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Overview on prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG

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Abstract

Atrial fibrillation (AF) is the most common supraventricular cardiac arrhythmia, resulting in high mortality rates among affected patients. AF occurs as episodes coming from irregular excitations of the ventricles that affect the functionality of the heart and can increase the risk of stroke and heart attack. Early and automatic prediction, detection, and classification of AF are important steps for effective treatment. For this reason, it is the subject of intensive research in both medicine and engineering fields. The latter research focuses on three axes: prediction, classification, and detection. Knowing that AF is often asymptomatic and that its episodes are often very short, its automatic early detection is a very complicated but clinically important task to improve AF treatment and reduce the risks for the patients. This article is a review of publications from the past decade, focusing on AF episode prediction, detection, and classification using wavelets and artificial intelligence (AI). Forty-five articles were selected of which five are about AF in general, four articles compare accuracy, recall and precision between Fourier transform (FT) and wavelets transform (WT), and thirty-six are about detection, classification, and prediction of AF with WT: 15 are based on deep learning (DL) and 21 on conventional machine learning (ML). Of the thirty-six studies, thirty were published after 2015, confirming that this particular research area is very important and has great potential for future research.

Keywords: Electrocardiogram, Electrocardiograph, Cardiac, Heartbeat, Computer-Aided Diagnosis, Arrhythmia, Atrial Fibrillation, Artificial Intelligence, Prediction, Classification, Detection, Wavelet Transform, Fast Fourier Transform.

1. Introduction

Atrial fibrillation (AF) is the most common arrhythmia, particularly in the elderly [1]. According to the World Stroke Organization [2], 17 million people worldwide suffer from a stroke caused by AF. AF is the

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leading cause of stroke-related death and morbidity. According to the Framingham heart study [3], the
5 lifetime risk of developing AF is 1 in 4 for men and women over the age of 40. Therefore, early detection
would be very useful for saving lives. Detection of AF can be performed by analyzing the electrical activity
of the heart [1]. The depolarization and repolarization of the atria and ventricles are represented in the
signals of the electrocardiogram (ECG).

Recently, AI has become increasingly popular in providing effective pattern detection solutions for computer-
10 aided diagnosis systems in many fields, particularly in biomedical. Using AI, it is possible to diagnose the
signs of AF at an early stage and predict the onset of AF attacks. It therefore becomes possible to
prevent many serious health problems [4]. The two most important factors in heartbeat classification are
the features extracted from the heartbeat and the classification model chosen [5]. In the literature, many
groups of parameters have been extracted to classify heartbeats [5]: morphological characteristics [6]-[7],
15 wavelet-based characteristics [5]- [8]- [7], and statistical parameters [6]-[9]. In recent studies, features are
extracted automatically from cardiac signals using deep learning (DL).

This article is a systematic review of the literature over the past decade on AF prediction, detection, and
classification using AI models and wavelet-based studies on ECG signals. This review complements the work
proposed by Matias et al. [4] which did not present work based on the wavelet transform (WT). Therefore,
20 the selected papers present the most recent work using WT for AF prediction, detection, and classification.

Indeed, there are two main approaches for feature extraction in ECG signals: (1) The first approach uses
the Fourier transform (FT) that describes a signal from the time domain to the frequency domain. (2) The
second approach uses the WT that describes a signal both in the frequency and time domains. The WT
analysis provides an alternative to FT for the study of one-dimensional and multi-dimensional data. It also
25 has multiple applications such as in physics, in mathematics, and in image processing.

The main contributions of this article are the following: (1) covering the most recent works for the
prediction and/or classification of AF using wavelets: datasets, feature extraction, preprocessing and
models for prediction/classification or detection; (2) conducting a study to compare models based on the
Fast FT (FFT) with those based on wavelets and conclude on which performs the best.

30 The paper is organized as follows: Section 2 deals with AF, papers selection strategy, and recent
detection, prediction/classification techniques. In Section 3 we summarize the results and present the
characteristics in tables. The results are discussed in Section 4. Finally, we conclude in Section 5.

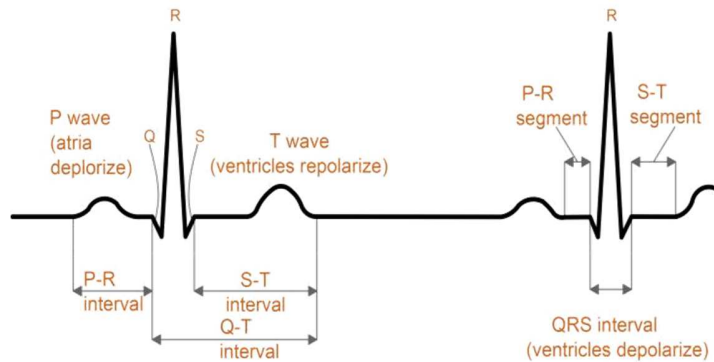


Figure 1: Two periods of a normal ECG signal

2. Materials and Methods

2.1. Atrial fibrillation overview

35 As shown in Figure 1, a normal ECG signal is composed of a P wave (depolarization of the atria), a QRS complex (depolarization of the ventricles), and a T wave (repolarization of the ventricles). The heart rate is the number of beats per minute (bpm) which can be calculated by counting the number of R peaks in an ECG wave during one minute of recording (60-100 bpm if normal). The P, Q, R, S, and T waves are the most important characteristic features in an ECG time series.

40

AF is an abnormal electrical activity of the heart due to irregular contraction of the atria. It might be accompanied by symptoms, such as atrial tachycardia (starting in the atria), defined by a heart rate over 100 beats per minute. During AF, RR intervals are absolutely irregular and the P-wave is replaced by the continuous irregular F-wave (small fibrillatory waves).

45 AF is classified as paroxysmal (less than 7 days), persistent (greater than or equal to 7 days), and per-manent (no intervention to restore normal sinus rhythm). The progression of AF known for several decades has been defined as the transition from paroxysmal to persistent/permanent AF or from persistent AF to permanent AF. As discussed in [10], progression of AF affects approximately 2% to 20% of patients annually. The most frequent progression is from persistent to permanent AF (>15%/year). Progression from
50 paroxysmal to persistent or permanent AF are less frequent (<10%/year: 9% in the first year and 25% in the next 5 years). Runnan et al. [11] mention that genetic factors, lifestyle, and medical risks are factors that can lead to AF.

The common symptoms of AF are: fatigue or difficulty in exercising, palpitations, shortness of breath,
55 and generalized weakness. AF diagnosis can be performed using ECGs (that measure the electrical activity

of the heart), echocardiograms (that generate moving images of the heart), and Holter monitors (a portable device that records ECG activity for over 24 hours).

To prevent a stroke, it is important to treat the symptoms of AF, which differ from one person to another, the cause, and any other health problems. There are a variety of treatments such as medication, electrical cardioversion, ablation of the affected area of the heart, pacemaker, lifestyle modification, and weight loss.

2.2. Computer Aided Diagnosis Systems

The main goals when analyzing ECG signals are abnormality detection, classification, or prediction. This can be performed through the use of computer aided diagnosis systems, such as those using AI, as described in the literature. Anomaly detection relies on adaptable sampling and extraction of ECG features using adaptable methods such as WT. However, early and automatic detection of AF remains an unresolved challenge which will limit the effectiveness of AF treatment strategies. Below, we describe three subsections for the detection, classification, and prediction methods.

2.3. Search Strategy

For bibliographic search, the most used free and open source databases in the biomedical field are: (1) PubMed¹, (2) IEEE Xplore², (3) Science Direct³, (4) Elsevier⁴, (5) BioMedical Engineering OnLine⁵, (6) Web of Science⁶, (7) Scopus⁷, (8) ACM Digital Library⁸. All of these databases were used to search publications published between 2010 and 2021. We looked for titles and abstracts using the following keywords: (“artificial intelligence” or “machine learning”) and (“ECG”) and (“atrial fibrillation”) and (“prediction” or “classification” or “detection”) and (“wavelet”).

We used the following two steps to collect the data from the sources: Step 1: searching articles related to the keywords specified above; Step 2: literature review and exclusion of articles that were not related to the research.

¹Free resources for biomedical literature to improve health on a global and personal level.

²The source of reliable journals, conferences, standards, e-books, and training courses.

³The source of medical, scientific and technical research (journals, books, and articles).

⁴An editor specialized in information technology.

⁵An open access database dedicated to publish research in all areas of biomedical engineering.

⁶A website that provides access to multiple databases for many different academic disciplines.

⁷The largest abstract and citation database of peer-reviewed literature (scientific journals, books, and conference proceedings). ⁸A database for all academic databases in computer science.

2.4. Study Selection

80 The selection criteria are focused on maximizing the nature of the search. Our objective was to find papers that use an AI approach and WT on ECG waveforms for AF detection, classification, or prediction. According to Table 1 that presents the inclusion/exclusion criteria, all the articles remaining after the analysis were reviewed and were the subject of a full synthesis of their text to verify their reliability.

Table 1: Selection criteria of the articles.

Type	Inclusion	Exclusion
Date	2010 to 2021	Under 2010
Language	English French	Any other language
Participants	All	None
Reported outcomes	At least one metric of performance	No metric reported
Preprocessing	WT; FFT	–

2.5. Selection Strategy for Research Articles

85 After searching for articles related to the above keywords, reviewing the appropriate bibliography and rejecting unwanted articles, some criteria were predefined to extract information from the selected publications:

- Information about the article: its reference and its date of publication;
- Inputs: evaluation of the inputs (data, the number and age of the patients) necessary to develop an algorithm;
- 90 • Signal processing: determination of the parameters extracted from the input ECG signals, the signal duration used for training, and the equipment required for processing;
- Methods: specification of the models using WT to preprocess the ECG signals, classification, AF detection/ prediction and their performance evaluation, as well as the number of repetitions and the distribution of data between training and testing;
- 95 • Performances: definition of the metrics used to evaluate detection, classification, and prediction.

2.6. Results of The Selection

At the beginning of the search, seventy-four papers were selected. According to the criteria indicated in Table 1, twenty-nine records were rejected. From the remaining forty five publications, five articles were on general information on AF, twenty-two studies reported research related to the classification of AF, nine
100 studies to the detection of AF, and five studies reported research related to the prediction of AF episodes.

In addition, we selected the four best works using FFT cited in [4], based on their accuracy of prediction, and compared them with the best works using the WT approach.

2.7. Editors Related Information

From the selected studies, 81% have been published since the year 2015. Table 2 presents a synthesis of these 45 selected articles.

Table 2: Percentage of articles by type of conference or journal/editor

Journal / Editor	Number of articles	Percentage
BioMedical Engineering OnLine	3	7%
Elsevier	12	27%
Computational and Mathematical Methods in Medicine	3	7%
IEEE	4	10%
Journal of Healthcare	2	5%
MDPI	2	5%
Biomedical Research	2	5%
International Journal of Computer Science	1	2%
Technology and Engineering Systems Journal	1	2%
Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence	1	2%
Proceedings of Engineering and Technology	1	2%
Frontiers in Philosophy	1	2%
IJIMAI	1	2%
Asian journal Pharm Clin Res	1	2%
Computers, Materials and Continua & Continua	1	2%
Indian Institute of Science Education and Research	1	2%
Journal of Electrical Bioimpedance	1	2%
Journal of Big Data	1	2%
Biomedical and Pharmacology Journal	1	2%
Earth and Environmental Science	1	2%
Journal of Korean Medical Science	1	2%
Proceedings of the third International Conference on bio-inspired system and signal processing	1	2%
European Journal of Preventive Cardiology	1	2%
www.thelancet.com	1	2%

2.8. Participants and Study Design

Table 3 lists the year of publication, authors, database used and number of participants.

Table 3: Data selected from articles. NP= Not published.

MIT-BIH AF database = AFDB; MIT-BIH paroxysmal AF database = PAFDB; Long Term AF Database = LTAfDB; MIT-BIH Normal Sinus Rhythm Database = NSRDB; MIT-BIH ECG arrhythmia database = ADB; BIDMC database = Beth Israel Deaconess Medical Center; PTB Diagnostic ECG Database = PTB

Year	Authors	Data	Nb of participants
2021	Xu et al. [5]	ADB	47
2020	Shen et al. [12]	AFDB	25
2020	Ullah et al. [2]	ADB	47
2020	Xie et al. [13]	AFDB / PhysioNet Challenge 2017	84043 segments ECG
2020	Singh et al. [6]	ADB / NSRDB / BIDMC (CHFD)	65536 samples ECG
2020	Zhao et al. [14]	PhysioNet-CINC challenge 2017	8528
2020	Nurmaini et al. [15]	AFDB	234
2020	Abdullah et al. [16]	PTB	290
2020	Petmezas et al. [17]	AFDB	23
2019	Chashmi et al. [18]	ADB	47
2019	Padmavathi et al. [19]	ADB	47
2019	Urtnasan et al. [20]	AFDB/PAFDB/NSRDB	19804 short-term ECG
2019	Alarsan et al. [21]	ADB	47
2019	Attia et al. [22]	Own database	210414 patients with 1 million ECG
2019	Wang et al. [23]	AFDB	23
2018	Xiaoyan et al. [3]	AFDB	25
2018	Runnan et al. [11]	AFDB	25
2018	Narin et al. [24]	AFDB	100
2018	Anwar et al. [25]	ADB	47
2017	Y.Xin et al. [26]	PAFDB	100
2017	Lassoued et al. [7]	ADB	47
2017	Peng et al. [27]	ADB	47
2017	Kaya et al. [28]	ADB	47
2017	Saraswat et al. [29]	LTAfDB-MITBIH Fantasia Database(MFD)	NP
2017	Filos et al. [30]	Own dataset	21 PAF and 17 healthy patients
2016	Dewangan et al. [31]	ADB	116137
2016	Daqrouq et al. [32]	ADB	47
2015	Rodenas et al. [33]	AFDB	23
2015	Sharmila et al. [9]	Physionet Database	NP
2015	Thomas et al. [34]	ADB	47
2013	Barmase et al. [35]	ADB	47
2013	Luz et al. [36]	ADB	47
2012	Alcaraz et al. [37]	Own data	50 Paroxysmal AF and 63 Persistent AF
2012	Alcaraz et al. [38]	Own data	50 Paroxysmal AF and 63 Persistent AF
2012	Sarkaleh et al. [8]	ADB	47
2011	Kim et al. [39]	ADB	47
2010	Alcaraz et al. [40]	Own dataset	30

2.9. Detection, Classification, and Prediction Methods

2.9.1. Detection Methods

110 Anomaly detection on ECG is an important process to identify signal irregularities for the purpose of improving diagnosis. Many studies have been proposed to automatically detect AF: some use random forests (RF) [12], decision trees (DT) [12], support vector machines (SVM) [13], convolutional neural network (CNN) [3, 13, 11, 17, 22], or an artificial neural network (ANN) [23]. Similarly, the stacking model presented in [12] combines DT, RF, gradient boosting DT (GBDT), XGBoost (an open-source library that provides a
115 gradient boosting regularization framework for several programming languages such as Python, R,..), and LightGBM (a gradient boosting framework that uses tree based learning algorithms).

2.9.2. Classification Methods

ECG classification plays an important role when dealing with irregularities of ECG signals which is very important in assessing the patient's condition. It is associated with the diagnosis of arrhythmias (any
120 distortion in the shape and duration of ECG waves). Classification of ECG signals can be performed using several algorithms such as binary or multi-class algorithms based on manually extracted features or automatically extracted features using DL approaches. However, for the feature extraction, we distinguish two main axes: the first one uses FT and leads to a frequency representation; the second one uses WT to represent signals in the time-frequency domain. The latter axis is efficient on non-stationary data, such as
125 ECG signals. Then, an appropriate classifier is needed to obtain the best classification of ECG signals. We identified two categories of models for the classification step: the first one is the conventional supervised learning models that use SVM models [6, 5, 18, 19, 26, 28, 36, 30], DT based models [5, 28, 21, 36], Extreme Learning Machine (ELM) [5, 39], K-Nearest Neighbour (KNN) [19, 5], RF [21], or Optimum-Path Forest (OPF) [36]. The second models use DL models such as: CNN [16, 2, 14, 15], multilayer ANN
130 [7, 31, 32, 34], Recurrent Neural Network (RNN) [15], Long Short-Term memory (LSTM) [6, 16], Deep Neural Network (DNN) [15], Probabilistic Neural Network (PNN) [29], Neural Network (NN) [18, 25, 28, 8], or Multilayer Perceptron (MLP) [7, 8].

2.9.3. Prediction Methods

Unlike detection and classification methods, predictive model approaches provide indicators of possible dis-
135 eases before they occur. In Table 4, we present the models found in the literature for AF disease prediction. As for detection and classification, the models are based on two categories: DL and conventional ML. Models for arrhythmia prediction are: CNN with Haar WT to predict paroxysmal AF (PAF) [20]; central tendency measure (CTM) for different wavelets families to predict PAF [38]; SVM using wavelet multiscale entropy to predict PAF [37], [40]; genetic algorithm (GA) using wavelet packet transform (WPT) to predict PAF [24].

140 The length of the signal used in all these works varies from 1 to 300 seconds. The different models used in the selected articles are presented in Table 4. The latter contains the preprocessing phase of the input data divided into two parts (training and testing) and the performance evaluation phase.

Table 4: Detection, classification, and prediction methods used in the selected works. NP=Not published; DWT = Discrete WT; DBWT = Discrete Biorthogonal WT; MFSWT = Modified Frequency Slice WT; CWT = Continuous WT; dbN = Daubechies wavelets where N is the order which determines the wavelet properties; WE = Wavelet Entropy; MODWT = Maximal Overlap DWT; WWT = Walsh WT; DTWT= Discrete Time WT; HOS = Higher Order Spectral; TEO = Teager Energy Operator; CRQA = Cross Recurrence Quantification Analysis; LPC = Linear Predictive Codes; MFCC = Mel Frequency Cepstral Coefficients; LDA = Linear Discriminant Analysis; LOMB = Lomb–Scargle; TNNP = Transmembrane potential; FL= Focal Loss Function

Method	Year	Ref	Preprocessing/Feature extraction	AI model method	Evaluation method	Training/test	Tools	Delay
Detection	2020	[12]	DWT	Stacking	fold cross validation	NP	NP	5 min
Detection	2020	[13]	DBWT	CNN	NP	NP	NP	9-60 s
Detection	2020	[17]	DWT (db4)	CNN-LSTM with FL	10-fold cross validation	NP	-	-
Detection	2019	[23]	WPT	ANN	10-fold cross validation	NP	Python 3.6	10 s
Detection	2018	[3]	MFSWT	CNN-12L	5-fold cross validation	NP	Matlab	1 s
Detection	2018	[11]	CWT(Db5)	CNN	fold cross validation	75/25%,	NP	5 beats
Detection	2017	[27]	WT	TNNP	NP	NP	NP	NP
Detection	2015	[33]	median filter+ WTE	Threshold	fold cross validation	NP	NP	5 beats
Detection	2015	[9]	DWT (db)	-	fold cross validation	NP	Matlab	NP
Classification	2021	[5]	DWT	SVM-KNN-DT-ELM	fold cross validation	70/30%	NP	17.42 s
Classification	2020	[6]	MODWT	SVM-LSTM	fold cross validation	88/22%	NP	22400 beats
Classification	2020	[16]	DWT	CNN-LSTM	fold cross validation	NP	NP	NP
Classification	2020	[2]	DWT	2-D CNN	fold cross validation	70/30%	NP	3 s
Classification	2020	[14]	DWT (dbN)	DCNN	fold cross validation	90/10%	Softmax	60 s
Classification	2020	[15]	WWT (Symlet)	CNN-RNN-DNNs	fold cross validation	80/20%	NP	25 s
Classification	2019	[19]	WT and DTWT	SVM-KNN	NP	NP	NP	NP
Classification	2019	[18]	DWT+HOS	NN-SVM	10-fold cross validation	NP	NP	200 samples
Classification	2019	[21]	DWT	DT-RF-GDB	fold cross validation	NP	Matlab	30 min
Classification	2018	[25]	DWT+RR interval+TEO	NN	3-fold cross validation	50/50%	Matlab	-
Classification	2017	[7]	DWT(db6)	ANN-MLP and neuro-fuzzy	GD +Momentum	NP	NP	60 s
Classification	2017	[26]	WTE	SVM	NP	NP	NP	NP
Classification	2017	[30]	CWT	SVM	NP	NP	NP	0.3 s
Classification	2017	[28]	WT	DT-SVM-NN	fold cross validation	NP	Matlab	200 samples
Classification	2017	[29]	DWT+CRQA	PNN	fold cross validation	NP	Matlab	200 samples
Classification	2016	[31]	DWT	ANN	NP	NP	NP	3 s
Classification	2016	[32]	WPT	ANN	fold cross validation +Threshold	NP	NP	10 s
Classification	2015	[34]	DWT+LPC+MFCC	ANN	fold cross validation	10%	NP	30 min
Classification	2013	[35]	CWT (Morlet)	Markov	fold cross validation	NP	NP	30 s
Classification	2013	[36]	WT	OPF	fold cross validation	NP	Matlab	NP
Classification	2012	[8]	DWT(db6)	MLP-NN	fold cross validation	NP	Matlab	2 s
Classification	2011	[39]	CWT+LDA	ELM	NP	NP	NP	6 beats
Prediction	2019	[20]	DWT 'Haar'	CNN	Cross-validation	80/20	MATLAB 2017 Python 3.5	30 s
Prediction	2018	[24]	FFT+WPT	K-nearest, GA, LOMB	10-foldcross validation	NP	NP	5 min
Prediction	2012	[38]	HP (0.5Hz)-LP (70 Hz)	CTM	CTM	NP	NP	30 s
Prediction	2012	[37]	WTE	Threshold	k-fold cross validation	NP	Matlab	NP
Prediction	2010	[40]	WT+non-linear	NP	NP	NP	NP	30 s

2.10. Collected Methods from the Chosen Studies

To give flexibility, to increase the performance, and to make any algorithm more efficient, features extraction 145 is needed [6]. Table 5 presents the number of features extracted in the frequency, time, and spatial domains and non-linear features from all studies.

Table 5: The features (feat.) extracted in the selected studies. "-" = Not published.

Year	Ref	Time feat.	Frequency feat.	Time-frequency feat.	Nonlinear feat.	Morphology feat.	Statistics feat.
2021	[5]	-	-	1	-	1	-
2020	[6]	-	-	-	-	6	12
2018-2018	[3]-[11]						
2012-2016	[8][38]	-	-	1	-	-	-
2016	[33]						
2019	[21]	9	-	-	-	4	-
2018	[25]		-	-	-	4	-
2018	[24]	10	6	5	5	-	3
2017	[7]	6	-	48	-	12	6
2017-2020	[28]-[12]	-	-	8	-	-	6
2017	[27]	-	1	-	-	-	-
2017	[29]		-	-	-	5	-
2016	[31]	-	-	-	4	-	-
2015	[34]	-	-	1	1	2	-
2015	[9]	-	-	-	2	-	5
2012-2010	[37]-[40]	-	-	-	1	-	-

In the selected studies, the accuracy, specificity, sensitivity, and F1-score values as well as the Area Under The Curve were analyzed. These measures are obtained from the evaluation phase of the model (learning/validation phase and test phase) [24]. Indeed, in the evaluation of a model, four parameters are generally defined: the number of true positives (TP), true negatives (TN), false negatives (FN), and false positives (FP). These results are often reported on a confusion matrix. The main metrics used to evaluate a model are defined as:

- Accuracy: accuracy measures the effectiveness of a model as the ratio of true outcomes to the total number of cases:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}}$$

- Precision: precision is the ratio of true outcomes over all positive outcomes:

$$\text{Precision (or positive predictivity } P_+) = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- Recall: recall is the ratio of all true outcomes to all observations. It is the capacity of a model to

correctly classify a patient as sick:

$$\text{Sensitivity} = \text{Recall} = \frac{TP}{TP+FN}$$

- F1_score: F1_score is the harmonic average of precision and sensitivity, with values between 0 and 1:

$$\text{F1_score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

- Area Under the Curve (AUC): AUC measures the area under the curve plotted with true positives on the y axis and false positives on the x axis. It is the measure of the ability of a model to compare between classes
- Average log loss: it is a single score used to express the penalty for wrong results. It is calculated as the difference between two probability distributions – the true one and the one in the model.

Table 6 contains the results of each study and Table 7 shows all the features selected in each study.

Table 6: Performance of the selected studies. NP= Not reported. ECV=Electrical Cardioversion

Method	Year	Ref.	Duration of the signal (Classification)	Accuracy%	Recall%	Precision%	F1 score	AUC
			Delay before prediction					
Detection	2020	[12]	4 s	99.1	98.9	98.9	0.989	0.994
Detection	2020	[17]	-	97.87	-	99.29	-	-
Detection	2019	[23]	10 s	98.7	-	98.9	-	-
Detection	2019	[13]	-	99.10	99.2	99.4	0.969	-
Detection	2018	[3]	1-4 s	84.85	79.05	89.99	-	0.92
Detection	2018	[11]	5 beats	99.23	99.41	98.91	-	-
Detection	2017	[27]	-	86.7	-	-	-	-
Detection	2015	[33]	5 beats	95.28	96.47	94.19	-	-
Detection	2015	[9]	-	-	-	-	-	-
Classification	2021	[5]	17.2 s	98.61	98.61	-	-	-
Classification	2020	[6]	5 min	99.44	-	-	-	-
Classification	2020	[16]	-	98.13	98	96.8	-	-
Classification	2020	[2]	-	99.11	97.91	99.61	0.98	-
Classification	2020	[15]	9-60 s	99.1	99.1	98.9	0.995	-
Classification	2020	[14]	30 s	87.8	-	-	86.46	-
Classification	2019	[19]	-	99.5 (kNN)	96.97 (kNN)	100 (kNN)	-	-
				94.07 (SVM)	86.4 (SVM)	100 (SVM)	-	-
Classification	2019	[18]	-	99.03 (NN)	97.58 (NN)	99.39 (NN)	-	-
				99.83 (SVM)	99.57 (SVM)	99.89 (SVM)	-	-
Classification	2019	[21]	-	97.98 (RF-M7)	98 (RF-M7)	97 (RF-M7)	-	-
Classification	2018	[25]	-	99.75	98.7	99.9	-	-
Classification	2017	[7]	30 min	99	-	-	-	-
Classification	2017	[26]	-	91.98	94.14	89.32	-	-
Classification	2017	[30]	-	93.75	-	-	-	-
Classification	2017	[29]	30 min	100	-	-	-	-
Classification	2017	[28]	-	99.3 (KNN+GA)	98.84 (KNN+GA)	97.58 (KNN+GA)	-	-
				98.92 (SVM)	98.84 (SVM)	98.4 (SVM)	-	-
Classification	2016	[31]	3 s	87	65.54	92.25	-	-
Classification	2016	[32]	10 s	-	84.75	83.33	-	-
Classification	2015	[34]	30 min	94.64	-	-	-	-
Classification	2013	[35]	3500 s	99.8	-	-	-	-
Classification	2013	[36]	30 min	-	-	-	-	-
Classification	2012	[8]	2 s	96.5	-	-	-	-
Classification	2011	[39]	30 min	97.94	97.51	85.07	-	-
Prediction	2019	[20]	30 s	98.7	98.7	98.91	-	-
Prediction	2018	[24]	5 min	90	92	88	-	-
Prediction	2012	[38]	-	92	92.3	91.67	-	-
Prediction	2012	[37]	-	93.6 (PAF)	95.38 (PAF)	91.67 (PAF)	-	-
				84.05 (ECV)	85.4 (ECV)	81.2 (ECV)	-	-
Prediction	2010	[40]	30 s	85.71	80.95	-	-	-

Table 7: List of extracted features. **For P wave energy:** Ultra-low-frequency (ULF), very-low-frequency (VLF), low-frequency (LF), and high-frequency (HF) bands, Ratio of LF-to-HF power (LF/HF), Power Spectral Density in W/Hz (DSP). **For time domain:** Standard deviation of RR-NN intervals (SDRR and SDNN); Standard deviation of the average NN intervals for each 5 min segment (SDANN); Percentage of successive RR intervals that differ by more than 50 ms (PNN50); Number of NN intervals between which the difference occurs greater than 50 ms (NN50); Root mean square of successive RR interval differences (RMSSD); Root mean square (RMS); Baseline width of the RR interval histogram (TINN). **For nonlinear domain:** Detrended fluctuation analysis (DFA), which describes short-term fluctuations (a_1) or long-term fluctuations (a_2)

Domain	Features	Studies
Time	SDRR; SDNN; SDANN ; PNN50; NN50; RMSSD; RMS (ms); RMSSD; TINN	[24]-[26]
P-wave	Duration, Amplitude, Variance, P-axis, PR interval	[6]
P wave energy	ULF; VLF; LF; HF power (ms^2); LF=HF(%); DSP	[24]-[26]
Nonlinear	Sample entropy	[38][33]-[26]-[37]
	DFA 1; DFA 2	[37]
	Laminarity, determinism, entropy, trapping time, and transitivity	[29]
Statistics	Mean, Standard deviation, Variance	[3]-[6]-[9]-[28]
	Skewness, Kurtosis	[28]

3. Discussion

The objective of this paper is to study recent research papers in the field of ECG-based models for AF detection, classification, and prediction using AI models and WT. Below is a discussion of important blocs related to the construction of an efficient classification, detection, and prediction model.

3.1. Databases Used in the Selected Papers

Very expensive equipments, a medical professional, and patient protocol adherence are often required to collect ECG data. Therefore, to advance ECG-based research for various applications, including AF, researchers have developed public databases. Thirty-seven studies (89%) were based on Physionet-MIT-BIH database where eleven of them used the MIT-BIH AFDB (25 long-term ECG) [3, 11, 12, 13, 15, 20, 24, 33, 29, 17, 23], three studies were based on MIT-BIH PAF Prediction Challenge Database PAFDB (each record set contains two 30-minute records with consecutive record names and two 5-minute “continuation” records with names ending) [26, 20, 29], seventeen were based on the MIT-BIH Arrhythmia database [2, 5, 6, 7, 8, 27, 19, 18, 21, 25, 28, 31, 32, 34, 35, 36, 39], and two studies were based on the Normal Sinus Rhythm Database [6, 20]. In addition, one study (3%) was based on Cinc/Challenge 2004. For PAF (80 ECG recording) [14], four studies (13.5%) used their own database [37, 40, 38, 30], three studies (8%) were based on PhysioNet/Computing-in-Cardiology Challenge 2017 (8528 ECG recordings short term between 30 s and 60 s) [6, 13, 14]. One study (3%) was based on myocardial ischemia from the European ST-T database BIDMC congestive heart Failure

database (15 long-term ECG recordings for 20 hours) [27], another study [9] used the Physionet database and Abdullah et al. in [16] used the PTB databas. Ma et al., in [41], trained and tested their ANN model on the AF Termination Challenge Database and MIT-BIH Arrhythmia Database using RR intervals as an
185 input feature for automatic classification of AF and achieve 99.3 % of sensitivity, 97.4% of specificity, and 98.3% of accuracy. We also found other existing databases such as the American Heart Association (AHA) database and the St Petersburg 12-lead arrhythmia database INCART (St Petersburg DB).

3.2. Preprocessing Algorithms

ML involves some preliminary steps that are essential to the development of an efficient and reliable model.

190 These preliminary steps include data cleaning and filtering.

ECG signals are often contaminated by noise, such as: contact noise, muscle artifacts, baseline variation, power line interference, electromyography noise, and electrode motion artifacts [18].

- Electromyogram (EMG) noise: Muscle artifact is caused by muscle activity near the electrode during patient contraction of the heart. It is often difficult to remove this artifact since it is strictly related to
195 the electrical impulse of the ventricles that determines the QRS complex on the ECG. Removing this artifact can result in an unwanted distortion of the signal. However, there are various types of filtering that could be employed, such as the adaptive filter, the DWT, and the band-pass filter. Low-pass filtering methods used to remove EMG artifacts reduce the purity of important Q, R, and S wave components by losing their shape and some important information.
- 200 • Power line interference is caused by electromagnetic external devices, and usually appears in the signal as 50-60 Hz sinusoidal oscillations.
- Baseline caused by the patient's movements is usually visible with frequencies below 0.5 Hz in the signal. It can be removed using high-pass filters, WT, notch filters (infinite impulse response (IIR), finite impulse response (FIR)), band-pass filters, and adaptive filters.

205 The methods used for preprocessing are presented in Table 4 for the detection, the classification models, and the prediction models.

3.3. Feature Extraction

In the literature, ECG feature extraction methods are classified into two categories: manual and automatic [5]. In DL, NN are adequate for ECG signals and allow automatic layer-by-layer feature extraction [5]. 210

Feature extraction has a direct impact on the ability of the model to predict AF with high accuracy. Feature extraction can be done in different domains: time, frequency, and time-frequency [18]. FT is used to

transform a signal in the time domain to a signal of in the frequency domain. This approach is suited for stationary signals (the frequencies present in the signal are independent of time). As ECG signals are non-stationary data, FT is not adapted for these signals [18]. In addition, frequency techniques do not give
215 access to temporal information. They are therefore not adapted for the prediction nor the classification of ECG signals [18]. To overcome this problem, the short time FT (STFT) with sliding window divides the original signal into segments of equal duration and FT is applied on each segment.

Most signals, such as ECG signals, are non-stationary or time-varying time series. The WT method is a time-frequency technique that is widely used [8] to analyze non-stationary (time-varying frequency) signals,
220 especially biomedical signals including ECGs. Unlike FT which has high-frequency resolution, STFT has medium resolution in time and frequency domains. The WT method offers an advantage over FT because it leads to a time-frequency representation of the signal [18].

The WT approach uses a family of wavelets that differ in shape, scale, and smoothness. Computing nonlinear features using DWT has been shown to be effective for automatic ECG arrhythmia detection.
225 However, to feed a deep neural network, it is necessary to use the continuous wavelet transform (CWT) method to obtain a two-dimensional representation. Filos et al. in [30] used CWT for distinguishing between normal subjects and PAF patients. The results of the wavelet decomposition contain relevant features at different scales. The authors of [19] used DWT to retrieve the features of ECG signal. Sarkaleh et al. [8] used DWT coefficients as features and a back propagation neural network (BPNN) classifier to construct
230 an intelligent model that yields 96.5% accuracy for multilayer classification of two types of arrhythmias. Using DWT, heart rhythm features (HRV) were extracted by Kim et al. [39] and ELM model was used for classification. Table 8 shows the different features identified by the selected articles. The Daubechies wavelet (orthogonal, biorthogonal, and asymmetric DWT used for signal processing applications such as denoising, classification, and compression will be written as dbN, where N is the order and db the “surname” of the
235 wavelet) is the most usable form in the selected papers at different levels because of its regularity, which allows a good reconstruction of ECG signals. Sharmila et al. [9], Lassoued et al. [7], Sarkaleh et al. [8], Chasmi et al. [18], and Rodenas et al. [33] used db6 wavelet to decompose the signal into six detailed coefficients and extract features from the fifth coefficient. Runnan et al. [11], Singh et al. [6], and Narin et al. [24] used db4 to decompose ECG into low frequency (LF) and high frequency (HF) components. Also
240 Petmezas et al. in [17] used db4 Butterworth high pass filter (order 7) and low pass filter (order 6) to denoise and db4 to detect the R peaks. Xin et al. [26] used db8 with 8 decomposition scales to ensure that each coefficient can represent the excitability of ECG signals. Xu et al. [5] used db1 to achieve the best accuracy to extract HRV features. Daqrouq et al. [32] used db5 to achieve the best recognition rate and guarantee the same amplitude level. Thomas et al. [34] used db2 with DWT to decompose the signal in scale (dilated) and
245 in time (translated). Xie et al. [13] used a biorthogonal wavelet; this family of wavelets exhibits the property

of linear phase needed for reconstruction of the signal by using two wavelets, one for the decomposition and the other for the reconstruction. Nurmaini et al. [15] used sym5 wavelet that gives the best denoising (the Symlet wavelet family is the modified version of Daubechies wavelets with increased symmetry). Barasme et al. [35] used Morlet wavelet to detect QRS (explicit CWT without scaling function). Ebrahimzadeh et al. [42] used the Haar wavelet (db1 wavelets that reproduce constant functions only) to eliminate noise and HF on the ECG. Furthermore, Wang et al. in [23] used WPT based on the correlation of coefficient series to extract features. Finally, Alcaraz et al. in [40], [37], and [38] used wavelet entropy (WE). Reference [40] shows that the sensitivity (80.95%) and the specificity (85.71%) are the same for the following wavelet families: Haar, db5, Coiflet (3), Biorthogonal (4.4), Inverse Biorthogonal (4.4) and Symlets (5).

255 **3.4. Detection, Classification, and Predictive Algorithms**

The most used AF detection algorithm is CNN [3, 11, 13, 17, 22]. There are other models such as RF [12], DT [12], SVM [13], stacking model (DT-RF-GBDT-XGBoost-LightGBM) [12], and ANN model [?], followed ANN [7, 31, 32, 34], CNN [2, 14, 15, 16], DT [5, 14, 21, 28], MLP [7, 8, 36], ELM [5, 39], and KNN [28]. Other studies applied either LSTM [16], bidirectional LSTM (BiLSTM) [6], RF [21], PNN [29], 260 gradient-boosted trees (GDB) [21], NN [18], or OPF [36].

CNN with Haar WT was used to predict PAFDB [20]; SVM using wavelet multiscale entropy was used to predict PAFDB [26, 40], and genetic algorithm using WPT was used to predict PAFDB [24]. The most used method for prediction is SVM (10 times) followed by CNN (9 times), DT (5 times), and ANN (5 times). To achieve an evaluative comparison on the performance of the models, several criteria are taken into 265 consideration: the use of the same database, the same duration for the input signal, and the use of the same AI prediction model. For detection, Ref. [12] using DWT for feature extraction and stacking model achieved the best accuracy (99.1%) if the length signal is 4 s. The authors in [33], using CWT for feature extraction and CNN model, achieved the best accuracy (99.23%) for 22 s ECG signal.

For classification, the authors in [28] using DWT for feature extraction and PNN model – achieved the best 270 accuracy (100%) for 30 min ECG signal.

For prediction, Ref. [42] using DWT (Haar) for feature extraction and CNN model, achieved the best accuracy (98.7%) for 5 s ECG signal.

For all studies, the authors in Ref. [28] used DWT for feature extraction and DNN model and achieved the best accuracy (100%).

4. FFT vs WT

The selected studies were analyzed, and the main results are summarized as follows: the wavelet analysis is an effective methodology for analyzing and processing non-stationary signals, recognizing patterns, compressing data, and detecting anomalies. WT allows complex information (images) to be decomposed into time (positions) and frequency (scales) and then reconstructed with high resolution. In general, the WT method allows detecting RR intervals in the ECG and then the LDA method is used to reduce the features. Finally, for classification, we can see that deep neural networks containing convolution layers give good results. Table 8 presents a comparison between the FFT approach and the wavelet decomposition approach for AF prediction. The studies use the same database.

Table 8: Comparison for predicting AF between FFT and Wavelet. MV= Morphologic Variability; ME=Mixture of Expert

Method	Year	Ref.	Models	Delays	Accuracy %	Recall %	Precision %
FFT	2018	[43]	SVM	900 s	87.7	86.8	88.8
FFT	2018	[42]	ME :MLP-KNN-SVM	300 s	98.21	100	96.55
FFT	2016	[44]	SVM	1800 s	80.2	81.1	79.3
FFT	2013	[45]	MV-HRV	300 s	90	89.44	89.29
Wavelet	2019	[20]	CNN	30 s	98.7	98.7	98.6
Wavelet	2018	[24]	KNN	300 s	90	92	88

Among the papers using FFT, Ebrahimzadeh et al. in [42] obtained the best accuracy (98.21%) using the expert model mixture (SVM- MLP and KNN). The results are validated by 100% as sensitivity, 95.55% as specificity and 98.21% as accuracy. The authors used a 300-s signal from the MIT-BIH AF Prediction Database (AFPDB). The database contains 53 two-lead signals. They calculated twenty-eight features extracted from the HRV signal (temporal, frequency, and nonlinear). Among the papers using WT, Urtunasan et al. in [20] obtained the best accuracy (98.7%) using the CNN model with a sensitivity of 98.7% and a specificity of 98.6%. They used a 30 s duration signal from the MIT-BIH AFDB. For a 300 s duration signal, the best accuracy, specificity, and precision are 92.18%, 94.88%, and 89.48% respectively [26], using WT for denoising, compared with 90%, 89.44%, and 89.29% respectively [45], using FFT.

The drawback using WT is that the number of studies using the WT approach to detect, classify, and predict AF is rather low (it is therefore more difficult to have a clear opinion on the results), whereas those

295 using FFT are more numerous.

5. Conclusion

In this paper, we presented a review of recent works for the detection, classification, and prediction of AF using WT with an AI approach. Indeed, tools are very promising as they speed up decisions making and improve efficiency, reliability, and accuracy. This paper completes the work presented by Matias et al. [4].

300 We discuss the databases used for such models, the procedures for the preprocessing, and the process of features extraction and selection.

The most used database is the MITBIH fibrillation: it was used in 31 of the 37 selected studies. For the classification, SVM provides the best results for accuracy (around 99.83%); for prediction KNN provides the best results for accuracy (around 99.3%); for detection, CNN provides the best results for accuracy (around
305 99.23%). Moreover, the results of the prediction using FFT and WT methods for the feature extraction are competitive. The best FFT-based model provides 96.55% of precision using the ME whereas the best WT-based model provides 98.6% using the CNN model. The most used wavelet for AF prediction is the Daubechies wavelet. It was implemented in 14 of the 45 selected studies.

We found that the FFT-based models are much more used for the prediction, whereas WT and FFT are
310 equally used for the classification and the detection.

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