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Enhancing Atrial Flutter and Fibrillation Classification in ECG Signals: A PCA-Enabled Approach

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Abstract: *Electrocardiogram (ECG) patterns are crucial for diagnosing various heart diseases, including serious conditions like Atrial Flutter (AFL) and Atrial Fibrillation (AFib). Significant variations in the QRS complex are observed in abnormal ECG patterns, making the R wave crucial for assessing heart rate variability (HRV) and identifying abnormal cardiac rhythms. This research aims to classify AFL and AFib ECG patterns using machine learning-based tree classifiers and statistical features. The main contribution is the use of Principal Component Analysis (PCA) for the classification problem. Temporal features such as HRV, RR interval, and SDNN are extracted from the ECG database using the Pan Tomkins algorithm for QRS peak detection. The proposed method combines tree-based classifiers with PCA, achieving a high accuracy of 94.4% in distinguishing between AFL and AFib. The significance of this research lies in its potential to improve the accuracy, efficiency, and accessibility of ECG pattern classification, which could have far-reaching implications for cardiac care and early detection of serious heart conditions. The simplicity and accuracy of the classifiers suggest that the method could be implemented with lower computational requirements, potentially extending battery life in portable devices and reducing costs. Future research could explore larger ECG databases, multi-class classification, and other classifiers like SVM and KNN for further improvement in accuracy.*

Keywords*:* ECG, HRV, Atrial Flutter, Atrial Fibrillation, QRS Complex, Principle Component Analysis, SDNN, Tree Classifiers, Accuracy

I. INTRODUCTION

The analysis of the heart electrocardiogram (ECG) signals is crucial for the many disease diagnosis and treatment. There are different heart diseases causes different heart rate variability's (HRV) and thus different ECG patterns. The study emphasizes the importance of early detection of ECG patterns for patient health and disease diagnosis. Accurate and timely identification of AFL and AFib patterns could enable earlier interventions, potentially reducing the risk of complications such as stroke or heart failure. The AFL and atrial AFihave distinct ECG patterns that can be identified through careful analysis. For typical counter clockwise AFL, the ECG shows a stereotypic appearance with predictive features in most cases (Medi & Kalman, 2008). The flutter wave morphology is characterized by positive deflections in leads I, V1, and V6, coinciding with lateral right atrial wall activation. The plateau duration in lead III strongly correlates with isthmus conduction time (Ndrepepa et al., 2000). Interestingly, atypical right atrial and left AFLs may have highly variable flutter wave morphologies, sometimes resembling typical flutter or appearing focal in origin (Medi & Kalman, 2008). For AFib detection, computer-aided diagnosis using ECG data has shown promise. A hybrid approach using local mean decomposition and ensemble boosted trees classifier achieved high classification accuracy (>90%) in distinguishing between terminating and non-terminating AFib episodes (Gupta et al., 2023). Additionally, recurrence quantification analysis features applied to ensemble classifiers demonstrated high accuracy (98.37%) in differentiating normal sinus rhythm, AFib, AFL, and ventricular fibrillation (Desai et al., 2016). The advanced techniques are required to help overcome the challenges of manually inspecting complex non-linear ECG signals and provide objective, accurate classification of arrhythmias.

The interpretation and acquisition of the QRS complex is among the most important steps with in treatment of ECG signals. The evaluation of heart rate variability and the detection of aberrant cardiac rhythms both depend heavily upon that R wave (HRV). Consequences for the peak detection methodologies are used as the feature set for the classification of the ECG signals. Various methods have been developed to accurately detect and classify QRS complexes in ECG signals. Non-invasive fetal electrocardiography allows for the acquisition of valuable information about fetal well-being during pregnancy (Castillo et al., 2018). The QRS complex, being the most noticeable feature in the ECG signal, is critical for ECG signal analysis (Xiang et al., 2018). Researchers have employed different techniques for QRS complex detection and classification, including wavelet transforms, neural networks, and convolutional neural networks (CNN) (Xiang et al., 2018; Yuen et al., 2019). Interestingly, some methods focus on low computational complexity while maintaining high accuracy. For instance, a real-time QRS detection and R point recognition method with low computational complexity has been proposed, achieving high sensitivity and positive prediction rates (Chen & Chuang, 2017). Additionally, the use of few-shot learning (FSL) for ECG signal proximity-based classification has shown promising results in classifying healthy/sick patients and different disease classes (Pałczyński et al., 2022). The acquisition and analysis of the QRS complex in ECG classification involve various techniques, from traditional signal processing methods to advanced machine learning approaches. These methods aim to improve accuracy, reduce computational complexity, and enhance the generalization ability of ECG analysis systems. Combination of different techniques, such as wavelet transforms, neural networks, and entropy-based features, has shown potential in achieving optimal results for QRS complex detection and classification (Śmigiel et al., 2021).

The method of the Pan and Tompkin is proposed to modify for better baseline wondering problem to eliminated line noises.is presented sequentially. The temporal time series features are extracted using the peak detection by Pan Tompkins method. The selected feature set is proposed to classify using machine teaching (ML) the various ECG disease patterns in this research. The high accuracy of classification is suggests as a potential for developing automated ECG analysis tools. Such tools could assist healthcare providers in quickly and accurately identifying cardiac arrhythmias, potentially reducing the workload on cardiologists and improving patient care.The challenge lies in developing a method that can accurately distinguish between these critical ECG patterns, potentially enabling earlier detection and intervention for serious cardiac conditions.

A. Problem: This research presents a study on ECG pattern classification using tree-based classifiers and statistical features. The ECG patterns have a variety of forms that are used to diagnose various heart conditions. Atrial Fibrillation (AFib) and Atrial Flutter (AFL) are two examples of these patternswhich are associated with the serious cardiac disease. The presence of these patterns may leads to high or low BP and may also cause heart attacks or even death of patient if not timely identified. Thus ECG pattern classification is open field of research. The problem may handle in two phases, first the ECG temporal features and HRV are calculated, and then in second pass the accuracy of the ML based classifiers are tested. This research problem is considering the most sever ECG patters as Atrial Flutter (AFL), and Atrial Fibrillation (AFib). The authors report a significant improvement in classification accuracy when using PCA (principal component analysis with a fine tree classifier.The application of Principal Component Analysis (PCA) not only improved classification accuracy but also potentially reduced the dimensionality of the data. This could lead to more efficient processing of ECG data, especially important in real-time monitoring scenarios.Integrating PCA features and classifiers for ECG patterns is a difficult set of problem.

B. Various EGC patterns

In this section various input ECG HRV patterns used are illustrated as example shown in the Figure 1. The two patter as AFL and AFiB are the most frequent after 2020. Thus these two attars are considered as the area of interest in this paper.

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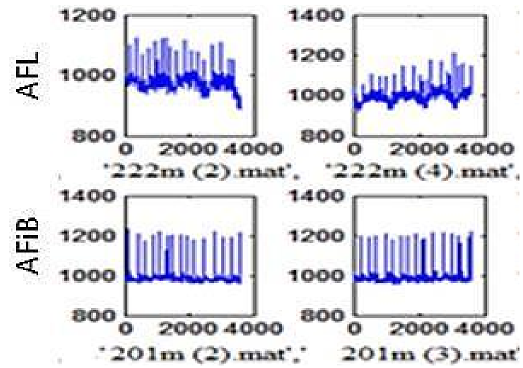

Figure 1 Example set of the input AFL and AFIB ECG patterns

(AFL) atrial flutter: Atrial flutter (AFL) is common dangerous arrhythmias. The AF and AFL are often misdiagnosed as well as easily confused for one another because of their comparable clinical indications. When AFL is identified quickly and precisely, patients may have less discomfort and injury; previous techniques of diagnosis are often inefficient and take a long time. Of all the arrhythmia disorders, atrial flutter, or AF, had higher incidence and mortality rates. Due to the large-scale entrance circuit phenomenon, AFL is a rather normal atrial beat.

Atrial Fibrillation (AFiB): When someone suffers from atrial fibrillation (AFib), a common cardiac arrhythmia, the top lobes of the heart exhibit rapid and unpredictable electrical activity. This unpredictable activity disrupts the cardiovascular system's normal rhythm, causing erratic ventricular responses and ineffective atrial spasms. During AFiB because blood coagulation inside the atria might embolism into the cerebral cortex thus produce ischemic strokes, this disorder increases the possibility of stroke.

As a result, in this paper a classification model for automatically classifying AFL data based on binary decision tree and enhanced features sets are primarily used.

C. Contribution of Work

The main contribution of this research is to categorise AFL and AFiB ECG patterns employing several tree-based binary classifiers based on machine learning. Using Principal Component Analysis (PCA) to solve the classification problem is the paper's primary contribution. Initially, the temporal characteristics are identified using the accessible ECG database. For the classification task, the HRV's, RR interval, and SDNN are employed as characteristics. The Pan Tomkins algorithms are utilised in the QRS peak detection approach to retrieve the temporal feature extracted from ECG data peak detection, including heart rate variability (HRV), RR interval, and SDNN, as features for classification. These features are extracted using the Pan Tomkins algorithm for QRS peak detection. The paper employs various tree-based classifiers for ECG pattern classification, with a focus on improving classification accuracy.This paper is aimed to assesses different tree based classifiers including, fine tree, course tree etc. as binary classification.The paper suggests that there is potential for further improvement in accuracy by using a larger ECG database and testing other classifiers like SVM and KNN in future research.

In rest of the paper first in section 2 the related literature is studied then the proposed feature extraction methodology is described in section 3. The proposed classification and testing approach is illustrated in the Section4. The expected outcomes and the parametric performance evaluation of classifiers for ECG patterns are described in section 5.Finally the future scope and observation from research are concluded in section 6.

II. LITERATURE REVIEW

In this section out of huge research take for EGC classification in past some of most relevant literatures re reviewed. The broad classification of the ECG signals classification methods are preseted in the Figure 2.it can be observed that SVM and tree classifiers are frequently used for ECG classification. But in recent past the deep learning based on convolutional neural network (CNN) are getting popular but it requires large dataset.

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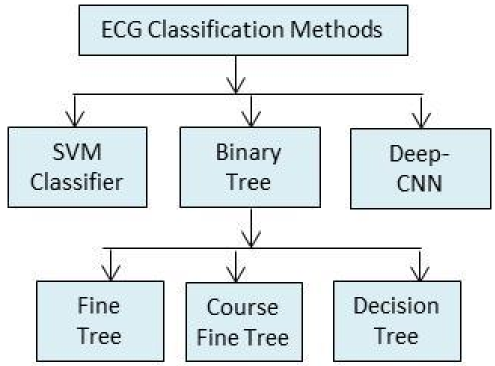

Figure 2 Classification of Various ECG classifiers

This paper section reviewed most relevant of these literatures sequentially.Medi & Kalman, [1] have indicated that AFL and atrial AFib exhibit unique ECG patterns that can be discerned through meticulous examination. In the case of typical counterclockwise AFL, the ECG typically presents a characteristic appearance with predictable features in most instances. In 2000, Ndrepepa et al. [2] have determined that in clockwise atrial flutter (AFL), the F wave exhibits notches in all ECG leads. The beginning of the wave corresponds to the activation of the septal and posterior walls of the right atrium, while the end of the wave is associated with the activity of the left atrium.Gupta et al. [3] have recently introduced a hybrid method that combines local mean decomposition and ensemble boosted trees classifier and achieves accuracy slightly above 90% in differentiating between terminating and non-terminating AFib episodes.

The use of binary tree classification for Atrial Flutter (AFL) and Atrial Fibrillation (AFib) ECG pattern classification has shown promising results in terms of accuracy: A study using ensemble classifiers, including Decision Tree (DT), Random Forest (RAF), and Rotation Forest (ROF), demonstrated high accuracy in classifying ECG beats for Normal Sinus Rhythm (NSR), AFib, AFL, and Ventricular Fibrillation (V-Fib)(as by Desai et al., 2016 [4]). The Rotation Forest (RF)and ensemble classifier achieved the highest overall accuracy of 98.37%, outperforming RF (96.29%) and DT (94.14%). Various methods have been developed to accurately detect and classify QRS complexes in ECG signals asCastillo et al [5] a fatel HRV detection, Xiang, Y., et al [6] use QRS complex method for CCN classifier, Yuen, B., et al [7] detected QRS complex using the CNN+LSTM approach, Chen, C et al [8] have used R peak detection for only single ECG sensor.Pałczyński et al [9] have suggested employing few-shot learning (FSL) for the classification of ECG signals based on proximity, which has yielded encouraging outcomes in distinguishing between healthy and sick patients as well as various disease categories. The Śmigiel et al. [10] has used R pead detection for deep learning based ECG classification approach. But these methods using DL are computationally complex and require larger datasets.

LazharKhriji et al [11] accomplish the AF identification in this scenario; we suggest a neural network (ANN) design that makes use of ECG characteristics. Three groups of ECG signals are distinguished: aberrant signals with AF, noisy ECG readings, and normal sinus rhythm. Using two distinct tests, the suggested approach has been applied to two different dataset types (MIT-BIH dataset and treated MIT-BIH). Ten-second data chunks have been used. The obtained research results demonstrated that the suggested ANN approach could reduce data variables without the necessity for extracting features, yielding high accuracy outcomes. Liu Y, Li Q, et al [12] have included previous information about categorization expenses and the nature of category inequalities in the development of a multi-label ECG algorithm, we suggest in this paper an innovative deep neural network model–based learning structure or a threshold technique, namely group asymmetry and cost-sensitive thresholds (CICST). A leftover neural net and a class-wise focus system are combined in the learning architecture. They assess our technique using many actual datasets and a cost-sensitive criterion. Next, we describe our approach to the multi-label ECG categorization issue. Our approach is divided into three sections: the learning model built around the use of deep neural networks (DNN), the initial processing for cleaning up data, and a thresholding method (i.e., CICST) to tackle the issues of cost-sensitive learning as well as imbalanced categories.

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Kora, Padmavathi et al [13] stated that who suffer from atrial fibrillation (AF), a prevalent cardiac arrhythmia can perish. The characteristics of AF are defined by the automatic regress (AR) parameters. Every 15 seconds, the ECG's AR values are determined, and Burg's approach is used to extract the characteristics. Several statistical classification algorithms, including k-nearest-neighbour (KNN) and Neural supported vector machine (KSVM), are used to classify these characteristics. These algorithms' efficacy is assessed using signals received from the MIT-BIH Heart Failure Dataset. Asl BM, Setarehdan SK, et al [14] proposed an efficient approach for classifying cardiac arrhythmias based on the heart rates variation (HRV) signal. The support vector machines (SVM) classification and the general discriminatory analysis (GDA) reduction of features strategy serve as the foundation for the suggested approach. Using both nonlinear and linear techniques, the source HRV signal is first processed to extract 15 distinct components. The GDA approach then reduces these characteristics to only five features. The SVM and the one-against-all tactic are employed to group the HRV signals. Fujita, Hamido et al [15] stated that electrocardiogram also called an ECG, is a tool used to evaluate the rhythm of the heart and identify aberrant patterns that may indicate problems with heart function. Although human analysis of these data is feasible, it can be challenging in some situations since noise frequently distorts signals. Moreover, manual patterning analysis is arbitrary and may result in an incorrect diagnosis. An autonomous machine learning diagnostic (CAD) method is one way to get rid of these drawbacks. There is no need to pre-process the ECG data when using this suggested CNN model; it only needs to extract features. This suggested system can serve as a choice guidance system and helper automated tool in a healthcare setting.Zahra Ebrahimi et al [16] have provided an extensive overview analysis of the latest deep learning techniques used to classify ECG signals. Convolutional neural networks (CNN), deep belief networks (DBN), recurrent neural networks (RNN), long-term short-term memory (LSTM), & gated recurrent units (GRU) are some of the DL approaches that are taken into consideration in this study. Employing a GRU/LSTM, CNN, and LSTM, accordingly, DL techniques demonstrated outstanding precision in correctly classifying cardiac fibrillation (AF) (100%), Supraventricular An ectopic Beats (SVEB) (99.8%), and Heart Uncommon Beats (VEB) (99.7%).Aldughayfiq, et al [17] has a purpose of AF categorization; we employed a combination neural network model in this study that consists of 1D CNN &BiLSTM. We proposed a unique strategy to solve the unstudied problem of using machine learning techniques to trans missive PPG data. We trained neural network algorithms for AF detection by combining ECG and PPG waves as multi-featured period data. Because they are accessible and simple to use, non-invasive techniques for detecting AF, such ECG and photo plethysmogram, are increasing popularity. ECG-based AF detection is not devoid its difficulties, though, and signals from PPG are becoming more and more important in this situation.

G. Latif et al [18]used the decision tree (DT) techniques, the study analyses the categorization problem of electrocardiogram, or ECG, and electroencephalographic (EEG) signals. In the past few decades, there has been a lot of study focused on the evaluation and categorization of beating hearts and cerebral traces linked to various forms of rhythm and seizures. In this study, we evaluate and classify ECG and EEG data using several classifying approaches. The suggested system beats different example training and guided artificial intelligence approaches with a precision of 97.45%.

G. Bin et al [19] stated that it is still difficult to identify atrial fibrillation, from electrocardiogram, or ECG, data. To divide the ECG recording into one of four classes—Normal timing, AF, Abnormal rhythm, and Noisy recordings—a novel AF identification approach was presented in this article. The suggested technique may be employed as a fresh approach to AF identification. B. U. Demirel et al [20]proposed a method for precisely and offline identification of noise and motion artefacts in ECG data is presented in this work. There are two steps in our grading methodology. Extracting various non-fiducially characteristics from the ECG is the initial step. Support vector machinery and binary tree structures are used in the second step of our method to grade signals. By contrasting two distinct classification algorithms, the suggested approach was evaluated on the PhysioNet/Computing in Heart Competition 2011 Dataset. On the labelled data, the SVM yielded the greatest categorization accuracy levels, coming in close to 94%.

Pham BT et al [21] propose a ECG, or electrocardiogram, is a vital component of remote healthcare technology and a simple, rapid diagnostic for assessing heart conditions. Clinical data must be measured, evaluated, archived, and sent in immediate fashion, all depending on a correct categorization of the ECG signal. Effective pulse categorization has been the subject of several investigations; sophisticated neural networks are being proposed as a solution for more simple

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and reliability. Eduardo José da S. Luz et al [22]concluded that several efforts have been produced in the past several decades to create automatic heartbeat categorization algorithms based on electrocardiograms. In this study, we provide the ECG signal preliminary processing, pulse separation methods, features definition methods, and training methods used to assess the latest methods currently employed for ECG-based automatic anomalies heartbeat categorization. Furthermore, we outline a few of the datasets used for assessing the approaches suggested by an established guideline created by the American Association for Advancement of Medical Instruments (AAMI) and documented in ANSI/AAMI.

Charfi, Faiza et al [23]have researchedand uses derivative-based/Pan-Tompkins-based methods for automated evaluation and extraction of characteristics of various ECG signal waveforms. The ECG signal is rich in data that may be used for a variety of purposes. It makes it possible to evaluate the state of heart health. Therapy for heart diseases and the management of cardiac arrhythmias depend heavily on the differentiation of signals from electrocardiograms use information mining decision tree algorithms. The MIT/BIH Heart Failure data base's various electrocardiogram (ECG) readings are used to gather and evaluate ECG characteristics. Rodriguez, Jimena et al [24] have aim to address three primary inquiries: can PDAs do a full ECG rhythm and beat classifier, can the classification algorithm have excellent accuracy, and lower actual time. To address these issues, we provide in this study the procedures we used to develop the beat-and-rhythm classification algorithm as well as the comparative precision of the results we were able to achieve. Additionally, we demonstrate that integrating the developed algorithms into the PDA is feasible. Over all it is still an open field of rest to design simple and efficient method of ECG pattern classification.

In another study, a novel Computer-aided Decision Support System (CDSS) using machine learning techniques was proposed for discriminating normal rhythm from AFib, AFL, and V-Fib. The Random Forest classifier consistently performed better for both 2-second and 5-second ECG duration studies. For the 2-second dataset, an accuracy of 98.2% was achieved, while the 5-second dataset yielded an accuracy of 98.8% (Pham et al., [25] 2021). Interestingly, a fully automated supraventricular tachycardia (SVT) classification method using a clinically based tree scheme achieved an average accuracy of 93.29% (95% CI: 92.13-94.28%) in classifying AFib, AFL, and other SVTs (Perlman et al., [26] 2015). This approach incorporated a hidden atrial electrical activity detector, which may contribute to its effectiveness in distinguishing between different arrhythmias. In conclusion, binary tree classification methods, particularly ensemble classifiers like Random Forest and Rotation Forest, have demonstrated high accuracy in classifying AFL and AFib ECG patterns. These machine learning approaches show promise in developing reliable computer-aided diagnosis tools for cardiac arrhythmias, potentially improving early detection and management of these conditions.

III. ECG PATTERNS AND FEATURE EXTRACTION

The QRS wave complex is a crucial part of an electrocardiogram, or ECG, as it shows how the ventricles depolarize during a heartbeat. It is critical to comprehend the significance of QRS peaks in order to diagnose different cardiac conditions and assess heart function as a whole. Certain QRS rhythms have been linked to an increased risk of side effects, such as ventricular abnormalities, heart arrest, and cardiovascular disease. The duration and morphology of the QRS complex can provide valuable information about the electrical conduction system of the heart. Abnormalities in the QRS complex, such as widening or fragmentation, may indicate underlying cardiac pathologies like bundle branch blocks or myocardial infarction. Regular monitoring and analysis of QRS complexes can help healthcare professionals detect early signs of cardiac dysfunction and implement appropriate interventions to prevent further complications.

The pre-processing stage of the proposed method is to apply the modified Pan Tompkins method for noise reduction from ECG signals. The RR peak is extracted using the Pan Tompkins approach and the statistical features are classified for the use of the RR intervals. The HRV are determined based on fluctuation in temporal feature of ECG for specific patterns. When it comes to identifying illnesses, including HRV, QRS peak detection is crucial. Creating time domain features assessment of the different ECG patterns enabling HRV detections serves as the paper's one of ultimate objective. To increase R peak detection accuracy In order to reduce outlier peaks and increase the actual positives of peak detection, the adaptive threshold is set.The calculated 8 statistical features for the ECG sample of AFL and AFIB categories are plotted in the Figure 3. Results of the Figure 3 a) presented the example of the accurate R peak detection approach as proposed using modified pan Tompkins approach. The Figure 3 B) displays extracted features for two

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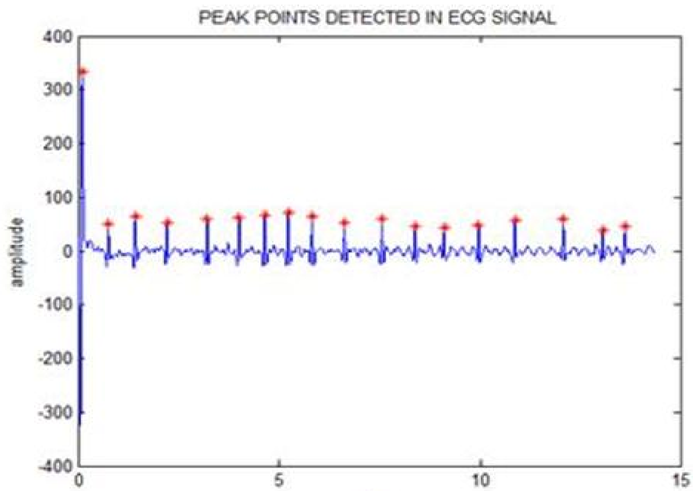
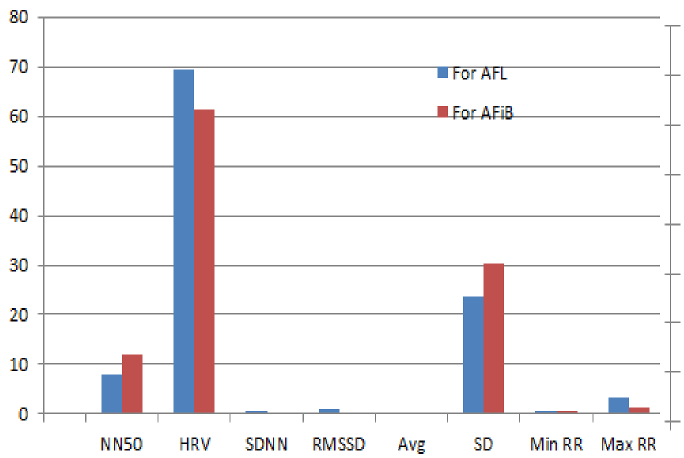
datasets, likely related to athletic performance or physiological data. The bar graph compares features for AFL and AFIB, potentially representing different groups or conditions. Different metrics like NN50, HRV, SDNN, RMSSD, Average, Standard Deviation, and Minimum/Maximum RR intervals are quantified. The graph helps to visualize the differences in these extracted features between the two ECG classes. The AFL offer more HRV while Afib has higher SD.



Example of R –R peak detection



Extracted features example for 222m (2).mat AFL and the 201m (3).mat AFiB

Figure 3 feature extraction example

IV. PROPOSED ECG PATTERN CLASSIFICATION

In this paper first the ECG database for the two calls as AFL and AFIB from the MIT scalp BIH database are taken. The 16 signals from the two categorises are exposed to feature extraction method. As a pre-processing stage the QRS peaks is extracted using the Pan Tompkins method of base line wondering. The proposed block diagram is illustrated in the Figure 4. The training and testing of the tree based classifiers are implemented and the accuracy is compared. The performance results are also evaluated based on confusion matrixes,

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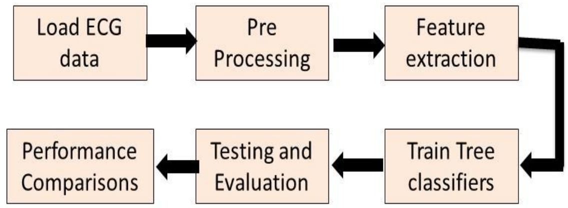


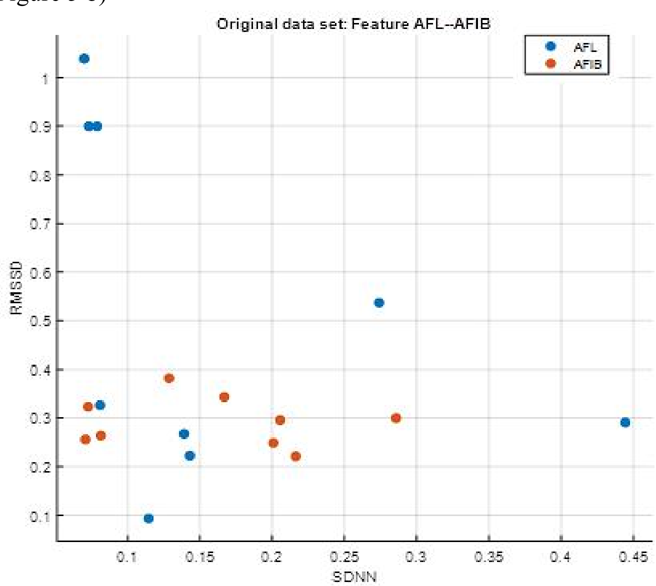
Figure 4Proposed block diagram of the ECG classification

In this manuscript, the initial step in the ECG processing is filtering using the conventional Pan Tompkins approach [2]. In order to eliminate line noise, it is recommended to modify the Pan and Tompkins approach for the improved baseline wandering problem.is provided in a methodical fashion. Temporal time domain properties are extracted using the Pan Tompkins technique to peak identification

V. RESULTS AND DISCUSSIONS

This section have preseted the results of proosed tree based classification for the AFL and AFiB patterns. The feature sets are first trained using the cross validation model with 5 layers it is found that for tree based clarification accuracy was very low up to only 46.4^. Thus in this proposed approach the tree based classification is proposed to implemented using the principal component analysis (PCA) enabled classifier. .

The results of the scatter plot before and after classification are illustrated in the Figure 5. The efficiency of classification is clear from Figure 5 b)



Scatter plot before classification test.

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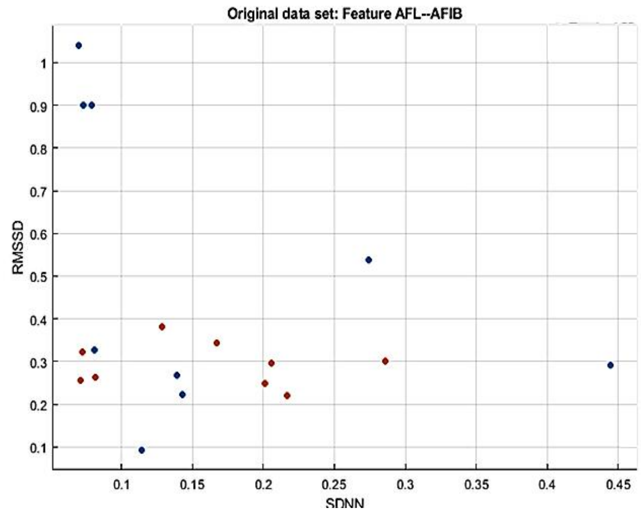

scatter plot after classification

Figure 5 results of the scatter plots

There were two classes as AFL and AFIB .Total of 18 ECG signal with 3360 samples each are taken in .mat file format with 9 ECG in each class.

Model1; Fine tree with PCA enabled.

In this paper for performance improvement it is proposed to use the fine tree based classifier and the PCA analysis is applied on features data.

PCA based Training with two cross layers:

Paper proposed a PCA-based training with two cross layers is an advanced ML approach that combines dimensionality reduction and neural network architecture. The process begins with PCA to reduce the dimensionality of input data, retaining the most significant features. This pre-processed data is then fed into a tree network that incorporates two cross layers. Cross layers, inspired by feature crossing techniques, enable the model to learn complex interactions between features automatically. These layers create higher-order feature combinations, potentially capturing non-linear relationships that might be missed by traditional fully connected layers. By integrating PCA and cross layers, this approach aims to enhance model efficiency, reduce training time, and improve overall performance, especially when dealing with high-dimensional data or complex feature interactions. For PCA training, 18 of 36 observations were ignored because they contained Infs or NaNs. The PCA is keeping enough components to explain 95% variance. After training, 2 components were kept. The features used for the classification model are Fine Tree model, with highest no. of splits set to 100 as default. The data split option is set to Gini's diversity index

Classification: The distribution of classification data is illustrated in a confusion (CFM) for a binary classification problem (AFL vs. AFIB) using a PCA-tree classifier on ECG patternsshown in Figure 6. It can be clearly seen that only one ECG out of 18 have not been successfully classified that is form AFL class. That means one AFL s identified as AFIB. Thus the overall accuracy of the proposed method with PCA is found to be 17/18 = 94.3 %.

The CFM of Figure 6 is used to represent the True positives as correctly predicted actual class, False Positive (Fp) as incorrectly predicted class, True negatives (Tn) correctly predicted wrong class, and False Negative (Fn) incorrectly predicted wrong class,

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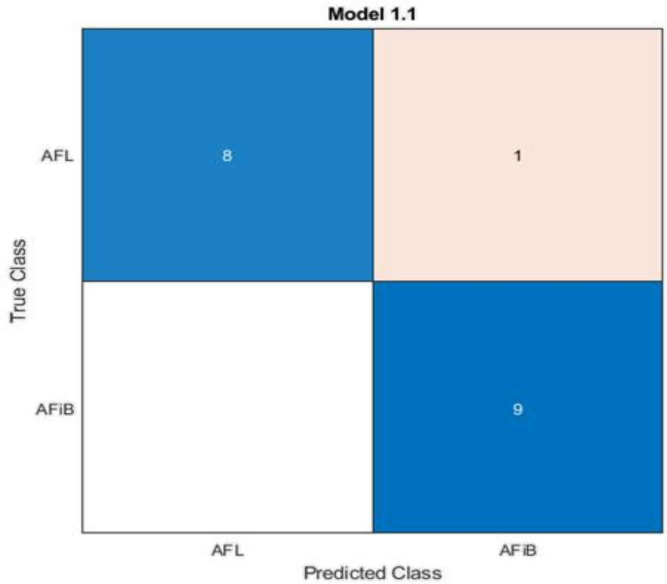

Figure 6 confusion matrix of the PCA – tree classification for ECG patterns

The true positives and false positives for each class are extracted from the Figure 6 and is represented in the Table 1. The table representing the true and false detection performance for two ECG classes.

Table 1 Representation of the True and False positives for AFL and AFiB classes.

ECG Class	Tp	FP	Tn	Fn
AFL	8	1	9	0
AFiB	9	1	0	9

The quantitative performance comparison of the ECG pattern classification for the AFL and AFiB classes are presented in the Table 2. The table presents the precision, recall, specificity, and F1-score for classifying two ECG classes.

Table 2 Representation of the Precision and Recall for AFL and AFiB classes

ECG Class	Precision	Recall	Specificity	F1-score
AFL	88.9%	100%	100%	0.941
AFiB	90%	100%	88.9%	0.947

It is observed from Table 2 that both classes demonstrate perfect recall (100%), meaning all instances of AFL and AFiB were correctly identified. AFiB shows slightly higher precision (90%) than AFL (88.9%). This indicates that the model made slightly fewer false positive classifications for AFiB.AFL exhibits perfect specificity (100%), while AFiB has a specificity of 88.9%. This means the model made more false positive classifications for AFiB compared to AFL (misclassifying non-AFiB as AFiB).AFiB has a marginally higher F1-score (0.947) than AFL (0.941), suggesting slightly better overall performance for AFiB, considering both precision and recall. The difference is very small however. Both scores are very high and represent good performance.

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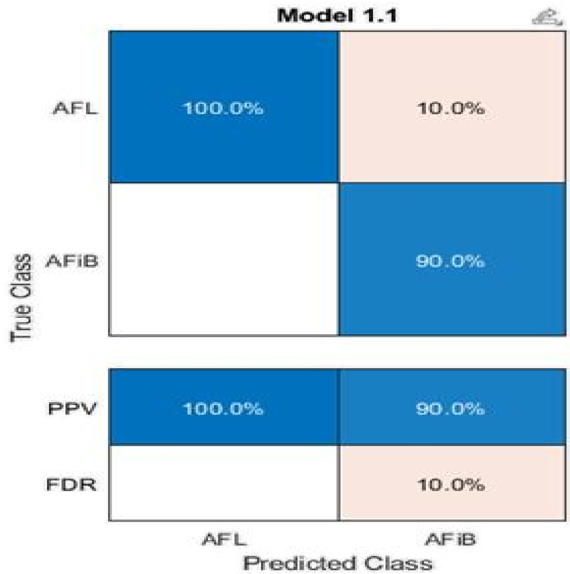

Figure 7 illustration of false detection rate (FDR) for tree classifier confusion matrix

With respective to the Figure 6 further detailed illustration of false detection rate for confusion matrix is presented in the Figure 7. The cross validation model with 5 layers is used for the classification. It is clearly observed from the Figure 7 that the FDR for AFL is less than the 10% mark which is significant and even for AFiB no false detection is observed.The low false detection rates for both AFL and AFiB demonstrate the high accuracy and reliability of the proposed classification model. This performance is particularly noteworthy given the complexity of distinguishing between different types of atrial arrhythmias. Further analysis of the confusion matrix could provide insights into any specific patterns or challenges in classifying other arrhythmia types, potentially guiding future improvements to the model.

The parametric performance of the validation accuracy, total cost, prediction speed and training time are shown in Table 3. It can be observed that in further research using fester classifier may reduce the training time.

Table 3 Parametric performance of classification with PCA

Parameters	Without PCA only Fine tree	Proposed method with fine tree + PCA
Accuracy (Validation)	46.4%	94.4%
Total cost (Validation)	1	1
Prediction speed	-68.6 sec	~53 obs/sec
Training time	1.06 Sec	9.9062 sec

Table 3 compares the performance of a fine tree classification model with and without the application of Principal Component Analysis (PCA).The results clearly demonstrate a significant improvement in classification accuracy when PCA is incorporated into the fine tree model. It can be observed that the as validation phase without PCA the accuracy was 46.4 % as shown in Table 3, which is significantly improved with use of PCA and has reached to 94.4%.for each class. This suggests that PCA effectively reduces the dimensionality of the data, removing noise and improving the fine tree's ability to learn relevant features.The prediction speed is speed at which the model makes predictions, measured in seconds per observation (obs/sec). A negative value in the Without PCA column might indicate a measure like time taken for a specific number of samples (e.g., -68.6 signify processing of a batch of samples took 68.6 sec).However, there is an increase in training time from 1.06 seconds to 9.9062 seconds when using PCA. This is expected as PCA involves computation of eigenvectors and projecting data into the reduced-dimension space. The trade-off between increased training time and significantly improved accuracy and prediction speed is usually acceptable in many applications, especially if the model will make many predictions. The overall gain in performance justifies the longer training time.

VI. CONCLUSIONS AND FUTURE SCOPES:

Paper proposes a method for classifying ECG patterns, specifically Atrial Flutter (AFL) and Atrial Fibrillation (AFib), using tree-based classifiers and statistical features. The main contribution is the use of PCA based feature analysis for the classification problem. The ultimately it is observed that early detection of ECG patterns is significant for patient health and disease diagnosis. Atrial Fibrillation (AFib) and Atrial Flutter (AFL) are two possible patterns associated with the grave cardiac conditions. The QRS packets and interval of typical ECG patterns may be considerably altered by the presence of these patterns.

This paper aims to classify these ECG patterns using different tree-based classifiers based on machine learning. Since significant variations in the QRS complex are observed in abnormal ECG patterns, the R wave is crucial for both the identification of abnormal cardiac rhythms (HRV) and the assessment of HRV.

Using PCA to solve the classification problem is the paper's primary contribution.

Initially,the temporal features like heart rate variability (HRV), RR interval, and SDNN, extracted using the Pan Tomkins algorithm, provides a robust set of indicators for ECG analysis. This approach could lead to more comprehensive and nuanced interpretations of ECG signals.

It is observed that for cross layer validation the use of PCA with classifier has improved the performance of classification efficiency.

The proposed method, combining tree-based classifiers with PCA, achieves a high accuracy of 94.4% in distinguishing between Atrial Flutter (AFL) and Atrial Fibrillation (AFib). This significant improvement in accuracy could lead to more reliable and precise diagnoses of these serious heart conditions.

Practical implications: The practical implications of enhancing atrial flutter and fibrillation classification in ECG signals through a PCA-enabled approach are significant for clinical practice and patient care. This improved classification method could lead to more accurate and timely diagnoses of cardiac arrhythmias, potentially reducing misdiagnoses and enabling earlier interventions. Healthcare providers may be able to make more informed decisions regarding treatment strategies, such as medication adjustments or the need for further cardiac procedures. Additionally, this approach could be integrated into existing ECG monitoring systems, enhancing their capabilities without requiring substantial hardware upgrades. The increased accuracy in distinguishing between atrial flutter and fibrillation could also contribute to more personalized patient management, potentially improving outcomes and quality of life for individuals with these cardiac conditions. Furthermore, this PCA-enabled method may have applications in remote patient monitoring and telemedicine, allowing for more effective long-term cardiac health management and reducing the need for frequent in-person clinical visits.

As the method achieves high accuracy with relatively simple classifiers, it could be adapted for use in portable or remote ECG monitoring devices, supporting the growth of telemedicine and remote patient monitoring. The significance of this research lies in its potential to improve the accuracy, efficiency, and accessibility of ECG pattern classification, which could have far-reaching implications for cardiac care and early detection of serious heart conditions. Furthermore, the simplicity and accuracy of the classifiers achieved in this method suggests that it could be implemented with lower computational requirements, potentially extending battery life in portable devices and reducing costs.

Limitations and Future scopes: The method may face limitation in real-world clinical settings due to computational complexity and the variations in ECG signal quality, patient-specific factors, and the presence of other cardiac abnormalities. Three is good improvement is observed with use of PCA but in near future the large number of ECG data base and for multi class classification can be tested for further improvement in accuracy. Also the SVM and KNN classifiers can be tested in further research. The NSR and APB are the other type of arrhythmia ECG patterns to be taken under consideration in future.

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DECLARATION

It is hereby declared that this manuscript is an original segment of our research and has not been published elsewhere. The data utilized is accessible globally and is cited within the text.§

All authors have agreed to the submission of this work, and there are no conflicts of interest related to it. Additionally, we declare that no external funding was received for this manuscript.

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The manuscript employs the complete worldwide database of facial images, with relevant links provided in the references.

Author 1 contributed to the validation of all results and the preparation of the manuscript. Author 2 revised the presentation and proofread the script, and made grammatical corrections and provided justifications for comments.

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