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Elektrokardiyogram (EKG) Verilerine Dayalı Yapay Zeka Destekli Atrial Fibrilasyonun Tespiti, Tahmini ve Sınıflandırılması Üzerine Bir Derleme

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ÖZ

Atriyal Fibrilasyon (AF), inme ve kalp yetmezliği gibi ciddi sağlık riskleri taşıyan yaygın bir kardiyak aritmi türüdür. Elektrokardiyogram (EKG) kayıtları ile AF tespiti geleneksel olarak manuel gözlem yoluyla gerçekleştirilmekte olup, bu yöntem zaman alıcı ve değişkenlik gösterebilmektedir. Yapay zeka (YZ) ve makine öğrenimi (MÖ) teknolojilerinin gelişmesiyle birlikte, EKG verilerine dayalı AF tespiti, tahmini ve sınıflandırmasını otomatikleştiren ve iyileştiren yeni yaklaşımlar ortaya çıkmıştır. Bu çalışma, AF analizinde kullanılan YZ ve MÖ yöntemlerini sistematik bir şekilde incelemekte olup, Konvolüsyonel Sinir Ağları (KSA) ve Uzun Kısa Süreli Bellek UKSB) ağları gibi derin öğrenme modellerinin yanı sıra Rastgele Orman (RO) sınıflandırıcıları gibi geleneksel modelleri ele almaktadır. Çalışma, modellerin güçlü ve zayıf yönlerini değerlendirerek doğruluk, duyarlılık, özgüllük ve F-skor gibi temel performans ölçütlerini tartışmaktadır. Ayrıca, veri değişkenliği, sensör sınırlamaları ve YZ'nin klinik iş akışlarına entegrasyonu gibi temel zorluklara dikkat çekmektedir. Hibrit modeller ve alan uyum tekniklerindeki güncel gelişmeler incelenerek, bu yeniliklerin model genelleştirilebilirliği ve veri kalitesine yönelik kısıtlamaları nasıl ele aldığı vurgulanmaktadır. Gelecekteki araştırmalar için açıklanabilir YZ, giyilebilir teknolojilerle sürekli izleme ve klinik deneylerle doğrulama gerekliliği öne çıkarılmaktadır. Bu gelişmeler, YZ araştırmaları ile pratik sağlık hizmeti uygulamaları arasındaki boşluğu kapatmada kritik bir rol oynamaktadır. Bu inceleme, YZ'nin AF teşhis ve yönetimindeki dönüştürücü potansiyelini ortaya koyarken, aynı zamanda mevcut teknik ve klinik zorluklara dikkat çekerek, daha güvenilir ve etkili YZ tabanlı çözümler geliştirilmesine katkı sağlamaktadır.

AI-Enabled Atrial Fibrillation Detection, Prediction, and Classification Based on ECG Data: A Review

Reviews

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ABSTRACT

Atrial Fibrillation (AF) is a prevalent and serious cardiac arrhythmia associated with significant health risks, including stroke and heart failure. Traditional AF detection using electrocardiogram (ECG) recordings relies on manual interpretation, which is time-consuming and prone to human error. Advances in artificial intelligence (AI) have enabled automated AF detection, prediction, and classification, leveraging deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, alongside traditional machine learning classifiers like Random Forest (RF). This review systematically examines AI-based

AF prediction

approaches for AF analysis, evaluating their advantages and limitations using key performance metrics, including accuracy, sensitivity, specificity, and F-score. Additionally, it discusses challenges such as data variability, sensor limitations, and the integration of AI into clinical workflows. The latest advancements in hybrid models and domain adaptation techniques are explored, addressing key constraints related to model generalizability and data quality. Future research directions emphasize the importance of explainable AI, continuous monitoring through wearable technologies, and clinical validation through real-world trials. While AI holds transformative potential for AF diagnosis and management, significant technical and clinical challenges remain for its widespread adoption in healthcare.

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1. Introduction

In accordance with the World Heart Federation, cardiovascular diseases (CVDs) have long been the primary contributor to mortality worldwide. In 2021, they accounted for 20.5 million deaths, which is about one-third of all global deaths. This figure has significantly increased from 12.1 million CVD deaths in 1990. Ischemic heart disease has become a major contributor to early mortality across diverse populations, affecting individuals of all genders in various countries. (Murray, 2022).

Among the various types of CVDs, arrhythmias are particularly concerning, as they can lead to sudden death. Arrhythmias are characterized by irregular heartbeats, which can be detected through electrocardiogram (ECG) recordings (Yildirim et al., 2019). Atrial Fibrillation (AF), a highly prevalent arrhythmia, has also been reported as one of the most commonly observed arrhythmias during COVID-19 (Guzik et al., 2020).

AF is clinically categorized into four primary types: paroxysmal, persistent, long-standing persistent, and permanent. Paroxysmal AF is defined by episodes that occur intermittently and spontaneously terminate within seven days. Persistent AF involves continuous arrhythmia lasting longer than seven days and typically necessitates medical intervention to restore sinus rhythm. Long-standing persistent AF refers to AF that has been sustained for more than 12 months. Permanent AF is diagnosed, when a joint decision is made by the patient and clinician to discontinue attempts at restoring sinus rhythm, representing a therapeutic approach rather than an inherent characteristic of the arrhythmia.

In addition to these classifications, the term first-detected AF is used to describe the initial documented episode of AF, regardless of symptom history. While not a distinct classification, first-detected AF serves as a clinically significant milestone in the progression and management of the condition (Joglar et al., 2024).

Many AF episodes are asymptomatic, making early detection difficult through conventional clinical approaches.Therefore, continuous and accessible cardiac monitoring is essential for timely AF detection and intervention.AF is linked to a high risk of ischemic strokes and heart failure, contributing to increased mortality rates (Petmezas et al., 2021). Early detection of AF is of critical importance, as it can significantly reduce the probability of stroke (Kirchhof et al., 2020). However, detecting AF in its early stages is challenging due to its intermittent nature, brief duration, and rapid disappearance of

symptoms. Smart technologies are becoming more popular in reaction to these constraints and the rising need for individualized disease prediction. These technologies allow constant, real-time data collecting and analysis by means of ultra-low-latency features. Such developments are essential for offering quick and precise forecasts, enabling early diagnosis, and helping individualized treatment strategies. Consequently, smart technologies are growing more essential to the domain of AF monitoring since they provide answers to the accessibility and efficiency issues connected with conventional ECG tools.

Furthermore, rather than depending just on large medical-grade devices, wearable devices have surfaced as quite successful substitutes. These wearables provide more consistent and immediate data collecting, so excelling in continuous monitoring, which is vital for the AF field. By means of continuous monitoring, one can close the gap between preventive and predictive medicine, so allowing earlier detection and intervention. Using wearable technology, healthcare professionals can improve the preventive and predictive features of AF care, therefore providing a more complete management of the disease.

From the standard 12-lead ECG systems to more portable alternatives like Holter monitors, e-patches, event recorders, implantable loop recorders, and single to multiple-lead ECG devices, ECG tools for AF monitoring include a range of devices. Despite the wearable device effectiveness, traditional 12-lead ECG is still considered as a gold standard for detecting CVDs, but they pose challenges due to their size, cost, and the time required for clinicians to place the device on the patient's body, so this is one of the reasons that using wearable technologies are becoming more and more popular.

ECG is an essential tool for assessing cardiac health by capturing the heart's electrical activity. It records a complete cardiac cycle, displaying characteristic waveforms such as the P wave, QRS complex, T wave, and occasionally the U wave. The P wave, associated with atrial depolarization, appears as a small, rounded shape, while the QRS complex represents ventricular depolarization with larger and more varied waveforms. The T wave indicates ventricular repolarization (Chen et al., 2021). Despite its importance, the ECG has limitations. The signals are collected through sensor leads on the skin, which can be affected by external noise, causing amplitude changes and glitch interference. These issues can affect the accuracy of both human and computer interpretations of cardiac activity, necessitating signal pre-processing to reduce or eliminate noise-induced errors (Chen et al., 2022).

In cases of AF, the ECG shows specific changes: the P wave disappears, replaced by irregular baseline fluctuations known as f waves, and there is an absolute irregularity of the RR interval (Chen et al., 2022). Furthermore, extended ambulatory cardiac rhythm monitoring for AF, such as through implantable loop recorders, often presents practical limitations due to its invasive nature, high cost, and the need for substantial monitoring infrastructure. In contrast, the development of an AI-driven, non-invasive, and widely accessible diagnostic tool holds the potential to transform current approaches to AF detection and management. A significant proportion of strokes have no known cause, and are frequently associated with previously undiagnosed AF. Detecting AF in these patients enables timely initiation of anticoagulation therapy, which can substantially reduce the risk of recurrent strokes and may contribute

to improved survival outcomes (Attia et al., 2019). Considering these limitations, artificial intelligence (AI) presents significant potential for advancing the detection, classification, and prediction of AF. By augmenting ECG analysis, AI can uncover patterns and subtle indicators that may elude even experienced clinicians, thereby supporting more precise and timely diagnoses. This is particularly advantageous for individuals who do not exhibit symptoms yet possess elevated CHA_2DS_2-VASc scores, as they are at increased risk for both asymptomatic AF and stroke (Hochstadt et al., 2019).

AI-based ECG analysis can detect**,** predict and classify AF with high precision, offering a quick, cost-effective, and point-of-care solution for identifying the condition (Attia et al., 2019). By means of 'real-time' dynamic evaluations and better medical management for patients with AF, AI/ML technologies have the capacity to augment and extend the application of AF detection and risk prediction (Olier et al., 2021).

In addition to the aforementioned, AI/ML technologies applied to AF prediction have the potential to transform the ECG into a powerful tool for both screening and predicting not only cardiac conditions but also non-cardiac diseases, even in individuals who are asymptomatic. (Attia et al., 2021). In conclusion, cardiovascular diseases, Arrhythmias, particularly AF, are a major health concern globally. While the ECG is a critical tool for AF identification, its limitations highlight the need for advanced methods. AI models offer innovative solutions for early detection, accurate classification, and effective prediction of AF, ultimately improving patient outcomes and preventing severe complications like stroke.

This paper systematically reviews and presents the literature, highlighting the essential steps in developing an AI/ML-based solution for AF detection using ECG data. In comparison to existing reviews in this area, which have focused on specific methodologies such as wavelet-based approaches (Serhal et al., 2022), introductory explanations of AI/ML concepts for clinical readers (Feeny et al., 2020), or broad discussion-centered summaries (Rizwan et al., 2021), the present review takes a different approach. Here, the primary aim is to summarize and directly compare key aspects of recently published AF detection studies, including the type of ECG representation used as well as different domains of an ECG and the modeling strategy adopted. By organizing 29 selected studies into structured tables that highlight their input data, feature choices, modeling approaches, and performance metrics, this review provides a clear, practical starting point for both clinicians and engineers who seek to understand how different AI strategies have been applied to AF recognition.The studies selected for this review showcase the most recent and state-of-the-art approaches in applying AI/ML techniques for the analysis of biomedical signals in the context of AF, based on the search criteria outlined in the following section. The structure of the paper is as follows: Section 2 outlines the methodology, Section 3 presents the results of the Systematic Literature Review (SLR), Section 4 provides the discussion, and Section 5 concludes the paper.

2.Material and Methods

2.1. Review protocol

The systematic review followed the established guidelines by (Kitchenham; Charters, 2007). A review protocol was created before the review began, starting with the development of research questions. After defining these questions, relevant studies were chosen from databases such as Science Direct, Scopus, Web of Science, and PubMed. These studies were then filtered, and evaluated based on exclusion and quality criteria. Data obtained from the selected studies were gathered and analyzed to address the research questions. The review process was structured into three primary stages: planning the review, conducting the review, and reporting the review. The preliminary stage, planning the review, includes formulating research questions, creating a protocol, and validating it to ensure practicality. This stage also involves specifying publication sources, initial search terms, and criteria for selecting publications. After detailing these elements, the protocol is re-evaluated to confirm its suitability as a review protocol. The systematic review process followed a structured methodology, encompassing planning, conducting, and reporting phases, as illustrated in Figure 1. When performing the review, publications were identified by thoroughly searching all databases. Data extraction involved screening the titles and abstracts of the publications for quality criteria, using the web application Rayyan QCRI (Ouzzani et al., 2016). Collecting information on authors, year of publication, and type of publication was stored using the Zotero application (Vanhecke, 2008) and details related to the research questions were stored using Excel. After ensuring all necessary data was accurately extracted, it was systematically integrated to deliver a comprehensive summary of the relevant literature published to this point. In the final stage, Reporting the review, the results were documented, and the research questions were addressed, as shown in Figure 1.

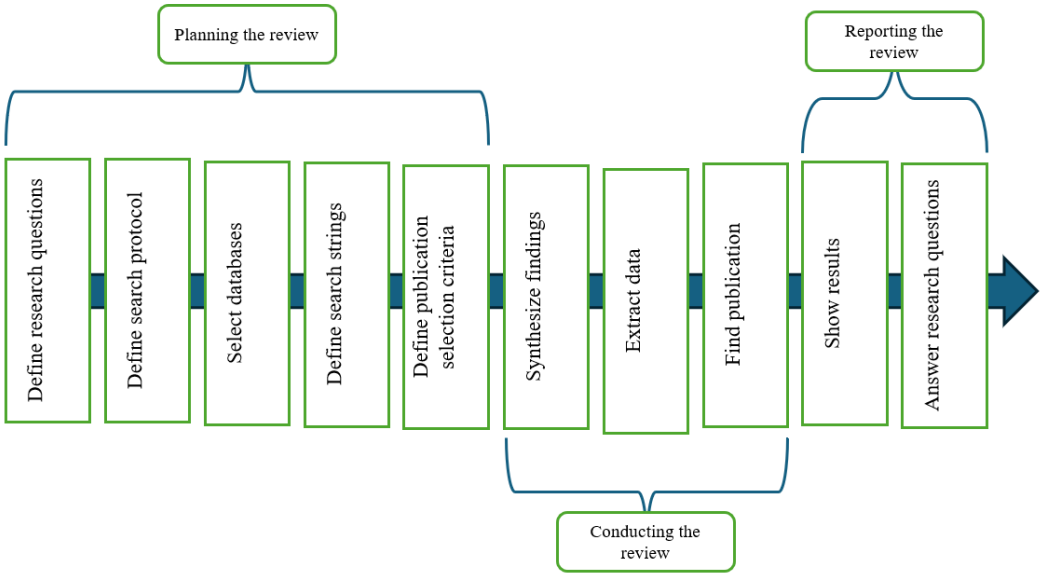


Figure 1. Phases of the review process.

2.2. Research questions

This systematic review intends to uncover trends in AI/ML studies related to AF. The studies have been evaluated from several perspectives to provide comprehensive understanding.

For this analysis, four specific research questions (RQs) have been posed.

- RQ1- What algorithms have been employed in the literature for detecting AF?
- RQ2- What features have been utilized in the literature for AF using AI algorithms?
- RQ3- What evaluation metrics and methodologies have been applied in the literature for AF?
- RQ4- What are the challenges encountered in the application of AI for AF?

2.3. Search strategy

The search is concentrated on the primary concepts relevant to this review's scope. AI's vast range of applications means many studies are likely beyond the article's focus. An automated search is used for the preliminary filtering.

The databases Web of Science, Scopus, PubMed, and Science Direct were used to search for relevant publications. The first two used databases are interdisciplinary databases. Finally, PubMed was used due to its content regarding research in biomedicine and Science Direct because of its high number of articles from thousands of books and journals. We searched titles and abstracts using the keywords presented below. The keywords used in each database are given as below:

Web of Science: ((“machine learning “OR “artificial intelligence” OR “deep learning”) AND (“ECG” OR “electrocardiogram” OR “EKG” OR “HRV”) AND (“Atrial fibrillation prediction” OR “Atrial fibrillation detection” OR “Atrial fibrillation classification”))

Scopus: ((“machine learning “OR “artificial intelligence” OR “deep learning”) AND (“ECG” OR “electrocardiogram” OR “EKG” OR “HRV”) AND (“Atrial fibrillation prediction” OR “Atrial fibrillation detection” OR “Atrial fibrillation classification”))

PubMed: ((“machine learning “OR “artificial intelligence” OR “deep learning”) AND (“ECG” OR “electrocardiogram” OR “EKG” OR “HRV”) AND (“Atrial fibrillation prediction” OR “Atrial fibrillation detection” OR “Atrial fibrillation classification”))

Science Direct: ((“machine learning “OR “artificial intelligence” OR “deep learning”) AND (“ECG” OR “electrocardiogram” OR “EKG” OR “HRV”) AND (“Atrial fibrillation prediction” OR “Atrial fibrillation detection”))

2.4. Exclusion criteria

In order to eliminate irrelevant studies, they were assessed and rated based on pre-determined exclusion criteria, which helped define the scope of the review. As outlined in Table 1, all articles that did not meet the exclusion criteria were subjected to a full-text review for eligibility. The data gathered aimed at determining whether the studies fulfilled the exclusion criteria and to address the research questions. The studies that met the exclusion criteria are presented in tables in the subsequent section. During the

data synthesis process, all extracted information was consolidated and integrated, and the research questions were addressed accordingly. The findings are presented in the following section.

Table 1. Inclusion and exclusion criteria applied in this review.

Type	Inclusion	Exclusion
Language	English	Any other language
Journal	Journal papers	All other
Authors	All	None
Setting	All	None
Research Design	Original research article	All others
Date of publication	After 2019	All other

3. Results

At the beginning of the search, we retrieved 669 papers from the resources given above; after applying exclusion and inclusion criteria, we were able to have 393 papers. Among those 393 papers, 291 were duplicates. After resolving duplication, we were left with 209 papers. After reviewing the abstract/title of those papers, 54 papers were left for full-text review, from those 54 papers we are left with 29.

Figure 2 illustrates the number of publications per year over the past five years. The data indicate a recent increase in papers focused on AF recognition utilizing AI on ECG data. We have normalized the number of publications annually versus the chosen publications to make the comparison more understandable.The orange line represents the synthesized publications from this systematic literature review, while the blue curve depicts the overall publications obtained from the databases.

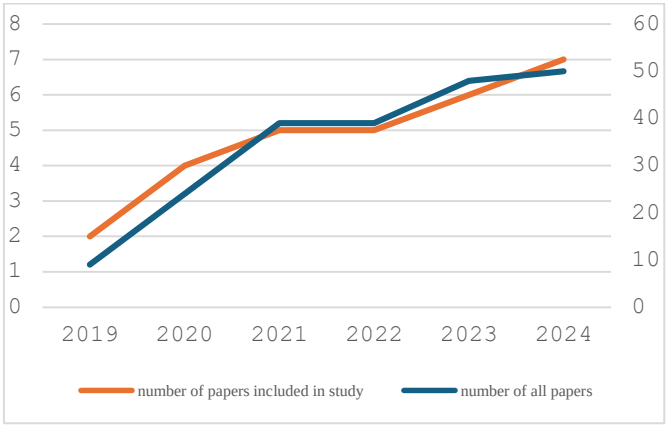


Figure 2. Publication trends in AI-based AF recognition.

3.1. Used datasets

MIT-BIH Arrhythmia Database (MITDB): The MIT-BIH Arrhythmia Database consists of 48 half-hour segments of two-channel ambulatory ECG recordings from 47 subjects, collected by the BIH Arrhythmia Laboratory between 1975 and 1979. Of these recordings, 23 were randomly selected from a pool of 4000 24-hour ambulatory ECG recordings taken from a diverse population at Boston's Beth

Israel Hospital, with approximately 60% being inpatients and 40% outpatients. The remaining 25 recordings were specifically chosen to represent less common but clinically important arrhythmias that would be underrepresented in a smaller random sample.

These recordings were digitized at 360 samples per second per channel with an 11-bit resolution over a 10-mV range. The annotations for each heartbeat, totaling around 110,000, were created by two or more cardiologists who independently reviewed the data. Any discrepancies were resolved to produce the final computer-readable reference annotations included in the database (Moody & Mark, 1992a).

MIT-BIH atrial fibrillation database (AFDB): The database consists of 25 long-term ECG recordings from human subjects, primarily with PAF. Each recording is 10 hours in duration and includes two ECG signals, sampled at 250 samples per second with 12-bit resolution over a range of ±10 millivolts. These recordings were originally captured at Beth Israel Hospital (now Beth Israel Deaconess Medical Center) using ambulatory ECG recorders, with a recording bandwidth of approximately 0.1 Hz to 40 Hz. Notably, 23 of the 25 records contain complete ECG data, while two records provide only rhythm and beat annotations. The data in this database are particularly useful for studying AF, as they encompass a significant amount of detailed, manually and automatically annotated information on heart rhythms (Moody and Mark, 1992b).

MIT-BIH Normal Sinus Rhythm Database (NSRDB): The database contains 18 long-term ECG recordings from patients who were referred to the Arrhythmia Laboratory at Beth Israel Hospital in Boston, now known as Beth Israel Deaconess Medical Center. The individuals in this dataset, who exhibited no significant arrhythmias, include 5 men aged 26 to 45 and 13 women aged 20 to 50 (Goldberger et al., 2000).

MIT-BIH Noise Stress Test Database: The database consists of 12 half-hour ECG recordings and 3 half-hour recordings capturing noise commonly encountered in ambulatory ECG recordings. The noise recordings were generated using physically active volunteers and standard ECG equipment, with electrodes positioned on the limbs in locations where the subjects' ECG signals were not clearly observable. These recordings predominantly feature baseline wander, muscle artifacts, and electrode motion artifacts (Moody et al., 1992).

The Long-Term AF Database (LTAF): The database comprises 84 long-term ECG recordings from individuals with either paroxysmal or sustained AF. Each recording features two ECG signals captured simultaneously, digitized at a rate of 128 Hz with 12-bit resolution over a 20-mV range. The duration of these recordings varies, but they typically span 24 to 25 hours (Petrutiu et al., 2003).

PTB-XL ECG dataset: The PTB-XL ECG dataset, consisting of 21,799 12-lead ECG records from 18,869 patients, is a valuable resource for training and evaluating automatic ECG interpretation algorithms. The dataset includes annotations by cardiologists, with 71 ECG statements categorized according to the SCP-ECG standard, covering diagnostic, form, and rhythm aspects. It also contains comprehensive metadata, including demographic details, infarction characteristics, and signal quality information, making it suitable for machine learning applications. The dataset offers both original and

down sampled waveform data, and a recommended 10-fold cross-validation strategy ensures comparability in algorithm evaluation. Publicly released in 2019, it supports both research and clinical uses, with ethical approval granted for its open-access distribution (Wagner et al., 2020).

PhysioNet/CinC Challenge 2017 (CinC2017): The 2017 PhysioNet/CinC Challenge seeks to create algorithms capable of categorizing four types of short ECG recordings 30 to 60 seconds into normal sinus rhythm, AF, another type of rhythm, or too noisy to classify. Detecting AF can be challenging because of its episodic character and resemblance to other irregular rhythms, as it is a prevalent arrhythmia connected to major health concerns. Detection methods generally analyze either atrial activity or ventricular response, with some combining both for improved accuracy (Clifford et al., 2017).

First China Physiological Signal Challenge 2018 Database (CPSC2018): The publicly accessible CPSC2018 dataset is meant to help algorithm development for identifying rhythm and morphology anomalies in 12-lead ECGs. This dataset has eight abnormal types and one normal ECG type. The accompanying paper outlines the data source, recording details, and clinical baseline parameters of the patients, such as age and gender (Liu et al., 2018a).

4th China Physiological Signal Challenge 2021 Database (CPSC2021): AF is the most common form of cardiac arrhythmia, yet its paroxysmal variant often remains undetected due to its intermittent and unpredictable nature. Early and accurate identification of PAF is essential for guiding timely interventions both pharmacological and surgical and for mitigating the risk of related complications. However, existing AF detection algorithms primarily focus on rhythm classification without precisely determining the onset and offset of AF episodes. This limitation hinders personalized treatment and complicates the clinical management of patients, particularly in the presence of other irregular rhythms that can obscure detection. In order to address these challenges, the 4th China Physiological Signal Challenge 2021 (CPSC 2021) introduced a dynamic ECG dataset specifically curated to support the development of advanced algorithms for PAF detection. This dataset is intended to enhance the accuracy, robustness, and efficiency of PAF identification in real-world dynamic ECG recordings. Furthermore, CPSC 2021 proposed a novel scoring metric tailored to evaluate the performance of algorithms in detecting PAF episodes, promoting innovation in both algorithmic precision and clinical applicability (Wang et al., 2021).

Clinical Outcomes in Digital ECG dataset (CODE): The dataset consists of annotated 12-lead ECG recordings, encompassing 345,779 exams collected from 233,770 unique patients. It represents a stratified sample comprising approximately 15% of the total patient population within the larger Clinical Outcomes in Digital Electrocardiography (CODE) dataset. These recordings were gathered by the Telehealth Network of Minas Gerais over a six-year period, from 2010 to 2016, ensuring a diverse and representative sample for research in ECG-based analysis (Ribeiro et al., 2021).

Table 2. Structured overview of papers selected through systematic filtering.

Reference	Title	Dataset used
(Wan X et al., 2024)	A novel atrial fibrillation automatic detection algorithm based on ensemble learning and multi-feature discrimination	AFDB
(Li et al., 2024)	M-XAF: Medical explainable diagnosis system of atrial fibrillation based on medical knowledge and semantic representation fusion	CODE, CPSC2018
(Zou et al., 2024)	A generalizable and robust deep learning method for AF detection from long-term ECG	AFDB, CPSC2021, LTAF, MITDB, NSRDB
(H. Zhang et al., 2024)	An AF classification method based on an outlier data filtering strategy and modified residual block of the feature pyramid network	CinC2017, AFDB, MITDB
(Xiong et al., 2024)	Short-term paroxysmal atrial fibrillation detection with intra- and inter-patient paradigm based on R-R intervals	AFDB, MITDB
(Deng et al., 2024)	An intelligent computer-aided diagnosis method for paroxysmal atrial fibrillation patients with nondiagnostic ECG signals	AFDB
(Liu et al., 2024)	Adaptive atrial fibrillation detection focused on atrial activity analysis	AFDB, MITDB, CPSC2021, (SMU) simulated an ideal noise-free dataset (own), MIT-BIH Noise Stress Test database
(Kumar et al., 2023)	An investigation of the contextual distribution of false positives in a deep learning-based atrial fibrillation detection algorithm	AFDB, MITDB, NSRDB, CACHET Contextualized Arrhythmia D. (CACHET-CADB)
(Laghari et al., 2023)	Deep residual-dense network based on bidirectional recurrent neural network for AF detection	CPSC2018
(Serhal et al., 2023)	An EMD-based approach for AF classification using wavelets and convolutional neural network	PAF database, PTB-XL ECG dataset
(Gündüz et al., 2023)	AF classification and detection from ECG recordings	CPSC2021
(J. Chen et al., 2023)	Implementing ultra-lightweight co-inference model in ubiquitous edge device for AF detection	CinC2017, CPSC2018, AFDB
(Bui et al., 2023)	Automatic varied-length ECG classification using a lightweight DenseNet model	CinC2017, CPSC2018
(Rahul & Sharma, 2022)	AI-based approach for AF detection using normalised and short-duration time-frequency ECG	AFDB, MIT-BIH, NSRD
(Y. Chen et al., 2022)	AF Detection Using a Feedforward Neural Network	CinC2017, MITDB
(Król-Józaga, 2022)	AF detection using convolutional neural networks on 2-dimensional representation of ECG signal	AFDB
(Liu et al., 2022)	MGNN: A multiscale grouped convolutional neural network for efficient AF detection	AFDB, MITDB, NSRDB, CinC2017, CPSC2018
(Subramanyan et al., 2022)	A novel deep neural network for detection of AF using ECG signals	AFDB
(Tutuko B et al., 2021)	AFibNet: an implementation of AF detection with CNN	AFDB, CinC2017, CPSC2018, LTAF, PAF, AF Termination Challenge, Fantasia, MITDB, ECG from Chapman Univ, Shaoxing People's H., two ECG DB.
(X. Zhang et al., 2021)	Over-fitting suppression training strategies for deep learning-based AF detection	Wearable ECG databases I and II (own), AFDB, CinC2017
(Parsi et al., 2021)	Prediction of paroxysmal AF using new heart rate variability features	AFPDB
(Petmezas et al., 2021)	Automated AF Detection using a Hybrid CNN-LSTM Network on Imbalanced ECG Datasets	AFDB
(Hirsch et al., 2021)	Atrial fibrillation detection using heart rate variability and atrial activity: A hybrid approach	AFDB
(Cai et al., 2020)	Accurate detection of atrial fibrillation from 12-lead ECG using deep neural network	The Chinese PLA General Hospital (own), wearable ECG devices (own), CPSC2018
(Jin, Qin et al., 2020)	Multi-domain modeling of AF detection with twin attentional convolutional LSTM networks	AFDB
(Cao et al., 2020)	A novel data augmentation method to enhance deep neural networks for detection of AF	CinC2017
(Jin, Liu, et al., 2020)	A novel Domain Adaptive Residual Network for automatic Atrial Fibrillation Detection	AFDB, MITDB, CinC2017
(Dang et al., 2019)	A Novel Deep Arrhythmia-Diagnosis Network for AF Classification Using ECG Signals	AFDB

(Attia et al., 2019)	An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction	Mayo Clinic Digital Data Vault(own)

CACHET Contextualized Arrhythmia Database (CACHET-CADB): This dataset consists of ambulatory single-channel ECG recordings collected in real-world, everyday settings, reflecting natural physiological conditions. It includes data from 21 patients 13 males and 8 females with a mean age of 58.7 ± 10.11 years. Participants were recruited from outpatient arrhythmia clinics located in India and Denmark, providing a diverse patient population for the study of arrhythmia in ambulatory contexts (Kumar et al., 2022).

PAF Prediction Challenge Database (AFPDB): This database of two-channel ECG recordings was created for the Computers in Cardiology Challenge 2001 an open competition designed to stimulate the development of automated techniques for predicting PAF. Further information regarding the competition can be found in the official challenge announcement. For a comprehensive overview of the clinical significance of PAF prediction, its implications, and suggested further readings, please consult the section titled Predicting the Onset of AF (Moody et al., 2001).

AF Termination Challenge: This collection of two-channel ECG recordings was assembled for the Computers in Cardiology Challenge 2004, an open competition designed to promote the development of automated methods for predicting the spontaneous termination of AF (Moody, 2003).

Fantasia: Twenty young adults (aged 21–34) and twenty older adults (aged 68–85), all rigorously screened for health, participated in a 120-minute continuous supine resting protocol. Throughout this period, continuous ECG and respiratory signals were recorded. In half of the participants from each age group, an uncalibrated, continuous, non-invasive blood pressure signal was also collected. Each subgroup was balanced for sex, comprising an equal number of male and female participants (Iyengar et al., 1996).

ECG recording from Chapman University and Shaoxing People’s Hospital: A newly established research database of 12-lead ECG signals, developed through a collaboration between Chapman University, Shaoxing People's Hospital, and Ningbo First Hospital, is designed to support and accelerate research into arrhythmias and other cardiovascular diseases. These conditions pose a significant burden on global public health, adversely affecting individuals' quality of life and contributing to rising healthcare costs. As a vital, non-invasive diagnostic tool, ECG plays a central role in the detection and monitoring of such diseases; however, the large volume of data it produces demands extensive human expertise for accurate interpretation. By providing high-quality, expert-annotated ECG recordings from 45,152 patients—sampled at 500 Hz and encompassing a wide range of common rhythms and cardiovascular conditions—this database enables the development, validation, and refinement of modern statistical and machine learning approaches. These data-driven methods have the potential to enhance diagnostic precision and reduce clinician workload. The resource also includes two additional

ECG signal recording datasets collected from an Indonesian hospital, further contributing to the diversity and applicability of the dataset for broader research and clinical application (Zheng et al., 2020).

As shown in Table 2, some studies have utilized either their own collected datasets or a combination of private and public datasets. Unlike the public datasets, I have not provided detailed explanations for the private datasets, as they are not readily accessible or available for public use.

The abbreviations used in the tables refer to the following databases: MIT-BIH AF Database (AFDB), Clinical Outcomes in Digital ECG Dataset (CODE), the first China Physiological Signal Challenge 2018 Database (CPSC2018), the 4th China Physiological Signal Challenge 2021 Database (CPSC2021), the Long-Term AF Database (LTAF), the MIT-BIH Arrhythmia Database (MITDB), the MIT-BIH Normal Sinus Rhythm Database (NSRDB), the PhysioNet/CinC Challenge 2017 atrial fibrillation prediction database (CinC2017), and the Atrial Fibrillation Prediction Database (AFPDB).

3.2. Preprocessing

Preprocessing and feature engineering play an important role in feeding accurate data to the model; therefore, the methods and the features extracted from the data in the studied papers will be explained as follows.

The main noise sources of ECG signals include baseline wander, powerline interference, electromyographic noise, and electrode motion artifact noise ("Signal Processing Techniques for Removing Noise from ECG Signals," 2019). Therefore, preprocessing is used for noise removal from the signals.

Baseline Wander: Low-frequency noise that causes the baseline of the ECG signal to drift up and down. It is often due to patient movement, respiration, or electrode motion. Power Line Interference (PLI) is a common type of noise affected by the electrical power supply, typically at 50 or 60 Hz, and its harmonics. Muscle Activity (Electromyographic Noise) is the electrical activity from the muscles, which can interfere with the ECG signal, especially during periods of muscle contraction. Motion Artifacts are the result from the movement of the patient or the electrodes, which can cause transient noise in the signal. External Electromagnetic Interference is the interference from other electronic devices, such as mobile phones or other medical equipment, can affect the ECG signal. Internal Instrumentation Noise is the noise generated by the ECG machine itself, including thermal noise and electronic noise from the components. In order to remove this kind of noise, the data is preprocessed by using the methods as it is shown in Table 3. So, in most of the studies, the preprocessing has been done and then after that the selected features will be fed to the model if not the raw data is fed to the model. The preprocessing techniques include the median filter (MF), Butterworth filter (BWF), Pan-Tompkins algorithm (PT), combination of local outlier factor and random oversampling algorithms (L-ROS), discrete wavelet transform (DWT), wavelet transform (WT), band-pass filter (BPF), high-pass filter (HPF), low-pass filter (LPF), fractional S-Transform (FrST), instantaneous heart rate (IHR), heart rate variability (HRV), mean RR interval (meanRR), standard deviation of the RR interval (SDNN), skewness of RR interval

Table 3. Methods utilized in the selected studies.

Study	Pre-processing method(s)	Model used	Evaluation method(S)	Type of problem
(Wan X et al., 2024)	MF, BWF, notch filter, PT	ELMD	NA	detection
(Li et al., 2024)	NA	M-XAF	NA	classification
(Zou et al., 2024)	PT, Hamilton algorithm, BWF	MIF-AFNet	5-fold cv	detection
(H. Zhang et al., 2024)	L-ROS, WT, minimum–maximum normalization	MRFPN	10-fold cv	classification
(Xiong et al., 2024)	DWT, PT, Hampel filter	RF	10-fold cv	detection
(Deng et al., 2024)	moving average filters, MF, wavelet packet decomposition and reconstruction, KPCA	AlexNet, VGG19, ResNet152, Inception-v3, Inception-ResNet-v2	NA	classification
(S. Liu et al., 2024)	BPF, BWF, PT	1D CNN	NA	detection
(D. Kumar et al., 2023)	BPF, Savitzky–Golay filter, PT	multi-layer CNN +RNN	5-fold cv	detection
(Laghari et al., 2023)	NA	DRDN via Bi-LSTM	NA	detection
(Serhal et al., 2023)	NA	2D-CNNs	NA	classification
(Fatih Gündüz & Fatih Talu, 2023)	BPF, DWT and EMD	CLSTM+ BiLSTM	NA	classification
(J. Chen et al., 2023)	HRV:(meanRR, SDNN, SKRR , PNN20, RCVΔRR), PT	MLP	NA	detection
(Bui et al., 2023)	NA	lightweight DenseNet	NA	classification
(Rahul & Sharma, 2022)	2-stage MF, Least-square filter	Bi-LSTM	10-fold cv	classification
(Yunfan Chen et al., 2022)	WT and sliding window filtering	FNN	10-fold cv	detection
(Król-Józaga, 2022)	NA	CNN	5-fold cv and 9:1	detection
(S. Liu et al., 2022)	PT, gqrs algorithm	MGNN	5-fold cv	classification
(Subramanyan & Ganesan, 2022)	LPF, HPF, FrST spectrogram	CNN and RNN with Multivariate AutoRegressive Algorithm	10-fold cv	detection
(Tutuko B et al., 2021)	DWT	1D-CNNs	10-fold cv	detection
(X. Zhang et al., 2021)	BWF, FFT and Hanning-window-based filter	LSTM, 1D-CNN	10-fold cv	detection
(Parsi, Glavin, et al., 2021)	cubic spline interpolation, IHR, McNames's algorithm + WT	SVM, K-NN, MLP, RF	10-fold cv	prediction
(Petmezas et al., 2021)	BWF, DWT	CNN-LSTM with FL	10-fold cv	detection
(Hirsch et al., 2021)	PT, MF	RF	4- fold cv	detection and prediction
(Cai et al., 2020)	NA	DDNN	5-fold cv	detection
(Jin, Qin, Huang, et al., 2020)	NA	TAC-LSTM	NA	detection
(Cao et al., 2020)	WT, Z-score normalization	LSTM	10-fold cv	detection
(Jin, Qin, Liu, et al., 2020)	resampling and z score normalization	DARN	NA	detection
(Dang et al., 2019)	peaks detection, segmentation, z-score normalization	CNN-BiLSTM	NA	classification
(Attia et al., 2019)	NA	CNN	NA	detection

(SKRR), proportion of the adjacent interval difference greater than 20 ms (PNN20), and the reciprocal of the coefficient of variation in ΔRR (RCVΔRR).

3.3. Extracted Features

In ECG analysis, features are primarily derived from either atrial activity, ventricular activity or both. Atrial activity is assessed through the absence of P waves and the presence of fibrillatory waves, while ventricular activity is analyzed through R waves. In order to extract meaningful insights from ECG data, various feature extraction methods are employed across different domains, methods used by each study can be found in Table 4.

Temporal Features: Temporal features play a crucial role in the analysis of physiological signals, as they offer valuable insights into the variability and temporal dynamics of RR intervals. One such feature, the Group Coefficient of Variation (CV_RR), captures the degree of heart rate variability by expressing the standard deviation of RR intervals relative to their mean. This measure provides a concise representation of the overall fluctuation in heart rate over time. Another important metric, the RR Interval Distribution Difference Curve (dRDDC), assesses how the distribution of RR intervals shifts across different time segments. By tracking these distributional changes, dRDDC enables a deeper understanding of the evolving patterns in heart rate behavior. In addition to advanced temporal features, fundamental statistical measures such as the mean, standard deviation, and skewness of RR intervals are integral to characterizing temporal patterns within physiological signals. The mean reflects the average duration between heartbeats, while the standard deviation captures the variability around this average, offering insights into heart rate stability. Skewness, on the other hand, reveals asymmetries in the distribution of RR intervals, which may indicate irregularities in rhythm. Collectively, these measures provide a foundational understanding of the temporal dynamics of cardiac activity.

Frequency Domain Features: Frequency domain analysis involves converting time-domain signals into their constituent frequency components, offering an alternative perspective for understanding signal characteristics. A commonly employed method for this transformation is the Fast Fourier Transform (FFT), which facilitates the conversion of time-domain data into the frequency domain. This process enables the extraction and analysis of various spectral features, including spectral centroid, spectral crest, spectral entropy, spectral flux, spectral kurtosis, spectral roll-off point, spectral skewness, and spectral slope. These features provide critical insights into the signal's frequency structure, such as the distribution of energy across frequencies and the overall configuration of the power spectrum.

Time-Frequency Features: Time-frequency analysis techniques integrate elements from both the time and frequency domains, offering a more detailed and dynamic understanding of signal behavior. Among these, the Continuous Wavelet Transform (CWT) stands out as a powerful tool for examining signals at various scales and positions, effectively capturing changes in both time and frequency. Similarly, the

Table 4. ECG signal treatment and feature extraction information from the studies.

Study	Feature Extraction Method	Feature Extracted	Signal duration
(Wan X et al., 2024)	CV_RR, dRDDC, FFT, Fast SampEn	RRI	NA
(Li et al., 2024)	NA	f-waves & RRI	10s
(Zou et al., 2024)	NA	RRI	30 s
(H. Zhang et al., 2024)	NA	NA	30s
(Xiong et al., 2024)	Mean, standard deviation, and skewness, Esh, CosEn, LZC, C0-complexity	RRI	10s
(Deng et al., 2024)	CWT	NA	15s
(S. Liu et al., 2024)	CosEn	RRI& AA	13 RRI
(D. Kumar et al., 2023)	NA	RRI	10s
(Laghari et al., 2023)	NA	NA	NA
(Serhal et al., 2023)	EMD-IMF and CWT	NA	NA
(Gündüz et al., 2023)	FFT, IFFT, spectral centroid, spectral crest, spectral entropy, spectral flux, spectral kurtosis, spectral-roll-off-point, spectral skewness and spectral slope features	p wave & RRI	10s
(J. Chen et al., 2023)	NA	RRI	32 RRI
(Bui et al., 2023)	NA	NA	30s
(Rahul & Sharma, 2022)	spectrogram of STFT	NA	4s
(Yunfan Chen et al., 2022)	Pan-Tompkin's algorithm	RRI	NA
(Król-Józaga, 2022)	Spectrogram, scalogram, AR	RRI	5s
(S. Liu et al., 2022)	NA	RRI	32 RRI
(Subramanyan et al., 2022)	NA	NA	5s
(Tutuko B et al., 2021)	NA	RRI	NA
(X. Zhang et al., 2021)	FFT, IFFT	NA	NA
(Parsi, Glavin, et al., 2021)	NN50, pNN50, PSD,Lm Sum of the logarithmic magnitude, SD1, SD2, The width (SD1) and the length (SD2) of the generated ellipse in Poincar´e plot. HRV feature(Difference Map Covariance, Univariate KDE Features, Bivariate KDE Feature)	RRI	5-min
(Petmezas et al., 2021)	DWT	RRI	NA
(Hirsch et al., 2021)	HRV (FD, ShEn, CosEn, LLE and Linear statistics and geometrical features), AA features (EMD&InA, SpEn, REn, RSP, TPN, InA trend, FD and CosEn)	RRI & AA	30 RRI
(Cai et al., 2020)	NA	NA	10s
(Jin, Qin, Huang, et al., 2020)	DWT, CWT	NA	5s
(Cao et al., 2020)	PanTompkins QRS detector	NA	NA
(Jin, Qin, Liu, et al., 2020)	NA	NA	10s
(Dang et al., 2019)	NA	RRI & heartbeat	NA
(Attia et al., 2019)	NA	NA	10s

Short-Time Fourier Transform (STFT) provides a time-frequency representation by applying a sliding window to the signal, though the use of a fixed window size can influence the balance between time and frequency resolution. For more complex and non-linear signals, methods such as Empirical Mode Decomposition (EMD) and its resulting Intrinsic Mode Functions (IMFs) are used to break down signals into simpler, more interpretable components. These approaches are particularly valuable for analyzing non-stationary signals. Visual tools like spectrograms and scalograms, which are generated through time-frequency analysis, help illustrate how the signal's properties evolve over time, offering intuitive insights into its underlying structure.

Non-Linear Features: Non-linear analysis offers valuable perspectives on the inherent complexity and irregularity present in physiological signals. Among these methods, Fast Sample Entropy (Fast SampEn) serves as a measure of signal regularity, capturing how predictable the signal is over time. In contrast, Information Entropy (Esh) quantifies the unpredictability or randomness within the signal. The Coefficient of Sample Entropy (CosEn), closely related to SampEn but utilizing different parameter settings, provides complementary insights into signal complexity.Lempel-Ziv Complexity (LZC) evaluates the structural complexity of sequences by examining their compressibility, thereby reflecting the degree of repetitiveness or novelty within the signal. Similarly, C0-Complexity stands as another non-linear metric, contributing additional information about the signal's dynamic characteristics. In the context of Poincaré Plot analysis a geometric method for visualizing heart rate variability two key features, SD1 and SD2, are derived from the shape of the plotted data. SD1 corresponds to the width of the resulting ellipse and reflects short-term variability, while SD2 represents the ellipse's length and captures longer-term trends and correlations in RR intervals.

Various tools and techniques are utilized in physiological signal analysis to enhance the accuracy of AF detection. The Pan-Tompkins Algorithm is essential for identifying QRS complexes in ECG signals, while methods like Discrete Wavelet Transform (DWT) and Inverse Fast Fourier Transform (IFFT) support time-frequency analysis and signal reconstruction. Bispectrum Analysis explores non-linear frequency interactions, and the Turning Point Number (TPN) captures irregularity through mean-crossing behavior. Collectively, these approaches contribute to a comprehensive assessment of signal features, which are typically categorized into temporal, frequency, time-frequency, and non-linear domains each offering unique insights into physiological processes such as heart rate variability and AF.

3.4. Model used

In the field of AF detection, prediction, and classification, a wide array of machine learning and deep learning models has been explored to improve diagnostic accuracy and system reliability. Traditional machine learning techniques, such as Random Forest (RF) and its classification variant, are frequently employed due to their robust performance in classification tasks. Support Vector Machines (SVM) are also widely used for their ability to handle complex decision boundaries. Other classical models, including K-Nearest Neighbors (KNN), Multi-layer Perceptron (MLP), and Feedforward Neural

Networks (FNN), are effective in identifying intricate patterns within AF datasets, thereby supporting enhanced predictive performance. Deep learning approaches have further advanced the analysis of AF data, particularly through the use of convolutional neural networks (CNNs). One-dimensional CNNs (1D-CNNs) are particularly suited for sequential data such as ECG signals, while two-dimensional CNNs (2D-CNNs) enable the extraction of spatial features, offering a more comprehensive understanding of signal morphology. Established CNN architectures such as AlexNet, VGG19, ResNet152, Inception-v3, and Inception-ResNet-v2 have demonstrated strong performance benchmarks in AF detection and classification. More recent innovations, including lightweight DenseNet and other Densely Connected Convolutional Networks (DenseNets), provide improved feature extraction capabilities and higher classification accuracy. Moreover, advanced models such as the deep residual-dense network and the Multiscale Grouped Convolutional Neural Network (M-GNN) introduce greater architectural complexity, enabling more nuanced analysis and better predictive outcomes. Hybrid frameworks that integrate convolutional and recurrent elements, such as Convolutional Long Short-Term Memory (CLSTM) networks combined with Bidirectional LSTM (Bi-LSTM), allow for a richer, multi-dimensional representation of AF-related temporal and spatial features. Recurrent neural networks (RNNs), particularly architectures like Bi-LSTM and multi-layer LSTM models, are instrumental in modeling the temporal dynamics inherent in AF signal sequences. Enhanced models such as the Twin-Attentional Convolutional Long Short-Term Memory Network (TAC-LSTM) incorporate attention mechanisms, further refining sequence learning and boosting performance in AF detection, prediction, and classification tasks.

3.5. Quantitative results

Among the evaluated methods for AF detection, the Ensemble Learning and Multi-Feature Discrimination (ELMD) model by Wan X. et al. (2024) achieved the highest performance, with an accuracy of 99.25%, sensitivity of 98.90%, specificity of 99.60%, and an F-score of 99.24%. For detecting short-term paroxysmal AF, Xiong et al. (2024) reported strong results using a Random Forest model, reaching over 99.5% accuracy on both AFDB and MITDB datasets. Similarly, Cai et al. (2020) employed a Deep Densely Connected Neural Network with wavelet denoising and Z-score normalization, achieving 99.35% accuracy. In AF classification, the 1D-CNNs model by Tutuko et al. (2021) outperformed others with 99.8% across all key metrics. Zhang et al. (2024) introduced a Modified Residual Feature Pyramid Network (MRFPN), achieving up to 97.58% accuracy and 98.35% sensitivity. Gündüz and Talu (2023) also obtained high performance with their CLSTM–BiLSTM model, reporting 97.72% accuracy. For AF prediction, Parsi et al. (2021) tested multiple models, with SVM performing best (97.7% accuracy, 98.8% sensitivity), while Jin et al. (2020) presented the Domain Adaptive Residual Network (DARN), achieving 98.84% accuracy and 98.97% sensitivity.

Table 5. Performance evaluation of the selected studies.

Study	Accuracy	Sensitivity	Specificity	F1-score
1	99,25	98,90	99,60	99,24
2	CPSC18: 97,15 CODE: 97,19	CPSC18: 95,39 CODE: 93,64	CPSC18: 99,02 CODE: 98,96	CPSC18:97,18 CODE:95,67
3	AFDB:98,63 LTAF 97,04 MITDB:98,07 NSRDB:100 CPSC21: 98,63	AFDB:97,35 LTAF:96,81 MITDB:98,45 NSRDB:NA CPSC21:99,08	AFDB:99,49, LTAF:97,31 MITDB:98,04 NSRDB:NA CPSC21:98,03	AFDB: 98,28 LTAF:97,23 MITDB:90,17 NSRDB:NA CPSC21:98,18
4	CinC2017: 96,85 AFDB:97,58 MITDB: 95,04	CinC17:96,85 AFDB:98,35 MITDB:94,63	CinC17: 96,84 AFDB:96,41 MITDB: 99,00	CinC2017: 98,25 AFDB: 97,99 MITDB: 97,19
5	AFDB:99,57 MITDB:99,56	AFDB:99,62 MITDB: 97,87	AFDB: 99,54, MITDB: 99,89	NA
6	90	90	90	NA
7	AFDB: 99,61, MITDB: 95,76	AFDB: 99,44 MITDB: 99,74	AFDB: 99,69, MITDB: 95,33	NA
8	AFDB:97,04 MITDB:87,98 NSRDB:5,56	AFDB:96,06 MITDB:96,87 NSRDB: 13,06	AFDB: 98,29, MITDB: 86,94, NSRDB: 94,44	NA
9	97,72	93,09	98,71	NA
10	PAF Dataset: 98,8 PTB-XL 95,7/98,8/95,8	NA	NA	NA
11	Spectral Features: 85,54 P wave: 87,65 R-R distances: 83,02	NA	NA	NA
12	AFDB: 87,29 CPSC18: 93,65	AFDB: 94,20 CPSC18: 93,81	NA	NA
13	NA	NA	NA	0,826 (±012)
14	98,85	98,90	98,80	NA
15	84,00	84,26	93,23	NA
16	5-fold CV / 9:1 ratio U B Spectrogram:93 89 / 0,94 0,95 Scalogram:95 93 / 94 94 Attractor:89 88 / 89 89	5-fold CV / 9:1 ratio U B Spectrogram: 91 90 / 92 95 Scalogram: 94 95 / 89 94 Attractor: 87 92 / 87 90	NA	5-fold CV / 9:1 ratio U B Spectrogram:91 90 / 92 93 Scalogram:93 92 / 92 94 Attractor: 86 88 / 87 89
17	AFDB:97,07 MITDB:92,23 NSRDB:96,86 Phy17:94,23 CPSC18:95,91	NA	NA	NA
18	99,16	98,64	99,01	NA
19	99,8	99,8	99,8	99,77
20	97,71	98,13	97,29	NA
21	SVM:97,7 KNN:91,7 MLP:97,2 RF:95	SVM:98,8, KNN:87,8 MLP:96,7 RF:97,8	SVM:96,7, KNN:95,6 MLP:97,8 RF:91,1	NA
22	NA	97,87	99,29	NA
23	97,4	95,9	96,1	88,4
24	99,35	99,19	99,44	90,7
25	98,51	98,14	98,76	NA
26	82,949 ± 1,437	NA	NA	0,82
27	98,84	98,97	98,75	NA
28	96,59	99,93	97,03	NA
29	79,4	79	79,5	39,2

Notes: NA stands for not available. U stands for unbalanced. B stands for balanced.

Overall, the models by Wan X., Xiong, and Cai excel in detection; Tutuko, Zhang, and Gündüz lead in classification; and Parsi and Jin demonstrate strong prediction capabilities. Detailed performance metrics are summarized in Table 5.

The methods abbreviations utilized in this study consist of ensemble learning and multi-feature discrimination (ELMD), medical explainable AF diagnosis system (M-XAF), multi-input fusion AF detection network (MIF-AFNet), modified residual block of the feature pyramid network (MRFPN), random forest (RF), one-dimensional (1D), convolutional neural networks (CNN), recurrent neural network (RNN), deep residual-dense network (DRDN), bidirectional recurrent neural network (BiLSTM), convolutional long short-term memory (CLSTM), multi-layer perceptron (MLP), densely connected convolutional networks (DenseNets), feedforward neural network (FNN), multiscale grouped convolutional neural network (MGNN), k-nearest neighbors (k-NN), support vector machine (SVM), focal loss (FL), deep densely connected neural network (DDNN), twin-attentional convolutional long short-term memory neural network (TAC-LSTM), long short-term memory (LSTM), and domain adaptive residual network (DARN). The evaluation method applied in most studies is cross-validation (CV). In general notes, the medical explainable AF diagnosis system (M-XAF) integrates one-dimensional CNNs with residual convolutional neural networks, while the multi-input fusion AF detection network (MIF-AFNet) incorporates residual convolutional neural networks and bidirectional long short-term memory networks. Additionally, "NA" indicates data that is not available across all tables.

4. Discussion

4.1. General discussion

One critical area of discussion in the field of AF monitoring is the comparative capability of various ECG configurations, particularly how they measure up against the 12-lead ECG. The 12-lead ECG is traditionally regarded as the gold standard for detailed cardiac assessment, providing comprehensive electrical activity data from multiple angles. However, variations such as single-lead, dual-lead, or 6-lead ECGs are increasingly being utilized for their convenience and cost-effectiveness, especially in continuous monitoring scenarios (Ramkumar et al., 2018). A pertinent question is whether these alternative ECG configurations are sufficient for accurate AF prediction, classification, and detection. While they offer some level of monitoring capability, their diagnostic precision may not match that of the 12-lead ECG. This limitation raises the possibility that continuous monitoring facilitated by advanced technologies such as 5G and 5G+ could bridge this gap. These technologies promise to enhance real-time data transmission, allowing clinicians to monitor patients continuously and potentially achieve predictive and preventive results more efficiently and cost-effectively than current methods.

Nevertheless, the deployment of these technologies is accompanied by several challenges. The lack of standardized data collection across different hospitals and the variability in sensor types can impede the integration of results. Even when data augmentation and domain adaptation techniques are employed,

discrepancies remain. Our review indicates that while deep learning models are commonly used to achieve novel results, the datasets and features utilized in these studies vary significantly. This variability underscores the need for a more unified approach to data collection and analysis to leverage the full potential of advanced monitoring technologies. In conclusion, although alternative ECG configurations and emerging technologies hold promise for enhancing AF management, several issues need addressing.

4.2. Search-related discussion

Some significant publications may have been inadvertently skipped. Using a wider range of synonyms and broadening the search criteria might have uncovered additional studies. Despite this, the search string led to a substantial number of publications.

4.3. Analysis-related discussion

Another issue that could undermine the validity of the analysis is the inconsistency in how it is conducted. For instance, not all publications specified the evaluation parameters used, and sometimes only a limited number of features were described. As a result, essential information needed to address the research questions was often missing. Consequently, data to answer these questions were derived from only a few of the 29 selected publications. While contacting the authors of these publications might have provided additional information, this approach was not feasible within the scope of this research and might not have resolved all the issues.

RQ1-Related (algorithm) discussion: Most of the studies reported in this work have increasingly leveraged deep learning for AF detection, prediction, and classification due to its ability to handle the complexity and variability inherent in ECG data. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), excel at processing large-scale, high-dimensional ECG signals, automatically learning and extracting relevant features without the need for manual engineering. This capability enhances the accuracy of AF detection, offering greater sensitivity and specificity than conventional diagnostic approaches.

Moreover, deep learning models are robust to the variability found in ECG data across different patients and conditions, making them suitable for diverse populations. Their ability to process data in real-time is particularly valuable for continuous monitoring systems, where timely detection is crucial. The scalability of deep learning also allows these models to be trained on large datasets, enhancing their generalizability. Additionally, the integration of deep learning with wearable technology has enabled real-time, continuous AF monitoring, contributing to the growing trend of personalized medicine, where models are tailored to individual patient data for more effective management of AF.

RQ2–Related (features) discussion: The features utilized in AF detection models derived from ECG data are varied, encompassing a broad spectrum from fundamental time-domain characteristics, such as RR intervals and heart rate variability (HRV) metrics, to more intricate nonlinear and frequency-domain

attributes, including entropy measures and wavelet transforms. The application of time-frequency analysis, particularly through Continuous Wavelet Transform (CWT) and Short-Time Fourier Transform (STFT) spectrograms, underscores the critical role of capturing the dynamic fluctuations in the ECG signal fluctuations that are pivotal for the accurate detection of AF. While the duration of signal segments may differ, shorter segments are often preferred to effectively capture the rapid temporal variations inherent in AF.

RQ3-Related (evaluation parameters and approaches) discussion: Cross-validation is an essential method in the evaluation of AF models, offering several key advantages that contribute to the accuracy and reliability of performance estimates. It helps address issues such as data imbalance, facilitates the optimization of hyperparameters, and ensures external validation, thereby maximizing the utilization of available data (Reps et al., 2020). These advantages collectively strengthen the robustness, generalizability, and efficiency of AF models, ultimately enhancing their reliability and potential for clinical application (Krstajic et al., 2014).

RQ4–Related (challenges) discussions: The challenges highlighted in the literature are primarily derived from explicit observations made in the identified articles, although there may be additional, unmentioned challenges. A central concern involves enhancing the performance of existing models. For example, increasing the volume of data available for training and testing is critical, as a larger dataset can significantly improve the precision and reliability of these models. Another major challenge is the integration of these models into AF management systems. The true value of these models can only be realized when they are applied in real-world clinical settings, where they can be utilized by both clinicians and patients, particularly during episodes of AF. Furthermore, the accuracy of predictions can be further improved by customizing models to incorporate individual-specific parameters, which would facilitate more personalized and precise management of AF.

4.4. Comparison With Existing Review Studies

Several review papers have previously discussed AI-based atrial fibrillation detection, prediction, and classification; however, the focus and structure of those works differ from the present review. For instance, “Overview on Prediction, Detection, and Classification of Atrial Fibrillation Using Wavelets and AI on ECG” (Serhal et al., 2022) places its primary emphasis on wavelet-based approaches, focusing mainly on time–frequency signal transformations rather than comparing multiple data representations or model architectures.

In “Artificial Intelligence and Machine Learning in Arrhythmias and Cardiac Electrophysiology” (Feeny et al., 2020) , the goal is different. The first objective of that review is to provide basic AI/ML literacy for readers who are new to this field by explaining commonly used methods, terminology, and challenges. The second objective is to discuss how AI/ML are influencing clinical practice, including disease detection and prediction of patient outcomes. The final objective is to highlight considerations for validation and deployment of AI tools in medical environments. In contrast, the present review does

not focus on explaining AI/ML concepts in depth. Instead, we summarize and compare the important features and methodological choices of the reviewed studies, presenting them in structured tables with focus on how these features were used to solve the AF detection problem.

The review titled "A Review on the State of the Art in Atrial Fibrillation Detection Enabled by Machine Learning" (Rizwan et al., 2021) has research objectives similar to ours; however, its approach is more discussion-based, organized around broader thematic areas within the domain. In our view, this paper can be read side by side with the present work, as they complement each other in perspective, but our work provides a more feature- and representation-focused comparison.

Other reviews also differ in primary scope. For example, "Artificial Intelligence in the Diagnosis and Management of Arrhythmias" (Nagarajan et al., 2021) discusses technological advances in data acquisition, including robotic catheter ablation systems and 3D imaging tools in addition to ECG. The review "Smartwatch for the Detection of Atrial Fibrillation" (Tajrishi et al., 2019) focuses primarily on differences among commercial wearable device brands rather than analytical or computational modeling. Meanwhile, "Computational Models of Atrial Fibrillation: Achievements, Challenges, and Perspectives for Improving Clinical Care" (Heijman et al., 2021) centers on cellular, subcellular, organ-level, and statistical modeling approaches, which represent a markedly different research direction from AI-based ECG analysis.

Taken together, these distinctions clarify the unique contribution of the present review: a structured comparison of 29 recent studies, organized according to the type of ECG representation (raw waveform, HRV-derived statistical features, or image-based transformations) and the modeling approach used (traditional ML, deep learning, or hybrid architecture). This provides a practical and accessible reference for both clinicians and engineers who aim to understand the variety of strategies employed in AI-enabled AF detection.

5. Conclusion

There is a growing trend toward incorporating smart technologies into the monitoring of AF, driven by the increasing demand for personalized disease prediction and the limitations of conventional ECG tools. These advanced technologies, characterized by ultra-low latency, enable continuous, real-time data collection and analysis, which are crucial for delivering timely and accurate predictions. This capability facilitates early diagnosis and supports the development of personalized treatment plans, positioning smart technologies as an increasingly vital component of AF monitoring.

The studies selected in this area showcase a diverse range of approaches to AF detection, classification, and prediction using AI algorithms. Each study differs in terms of the features and datasets used, reflecting the research scope and available data. Interestingly, while models incorporating more features might be expected to yield better results, the findings suggest this is not always the case for AF. As a result, it is essential to evaluate models with varying numbers of features to identify the most effective configuration.

Despite the variety of algorithms employed, no single model has been established as the best across all studies. However, deep learning models, particularly variations of CNN and RNN, are commonly used, highlighting their central role in this field of research. As smart technologies continue to advance, they hold promising potential in overcoming the accessibility and efficiency limitations of traditional methods, complementing ongoing efforts to refine AI-based models for AF detection, classification, and prediction.

Statement of Conflict of Interest

The authors declares that there is no conflict of interest.

Author's Contributions

The authors declare that they have contributed 100% to the manuscript.

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