Wavelet transformation approaches for prediction of atrial fibrillation

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***Abstract*—Prediction of atrial fibrillation (AF) is a major issue in medicine. This is due to the fact that AF is often asymptomatic. In this work, we present approaches based on wavelet decomposition to find features in the signal that can predict this disease. Our model consists of four parts: pre-processing, feature extraction, feature selection, and classification for prediction. The presented work shows a good predictive performance (94% accuracy) before 5 min of AF onset and a prediction accuracy of 85.5%, 110 min before AF onset. Our code will be available for researchers upon request.**

***Index Terms*—Prediction, paroxysmal atrial fibrillation, MIT-BIH database, continuous wavelet transform, wavelet packet decomposition, XGBoost, feature engineering.**

I. Introduction

The heart propels blood, provides oxygen and nutrients to all parts of the body through the circulatory system. The blood pumped by the heart rejects carbon dioxide and other substances that are not needed by the body [1]. The heart rate variability (HRV) refers to the signal computed from the time variations of the RR intervals. In the absence of pathology, an adult has a regular heart rate: between 60 and 100 beats per minute (bpm) during the day and between 40 and 80 bpm at night. Outside these limits, disturbances might be present in the cardiac activity [2], [3]. For example, bradycardia is characterized by a heart rate lower than 60 bpm and can be of sinus, junctional, or ventricular origin. Tachycardia is characterized by a rate of more than 100 bpm and can be of sinus, atrial, or ventricular origin. Also, atrial fibrillation (AF) is caused by irregular electrical activations of the atria, which further affect the regular function of the ventricles. AF can be diagnosed from irregular RR intervals and/or the presence of a continuous, time-varying atrial fibrillatory signal (F wave) instead of P waves [4]. AF may have various forms. It starts as paroxysmal (usually stops in less than 24 hours but may last up to a week and spontaneously return to normal sinus rhythm and is asymptomatic in general), be more persistent with time (for more than a week), and permanent (cannot be corrected by treatments) [5], [6]. In addition, COVID-19 causes non-generalized heart rhythm abnormalities and increases episodes of AF [7]. AF increases the risk for stroke that can happen when the blood flow to the brain is blocked by a blood clot or by fatty deposits, called plaque, in the blood vessel lining. It is estimated that 15.9 million people in the United States by 2050 and 17.9 million people in Europe by 2060 will suffer from AF [8]. Therefore, early detection of AF is very important. For this purpose, many studies using artificial intelligence (AI) have been proposed in the literature to distinguish normal from abnormal beats. These approaches can be classified into two categories: machine learning (ML) and deep learning (DL) algorithms. Many studies address AF classification with great precision. However, prediction remains a great challenge since, as discussed above, AF is asymptomatic for patients. In this study, we look for symptoms by analyzing features extracted from electrocardiograms (ECG) sequences to predict the occurrence of AF. For this purpose, we developed a pipeline that studies the sequence and, using a classification on the sequence, can predict the occurrence of AF in an ECG. The motivation to predict AF very early comes from the possibility for the patient to start an adequate preventive treatment.

The originality of our work is to go further than the literature for AF prediction. Indeed, to predict AF 30 min before its onset, Wu et al. [9] obtained 89%, 88%, and 92% with three different ensemble learning methods respectively: Bagging, AdaBoost, and Stacking. To predict AF 5 min before its onset, Narin et al. [10] achieved an accuracy of 98.7%. Erdenebayar et al. [11] obtained an accuracy of 98.7% to predict the onset of AF 30s before it starts.

This paper is organized as follows: Section II presents the materials and methods used, including the database, the pre-processing methods, the feature extraction and selection. Section III presents the classification process. In Section IV and V, we present and discuss the results obtained using the MIT-BIH Prediction Challenge dataset. Finally, in section VI, we conclude our work and present the perspectives.

II. Materials and Methods

A. Overview

To perform the classification for AF prediction, the MIT-BIH paroxysmal atrial fibrillation (PAF) database was used in this study. Two different types of heartbeats (signals without AF and with AF) were examined. Our method, as shown in Fig. 1, is divided into four major steps: pre-processing, feature extraction, feature selection, and classification. In the pre-processing phase, we grouped the signals per patient to reconstruct the ECG. The PAF dataset has the advantage of having denoised signals, so we did not use any filter for noise removal. Then, we used two different wavelet transform (WT) approaches for the feature extraction process. The first one is the continuous wavelet transform (CWT) using the Mexican hat wavelet (mexh). The second approach is the wavelet packet decomposition (WPD) using the Daubechies wavelet 4 (db4). The results of both approaches were used to calculate statistical features, gray level co-occurrence matrix (GLCM) and Hu invariant moments. The GLCM method is very useful to extract ECG signals features such as periodicity and distortions. It generates a square matrix whose dimension equals the number of gray levels in the image [7]. We also investigated the effect of the principal component analysis (PCA) for feature reduction. We split our dataset to test and training datasets, and, finally, we used the random forest (RF) and the extreme gradient boosting (XGBoost) models for the classification. We considered different metrics such as accuracy, sensitivity, specificity, and F1-score for the validation of our models [11]–[13].

B. ECG data

A variety of cardiac arrhythmia databases are available online. In this paper, the paroxysmal atrial fibrillation (PAF) MIT-BIH database available on Physionet has been used. Each record contains two-channels (derivation 0, derivation 1) and was sampled at 128 Hz with an 11 bits resolution. This database contains three types of record sets. The first set of 50 records (30 minutes), that comes from 50 subjects with name beginning with "n", are without AF. The second set contains records from 25 different subjects whose names start with "p": two 30-minutes and two 5-minutes for each ECG records. Odd signal identifications without the 'c' (e.g., p01.dat) represent the first 30 minutes of signal acquisition, whereas even signal identifications without the 'c' (e.g., p02.dat) represent the 30 minutes of ECG just before the onset of AF. Odd signal identifications with 'c' (e.g., p01c.dat) represent the ECG after the first 30 minutes of signal acquisition. Finally, the third learning set contains 99 records (30 minutes long) whose names start with "t" [14].

C. Pre-processing

Our goal is to extract characteristics that would allow identifying the onset of AF over time. For this purpose, in the pre-processing step, five new databases were constructed by concatenating the first R peak of the first signal with the last R peak of the second signal and so on: the first one (db1) contains all signals (with or without AF); the second one (db2) contains the ECG signals of 50 records, 110 min before the onset of AF; the third one (db3) contains the signals, 35 min before the onset of AF; the fourth one (db4) contains the signals 30 min before the onset of AF; finally, the fifth one (db5) contains 5 min of the signals with or without AF. As an example, for the first patient: the record p01 concatenated to p01c and p02 represents the signal 110 min before the onset of AF, p01c concatenated to p02 represents the signal 35 min before the start of AF, p02 represents the signal 5 min before the onset of AF. This procedure has been applied to all the patients. After the pre-processing phase, different steps were applied on each of the generated datasets, as mentioned below.

III. Feature Extraction

A. Wavelet transform

The WT is a transform using a variety of mother wavelets that decomposes a signal in time and in frequency simultaneously. There are two types of WT: the continuous WT (CWT) and the discrete WT (DWT). The main differences between the two is that the CWT uses an infinite number of scales and locations, while the DWT uses particular sets of scales and locations [13], [15], [16]. In this paper, we applied WT to the whole ECG signal.

1) CWT: CWT uses mother wavelets as Gaussian, Mexican hat, Meyer, and other complex wavelets. The CWT of a signal $x(t)$ is given by:

$$X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \times \psi^{*}(\frac{t-b}{a})dt, \tag{1}$$

where $x(t)$ is the original signal, * is the complex conjugate symbol, ψ is the mother wavelet which gets scaled by a factor of 'a' and translated by a factor of 'b'. The CWT generates a 2D image.

2) DWT and WPD: DWT uses a low pass ($h(n)$) and a high pass ($g(n)$) filter to decompose a signal into detail coefficients (cD: high frequencies) and approximation coefficients (cA: low frequencies).

WPD is a generalization of the DWT as it is an orthogonal linear combination between wavelet functions ψ^i:

$$\psi^i_{j,k}(t) = 2^{j/2} \times \psi^i(2^j t - k), \tag{2}$$

where $\psi^i_{j,k}(t)$ is a wavelet packet function with three indices: i represents the modulation parameter, j is the scale parameter, and k is the translation parameter. The wavelet function ψ^i is derived from equations (3) and (4):

$$\psi^{2i}(t) = \sqrt{2} \times \sum_{k=-\infty}^{+\infty} h(k) \times \psi^i(2t-k), \tag{3}$$

$$\psi^{2i+1}(t) = \sqrt{2} \times \sum_{k=-\infty}^{+\infty} g(k) \times \psi^i(2t-k), \tag{4}$$

where $h(k)$ and $g(k)$ are high-pass and low-pass filters, respectively.

The wavelet packet coefficients, $c^i_{j,k}$, which represent the

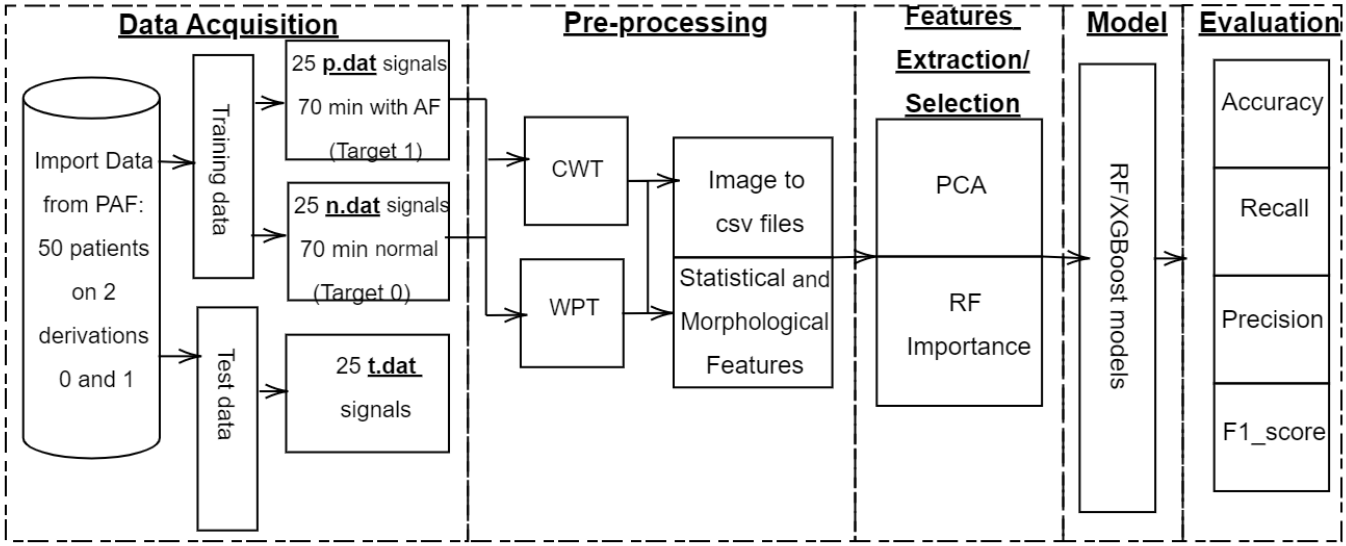

Fig. 1. Schema of the proposed methodology

amplitudes at a given time k and scale j for the signal $x(t)$, are calculated as:

$$c_{j,k}^{i} = \int_{-\infty}^{+\infty} x(t) \times \psi_{j,k}^{i}(t)dt. \tag{5}$$

WPD provides a complete level-by-level decomposition of a signal. Unlike DWT, in WPD cA and cD coefficients will be decomposed to obtain a high resolution [17].

3) Computed Features: From the wavelet decomposition results, 37 quantative features were computed, including:

1) The first order statistics that provide information about the distribution of brightness in images, that were generated by CWT, such as mean, standard deviation, median, percentile 25%, 50%, and 75%.
2) The GLCM (the second order statistics) for texture analysis to capture the spatial dependence of gray level values that we use on the image generated by CWT. It defines the occurrence probability of a gray level I_1 in the neighbor of another gray level I_2 at a given distance d and angle θ. The co-occurrence matrix depends on the d value and θ that takes four directions in degrees (0, 45, 90, and 135). Then, we compute the GLCM features (contrast, dissimilarity, homogeneity, energy, angular second moment, and correlation). Each feature consists of a vector of four values that were concatenated to obtain a total vector of 24 features representing the GLCM features. The six GLCM features computed are presented as follows :
   - The contrast that is a feature measuring the local level variations and takes high values for high contrast images
   - The dissimilarity that provides a measure of the randomness of pixels and takes low values if we have the same pixel pairs
   - The homogeneity that is a measure that takes high values if we have similar pairs of pixels
   - The energy features which return the sum of squared elements in the GLCM
   - The angular second moment (ASM) that is used to measure the smoothness of an image
   - The correlation that measures the correlation between pixels in two different directions
3) The Hu invariant moments that are used in the field of image pattern recognition, classification, and target recognition and describe the geometric characteristics in the images area output of CWT. We calculated seven Hu invariant moments (h1 to h7).

B. Feature selection: Principal Component Analysis

The purpose of PCA is to condense the information from a large set of correlated variables into a few variables (the "principal components"), without loosing much of the variability present in the dataset [18]–[21]. In this paper, PCA is used to reduce dimensionality. In the literature related to ECG analysis, PCA was used for many purposes such as data compression, beat detection and classification, denoising, separation signal, and extraction [21], [22].

C. Classification

From the two different feature extraction approaches (CWT and WPD), a total of 37 features were calculated. These features include images from CWT and coefficients from WPD. These features were reduced by PCA and RF importance. The reduced features were next fed into two ML classifier models: RF and XGBoost.

1) Random Forest: RFs, first used by Breiman, are popular classification algorithms to handle large amounts of data [23]. These are collections of multiple decision trees. Bootstrap-aggregated (bagged) decision trees can reduce the effects of over-fitting and improves generalization by combining the results of many decision trees.

2) XGBoost: XGBoost is an implementation of extreme gradient boosting that uses ML decision trees algorithms. It has a great ability to handle missing data, skewed class distributions, and large data. Rezaei et al. [24] achieved 87.22%, 88.55%, and 85.95% for F1-score, sensitivity, and specificity, respectively, to classify ECG into normal and abnormal signals. Wu et al. [25] achieved an overall accuracy of 95.12% with intrinsic time scale decomposition, 90.94% with empirical mode decomposition (EMD), and 87.2% with WT to classify AF using P-wave and RR interval features. Derevitskii et al. [26] achieved 87.6% as accuracy to detect AF. Bao et al. [27] classified arrhythmia heartbeats and used PCA to choose suitable features. Yue et al. [28] achieved 86% as accuracy to detect normal rhythms, AF, and other rhythms using EMD filter.

IV. Results

In all our results, we obtained the best accuracy with derivation 1. First, the db1 with CWT features achieved an average accuracy of 74.5% (PCA+RF) and 75.5% (PCA+XGBoost). The accuracy achieved with the db1 with WPD features was 98% with both RF and XGBoost classifiers. Then we combined the CWT and WPD features. Our model achieved an accuracy of 85.5% with db2 (110 min before AF), 92.5% with db3 (35 min before AF), 94% with db4 (5 min before AF) and 100% with db5 (with or without AF) with XGBoost. Figure 2 shows the performance of the model trained and tested by splitting data 25 times in terms of average accuracy and time (in min) before AF.

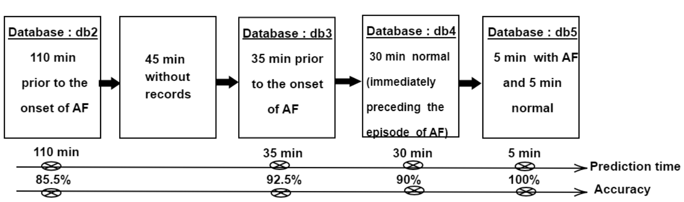

Fig. 2. Classification for prediction

Table I presents results in detail. From table II, we analyse the combinations of characteristics groups extracted from the signals (the first order statistical, GLCM and the Hu invariant moments). We obtain the best accuracy with PCA: 91.2% with XGBoost on derivation0, and 93.3% and 94% on derivation1 with RF and XGBoost, respectively.

V. Discussion

In this study,our goal was to predict FA. For this purpose, 37 features (first and second order statistics and the Hu invariant moments) were computed from the output of CWT and WPD. Then PCA was proposed to reduce features dimension. We evaluated the performance using RF and XGBoost models.

TABLE I

Accuracy performances for two models (RF and XGBoost) with and without PCA for all features on both derivations. db1 = first database extracted on all signals (with or without AF); db2= second database containing the signals 110 min before the onset of AF using CWT; db3= third database containing the signals, 35 min before the onset of AF; db4 = fourth database containing the signals 30 min before the onset of AF; db5 = fifth database containing 5 min of the signals with or without AF.

Accuracy %	Derivation 0				Derivation 1			
	Without PCA		With PCA		Without PCA		With PCA	
	RF	XGBoost	RF	XGBoost	RF	XGBoost	RF	XGBoost
db1 + CWT	63.7	70.5	63.8	73.7	70.0	72.0	74.5	75.5
db1 + WPD	91.2	92.0	92.5	93.0	98.0	98.0	98.0	98.0
db2	66.6	68.0	67.7	67.7	80.0	82.0	82.5	85.5
db3	60.0	60.0	66.6	60.0	87.7	91.0	90.1	92.5
db4	90.0	80.0	92.0	80.0	93.0	93.3	90.0	94.0
db5	93.0	93.3	90.0	94.0	100	100	100	100

TABLE II

Accuracy performances for two models (RF and XGBoost) with and without PCA for all features on two derivations.

Accuracy %	Derivation 0				Derivation 1			
	Without PCA		With PCA		Without PCA		With PCA	
	RF	XGBoost	RF	XGBoost	RF	XGBoost	RF	XGBoost
Statisticals features	66.0	73.3	53.3	80.0	67.0	76.0	68.0	91.2
GLCM	46.0	60.0	46.6	83.0	78.0	86.0	85.5	92.5
Hu invariant moments	46.7	73.3	66.7	82.0	56.0	72.0	69.0	75.0
Statistical features + GLCM + Hu invariant moments	70.0	80.0	75.0	91.2	90.0	93.3	93.0	94.0

A. *Data without PCA*

Without PCA, on derivation 1 and using all extracted features, we reached 90% and 93.3% with RF and XGBoost, respectively, see Table II. Wu et al. [25], who classified normal sinus rhythm (NSR) and AF, achieved their best results with XGboost and achieved an overall accuracy of 95.12%. Derevitskii et al. [26] used 13 features with XGBoost model to detect AF; they achieved 87.6% as an average accuracy.

B. *Data with PCA*

To improve the representation of the features, PCA was also used to reduce the data. The results of the classification with the use of PCA were better as confirmed by the metrics of evaluation: we achieved an accuracy of 93% and 94% for RF and XGBoost, respectively, on derivation 1 and using all extracted features, see Table II. As shown in Table III, the precision, the recall (sensitivity), the accuracy, and the F1-score are respectively 100%, 86%, 90%, and 92% to classify AF arrhythmia. Table III shows the confusion matrix of our model. In the classification results, AF has a higher precision than normal (+25%), but normal has a higher recall than AF (+14%).

VI. Conclusions

This paper focused on the prediction of AF using a feature engineering classification approach for the whole signal with a duration of 110 min while other authors made the prediction for the delays: 30 s, 2 min, 5 min, and 30 min.

TABLE III
CLASSIFICATION REPORT ABOUT AF AND NORMAL BEATS. SUPPORT IS THE NUMBER OF OCCURRENCES OF THE GIVEN CLASS IN OUR DATASET; MACRO AVG IS THE SIMPLE MEAN OF SCORES OF ALL CLASSES; WEIGHTED AVG IS THE SUM OF THE SCORES OF ALL CLASSES AFTER MULTIPLYING THEIR RESPECTIVE CLASS PROPORTIONS.

	Precision	Recall	F1-score	support
AF	100	86	92	7
Normal	75	100	86	3
Accuracy			90	10
Macro avg	88	93	89	10
Weighted avg	93	90	90	10

Two methods were used for the feature extraction: the CWT and WPD. In order to reduce the number of features without affecting the quality of images (output of CWT), we used the PCA method to select the most important features in ECG signals. Finally, RF and XGBoost were used as classifiers. All the analyses were conducted on the publicly available PAF MIT–BIH database. Based on numerous experimental results, we achieved an accuracy of 94% for AF prediction, 5 minutes before onset. In contrast, we obtained 85.5% accuracy for AF prediction, 110 minutes before onset. These results were obtained using the XGBoost classifier with feature selection using PCA. Our results are superior to existing models using the same dataset. Generalization of our method to other databases, such as the Long-Term Atrial Fibrillation Database (LTAFDB), the association for the advancement of medical instrumentation (AAMI), and other databases is in progress.

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