A Review on Atrial Fibrillation Detection From Ambulatory ECG

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***Abstract*—Atrial fibrillation (AF) is a prevalent clinical arrhythmia disease and is an important cause of stroke, heart failure, and sudden death. Due to the insidious onset and no obvious clinical symptoms of AF, the status of AF diagnosis and treatment is not optimal. Early AF screening or detection is essential. Internet of Things (IoT) and artificial intelligence (AI) technologies have driven the development of wearable electrocardiograph (ECG) devices used for health monitoring, which are an effective means of AF detection. The main challenges of AF analysis using ambulatory ECG include ECG signal quality assessment to select available ECG, the robust and accurate detection of QRS complex waves to monitor heart rate, and AF identification under the interference of abnormal ECG rhythm. Through ambulatory ECG measurement and intelligent detection technology, the probability of postoperative recurrence of AF can be reduced, and personalized treatment and management of patients with AF can be realized. This work describes the status of AF monitoring technology in terms of devices, algorithms, clinical applications, and future directions.**

***Index Terms*—Atrial fibrillation (AF), electrocardiogram (ECG), ambulatory ECG.**

I. Introduction

ATRIAL fibrillation (AF) is a progressive and insidious disorder that typically begins intermittently and terminates spontaneously. The prevalence of AF is about 1%–2% of the total population [1], [2]. The incidence of AF has increased significantly in patients with various cardiovascular diseases, particularly for the elderly. It has been found that the lifetime risk of AF by the age of 40 is 25% [3]. AF can increase the risk of stroke by five-fold [4]. The annual cost of related treatment, nursing and drugs for AF is enormous [5].

According to lasting time, AF is divided into four types in the 2020 European Society of Cardiology (ESC) Guidelines: paroxysmal, persistent, long-term persistent, and permanent [6]. Paroxysmal AF (PAF) is the initial stage of AF and is characterized by spontaneous termination or intervention within seven days of onset, where about 18% of PAF evolve into permanent AF over 4 years [7]. Monitoring and treatment of AF in its early stages is very important. Persistent AF persists for more than seven days. Long-term continuous AF is staying for more than 12 months. Permanent AF refers to being accepted by the patient, and the physician will no longer attempt to maintain sinus rhythm.

The challenges in diagnosing AF arise from its intermittent and asymptomatic nature, as symptoms commonly associated with AF, such as fatigue, shortness of breath, and palpitations, may coexist with cardiovascular diseases such as heart failure [8]. Many AF patients fail to recognize symptoms associated with AF, hindering prompt treatment that can lead to high risk consequently. A report from the British National Clinical Guideline for Management of Atrial Fibrillation in Primary and Secondary Care found that less than one-third of patients with AF were found to have AF and entered the clinical intervention phase [9]. A British study reported that in the decade between 2020 and 2030, the number of newly diagnosed AF patients over the age of 65 will increase [10]. A higher 1-year mortality was evident in asymptomatic AF patients compared with symptomatic AF patients [11]. Early detection of AF is essential for its management promptly. 2020 the ESC Guidelines for the diagnosis and management of AF recommend its screening for individuals over the age of 65 or at increased stroke risk. Early intervention and therapy reduce the risk of adverse cardiovascular outcomes in early-stage AF patients over 75 years [6]. A recent study conducted in China determined the prevalence of AF and gaps in AF awareness and management in the country. The study found that the prevalence of AF in China has significant treatment gaps and a low awareness rate,

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and varied from 0.9% to 2.4% across geographical regions [12]. AF rarely occurs alone, therefore the assessment of risk factors and comorbidities is essential for early AF management [13]. Sustainable ECG monitoring devices can be used to monitor the high incidence of AF and stroke risk factors in AF patients, enabling real-time and long-term patient management for those at high risk of stroke [14]. Furthermore, the primary reason for the recurrence rate after surgery is the difference in surgical plans and the severity of AF [15]. Continuous monitoring of patients before surgery, quantifying the type and severity of AF, may help reduce postoperative recurrence of AF [16].

With the popularization of mobile terminals and the rapid development of technologies such as the Internet of Things, Big Data, cloud computing, and artificial intelligence (AI), wearable ECG monitoring has begun to be widely accepted by the public as a new method for monitoring people's heart health in their daily life [8], which can be used in different living scenarios or activities such as standing, walking, eating, and sleeping [17]. As a low-load physiological monitoring technology, wearable ECG can provide a new way of monitoring, evaluating, and managing AF [18]. A recent study examined the effect of wearable continuous ECG monitoring patches on the detection of undiagnosed AF. The study found that wearable ECG monitoring devices reported higher rates of AF diagnosis among individuals who were at an increased risk for AF. Individuals who used wearable ECG monitoring also had better initiation of anticoagulants and increased utilization of healthcare resources one year later [19]. In the future, wearable devices may provide more precise anticoagulant targeting while reducing the overall risk of stroke and the social care costs of AF-related disease [20], [21]. For individuals at high risk of having AF, using home-based wearable ECG monitoring can lead to a higher diagnosis rate of AF and timely use of anticoagulants, resulting in improved clinical outcomes [19], [22]. The 7-day ECG monitoring should be required as a practical first-line approach to improve diagnosis and therapeutic management after stroke [23]. Additionally, frequent monitoring using single-ECG devices can reduce the incidence of thromboembolic events, severe bleeding, and death [24].

Ambulatory ECG continuous monitoring can continuously collect massive ECG data. To detect AF, AI-driven approaches have been applied to analyze enormous ECG signals, which has dramatically improved the detection rate of AF. Such achievement has been accelerated because of the publicly available datasets from multiple sources. For example, the PhysioNet/Computing in Cardiology (CinC) Challenge 2017 [25] aims for AF classification from short single-lead ECG recordings, and the contestants developed several AF detectors using AI models. The China Physiological Signal Challenge 2019 (CPSC 2019) [26] aims to encourage the development of algorithms for QRS detection from ambulatory single-lead ECG recordings, often with relatively low signal quality and abnormal rhythm waveforms. The China Physiological Signal Challenge 2021 (CPSC 2021) [27] aims to encourage the development of algorithms for searching the PAF from ambulatory ECG recordings.

Although the AF monitoring technology based on wearable ECG has been developed for many years, the current AF monitoring faces several challenges, briefly described in the following:

- *Wearable sensing:* The environment of wearable ECG monitoring involves daily life with various living scenarios and activities. Therefore, developing wearable devices with accurate ECG measurements while ensuring portability and convenience is a significant challenge.
- *AF detection accuracy:* AF detection based on low-quality ECG signals is more challenging due to motion artifacts and noise interference, compared to static ECG data measured in a controlled environment.
- *Clinical application:* The generalization ability of AF detection algorithms is limited due to variations in personal data. Improving the detection rate of AF in clinical data is a big challenge. Meanwhile, the interpretability of deep learning-based AF detection algorithms in clinical applications is a challenge.

This article introduces an overview of wearable AF monitoring. Section II presents AF monitoring methods. Section III describes the influencing factors of AF analysis algorithms. Section IV describes wearable AF analysis and processing methods. Section V discusses AF clinical application. Section VI highlights the future directions. Finally, conclusions are drawn in Section VII. For a comprehensive review, we searched multiple platforms, including IEEEXplore, ScienceDirect, Google Scholar and PubMed databases, and mainly selected studies published in reputable journals and conferences, which are ranked by reputable citation indexes (e.g., Science Citation Index). In each sub-section of the literature selection, we used keywords to search out relevant literature, screened representative articles through literature reading, compared these recent studies, outlined their limitations, and provided directions for future development. This will enable researchers to easily access the required information and select the appropriate algorithm for their specific application.

II. Atrial Fibrillation Monitoring Methods

AF, particularly PAF, is a challenging disease to detect, with a low detection rate at onset. One study [28] found that the detection rate of PAF using 12-lead routine ECG and ECG monitoring was only 0.6% and 0.5%, respectively, while the detection rate from 12-lead Holter was 16%. The detection rate of AF is closely related to the duration of AF monitoring, highlighting the need for convenient and continuous monitoring technology to facilitate AF detection.

Wearable health monitoring is an emerging technology that enables continuous monitoring of vital signs and is widely adopted to diagnose and assess significant health risks and chronic cardiac diseases. In the future, these devices may be used to screen for cardiovascular disease at home, making it possible to monitor occult cardiovascular disease. With the progress of sensing technology, long-term physiological signal monitoring equipment has become more comfortable to use. Several

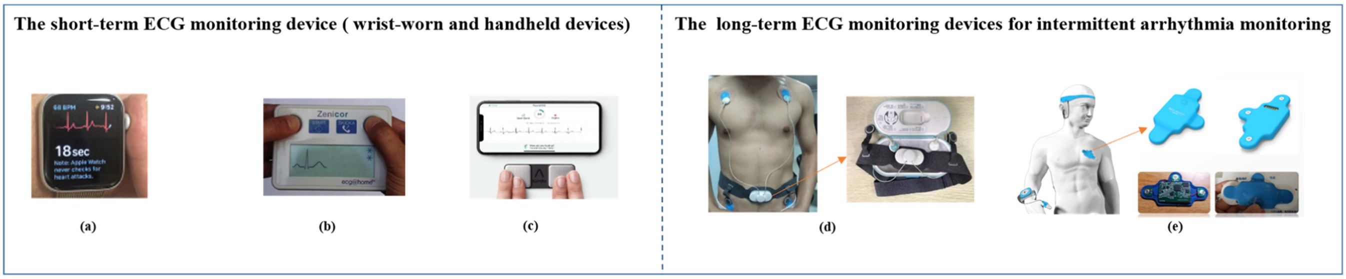

Fig. 1. Portable ECG monitoring devices. (a) Apple Watch [40]. (b) Zenicor ECG device [43]. (c) AliveCor ECG device [44]. (d) The 3-lead wearable ECG device with 72-h monitoring. (e) The single-lead ECG device with 24-h monitoring.

portable wearable devices are used for AF screening, including Photoplethysmography (PPG) signal monitoring and Ballistocardiogram (BCG) signal monitoring. BCG signal and PPG signal can only reflect cardiac rhythm information, and they are typically used for arrhythmia disease screening rather than disease diagnosis. In particular, the BCG signal sensor is usually placed in the mattress or cushion, not a portable monitoring method.

The primary portable AF monitoring devices currently available are PPG-based AF screening devices and ECG-based wearable monitoring devices [29]. The ECG is the direct measurement of the electrical conduction in the heart and thus clearly reflects AF. ECG-based AF monitoring can meet the diagnostic needs of clinicians. While the PPG is a more indirect optical measurement of electrical/electromagnetic physical phenomena, and thus PPG-based AF monitoring is only suitable for AF screening.

A. PPG-Based AF Monitoring Devices

The top problems faced by physicians managing suspected AF patients are low detection rates and non-adherence. The integration of PPG and mobile health technologies may offer a promising approach by combining screening methods with interventions to facilitate earlier AF detection and improve the management of the condition [30].

The watches such as Apple [31], Huawei [32], Huami [33], and Xiaomi [34] all utilize PPG to screen for AF. These research results indicate that continuous monitoring of AF through smart PPG devices is a practical screening method. This monitoring is expected to reduce AF-related complications, especially stroke, through early intervention. In 2019, The Huawei Heart Study reported that approximately 187000 individuals used smart devices to monitor their pulse rhythm, and demonstrated that mobile Health (mHealth) technology can provide integrated care management for patients with AF [35]. In the same year, the Apple Heart Study enrolled 419093 participants to identify pulse irregularity and variability using PPG from the wrist. These studies will serve as a foundation for how wearable technology can inform clinical approaches to AF screening [31].

The PPG-based AF detector analyzes AF by measuring pulse-pulse intervals only. However, arrhythmias with an irregular pulse rhythm are not exclusive to AF. Therefore, PPG-based AF analysis is considered a pre-screening method [36]. Clinically, ECG is a potent noninvasive tool for monitoring the occurrence, maintenance, and termination of AF [37].

B. ECG-Based AF Monitoring Devices

During AF episodes, ECGs demonstrate two distinct features: the disappearance of the P wave and the appearance of the F wave, which is a series of continuous and irregular atrial excitation waves, as well as the absolute irregularity of the RR interval [38], [39]. Currently, ECG monitoring devices mainly include the short-term ECG monitoring devices used for examinations in outpatient settings or home monitoring and wearable devices used for long-term ECG monitoring, as shown in Fig. 1.

1) The Short-Term ECG Monitoring Device: The wrist-worn ECG devices, like the Apple watch [40], are capable of 30-s ECG monitoring and can be used to monitor AF in the home. Single-lead handheld ECG devices have been used for AF screening in outpatient clinics [41]. The single-lead handheld ECG devices such as the Omron heartscan device [42], the Zenicor ECG device [43], and the AliveCor ECG device [44] record 30-second ECG readings in outpatient or home settings for screening arrhythmias, including AF. The STROKESTOP study [24] presented at the annual congress of the European Heart Rhythm Association in 2021, screened patients aged 75-76 years old using single-lead handheld ECG devices twice daily for two weeks. The study reported a 4% reduction in the composite of thromboembolic events, severe bleeding, and death at a minimum follow-up of 5.6 years.

The more frequent or longer ECG monitoring, the more the AF is detected. A recent study [45] compared daily ECG transmission to serial 6-day Holter ECG for assessing the efficacy of AF ablation. Each patient underwent daily 30-second ECG trans-telephonic monitoring (TTM) and standard 6-day ambulatory ECG monitoring at 3, 6, and 12 months after ablation. The results showed that daily 30-second ECG monitoring detected more patients with AF recurrences than the standard 6-day Holter ECG monitoring.

Although the daily 30-second ECG TTM may replace standard Holter ECG for AF detection after ablation, short-lasting ECG monitoring, such as those performed using TTM, is unsuitable for AF burden assessment. For AF burden assessment, wearable devices with continuous rhythm monitoring are more appropriate.

2) The Long-Term ECG Monitoring Device: Long-term ECG monitoring is a well-established strategy for identifying individuals who require further cardiac examination and treatment. Occult arrhythmia often requires long-term ECG monitoring.

Since the 1990s, wearable ECG devices have been the subject of research by numerous units, taking advantage of the development of microprocessors, micro-sensors, communication technology, and fabric electrode materials. The AliveCor Kardia Mobile Home Monitoring Device is most beneficial for large-scale AF screening, especially outside of traditional healthcare settings [46]. The rhythm ZioXT is a single-use, 14-day ambulatory ECG monitoring patch that provides continuous monitoring for up to two weeks [19]. The Corventis NUVANT/Medtronic SEEQ mobile cardiac telemetry (MCT) system utilizes a simple patch design and can monitor ECG for up to 30 days by serially using four sensors [47]. Furthermore, a three-lead wearable device developed jointly by Southeast University and Lenovo can provide continuous ECG monitoring for 72 hours [48].

Asymptomatic AF is often intermittent, making it difficult to diagnose with periodic surveillance alone. Continuous monitoring has been found to detect more AF in a shorter period [49]. In a study, remote heart rhythm sampling using the AliveCor Heart Monitor for AF screening was assessed, and it was reported that single-lead ECG screening was significantly more effective in diagnosing AF events compared to routine care [50]. Yet, another study published in the American Journal of Cardiology, compared the diagnostic outcomes of monitoring by a 14-day Zio XT (a patch-based continuous monitor), a 24-hour Holter monitor, and a 30-day event monitor (an external loop recorder). It was found that newly detected AF/AFL lasting $\geq$30 seconds was recorded more frequently using 14-day continuous monitoring compared to 24-hour Holter, but not significantly different from 30-day event monitoring [51].

Continuous ECG monitoring can cause discomfort for the person being monitored since the electrode needs to remain in constant contact with the skin surface. Additionally, some individuals may be allergic to the electrode material, making this type of monitoring unsuitable for them. However, non-contact vital signs monitoring technology has emerged as a new approach in recent years. This technology can measure physiological signals generated by cardiopulmonary activities without the need for direct skin contact. This type of monitoring can be worn as a medical monitoring system on the body or integrated into daily health care. This enables real-time acquisition of vital sign signals while not interfering with people's daily activities in their living environment.

Non-contact ECG sensor technology offers a convenient solution for ECG monitoring in non-hospital settings [52]. To enhance comfort and ease of use, various ECG measurement systems have been developed that can be adapted to chairs, beds, and clothing [53], [54], [55]. For remote monitoring, a smartphone Internet of Things server and a web interface can be integrated into the system [56], providing a more user-friendly approach to home monitoring of AF. Rachim et al. [53] have devised a low-power-transmission ECG monitoring system consisting of capacitive-coupled electrodes embedded in an armband. In 2019, Leicht et al. [54] designed an ECG signal measurement system with electrodes implanted in car seats to collect ECG signals. Furthermore, Xiao et al. [57] proposed an ECG signal acquisition system based on capacitive coupled textile electrodes to monitor ECG signals during sleep.

TABLE I
OPEN-SOURCE AF ALGORITHMS

Source	Website
PhysioNet/CinC Challenge 2017 [25]	https://www.physionet.org/content/challenge-2017/1.0.0/
The CPSC 2018 [58]	http://2018.icbeb.org/Challenge.html
The CPSC 2021 [27]	http://www.icbeb.org/CPSC2021
HRV analysis plat [59]	https://physiozoo.com/

HRV: heart rate variability.

At present, non-contact ECG monitoring is also a research hotspot due to its potential for providing convenient and comfortable ECG monitoring. However, the technology is not yet mature, and the monitored signal is greatly affected by noise, posing significant challenges to algorithm analysis. As a result, more research is needed to improve the accuracy and reliability of non-contact ECG monitoring technology. Nonetheless, with further development, non-contact ECG monitoring has the potential to revolutionize ECG monitoring by providing a more comfortable and convenient experience for patients while maintaining accurate readings.

III. The Influencing Factors of Atrial Fibrillation Analysis Algorithm

With the rapid development of computer technology, researchers are increasingly incorporating artificial intelligence (AI) technology to diagnose and treat diseases by establishing automated diagnosis models through data mining and machine learning methods. AI algorithms for AF analysis include four types: AF analysis based on atrial activity, AF analysis based on ventricular activity, AF detection based on traditional machine learning, and AF detection based on deep learning. There are several open-source AF algorithms from challenges [25], [27], [58] or websites based on heart rate variability analysis [59], as shown in Table I.

Machine learning and deep learning present a unique opportunity to provide an accurate automated diagnosis of AF. Yet, these models must demonstrate generalizability to external datasets integrating a range of population samples [60]. FDA approved the algorithm presented by Noseworthy et al. [61] which was tested in diverse populations and presented good results across race and ethnicity for left ventricular systolic dysfunction [24]. However, studies about the generalization of AI algorithms in the context of AF are scarce. Biton et al. [60] assessed the generalization ability for the task of AF events detection and AFB estimation across four geographical centers (Israel, USA, China, Japan) ages, and sexes. The resulting ArNet2 algorithm was demonstrated to be robust, i.e., highly performing, and generalizable, and provided the new state-of-the-art performance for the task of AF events detection based on the beat-to-beat interval time series.

However, in practical applications, the accuracy of AF analysis still needs improvement [62]. In the following, we will analyze the reasons from the open-access databases and the wearable ECG signal.

TABLE II
DETAIL OF THE AF DATABASE

Database	Monitoring state	# AF Patients	#Lead	#Time	Website
MIT-BIH AF database [63], [64]	resting	21 PAF +2 persistent AF	two	About 10h	https://www.physionet.org/content/afdb/1.0.0/
MIT-BIH arrhythmia database [65]	resting	7 PAF	two	About 30min	https://www.physionet.org/content/mitdb/1.0.0/
Long Term AF Database [66]	resting	84 subjects with paroxysmal or sustained AF	two	24-25hour	https://physionet.org/content/ltafdb/1.0.0/
PhysioNet/CinC Challenge 2017 [25]	wearable	771 AF recordings	single	9-60s	https://www.physionet.org/content/challenge-2017/1.0.0/
The CPSC 2018 [57]	resting	1098 AF recordings	twelve	6-60s	http://2018.icbeb.org/Challenge.html
Chapman-Shaoxing 12-lead ECG Database [67]	resting	1780 recordings	twelve	10s	https://www.kaggle.com/datasets/erarayamorenzomuten/chapmanshaoxing-12lead-ecg-database?resource=download
The CPSC 2021 [27]	wearable	233PAF+472 persistent AF	two	10s-30min	http://www.icbeb.org/CPSC2021

AF: Atrial Fibrillation, PAF: Paroxysmal AF

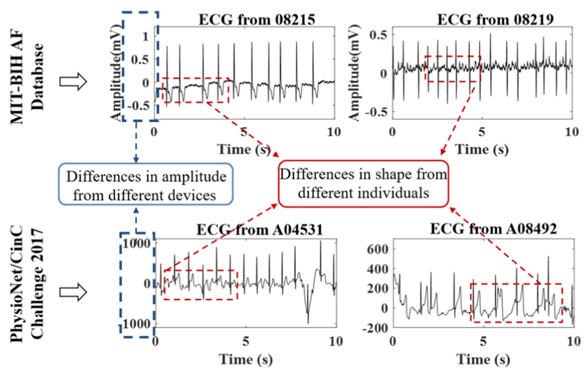

Fig. 2. Signals from different individuals.

A. The Impact of Open-Source Database

There are several databases and challenges in AF detection, including the MIT-BIH AF database [63], [64], the MIT-BIH arrhythmia database [65], the long-term AF database [66], the PhysioNet/CinC Challenge 2017 [25], the CPSC2021 [27], the CPSC2018 [57], the Chapman-Shaoxing 12-lead ECG database [67]. These databases are detailed in Table II.

In addition, the wearable database in this article was approved by the Ethics Committee, and study Number: 2020-SRFA-183.

1) The Waveform Difference of Different Databases and Individuals: The generalization ability of AF detection algorithms based on machine learning and deep learning is limited to different databases and individuals. ECG signals can differ between individuals and databases, as shown in Fig. 2, where ECG shape has differences from different individuals. The data from these two databases were collected using different monitoring devices, and the amplitude of the 2017 Challenge data was not converted to standard units. The differences between individuals and monitoring devices pose a challenge to the generalization ability of machine learning and deep learning-based AF detection models.

Ma et al. [68] proposed an AF detector based on the integration of results from the convolutional neural network (CNN) in a support vector machine (SVM). When the model was trained using 5-fold cross-validation on the MIT-BIH AF database, the data were divided into five groups based on recordings and stratified sampling. The results shown in Table III indicate that personal ECG differences can affect the performance of the model.

TABLE III
RESULTS OF AF DETECTION COMBINED CNN WITH SVM FROM DIFFERENT GROUPING FORMS ON THE MIT-BIH AF DATABASE

Time window	Data grouping form	Acc	Se	Sp
30-s ECG episode	Recordings	97.87	97.91	97.82
	Stratified sampling	99.70	99.64	99.75
10-s ECG episode	Recordings	96.09	96.14	96.02
	Stratified sampling	99.57	99.39	99.54

Table IV demonstrates the performance of different AF detection algorithms on independent datasets. The performance of AF detection algorithms [68], [69], [70], [71] decreases when tested on datasets with distinct differences between training and testing databases, particularly on datasets from different sources. The MIT-BIH AF database contains only resting data from 23 patients, mostly consisting of AF and normal sinus rhythm (N) episodes. AF detectors trained on the MIT-BIH AF the PhysioNet/CinC Challenge 2017 and the MIT-BIH arrhythmia database, which contain other arrhythmia data and ambulatory data, respectively. Models trained by Zhang et al. [71] on the Wearable database performed well when tested on the PhysioNet/CinC Challenge 2017 dataset despite a decrease in performance. This suggests that the diversity of data used for model training affects model performance, particularly for deep learning models, which are more dependent on waveform data.

2) The Interference With Other Rhythm Abnormalities: The open-access AF database usually contains healthy individuals and AF patients. It rarely contains ECG signals with abnormal rhythms. Clinically, the ECG recordings monitored are not only from AF patients but also from patients with other arrhythmias, such as atrial tachycardia, premature beats, etc. These arrhythmias patients also have irregular rhythms. As shown in Fig. 3, the delta RR interval distribution from sinus rhythm is approximately a straight line, while the delta RR interval distributions from AF and premature are similar. Therefore, using only RR interval analysis can lead to confusing

TABLE IV
PERFORMANCE OF METHODS TESTED ON THE INDEPENDENT DATABASES

Author	Method	Training set	Validation Performance *Se* (%)	*Sp* (%)	*Acc* (%)	Test set	Test performance *Se* (%)	*Sp* (%)	*Acc* (%)
Aderson et al. [69]	30 RR interval +LSTM+CNN	MIT-BIH AF database	98.98	96.95	97.80	MIT-BIH arrhythmia database MIT-BIH NRS database	98.96	86.04	87.40
Chang et al. [70]	12s ECG +STFT+LSTM	Six databases	97.80	99.20	98.50	Separate data PhysioNet/CinC Challenge 2017	86.88 70.17	79.55 -	83.21 75.60
Ma et al. [68]	10s ECG+10s RR interval+SVM +CNN	MIT-BIH AF database	96.14	96.02	96.09	PhysioNet/CinC Challenge 2017 CPSC2018 database Wearable long-term record	89.25 97.67 94.58	96.80 99.55 99.50	93.03 98.61 97.04
Zhang et al. [71]	10s ECG +LSTM+CNN	Wearable databese	98.13	97.29	97.71	PhysioNet/CinC Challenge 2017	92.09	96.66	96.23

Acc: Accuracy, *Se*: Sensitivity, *Sp*: Specificity.

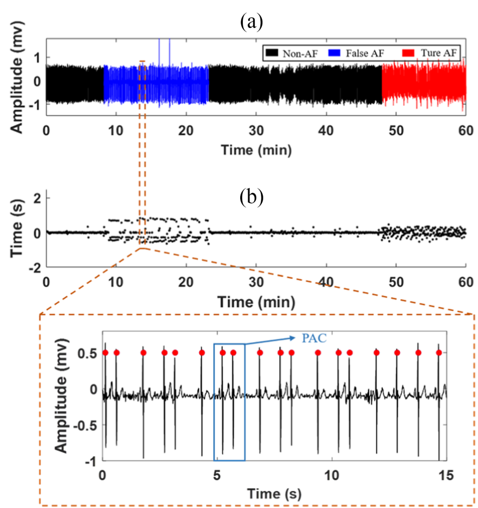

Fig. 3. Example of PAC confusing AF. (a) 60-min ECG. (b) Distribution of delta RR interval.

TABLE V
RESULTS OF 10-FOLD CROSS-VALIDATION FROM SVM AND RR INTERVAL ON WEARABLE DATABASE

Fold	*Acc* (%)	*Se* (%)	*Sp* (%)
1	98.12	99.21	96.62
2	83.50	75.38	99.26
3	97.41	99.07	95.84
4	93.7	89.58	98.77
5	97	99.37	94.85
6	97.90	98.68	97.14
7	90	83.90	98.78
8	97.95	96.24	99.79
9	97.8	99.69	96.05
10	98.5	97.92	99.09

other arrhythmias and AF. Typically, AF/sinus rhythm detection accuracy is high, but accuracy in identifying AF/non-AF is lower. To evaluate the performance of an AF detection model based on reference [68], this work selected 10 non-AF recordings (including 2 premature beats) and 10 AF recordings from the wearable database and performed 10-fold cross-validation. The results are presented in Table V. Specifically, fold 2 and 7 contained premature beats, with corresponding sensitivities of 75.38% and 83.90%. When applying the AF recognition model

TABLE VI
TEST RESULTS FROM SVM AND RR INTERVAL ON WEARABLE DATABASE

Recording	*Acc* (100%)	label
1	88.10	The patients without AF, presence of ventricular or atrial premature
2	97.66	The healthy individual
3	95.86	The healthy individual
4	71.86	The patients without AF, presence of ventricular or atrial premature
5	95.42	The healthy individual
6	98.57	The healthy individual

trained on the MIT-BIH AF database in reference [68] to the wearable database, the test results are shown in Table VI. When the recordings are obtained from patients without AF or premature beats, the model's performance is poor, with test accuracies of 88.10% and 71.86% for Recordings 1 and 4, respectively.

In addition, the waveforms of AF and atrial flutter (AFL) are very similar. When AF occurs, the P wave disappears and a series of f waves appear on the ECG, and the RR interval is absolutely irregular. When AFL occurs, the P wave disappears, and several series of F waves appear on the ECG. However, the RR interval may be absolutely irregular or relatively regular when AFL occurs. As shown in Fig. 4, it is the wave and RR interval of N, AF and AFL. At present, many AF detection algorithms, especially the AF analysis algorithms based on ventricular activity, cannot identify AF from AFL. Many scholars group AF and AFL into one category when they develop AF detection algorithms [72], [73], [74].

3) Lack of ECG With Long-Term Wearable Paroxysmal AF From the Open Database: As shown in Table II, it is the detail of AF from the open database. Most of the AF recordings were short-term and collected in a rest environment. The number of wearable AF recordings is less. Most of the recordings collected from the practical application environment are paroxysmal AF, usually from wearable devices. The annotated long-term wearable paroxysmal AF recordings are needed to develop an AF detector with good performance.

B. The ECG Differences Between Wearable and Resting ECGs

Wearable ECG monitoring devices are usually highly susceptible to noise interference and motion artifacts. When monitoring

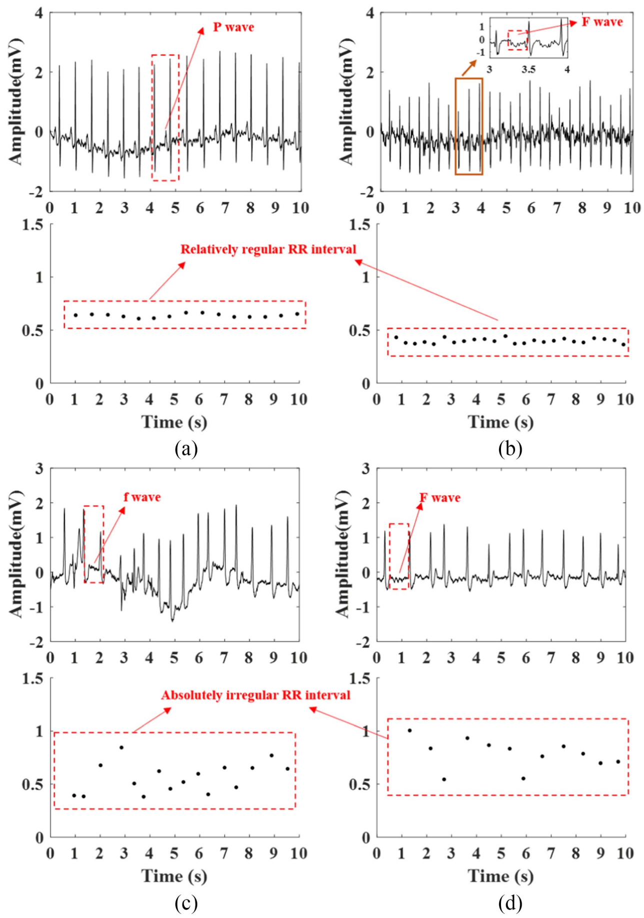

Fig. 4. Wave and RR interval of N, AF, AFL (N and AFL from 04908 recording of the MIT-BIH AF database, AF and AFL2 from 203 recording of the MIT-BIH arrhythmia database). (a) N. (b) AFL1. (c) AF. (d) AFL2.

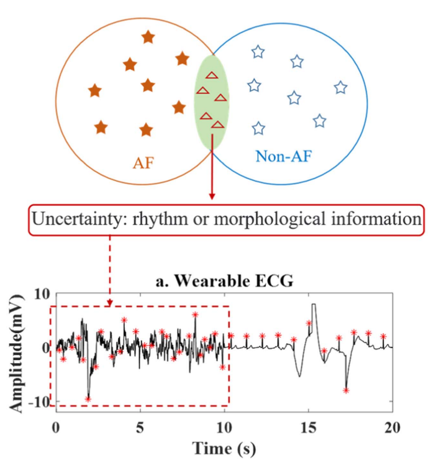

Fig. 5. Uncertainty ECG segment in wearable ECGs.

AF using wearables, there may be a significant number of uncertain ECG fragments that contain only rhythm information, or neither rhythm nor waveform information, as depicted in Fig. 5. False detections of AF in wearable ECGs can be attributed to

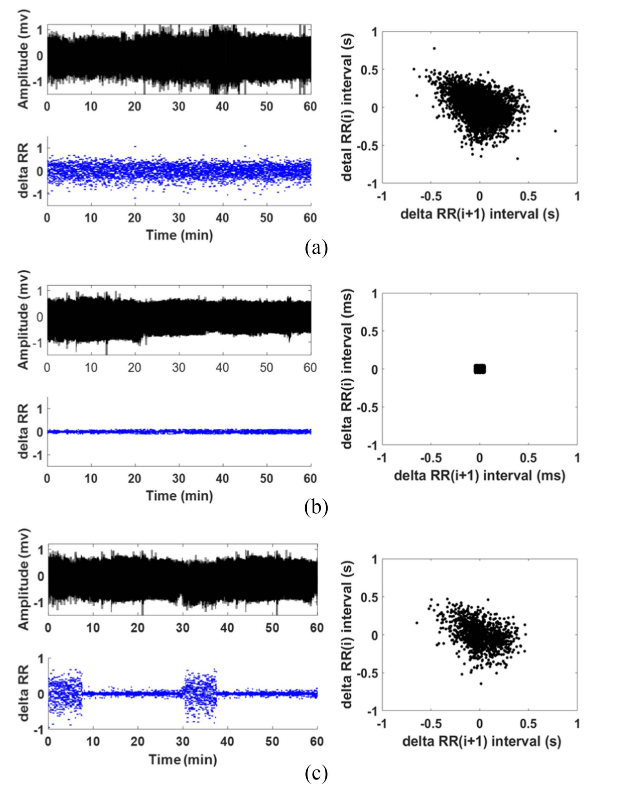

Fig. 6. Examples of AF recordings screening. (a) Delta RR interval and Lorenz plot from AF. (b) Delta RR interval and Lorenz plot from N. (c) Delta RR interval and Lorenz plot from PAF.

two factors: the impact of rhythm information and waveform information from wearable signals.

1) The Influence of Rhythm Information From Wearable Signals: R peak is the most significant characteristic of the ECG signal. The irregularity of the RR interval is the most obvious feature to judge AF, which is also the main method to detect wearable AF. The precise detection of the R peak is essential for screening AF in wearable ECG continuous monitoring. Fig. 6 illustrates examples of AF recording screening, where suspected AF can be detected based on the distribution of the ΔRR interval. The distribution of ΔRR interval for non-AF recordings appears as a straight line, clustered around 0. Conversely, the distribution of ΔRR interval for suspected AF is not centered around 0, but typically ranges between -1 and 1. The Lorenz plots from AF and PAF recordings are not clustered at 0.

Many AF detection algorithms are based on the heart rhythm information from ECG signals to identify the AF. Ma et al. [62] trained various AF detectors on the MIT-BIH AF database. When these AF detectors were tested on the CPSC2021 database, they exhibited varying levels of performance, and the testing accuracy decreased for all of them. The RR interval feature-based AF detector demonstrated better testing performance than the deep learning-based AF detector, indicating that machine learning-based AF detectors have better generalization performance on limited training data.

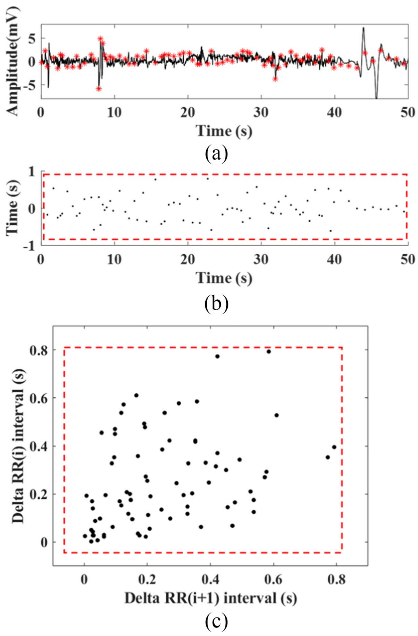

Fig. 7. Example of a non-AF ECG signal judged as AF. (a) Wearable signal. (b) Delta RR interval. (c) Lorenz plot.

TABLE VII
PERFORMANCE OF AF DETECTOR WITH DIFFERENT QRS DETECTION METHODS

QRS methods	*Acc* (%)	*Se* (%)	*Sp* (%)
Manually annotated	93.43	94.97	91.89
Pan Tomkin	92.99	93.03	92.95
Paoletti	93.11	93.82	92.40

The QRS complex wave detection algorithm has a great impact on the AF detector based on heart rhythm information. In wearable signals, poor signal quality will lead to false detection of QRS complex waves, resulting in misjudgment of AF. Fig. 7 shows the 50-s non-AF ECG signal. The QRS complex wave detection algorithm proposed by Pan Tomkin [58] is used to detect QRS complex waves in the 50-s non-AF ECG signal. The 50-s non-AF ECG signal will be judged as AF from the distribution of ΔRR interval and Lorenz plot.

The reference [68] trained an SVM-based AF classifier using RR interval features. In this work, different QRS complex wave detectors were selected to obtain the RR interval, and the SVM-based AF classifier was retrained to compare the effects of different QRS complex wave detectors on AF detection. The QRS complex waves detection algorithms include the QRS complex waves detection algorithm proposed by Pan et al. [75], the improved QRS complex waves detection algorithm proposed by Paoletti et al. [76]. The labeled QRS complex waves directly were obtained on the MIT-BIH AF database. The 5-fold cross-validation was carried out on the MIT-BIH-AF database. We divided 22 recordings from the MIT-BIH AF database into 5 folds, and each fold is 3 or 4 recordings for testing, leaving 18 or 19 recordings alone for training, the result is as TableVII. In addition, the CPSC2021 database was taken as an independent test set the test results are shown in Table VIII.

TABLE VIII
TEST RESULT OF AF DETECTOR WITH DIFFERENT QRS DETECTION METHODS

Database	Methods	*Macc* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)
CPSC2021-Dataset1	Pan Tomkin	91.73	89.77	95.60	87.86
	Paoletti	93.72	91.75	97.59	89.83
CPSC2021-Dataset2	Pan Tomkin	86.74	87.24	92.56	80.92
	Paoletti	87.55	88.28	96.46	78.64

Macc: *Macc=(Se+Sp)/2*.

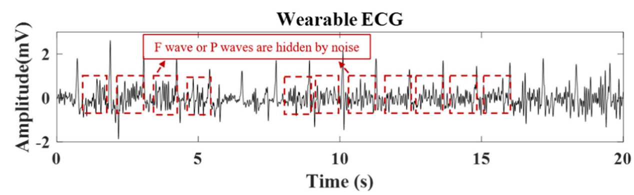

Fig. 8. Wearable ECG signal polluted by noise.

MIT-BIH AF database is collected in the resting environment, the QRS complex waves detection has almost no influence on AF detection on the MIT-BIH AF database. CPSC2021 database from the wearable database with noise. When the improved QRS complex wave detector proposed by Paoletti et al. was used, the accuracy of AF detection was higher on the CPSC2021 database, implying that the QRS complex wave detectors have an influence on the results of AF detection for wearable ECGs.

2) The Influence of Wave Information From Wearable Signals: The P-waves disappearing, and F waves appearing in atrial activity are the basis for clinicians to diagnose AF. But P-wave and F-wave have small amplitude, and they are extremely susceptible to noise interference. Due to many complicated interferences from daily activities, this situation can be worse in the wearable ECG. As shown in Fig. 8, it is a 20-s wearable ECG signal. The signal cannot identify P or F waves that are discernable in heartbeats. When the P or F waves are drowned out by noise, there is no way to determine if the heartbeat is AF.

IV. WEARABLE AF ANALYSIS AND PROCESSING METHODS

A. The Analysis of Effective ECG Signals for Wearable AF Analysis

Different environmental noises, motion artifacts, and ECG signals are mixed in real-time and wearable environments, resulting in complex and variable signal quality. The ECG signal even becomes pure noise, losing diagnostic value. Therefore, it is imperative to evaluate the signal quality and screen out clinically effective ECG signals for AF analysis. At present, there is no unified signal quality evaluation standard. The evaluation criteria of signal quality are different according to different ECG signal analysis requirements. For the screening of AF, only visible QRS complexes are required. P wave and QRS complex are visible from the perspective of AF diagnoses.

TABLE IX
THREE CLASSES OF WEARABLE ECG SIGNAL QUALITY

Class	Define
Class A	All significant waveforms (P wave, T wave, and QRS complex) are clearly visible.
Class B	The significant points (PR interval and/or QRS duration) in the ECG are unclear, but QRS complexes are clearly visible.
Class C	QRS complexes cannot be detected reliably and the signal is unsuitable for any analysis.

TABLE X
PERFORMANCE OF QUALITY ASSESSMENT ALGORITHMS

Author	Database	Class	Method	Performance
Clifford, 2012 [81]	CinC 2011 MITBIHNST	C1,C2, C3	QRS complex features+ MLP + SVM	Acc= 97%
Behar, 2013 [82]	CinC 2011 MITBIHA MIMIC II	Good/ Bad	QRS complex features+ SVM	Acc = 99% on NSR and 95% for arrhythmias
Clifford, 2011 [79]	CinC 2011	C1,C2, C3	ECG wave features +SVM +MLP	Ac = 92.6%
Zaunseder, 2011 [80]	CinC 2011	Good/bad	ECG wave features + DT	Ac = 90.4%
Zhou, 2018 [83]	CinC 2011 CinC 2017	Good/bad	ECG+CNN	Ac=94.30%
Jin, 2023 [87]	CinC 2011	Good/bad	ECG+DAC-LSTM	Ac=94.0%
Liu, 2023 [88]	CinC 2011	Good/bad	ECG+ResNet+ Self-Attention	Ac=92.8%
Huerta, 2019 [84]	CinC 2017	Good/bad	ECG+CWT+CNN	Ac=91.20%
Zhao, 2018 [85]	Dynamic ECG	C1,C2, C3	ECG+MFSWT +CNN	Ac=86.30%
Zhang, 2022 [86]	CPSC2020	C1,C2, C3	ECG+Residual block	Ac=92.31%

There are many ECG signal quality evaluation algorithms, but the databases about ECG quality evaluation are lacking. The PhysioNet/Computing in Cardiology Challenge 2011 (cinc2011)(https://www.physionet.org/content/challenge-2011/1.0.0/) [77]. The datasets are divided into three categories: acceptable group, indeterminate group and unacceptable group. Andrea Nemcova et al. [78] published a database: the Brno University of Technology ECG Quality Database (BUT QDB) (https://physionet.org/content/butqdb/1.0.0/). The database was grouped into three quality classes. The details of the quality assessment grades are shown in Table IX. Class A and B signals are suitable for scanning AF. Class A signals are suitable for the diagnosis of AF.

Present ECG signal quality evaluation algorithms can be divided into 3 categories. The first is ECG signal quality assessment based on ECG morphological features [79], [80]. The second is to evaluate the signal quality based on the matching results from different QRS complex wave detection algorithms[81], [82]. It can only screen signal segments containing clear QRS, which is suitable for screening AF. The third is the ECG quality assessment algorithm based on ECG waveforms and deep learning [83], [84], [85], [86], [87], [88]. Table X demonstrates the performance of quality assessment algorithms. In addition, Markus et al. presented a machine learning-based signal quality assessment for the early detection of silent AF, which yielded a high correlation of 0.60 with the clinical expert ratings during testing [89].

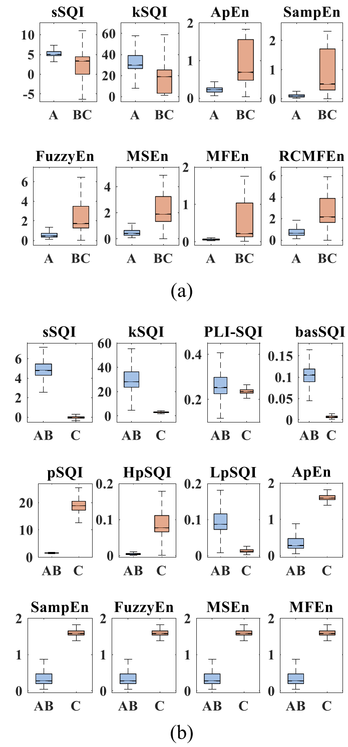

Fig. 9. Features analysis of ECG availability based on AF diagnoses and scanning. (a) Features analysis of ECG availability based on AF diagnose. (b) Features analysis of ECG availability based on AF scanning.

This work performed the feature analysis based on ECG signal morphology on the BUT QDB Database. Eight features of ECG availability were analyzed for AF diagnoses, including sSQI, kSQI, ApEn, SampEn, FuzzyEn, MSEn, MFEn, and RCMFEn [90], [91], [92], [93], [94], [95], [96]. Twelve features of ECG availability were analyzed for AF scanning, including sSQI, kSQI, PLI-SQI, basSQI, pSQI, HpSQI, LpSQI, ApEn, SampEn, FuzzyEn, MSEn, MFEn [90], [91], [92], [93], [94], [95], [96]. As shown in Fig. 9, it is the features analysis of ECG availability based on AF diagnoses and scanning. At the same time, GbSQI [97] is an ECG signal quality evaluation method. It was calculated on the ECGs of three different signal qualities from the BUT QDB database. U3 [98], UNSW [99], DOM [100], and OKB [101] detectors were recommended for calculating GbSQI in the [97]. Fig. 10 shows results based on GSQI from the BUT QDB database. Class A and B signals can be picked out by GbSQI.

B. The QRS Complex Waves Detection for Wearable AF Analysis

The traditional QRS complex wave detection algorithm has been studied for many years, and a high detection rate has been achieved in ECG signals from a resting state. ECG signals are often submerged by noise in wearable ECG continuous monitoring. QRS complex wave detection from wearable ECG signals is still tricky and full of challenges. The research results

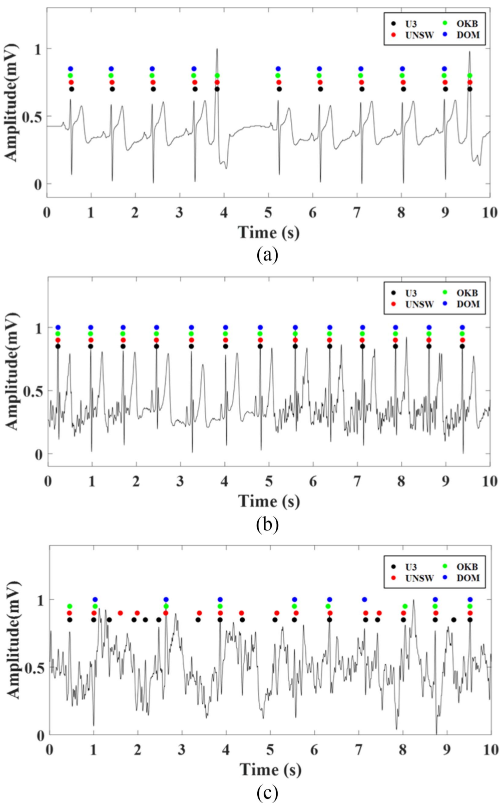

Fig. 10. Results based on GSQI from BUT QDB database. (a) Class A (GSQI = 0.8182). (b) Class B (GSQI = 0.987). (c) Class C (GSQI = 0.3125).

from a study show that the best recognition rate of the common QRS complex wave detection algorithm is only 80% in wearable noisy ECG databases [102]. The CPSC 2019 aims to encourage the development of algorithms for challenging QRS complex wave detection from short-term single-lead ECG recordings, usually with low signal quality [26]. The best QRS complex wave detection accuracy was 92.1% from CPSC 2019.

The AF analysis from the wearable continuous ECG detection was combined with ECG signal quality assessment to determine the reliability of the QRS complex wave detection. For AF screening, the final position of QRS complex waves can be determined by voting from several QRS complex wave detection algorithms. For ECG signals from multiple leads, ECG information of different leads can be fused to detect QRS complex waves.

C. The Wearable AF Detection

1) Reducing the Difference From the ECG Signal: The ECG recordings are personality differences from the different individuals and databases. The poor generalization capability can be inevitable when tested on wearable ECGs which limits the developed AF detectors to be robustly used in wearable monitoring situations. Zhang et al. [71] proposed training strategies for deep learning-based AF detection. He used the Fast Fourier transform (FFT) and Hanning window-based filter to suppress the influence of the individual difference and trained the model on the wearable ECG data to improve the robustness of the model.

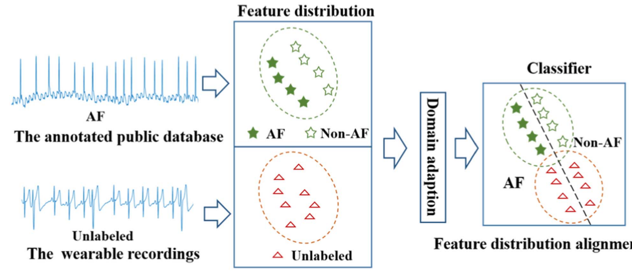

Fig. 11. Frame of the AF detector based on domain-adaptation.

The main goal of transfer learning is to exploit the similarity between different domains to improve the performance of the model in the target domain. The generalization ability of the model can be improved by the feature space alignment of data between different databases. As shown in Fig. 11, it is the frame of the AF detector based on domain adaptation. Jin et al. [103] propose a novel domain adaptive residual network to detect AF of unlabeled datasets with the aid of detection knowledge of labeled datasets.

2) Excluding the Interference From Other Arrhythmia Diseases: The AF detector based on RR interval easily misjudges non-AF patients with irregular RR intervals as AF. Those with frequent premature beats have a high probability of AF. However, the rhythm of premature contractions is easily misjudged as AF, and the interference of premature contractions on AF detection should be excluded. Ma et al. [62] proposed a multi-step AF detection strategy integrating rhythm and P information. In the multi-step AF detection strategy, the premature beats rejection strategy on PAF detection was presented.

3) Developing Interpretable AF Detection Algorithms: The ability of artificial intelligence-based AF detection methods to meet the clinical interpretability is a crucial concern in the clinical application. Atrial and ventricular activity-based AF analysis methods detect AF through waveform information (P-wave) and rhythm information (RR intervals) respectively, therefore AF detection algorithms based on atrial and ventricular features and machine learning can also meet the need for AF interpretability. However, most deep learning-based AF detection algorithms are unable to explain the reasons for the model's decisions. Techniques like saliency maps and attention maps offer the potential to shed light on the decision-making process by visually highlighting the specific regions or features that the model focuses on during predictions. For instance, Khurshid et al. [104] trained a convolutional neural network (ECG-AI) to predict the risk of incident AF over five years and employed saliency maps to demonstrate that the P-wave and its surrounding regions had the most significant influence on AF risk assessment of ECG-AI model. Similarly, Hicks et al. [105] introduced the electrocardiogram gradient class activation map technique, which generates attention maps to provide explanations for deep learning-based decision-making in ECG analysis.

TABLE XI
AF ANALYSIS AND CLINICAL APPLICATION BASED ON MEDICAL BIG DATA

Author (Year)	Method	Data	Performance
Hannun et al. [106] 2019	DNN	12 rhythm classes using 91,232 ECGs from 53,549 patients	ROC: 0.97, F1 score: 0.837
Ribeiro et al. [107] (2020)	ResNet	2,322,513 ECG records from 1,676,384 different patients.	F1 scores: above 80%, *Sp*: over 99%.
Attia et al. [108] (2019)	CNN	180,922 patients and 649,931 normal sinus rhythm ECGs.	*AUC*: 0.9, *Se*: 82·3%, *Sp*: 83·4%, F1 score: 45·4%, *Acc*: 83·3%.
Hughes et al. [109] (2021)	CNN	992,748 ECGs from 365,009 adult patients.	F1 score: 0.847
Yong et al. [110] (2021)	ResNet	PTB-XL ECG dataset, Chapman ECG dataset from China, PhysioNet ECG dataset.	*AUC*: 0.997-0.999 (12-lead), 0.990-0.999(6-lead and single-lead)
Raghunath et al. [111] (2021)	DNN	1.6 M resting 12-lead digital ECG traces from 430,000 patients.	ROC：0.85.
Baek et al. [112] (2021)	RNN	Healthy: 1057 ECGs; PAF: 1355 ECGs; Healthy: 727 ECGs; PAF: 564 ECGs.	*ROC*:0.79 and 0.75, Sp:78% and 72%, F1 score:75% and 74%, Acc:72.8% and 71.2%.
Park et al. [113] (2022)	ResNet	13,241 12-lead ECG recordings	F1 score: normal (98.7%), AF (98.2%)

DNN: Deep neural network, ResNet: Residual block of the neural network, PAF: Paroxysmal AF, *ROC*: the receiver operating characteristic curve, *AUC*: Area Under Curve.

It is important to note that while interpretability techniques offer valuable insights, they also possess certain limitations. Achieving interpretability in deep learning-based AF detection algorithms remains an ongoing area of research.

V. Clinical Monitoring of Atrial Fibrillation

Many scholars have applied artificial intelligence algorithms to the clinical data analysis of AF. The clinical data is usually extensive, which brings a lot of work to clinicians. The clinical analysis algorithm based on artificial intelligence can reduce the burden on doctors. This work introduces the AF analysis based on big clinical data and AF monitoring in prospective settings in this section. Next, clinical applications are described, including early risk screening, home and clinical management.

A. AF Analysis Based on Big Clinical Data

1) AF Classification From the 12-Lead ECG: Deep Learning can detect new-onset AF in patients based on ECG, which can help identify patients with AF-related complications such as stroke. The performance of AF analysis and application based on big medical data is shown in Table XI, which implies that AF detection algorithms based on artificial intelligence can be used as the solution in AF management. Hannun et al. [106] developed a deep neural network to classify 12 rhythms, including AF using 91232 single-lead ECGs from 53549 patients and published in Nature Medicine. Ribeiro et al. [107] trained a convolutional neural network similar to the residual network on more than 2 million labeled exams to detect six arrhythmias, including AF. In 2019, Attia et al. [108] presented an artificial intelligence-enabled ECG algorithm to recognize AF on 180922 patients and 649931 normal sinus rhythm ECGs. In 2021, a CNN was trained by Hughes et al. [109] to predict the presence of 38 diagnostic classes of 992748 ECGs from 365009 adult patients. For AF, the CNN F1 score is 0.847, and the cardiologist F1 score is 0.881. Yong et al. [110] used four residual blocks of the neural network to learn AF features on several non-restricted ECG datasets, including the PTB-XL ECG dataset (21837 12-lead ECGs); the Chapman ECG dataset 10605 12-lead ECGs); and the CinC 2017 (8528 single-lead ECGs). Raghunath et al. [111] trained DNN on 1.6 M resting ECG traces from 430000 patients. Baek et al. [112] used RNN on 3703 ECGs for analysis. Park et al. [113] verified the SE-ResNet-based AF detector on 13241 12-lead ECG recordings.

2) AF Risk Prediction From the 12-Lead ECG: Because of AF prevalence and clinical importance, it is a good case for the development of new risk prediction algorithms. Risk prediction models have been developed to identify patients at risk of AF but with limited success [114] (e.g., C-statistic, 0.765 in CHARGE-AF [115]). Three recent works by Christopoulos et al. [116], Raghunath et al. [117] and Biton et al. [118] made use of a DL approach using the raw 12-lead ECG signal as input for the task of AF risk prediction. These recent experiments used the world's largest existing databases of raw 12-lead ECG with up to >1M recordings for the largest experiment by Biton et al. [118] Interestingly, it was demonstrated that a DL approach for this task was performing the same as a feature engineering approach [119]. However, all these studies have a significant limitation: the definition of their clinical endpoint. Indeed, AF as a clinical endpoint was defined as a newly documented AF diagnosis after a follow-up 12-lead ECG, or documented within a single hospital electronic medical record. Since patients may change hospital/health providers with time and hospital databases lack clinical information from primary care it makes the clinical endpoints weak. Also, all the presented studies lack the generalization performance of their models on external datasets.

B. AF Monitoring Based on Wearable ECG Device in Prospective Settings

AF is an insidious disease, and individuals at risk of AF require ongoing monitoring for AF screening to enhance the detection of paroxysmal and new-onset AF. This section provides an overview of AF monitoring based on wearable ECG in prospective settings, including wearable AF monitoring devices and AF detection based on wearable ECG devices.

1) Wearable AF Monitoring Devices in Perspective Setting: Grond et al. [120] conducted a prospective, multicenter cohort study involving 11135 patients with ischemic stroke. They found that 72-hour Holter ECG monitoring detected more silent AF than 24-hour monitoring. Similarly, Alves et al. [121]

conducted an 11-month prospective study with 67 patients with acute ischemic stroke. By utilizing an extended Holter recorder for up to 6 days, they observed a higher detection rate of new-onset paroxysmal AF. Furthermore, Kwon et al. [122] conducted a prospective single-center cohort study involving 210 patients with clinically indicated AF. They compared the effectiveness of a 72-hour single-lead ECG monitoring with an adhesive patch-type device to a 24-hour Holter test and found that the former improved the detection rate of AF. Overall, these studies highlight the potential of wearable ECG devices for AF monitoring in prospective settings, leading to improved detection rates of paroxysmal and new-onset AF.

2) AF Detection Based on Wearable ECG Device in a Perspective Setting: Handheld ECG monitoring devices have gained significant usage in primary care, and several prospective studies have validated their performance in detecting AF. Orchard et al. [123] conducted a screening of 2467 individuals for AF using a smartphone electrocardiograph (iECG). The ECG automated algorithms demonstrated a sensitivity of 95% and specificity of 99%. Desteghe et al. [124] evaluated two handheld single-lead ECG devices, namely MyDiagnostick and AliveCor, for AF screening in hospital populations at increased risk (cardiology or geriatric wards). The sensitivity and specificity were reported as 81.8% and 94.2% for MyDiagnostick in cardiology wards, 54.5% and 97.5% for AliveCor in cardiology wards, 89.5% and 95.7% for MyDiagnostick in geriatric wards, and 78.9% and 97.9% for AliveCor in geriatric wards. William et al. [125] monitored 233 patients using the AliveCor Kardia Mobile (KM) and its algorithm. The KM algorithm classified 59% as sinus rhythm (SR), 22% as possible AF, 17% as unclassified, and 2% as unreadable. The study emphasized that the current performance of the KM algorithm renders the device inadequate as a standalone application and necessitates evaluation by physicians. In 2020, a prospective multi-center validation study was conducted in an inpatient hospital setting [126]. The study involved 439 single-lead Intelligent ECGs in 200 patients from three tertiary centers. Using the KardiaBand, the sensitivity and specificity were determined as 94.4% and 81.9% respectively, with a positive predictive value of 54.8% and a negative predictive value of 98.4%. Despite potential future improvements in automated algorithms, physician involvement is likely to remain crucial when assessing the utility of these devices for arrhythmia screening.

The 24-hour patch ECG monitoring device is a portable device widely utilized in home monitoring for individuals at high risk of AF. It has undergone validation through some prospective studies. In 2021, Santala et al. [127] conducted a study with 73 cases of AF and 86 cases of sinus rhythm. They employed an mHealth arrhythmia monitoring system, comprising a heart rate band ECG, a mobile phone app, and automated AF detection. The accuracy of AF detection from the heart belt ECG recording was found to be high at 97.5%, with a sensitivity of 100% and specificity of 95.4%. In another study by Santala et al. [128] in 2022, patients (N = 178) with AF (n = 79, 44%) or sinus rhythm (n = 99, 56%) were recruited. The mHealth patch device was used for 24-hour heart rate variability (HRV) monitoring in these populations to monitor and automatically analyze AF. The subject-based AF detection accuracy was reported as 97.2%, with a sensitivity of 100% and specificity of 94.9%. The 24-hour patch ECG monitoring device demonstrates relatively high performance in detecting AF among individuals in sinus rhythm. It is important to note that these patch AF detection performances were observed in selected populations of AF and sinus rhythm, and the performance of these devices for AF detection in the presence of other rhythm disturbances cannot be adequately described.

C. Early Risk Screening and Home Management of AF

Wearable technology and artificial intelligence are being used for AF risk screening and home management. Mobile Health (mHealth) and TeleCheck-AF are entering the life of ordinary families.

In 2016, Steven et al. [129] designed a home-based trial using wearable sensors for asymptomatic atrial fibrillation in a targeted population. The mHealth screening to prevent strokes (mSToPS) trial, and initiated the world's first randomized controlled trial of mHealth for the management of atrial fibrillation. In 2017, THickey et al. [130] evaluated the utility of mHealth ECG heart monitoring for the detection and management of AF in clinical practice, and verified that mHealth self-monitoring is a feasible and effective mechanism for enhancing AF/AFL detection that improves the quality of life. In 2019, Guo et al. [131] evaluated mHealth for improved screening, patient involvement and optimizing integrated care in AF. The mAFA (mAF-App) II randomized trial verified that mHealth can reduce AF-related stroke/systemic thromboembolism, all-cause death, and hospitalizations. In 2020, Linz et al. [132] reported the TeleCheck-AF project on remote app-based management of AF during the COVID-19 pandemic. The remote rate and rhythm monitoring around teleconsultation by the TeleCheck-AF approach may be an alternative to traditional face-to-face consultations in the future. In 2021, Yao et al. [133] found that mHealth technology–based integrated care reduced meaningful clinical adverse events in older patients with AF and multimorbidity vs. usual care.

These studies demonstrate the application prospect of wearable devices in the early screening and management of AF, which can achieve timely diagnosis and effective treatment for high-risk AF patients, and early risk intervention for low-risk people to prevent the disease before it develops.

D. Clinical Management of AF

1) AF Burden Estimation From Long Continuous ECG: Characterization of patient clinical phenotype is central to enable personalized medicine. In the context of AF phenotyping, this can be enhanced by exploring the relationship between AF features such as the AF Burden (AFB) and clinical endpoints, for example, stroke. Chen et al. [134] and Go et al. [135] showed that AFB is highly correlated with a higher risk of stroke among other cardiological and neurological outcomes. Also, Han et al. [136] studied the use of daily AFB from continuous cardiac implantable electronic device tracings for stroke prediction. This motivates us to estimate the AFB measure accurately. Furthermore, a large proportion of AF patients are paroxysmal or asymptomatic and thus go undetected since these patients are harder to identify from short ECG recordings [137]. To better understand how AF episode patterns are captured, several studies have investigated the regularity and length of AF events across individuals [138]. Moreover, it was shown that diagnostic yield increases with prolonged duration and an increased number of screenings [139], [140]. However, long-term screening can significantly increase the workload of the medical staff. Noseworthy et al. [141] proposed an AI-guided screening approach for addressing underdiagnosed atrial fibrillation patients which might not be addressed in current practice and showed increased detection of AF using a guided AI approach over usual practice. Biton et al. [60] developed a recurrent DL model denoted ArNet2 builds upon ArNet [142] to analyze long-term continuous ECG recordings for AF diagnosis and phenotyping using robust AFB estimation. ArNet2 demonstrated state-of-the-art performance in detecting AF events with $F1 = 0.92$ and was very robust in estimating the AFB with an absolute error of $|E\_AF\,(\%)| = 0.32$.

2) Monitoring of Atrial Fibrillation Before and After Surgery: The conventional treatment for AF patients with obvious clinical symptoms is catheter radiofrequency ablation (CAP). To formulate AF treatment plans, it is necessary to quantify the type and severity of AF. In addition, the postoperative recurrence rate of AF is very high, and continuous ECG monitoring is required [16].

According to research from Sanhoury [143], patients with persistent AF with increased left atrial volume and decreased function have a longer ablation time and higher postoperative recurrence rate. Tilz et al. [144] counted the recurrence of AF radiofrequency ablation within ten years. The recurrence rate after ten years of single radiofrequency ablation was as high as 67.1%, and the recurrence rate of multiple ablations was 37.3%. In addition, the recurrence rate is affected by the severity of AF. Efremidis et al. [15] conducted a long-term follow-up of 520 patients with AF who underwent a single radiofrequency ablation procedure, and the recurrence rate at 1, 2 and 5 years after paroxysmal AF. They were 23.1%, 27%, and 28.7%, respectively, and the recurrence rates at 1, 2, and 5 years after persistent /permanent AF increased to 31.3%, 36.6%, and 38.4%. The main reasons affecting the postoperative recurrence rate are the differences in the surgical plan and the degree of disease. If AF patients can be continuously monitored before surgery, accurately quantifying the severity of AF, will significantly reduce the recurrence of AF. Wearable ECG continuous monitoring of patients after AF ablation resulted in closer patient management, improved outcomes, and similar total costs.

Zvuloni et al. [145] developed a feature engineering approach to evaluate whether CAP was successful without a long follow-up assessment for AF recurrence. The authors obtained an AUROC of 0.64 using pre-CAP ECG and an AUROC of 0.74 using post-CAP ECG. Ma et al. [62] developed a multi-step paroxysmal atrial fibrillation scanning strategy in long-term ECGs, hoping to help the clinical management of AF.

VI. Future Directions

Based on the past and current studies on ambulatory AF monitoring technology (such as the wearable AF monitoring device, AF analysis algorithm for wearable AF monitoring device and AF clinical management), we highlight key challenging practical issues of existing AF monitoring technology. We further present future research directions for intelligent AF monitoring.

A. AF Screening

AF screening is typically targeted toward middle-aged and elderly individuals in a home setting, which places certain demands on AF monitoring devices. First and foremost is the issue of device comfort to avoid itching, festering, and other problems during long-term use. Secondly, the ease of use of contact devices must be improved. In out-of-hospital healthcare scenarios where there may be a lack of trained professionals, incorrect placement of electrodes and other components can cause the device to malfunction.

The monitoring device for AF screening will be convenient and comfortable under the premise of a high-reliability ECG signal. The monitoring device for home AF monitoring will be developed towards non-contact monitoring to achieve early screening for AF.

B. AF Diagnosis

AF diagnosis needs accurate and reliable AF detection. It is essential to identify effective ECG to AF analysis and locate the R peak to monitor heart rate in the presence of noise interference. Thus, ECG signals quality evaluation and the fusion of multiple QRS complex wave detection algorithms or multi-lead fusion can be utilized.

Developing an AF detection model with generalization ability can enhance the accuracy of detection across separate sets of tests. Future research in developing an AF diagnosis algorithm must include an assessment of the algorithm performance across multiple external test sets that include a diversity of ethnic/geographic groups, age and sex. Interpretability of deep learning-based AF detection methods is also an ongoing direction, which enhances the application and acceptance of algorithms in clinical practice and promotes safer, more reliable and sustainable medical practices.

In addition, there is a need to establish a precisely labeled clinical database for paroxysmal AF and develop suitable AF burden assessment algorithms for long-term ECG monitoring, which can help optimize individualized treatment plans for AF patients.

C. AF Risk Prediction

Due to the high prevalence of AF, AF risk prediction is crucially important. Currently, there are relatively few and immature AF prediction algorithms available. Future AF prediction algorithms can be personalized based on an individual's physiological characteristics and medical history. This personalized approach can improve the accuracy and specificity of AF prediction, thereby providing better guidance for clinical treatment and prevention.

In the future, intelligent ECG monitoring will significantly contribute to the continuous monitoring of AF, the management of patient information, and the construction of disease risk early warning models. The purpose of early detection and treatment is to prevent the deterioration of the patient's condition, effectively save medical costs, reduce the burden on families, and alleviate the problem of insufficient medical resources.

VI. Conclusion

The development of portable and comfortable ECG monitoring devices and the design of high-precision non-invasive solutions for automatic detection and prediction of AF and its types have a great demand in the field of intelligent medicine, especially in the field of AF management. In this work, we reviewed the ambulatory monitoring techniques currently used in AF management, the challenges associated with ECG data processing brought about by ambulatory monitoring technology, such as analysis of available ECG signals and the impact of QRS detectors on AF analysis, and the AF analysis algorithm. Moreover, we discussed the application of the AF analysis algorithm in clinical Big Data and clinical management of AF and proposed the future research directions of AF monitoring technology.

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