Detection of Persistent Atrial Fibrillation Using ECG Signal

Md Mayenul Islam[1], Mohammod Abdul Motin[1]

[1] Department of Electrical & Electronic Engineering,
Rajfshahi University of Engineering & Technology, Rajshahi- 6204, Bangladesh

Abstract

Persistent atrial fibrillation (PersAF) is a category of atrial fibrillation (AF) that endures for approximately a week and can easily revert back to a normal rhythm. Nonetheless, if left untreated, it can progress to chronic AF due to increasing complexity. Thus, the timely identification of PersAF necessitates more effective automatic detection algorithms. This research introduces a machine learning-driven automated algorithm designed to detect PersAF using a single-lead electrocardiogram (ECG) signal. By analyzing various time, frequency, and entropy features extracted from 10-second ECG segments, the best combination of features selected by deploying feature selection algorithms was used to train the k-nearest neighbor (KNN), decision tree (DT), and random forest (RF) classifiers. The training and testing phases involved 105 subjects, and the model's performance was validated using the 10-fold cross-validation technique. Among the classifiers, RF demonstrates the highest efficacy, achieving 95.40 $\pm$ 2.28% accuracy, 96 $\pm$ 2.81% sensitivity, 93.42 $\pm$ 5.81% specificity, and 0.94 $\pm$ 0.04 F1 score. The proposed method is thus shown to predict PersAF incidents with notable precision using shorter ECG segments.

1. Introduction

Atrial fibrillation (AF) is the most common arrhythmia and has become a global health interest. AF increases the risk of heart failure, stroke, myocardial infarction, chronic kidney disease, and other complications [1]. AF is broadly classified into four categories [2], of which persistent atrial fibrillation (PersAF) is a cardiac arrhythmia that can turn into chronic AF if left untreated and gradually causes heart failure. Therefore, early detection of PersAF is pretty necessary to avoid further complications. The researchers prefer electrocardiogram (ECG) signals for a long time to predict PersAF. As AF causes due to the intermittent squeezing of atria that causes the heart wall to fibrillate, the ECG recordings of AF patients differ from the normal recordings as shown in Fig. 2.

Several computer-aided AF detection algorithms have been proposed based on machine learning (ML) and deep learning (DL) techniques [3, 4]. In automated feature-based techniques, the irregularity of the RR interval and the abnormality of the P waves [5] were investigated to detect AF. The reflection of the premature atrial complex (PAC) and heart rate variability (HRV) was explored in [6] to detect AF. However, P-wave-based features are sensitive to noise and patient-wise diversity of atrial activities [7] that mislead AF detection. Therefore, ventricular activity-based features have been preferred for AF detection. In addition, various time, frequency, statistical, HRV spectral, Poincare, and discrete wavelet transform-based features were studied in [6, 8] for AF prediction. The irregular nature of the ventricular response and the similarity of this response with other arrhythmia affects the robustness of AF prediction algorithms. To overcome these challenges, several advanced features were extracted from higher-order statistics and spectro-temporal domain [7]. However, irregular ventricular activity degrades the HRV feature-based AF detection performance in the case of shorter segments because of the requirement of longer segments of 1 minute or more to conclude [9].

Furthermore, several DL algorithms have been proposed for automated AF detection from long-term ECGs [10–12]. A combination of convolutional neural network (CNN) and recurrent neural network (RNN) is used to extract high-level features from the segmented RR interval in [10]. In [11] a ResNet-based model was proposed for a better prediction of AF for highly imbalanced data. An ensemble of multiple deep CNN (DCNN) classifiers was proposed in [12] where multiple scale-dependent DCNN classifiers were designed for better prediction. The combination of hand-crafted features along with CNN and bidirectional LSTM network was also used for AF detection [13]. For AF detection, although the DL approaches have higher accuracy compared to the ML approaches, they require a larger dataset, higher computational cost, and limited explainability and interpretability.

This paper presents an automated approach to separate PersAF, a special class of AF, from normal events (non-AF) using a set of HRV, and entropy features extracted from shorter ECG segments lasting 10 seconds. PersAF

 ISSN: 2325-887X DOI: 10.22489/CinC.2023.254

detection via ECG has not been extensively investigated in the existing literature to the best of our knowledge. We have deployed two feature selection techniques to reduce the computational burden without compromising performance and validated the model using two publicly available highly imbalanced datasets.

2. Database Description

This study leverages two openly accessible databases (CPSC2021) [14] containing 1436 ECG recordings from 105 subjects. These datasets were designed with the aim of constructing resilient and adaptable algorithms for AF detection. All the ECG recordings were sampled at 200 Hz and saved in WFDB format. Comprehensive details about these datasets are tabulated in Table 1.

Table 1. Database Description

Category	Dataset I	Dataset II
Sampling Frequency (Hz)	200	200
No. of Subjects	54	51
No. of Records	730	706
No. of Non-AF Subjects	42	14
No. of AF Subjects	12	37
Max Record Length (sec.)	23712	24666
Min Record Length (sec.)	14	8

3. Methodology

The proposed method consists of three key steps: i) ECG pre-processing and segmentation, ii) feature extraction and feature selection, and iii) ML-based PersAF classification. Following the preprocessing and segmentation phase, the ECG signals were delineated through the utilization of the ECG kit [15]. A comprehensive set of 45 features including time and frequency domains, entropy measurements, and complex correlations derived from Poincaré analysis are extracted to train classifiers.Two distinct feature selection techniques are employed to reduce the number of features and finally, different classical machine learning algorithms are harnessed to discern PersAF occurrences from non-AF events. The schematic depiction of the proposed model is shown in Fig. 1.

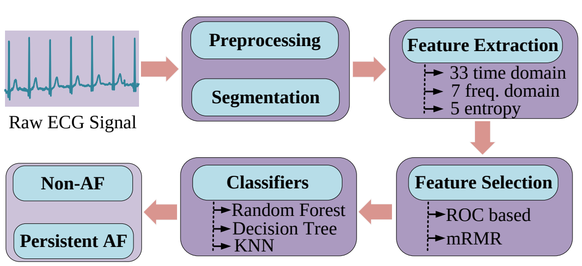

Figure 1. An overview of the proposed model for persistent AF classification using ECG-derived features.

3.1. Pre-processing and Segmentation

The correct identification of onsets and ends of P, Q, R, S, and T waves is very crucial and can be misleading due to noise and artifacts. Firstly, to remove the artifacts from ECG, we deployed discrete wavelet transform-based denoising. We used 'db10' as the vanishing moment. Secondly, the pre-processed recordings were divided into 10-second non-overlapping segments.Finally, we deployed the ECG-kit toolbox [15] to delineate ECG and identify the magnitude and position of the P, Q, R, S, and T waves. An example of preprocessed ECG signals during normal (Non-AF) and persistent AF conditions is shown in Fig. 2.

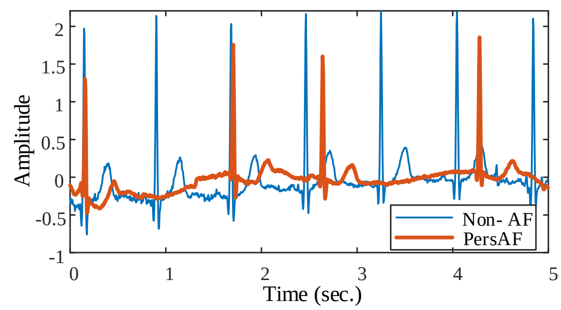

Figure 2. An example of ECG signals during normal (Non-AF) and persistent AF (PersAF) conditions.

3.2. Feature Extraction

A comprehensive set of 45 distinct features is derived from each segmented record including 33 features related to the time domain, 7 to the frequency domain, and 5 entropy. These time domain features include fundamental statistical measures like mean, median, variance, standard deviation, minimum, and maximum values of RR, QT, and PP intervals. Additionally, non-linear features such as Poincaré SD1, Poincaré SD2, complex correlation measure (CCM), SDSD, NN50, pNN50, mean and variance of the 2^{nd}, 3^{rd} and 4^{th} central moments, as well as the covariance of RR intervals are incorporated. Frequency domain features include logarithmic LF, HF, and VLF power of RR intervals, the LF-to-HF ratio, as well as the indices for the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS), along with their corresponding ratio. Entropy-based features are approximate entropy, multi-scale sample entropy, log entropy, fuzzy entropy, and permutation entropy.

3.3. Feature Selection

The area under receiver operator characteristics (ROC) curve-based selection algorithm [16] and the minimum redundancy maximum relevance (mRMR) feature selection method [17] are applied to reduce the number of features.

ROC is simply the graphical representation of the true positive rate versus the false positive rate. The area under the ROC curve (AUC) thus provides the indication of the importance of a particular feature for maximizing the probability of correct prediction. The features with corresponding AUC values are demonstrated in Fig. 3.

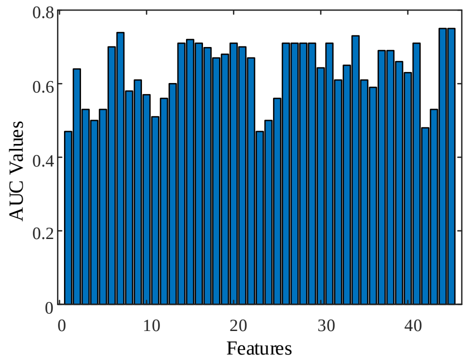

Figure 3. Bar chart representation of AUC values of the features.

The mRMR algorithm ranks the features based on two correlation values; one with the output class (relevance) and the other between the features themselves (redundancy). The strategy is to make relevance high and redundancy low. The F statistic is considered to determine relevance, whereas the Pearson correlation coefficient is used for redundancy calculation. Thereafter, each feature is assigned a performance score based on the approach to maximize the objective function formed of relevance and redundancy. Thus features are selected based on the assigned score. The features with their prediction performance score values are demonstrated in Fig. 4.

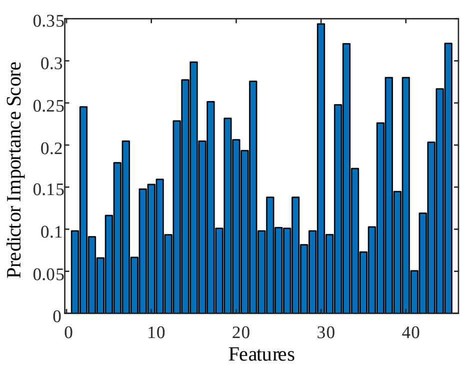

Figure 4. Bar chart representation of the feature scores assigned by mRMR algorithm.

4. Results and Discussion

The PersAF classification using two different feature selection techniques is shown in Fig. 5. From Fig. 5, it is found that the accuracy increases gradually up to 33 and 30 features for ROC and mRMR-based feature selection techniques respectively. So the optimal number of features for ROC and mRMR were 30 and 33 respectively. The accuracy either remained unchanged or decreased above the optimal number of features.

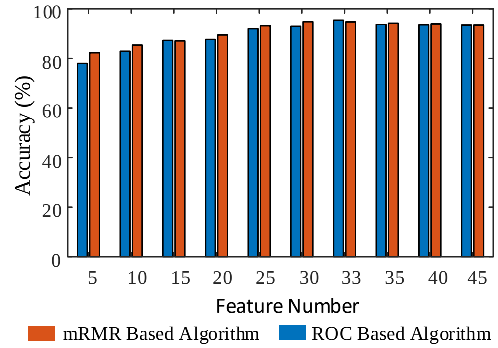

Figure 5. Bar chart comparing accuracies of RF classifier for different feature counts ranked by AUC-based and mRMR algorithms.

The performance of the three different classifiers (KNN, DT, RF) using the optimal and total number of features is shown in Fig. 6. Among the three different classifiers, RF outperforms the rest of the classifiers.

The proposed model was validated using the 10-fold cross-validation technique. The average performance of the model was assessed using the top 33 features selected by the ROC-based approach and is shown in table 2. The average and standard deviation of classification accuracy for KNN, decision tree, and random forest were $88.20 \pm 4.52\%$, $92.70 \pm 2.92\%$, and $95.4 \pm 2.28\%$ respectively. Random forest classifiers had not only the highest accuracy but also the lowest standard deviation. Compared to the other performance metric such as sensitivity, specificity, and F1-score, random forest outperformed.

In this study, we emphasized on HRV and QT features to differentiate PersAF from Non-AF. Among the top 33 features selected by ROC, 75.76%, 21.21%, and 3.03% features were time domain, frequency domain, and entropy features respectively. On the other hand for mRMR-based top 30 features, 76.67%, 10%, and 13.33% features were time domain, frequency domain, and entropy features respectively. This is a clear indication of the importance of

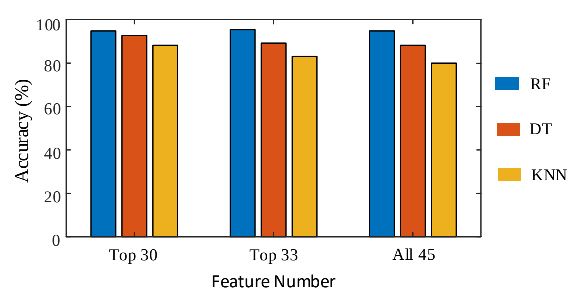

Figure 6. Bar chart comparing classifiers accuracies for top 30 by mRMR, top 33 by ROC, and all 45 features.

Table 2. The classification performance with ROC-based top 33 features

Classifier	Accuracy (Mean±SD)	Sensitivity (Mean±SD)	Specificity (Mean±SD)	Precision (Mean±SD)	F1 Score (Mean±SD)
KNN	88.20 ± 4.52	90.24 ± 5.62	83.40 ± 10.32	84.40 ± 8.70	0.86 ± 0.07
Decision Tree	92.70 ± 2.92	94.27 ± 3.16	89.51 ± 6.70	90.00 ± 6.20	0.91 ± 0.04
Random Forest	**95.40 ± 2.28**	**96.00 ± 2.81**	**93.42 ± 5.81**	**93.00 ± 5.70**	**0.94 ± 0.04**

time domain morphological features such as P waves, QT interval, and R peak having the distinguishable characteristics to differentiate PersAF from Non-AF. Since we focused on identifying PersAF with shorter segments, due to the very shorter segment length, the frequency and entropy information was not prominent to differentiate PersAF from Non-AF.

5. Conclusion

Patients with PersAF are at high risk of suffering from chronic AF if remains undetected. Thus, it is critical to detect PersAF at an early stage. In this work, we proposed an automated approach to identify PersAF from non-AF using ECG. The model's overall classification results were 95.40 ± 2.28% accuracy, 96 ± 2.81% sensitivity, 93.42 ± 5.81% specificity, and 0.94 ± 0.04 F1-score. In the future, wavelet and empirical wavelet-based features will be investigated to identify PersAF along with other classes of atrial fibrillation.

References

[1] Kornej J, Börschel CS, Benjamin EJ, Schnabel RB. Epidemiology of atrial fibrillation in the 21st century: novel methods and new insights. Circulation Research 2020; 127(1):4–20.

[2] Bao X, Hu F, Xu Y, Trabelsi M, Kamavuako EN. Paroxysmal atrial fibrillation detection by combined recurrent neural network and feature extraction on ecg signals. In BIOSIGNALS. 2022; 85–90.

[3] De Giovanni E, Aminifar A, Luca A, Yazdani S, Vesin JM, Atienza D. A patient-specific methodology for prediction of paroxysmal atrial fibrillation onset. In Computing in Cardiology (CinC). IEEE, 2017; 1–4.

[4] Mohonta SC, Motin MA, Kumar DK. Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model. Sensing and Bio Sensing Research 2022;37:100502.

[5] Wang J, Wang P, Wang S. Automated detection of atrial fibrillation in ecg signals based on wavelet packet transform and correlation function of random process. Biomedical Signal Processing and Control 2020;55:101662.

[6] Parsi A, Glavin M, Jones E, Byrne D. Prediction of paroxysmal atrial fibrillation using new heart rate variability features. Computers in Biology and Medicine 2021; 133:104367.

[7] Rizwan A, Zoha A, Mabrouk IB, Sabbour HM, Al-Sumaiti AS, Alomainy A, Imran MA, Abbasi QH. A review on the state of the art in atrial fibrillation detection enabled by machine learning. IEEE Reviews in Biomedical Engineering 2020;14:219–239.

[8] Bashar SK, Han D, Zieneddin F, Ding E, Fitzgibbons TP, Walkey AJ, McManus DD, Javidi B, Chon KH. Novel density poincaré plot based machine learning method to detect atrial fibrillation from premature atrial/ventricular contractions. IEEE Transactions on Biomedical Engineering 2020; 68(2):448–460.

[9] Wang H, Dai H, Zhou Y, Zhou B, Lu P, Zhang H, Wang Z. An effective feature extraction method based on gds for atrial fibrillation detection. Journal of Biomedical Informatics 2021;119:103819.

[10] Andersen RS, Peimankar A, Puthusserypady S. A deep learning approach for real-time detection of atrial fibrillation. Expert Systems with Applications 2019;115:465–473.

[11] Jalali A, Lee M. Atrial fibrillation prediction with residual network using sensitivity and orthogonality constraints. IEEE Journal of Biomedical and Health Informatics 2019; 24(2):407–413.

[12] Prabhakararao E, Dandapat S. Multi-scale convolutional neural network ensemble for multi-class arrhythmia classification. IEEE Journal of Biomedical and Health Informatics 2021;.

[13] Feng K, Fan Z. A novel bidirectional lstm network based on scale factor for atrial fibrillation signals classification. Biomedical Signal Processing and Control 2022; 76:103663.

[14] Wang X, Ma C, Zhang X, Gao H, Clifford G, Liu C. Paroxysmal atrial fibrillation events detection from dynamic ecg recordings: The 4th china physiological signal challenge 2021. In Proc. PhysioNet. 2021; 1–83.

[15] Demski A, Soria ML. Ecg-kit: a matlab toolbox for cardiovascular signal processing. Journal of Open Research Software 2016;4(1).

[16] Peng Y, Wu Z, Jiang J. A novel feature selection approach for biomedical data classification. Journal of Biomedical Informatics 2010;43(1):15–23.

[17] Radovic M, Ghalwash M, Filipovic N, Obradovic Z. Minimum redundancy maximum relevance feature selection approach for temporal gene expression data. BMC Bioinformatics 2017;18(1):1–14.

Address for correspondence:

Dr. Mohammod Abdul Motin

Department of Electrical & Electronic Engineering,

Rajshahi University of Engineering & Technology, Rajshahi-6204, Bangladesh

m.a.motin@ieee.org