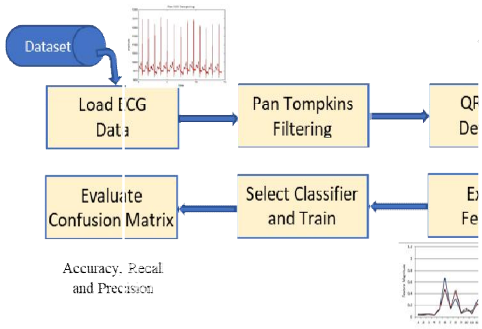

Figure 3 ECG Peak Detection Block Diagram

The Figure 3 illustrates the proposed system diagram of processing and classifying electrocardiogram (ECG) signals. It begins with loading the ECG data, which is then processed using the Pan-Tompkins algorithm. The algorithm detects QRS complexes, which are crucial for determining heart rate and rhythm.

Relevant features are extracted, and a machine learning model is selected and trained using these features. The performance of the trained classifier is evaluated using a confusion matrix, providing insights into its effectiveness in classifying ECG signals.

4.1 Proposed Preprocessing Pan Tompkins Method.

Over the R-R intervals, heart rates are monitored in beats per minute. This study's main objective is to demonstrate how using a Pan Tompkins filter design can enhance the ECG classifier performance. The algorithm of the Pan Tompkins method implementation proposed filter uses 32 order Low and high pass filter (LPF/HPF) and 4 point derivative band pass filter for base line noise removal. Accurate filtering is responsible for beater peak detection.

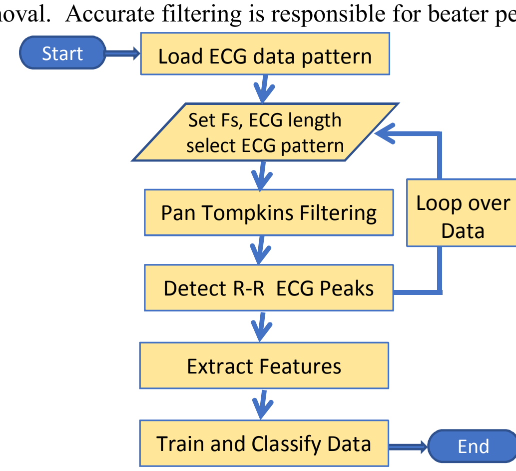

Figure 4 Flow chart of ECG pattern classification

4.1 Proposed Peak detection method.

The identification of QRS peaks is essential for calculating heart rate variability (HRV) and diagnosing illnesses. The proposed method for detecting HRV peaks is significantly influenced by the sequential recorded analysis. To categorize cardiac arrhythmias from abnormal ECG readings, the MIT-BIH certified Arrhythmia ECG measurements database is utilized. Figure 4 illustrates the workflow of the suggested approach.

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The proposed design flow algorithm for the ECG classification is shown in the Algorithm 1

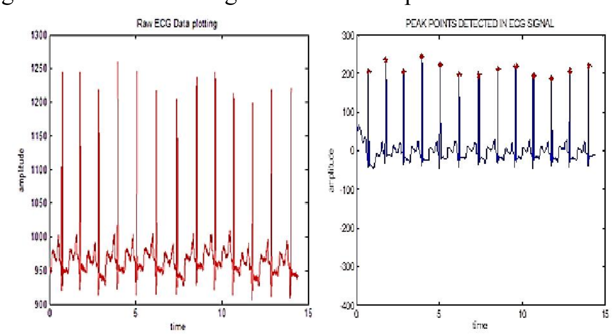
Algorithm 1: ECG Pattern Classification
Load ECG data ← $ECG(t)_i$ and select desired ECG
Select suitable sample frequency Fs,
Loop over no of ECG signals in selected data
for i=1:lrngth(ECG)
Pan Tompkins Filter
Apply 32 order LPF ← $[b_1 a_1,]$ as coefficients
Apply 32 order HPF. ← $[b_h a_h,]$ as coefficients
Apply 4 point Derivative Filter ← $[\frac{-1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{-1}{4}]$
Apply average filter
Peak detection RR(t), among R-lo R
Calculate time domain features ← $NN50, SDNN, RMSSD$
end
Load feature vector and remove outlier.
Train and test the classifiers accuracy
Plot confusing matrix an evaluate
end **Algorithm**

V. RESULTS AND DISCUSSIONS

In this paper the time domain festers are extracted for the 30 ECG patterns with 10 data for each class as NSE (1), APB (2) and AFL (3).

ECG Peak Detection

The results of the extraction of ECG peaks are given in the Figure 5. It can be clearly observed after proper filtering the proposed method is capable of detecting the R peaks accurately. The accurate detection of R peaks is crucial for various ECG analysis tasks, including heart rate variability assessment and arrhythmia detection. Furthermore, the proposed method demonstrates robustness in the presence of noise and artifacts commonly encountered in real-world ECG recordings. This improved peak detection performance can potentially enhance the reliability of automated ECG interpretation systems, leading to more accurate diagnoses and better patient care.



a) Input ECG data b) detected R Peaks

Figure 5 Results example of the R peak detection using the pan Tompkins filtering approach

Feature extraction

The extracted SDNN and RMSSD features are shown in Figure 6. It is clear that for APB the SDNN reduces while for AFL values increases representing the contraction expansion of pattern.

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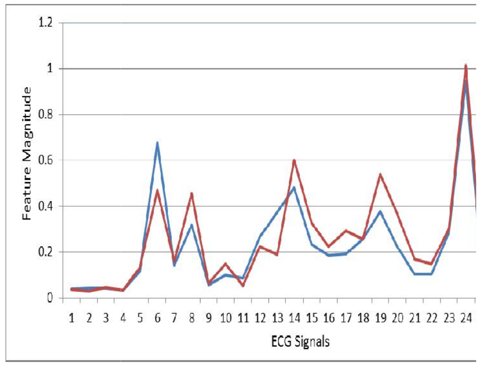


Figure 6 Results of the Statistical Feature Extraction for multi class ECG data with peak detection

The results of the extracted HRV values corresponding to each ECG pattern are illustrated as bars plot in Figure 6. It can be observed that for APB beats and AFL the HRV values significantly increases and representing the risk of disease.

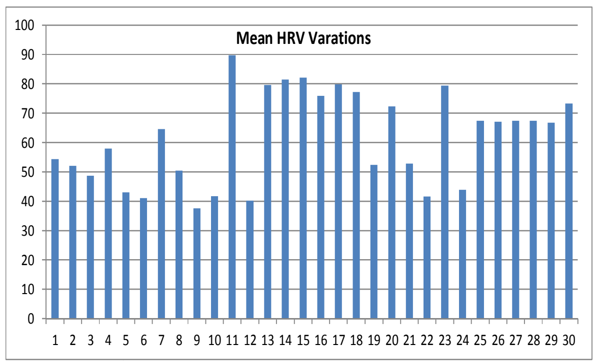


Figure 7 bar representation of the HRV calculated from the R peak Detections

These features are used for testing and performance evaluation of the classification accuracies. Precision ad recall refined as follows;

$$Accuracy = A_{CC} = (T_P + T_N)/(T_P + T_N + F_P + F_N) \quad (1)$$

$$\text{Precision} = P_{rec} = (T_P)/(T_P + F_P) \quad (2)$$

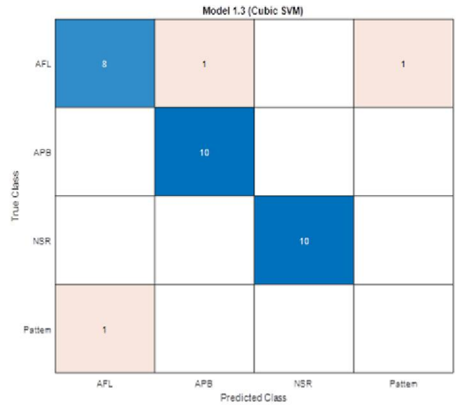
$$Recall\ (Sensitivity) = R_{ec} = (T_P)/(T_P + F_N) \quad (3)$$

Where TP: true positives, TN: True Negatives, FP: False Positive, FN: false Negative.

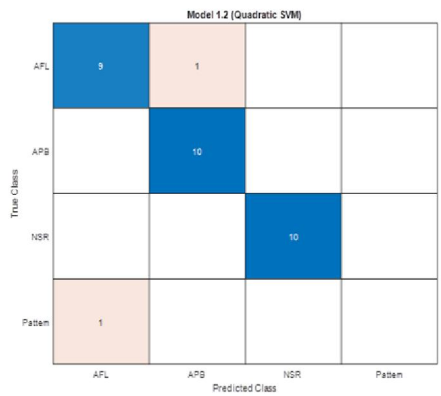
Results of ECG classification

In this research the multi class SVM based classifiers are trained using the 5 layer cross validation model. The confusion matrix evaluated the model's performance on four classes: AFL, APB, NSR, and Patterns. Research prosed using Bayesian optimization based SVM for performance improvement. The Figure 8 has presented the Confusion matrixes for SVM classifiers for ECG patterns. It can be clearly that the proposed Bayesian optimization based SVM with the 30 iterations and quadratic kernel gives the maximum possible 96.8% accuracy.

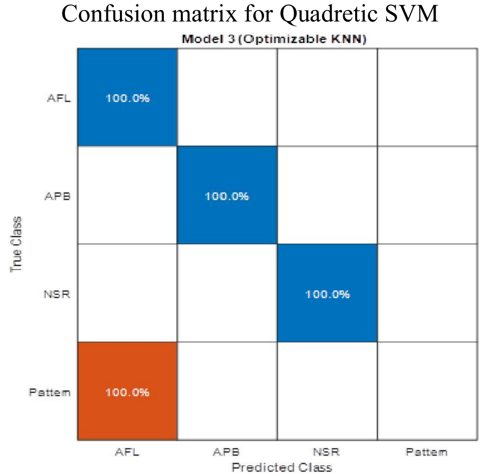
The Figure 8 a) has presented the matrix for Cubic SVM. It is clear that method has two classes as wrong predictions thus have lower accuracy. The proposed SVM classifiers performance comparison is given in the Table 1. It is clear the proposed use of Bayesian Optimization offers the lowest total cost and thus reduced the false negatives. The optimized SVM offers 6.5% improvement over Cubic SVM and 3.3% improvement over Quadretic SVM. The speed of training is also higher for optimized SVM. Although offering similar speed of training but since quadratic SVM has less total cost thus have slight edge over Cubic SVM for the problem in hand.



Confusion matrix for Cubic SVM



Confusion matrix for Quadretic SVM



Confusion matrix for Optimized SVM

Figure 8 Confusion matrixes for SVM classifiers for ECG patterns

TABLE 1: QUALITATIVE PERFORMANCE COMPARISON OF SVM CLASSIFIERS

ECG classes	Accuracy	Speed	Total cost
Cubic SVM	90.3%	~480 obs/sec	3
Quadretic SVM	93.5%	~480 obs/sec	2
Optimized SVM	96.8%	~630 obs/sec	1

The qualitative performances of the class wise precision and recall for the optimized SVM are given in the Table 2.

TABLE 2: QUALITATIVE PERFORMANCE COMPARISON OF OPTIMIZED SVM CLASSIFIERS

ECG classes	Precision	Recall
NSR	100%	100%
APB	100%	100%
AFL	100%	90.3%

From the Table 2 it can be observed that proposed optimized SVM offers 100% Precision but for the worst case of AFL ECG class the recall is reduced to 90.3% due to one false deception.

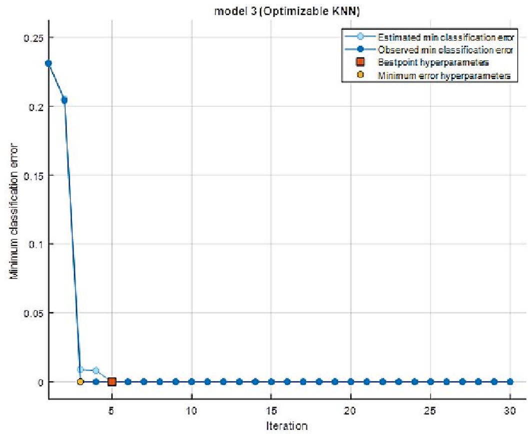


Figure 9 estimation and training error for optimized SVM classifier

The estimation error for the classifier for optimized SVM for each iteration is given in the Figure 9. The lower the error better the classifier accuracy the optimal minimum error is achieved at the 9th iteration itself and is of the order of nearly zero. This signifies that maximum classification accuracy can be achieved.

TABLE 3: STATE OF ART ACCURACY PERFORMANCE COMPARISONS

ECG classes	Method/ ECG Classified	Accuracy
Aviral et al [17]	SVM is used for AFL	95.20 %.
Sara et al [19]	Deep CNN used for AFIB	93.16%
Çınar et al [8]	Hybrid Alexnet-SVM NSR,APB & AFL	96.77%
Proposed	Optimize SVM for NSR,APB & AFL	96.8%

The state of art performance comparison of various ECG pattern classification methods are presented in the Table 3. It can be observed that proposed method have slight edge in terms of Accuracy due and classified multi class problem. It is due to use of optimization and modified smoothening. The comparison of the bar chart of the state of art methods accuracies is given in the Figure 10

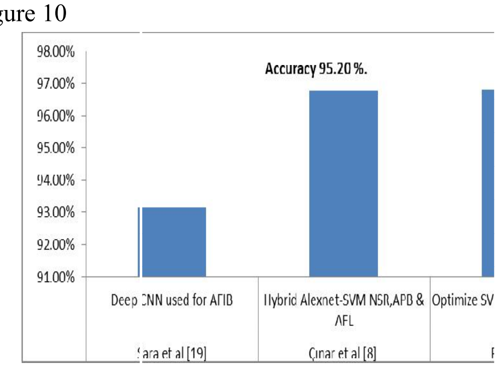


Figure 10 the bar chart representation of the state of art methods

The improvement in accuracy is clearly visible from the Figure 10 with the proposed optimizebale classifier.

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VI. CONCLUSIONS AND FUTURE SCOPES

This research introduces an innovative method for classifying multiple types of ECG arrhythmias using machine learning algorithms. The approach utilizes the Pan-Tompkins algorithm for data preprocessing and noise elimination, followed by the extraction of temporal features including NN50, SDNN, mean HRV, and RMSSD. These extracted features are then used to train and assess SVM classifiers on the MIT-BIH Arrhythmia ECG measurement database, categorizing three cardiac arrhythmia types: NSR, APB, and AFL.

It is concluded that the SVM classifier optimized through Bayesian techniques demonstrates superior performance, achieving a 96.8% accuracy rate and surpassing both cubic and quadratic SVM classifiers.

Additionally, Optimized SVM demonstrated faster training speeds, processing ~630 observations per second. A detailed analysis of class-specific precision and recall shows that the optimized SVM attains 100% precision across all three ECG classes, with perfect recall for NSR and APB, and 90.3% recall for AFL.

The effectiveness of this proposed methodology in accurately identifying ECG arrhythmia patterns underscores its potential to enhance clinical decision-making and improve cardiovascular patient outcomes.

In the coming years, larger ECG datasets could be utilized in conjunction with deep learning and neural network techniques to enhance the precision and efficiency of ECG classification. Researchers may develop customizable SVM models that can be adjusted to match individual patients ECG patterns, leading to more precise personalized diagnoses. Additionally, exploring hybrid models that combine SVM with deep learning methods such as Convolutional Neural Networks (CNNs) could potentially yield superior results in feature extraction. Incorporating time frequency features may also improve performance in future.

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