International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Operating Publisher
SciFormat Publishing Inc.
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,
Calgary, Alberta, T3E0A7,
Canada
+15878858911
editorial-office@sciformat.ca

ARTICLE TITLE	DETECTION OF ATRIAL FIBRILLATION BASED ON ECG - TESTING THE EFFECTIVENESS OF A SIMPLE AI ALGORITHM IN IDENTIFYING ARRHYTHMIAS ON ECG RECORDINGS
DOI	https://doi.org/10.31435/ijitss.1(49).2026.4865
RECEIVED	21 November 2025
ACCEPTED	16 January 2026
PUBLISHED	27 January 2026
LICENSE	The article is licensed under a **Creative Commons Attribution 4.0 International License.**

DETECTION OF ATRIAL FIBRILLATION BASED ON ECG - TESTING THE EFFECTIVENESS OF A SIMPLE AI ALGORITHM IN IDENTIFYING ARRHYTHMIAS ON ECG RECORDINGS

Patryk Iglewski *(Corresponding Author, Email: patryk.iglewski01@gmail.com)*
Ludwik Rydygier Provincial Combined Hospital in Torun, Torun, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0004-6611-2168

Klaudia Brzoza
Jan Biziel University Hospital No. 2 in Bydgoszcz, Bydgoszcz, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0006-0950-4514

Filip Matusiak
Jan Biziel University Hospital No. 2 in Bydgoszcz, Bydgoszcz, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0002-0538-6443

Michał Kociński
Jan Biziel University Hospital No. 2 in Bydgoszcz, Bydgoszcz, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0007-7651-7929

Michał Pietrasz
Ludwik Rydygier Provincial Combined Hospital in Torun, Torun, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0000-8148-7487

Anna Komarczewska
Ludwik Rydygier Provincial Combined Hospital in Torun, Torun, Kujawsko-Pomorskie, Poland
ORCID ID: 0009-0006-7378-2607

ABSTRACT

Atrial fibrillation (AF) is the most common cardiac arrhythmia and a growing cardiovascular epidemic characterized by uncoordinated atrial activation. It is a significant risk factor for ischemic stroke, heart failure, and cognitive decline. Despite its rising prevalence, driven by aging populations and lifestyle factors, early detection remains a diagnostic challenge due to the often asymptomatic and paroxysmal nature of the condition. Traditional screening methods, relying on standard electrocardiograms (ECG) and manual interpretation, are resource-intensive and limited in their ability to provide continuous monitoring.

The rapid development of digital health technologies has introduced artificial intelligence (AI) as a pivotal tool for automating arrhythmia detection. This review assesses the effectiveness of "simple" machine learning algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN), in comparison to complex deep learning architectures like Convolutional Neural Networks (CNN).

The analysis indicates that simple AI models demonstrate high diagnostic accuracy (up to 99.1%), comparable to deep learning models, while requiring significantly less computational power and offering greater interpretability. These features make them highly suitable for deployment in battery-operated consumer devices, such as smartwatches and handheld ECG recorders. The integration of these efficient algorithms into telemedicine infrastructures supports a hybrid care model, facilitating large-scale screening and early diagnosis, which is essential for mitigating the burden of AF-related complications.

Methodology: This article is a review. The data presented is based on a comprehensive analysis of peer-reviewed scientific articles, systematic reviews, and clinical reports published in reputable medical journals. The review focuses on studies evaluating the performance of AI algorithms using publicly available physiological signal databases, such as the MIT-BIH Atrial Fibrillation Database and PhysioNet Challenge datasets, as well as data collected from wearable mobile devices. The literature selected for this overview covers the period from 2010 to 2025, including foundational research and the most recent developments in mobile health technologies, approved medical devices, and algorithmic efficiency. The review critically compares the utility, accuracy, and computational requirements of various machine learning approaches in the context of remote patient monitoring and clinical diagnostics.

KEYWORDS

Atrial Fibrillation, Artificial Intelligence, ECG, Machine Learning, Wearable Devices, Telemedicine, Arrhythmia Detection, Screening, Deep Learning

CITATION

Patryk Iglewski, Klaudia Brzoza, Filip Matusiak, Michał Kociński, Michał Pietrasz, Anna Komarczewska (2026) Detection of Atrial Fibrillation Based on ECG – Testing the Effectiveness of a Simple AI Algorithm in Identifying Arrhythmias on ECG Recordings. *International Journal of Innovative Technologies in Social Science*. 1(49). doi: 10.31435/ijitss.1(49).2026.4865

1. Introduction

Atrial fibrillation (AF) is the most common supraventricular tachyarrhythmia, characterized by rapid (350–700 impulses per minute) and uncoordinated atrial activation, resulting in the loss of effective atrial contraction and an irregular ventricular rhythm. The prevalence and incidence of AF are increasing globally. According to data from the Framingham Heart Study (FHS), the incidence of AF has tripled over the past 50 years [1]. The lifetime risk of developing AF is estimated at approximately one in three among individuals of European descent and one in five among African American populations [2]. It is now increasingly recognized that the epidemiology of AF differs between men and women. Age-adjusted prevalence rates of AF are higher in men compared to women in North American and European populations [3]. Advanced age remains the most significant risk factor for AF, and understanding its impact is crucial for assessing how changes in life expectancy may affect future AF prevalence [3]. Additionally, lifestyle-related diseases such as obesity, elevated body mass index (BMI), and diabetes mellitus significantly contribute to increased AF risk [3]. Population-based studies have also demonstrated that a family history of AF is associated with a 40% increased risk of developing AF among first-degree relatives [3].

Lifestyle factors play an important role in AF risk modulation. A sedentary lifestyle is linked to a higher risk of AF; however, paradoxically, extreme levels of physical activity are also associated with an elevated risk of this arrhythmia. Tobacco smoking has similarly been correlated with an increased incidence of AF [3]. Considering these factors, it is evident that the risk of atrial fibrillation is particularly significant in modern society. AF is associated with numerous adverse clinical outcomes, including heart failure [4], ischemic stroke [5], systemic thromboembolic disease, cognitive decline, dementia [3] and many other diseases. Early detection and appropriate management of AF are therefore essential to mitigate these complications. While conventional electrocardiographic (ECG) analysis remains a valuable diagnostic tool, it is time-consuming and often requires the availability of experienced specialists. Certain arrhythmias may mimic AF on ECG recordings, posing diagnostic challenges for less experienced clinicians [6]. Consequently, there is growing interest in the application of artificial intelligence (AI) to the analysis of biological signals, including ECG recordings and pulse waveforms from wearable devices such as pulse oximeters [7], to facilitate early and accurate detection of AF.

The aim of this review is to assess the current evidence on the effectiveness of simple AI algorithms in detecting atrial fibrillation based on electrocardiographic data.

2. Atrial Fibrillation: Clinical Characteristics, Epidemiology, and Management

2.1 Introduction: Definition and Classification

Atrial fibrillation (AF) is the most common clinically significant cardiac arrhythmia, characterized by irregular and disordered atrial electrical activity that suppresses normal sinus rhythm [8]. It is considered a 21st-century cardiovascular disease epidemic, with global prevalence estimates rising from 33.5 million in 2010 to approximately 59 million in 2019 [9]. The condition imposes a substantial burden on healthcare systems due to its association with increased morbidity and mortality [8, 3]. AF is traditionally classified based on its temporal pattern and mode of termination:

- Paroxysmal AF: Episodes terminate spontaneously or with intervention within 7 days.
- Persistent AF: Episodes are sustained beyond 7 days and require cardioversion for restoration of sinus rhythm.
- Long-standing persistent AF: Continuous AF lasting more than 12 months.
- Permanent AF: The arrhythmia is accepted by the patient and physician, and no further rhythm control attempts are made [8].

From a pathophysiological perspective, early AF is often driven by focal triggers, typically originating from muscular sleeves within the pulmonary veins. Over time, structural and electrical remodeling of the atria characterized by fibrosis, dilatation, and changes in refractoriness creates a substrate that perpetuates the arrhythmia [8, 3].

2.2 ECG Characteristics in Atrial Fibrillation

The diagnosis of AF requires documentation via an electrocardiogram (ECG). The hallmark features on a 12-lead ECG are the absence of distinct P waves and an irregular R–R interval (irregularly irregular ventricular rhythm) [8]. European Society of Cardiology (ESC) guidelines accept a standard 12-lead ECG or a single-lead rhythm strip of ≥30 seconds showing AF as diagnostic [8, 9]. While the absence of P waves is definitive for AF, specific P wave indices during sinus rhythm can serve as predictors for the development of the condition. Prolonged P wave duration, which quantifies the time required for atrial depolarization, is indicative of delayed intra- or interatrial conduction and has been consistently associated with incident AF [10]. Additionally, P wave terminal force in lead V1 (PTFV1), a marker of left atrial conduction abnormality and potentially fibrosis, is an independent predictor of AF and stroke [10]. These ECG markers reflect the underlying adverse atrial remodeling (electrophysiological changes) that precedes the clinical manifestation of the arrhythmia [10].

2.3 Detection of AF: Algorithms and Digital Health

The landscape of AF detection has evolved with the advent of digital health technologies. Conventional screening relies on opportunistic pulse palpation or 12-lead ECGs in clinical settings. However, recent technological advancements have introduced wearable devices (e.g., smartwatches, handheld ECG recorders) capable of producing single-lead ECGs or utilizing photoplethysmography (PPG) for rhythm monitoring [8, 9].

AI and Digital Algorithms in Detection

Simple algorithms and more advanced artificial intelligence (AI) integrated into mobile health (mHealth) devices play a pivotal role in screening. These devices typically use algorithms to analyze high-frequency signals or pulse wave irregularities.

- PPG-based algorithms: These detect irregularity in the pulse wave. While accessible, PPG can underestimate heart rate during AF due to pulse deficits and is susceptible to artifacts from motion or poor skin contact [9].
- Single-lead ECG algorithms: Handheld devices and smartwatches can record a single-lead ECG to detect the absence of P waves and R-R irregularity. These provide higher diagnostic accuracy than PPG alone but are still prone to noise and artifacts, which can lead to false-positive detections if not manually verified by a clinician [8].

Studies indicate that while digital screening strategies (systematic or opportunistic) increase the detection of AF compared to routine care, the translation into improved hard clinical outcomes (e.g., reduction in stroke or mortality) remains complex. For instance, while screening detects more patients with AF, randomized trials like the LOOP study and STROKESTOP have shown mixed results regarding the net clinical benefit of anticoagulation based solely on screen-detected cases, suggesting that the burden of AF matters [9].

2.4Epidemiology and Clinical Significance

The epidemiology of AF is inextricably linked to age and comorbidities. The lifetime risk of developing AF is approximately 1 in 3 to 1 in 5 for individuals over the age of 45 [9]. Advancing age is the most prominent risk factor, with prevalence increasing steeply in older populations [3]. Other key risk factors include hypertension, heart failure, obesity, diabetes mellitus, and obstructive sleep apnea [3]. Clinically, AF is a major cause of adverse cardiovascular outcomes. It is associated with a two-fold increase in the risk of myocardial infarction, a five-fold increase in the risk of stroke, and a three-fold increase in the risk of heart failure [8, 9]. Furthermore, AF is independently associated with cognitive decline and vascular dementia, likely due to cerebral hypoperfusion and silent micro-thromboembolism [3].

2.5Consequences of Undetected AF: Stroke and AF Burden

One of the most critical consequences of undetected AF is ischemic stroke. The risk of stroke is not uniform; it is modulated by the burden (duration and frequency) of the arrhythmia. A systematic review and meta-analysis demonstrated a dose-response relationship between AF burden and stroke risk [11]. Specifically, an AF burden of greater than 5 minutes was associated with a significant increase in the risk of stroke (Adjusted Risk Ratio = 2.49) compared to burdens of less than 5 minutes [11].

Furthermore, the risk of stroke was found to increase linearly by approximately 2.0% to 3.0% for every additional hour of AF burden [11]. This highlights the importance of early detection strategies. While short episodes of subclinical AF detected by devices may carry a lower absolute risk than clinical AF, burdens exceeding certain thresholds (e.g., >24 hours) approach the stroke risk profile of clinical AF, necessitating consideration for anticoagulation therapy in high-risk patients [8, 11].

3. Review of Traditional ECG Analysis Methods

3.1. Manual Analysis by Specialists

The electrocardiogram (ECG) is one of the most important and useful diagnostic tools in modern medicine. It is a non-invasive, widely available, and relatively inexpensive method used in the diagnosis of arrhythmias, conduction disorders, and ischemia. ECG can also be used to assess pacemaker activity and other implantable devices. Medical personnel worldwide routinely use automatic ECG analysis and interpretation to support the clinical evaluation of patients' electrocardiograms [3]. Manual ECG analysis can be divided into seven stages: Assessment of the leading rhythm.

- Assessment of the electrical axis of the heart.
- Assessment of conduction disturbances.
- Assessment of heart chamber hypertrophy.
- Assessment of ischemia.
- Assessment of rhythm disorders.
- Assessment of cardiac defibrillator stimulation [1].

3.2. Classical Algorithms

In the 1950s, it became possible to convert the analog ECG signal into a digital form, and in the 1960s, digital ECG recording enabled the development of algorithms for computer interpretation of ECGs [12]. Since then, many algorithms have been developed to analyze ECGs based on: detection and classification of heartbeats, analysis of ECG series, determination of wave boundaries and corresponding intervals, and further processing including contour analysis by measuring specific points of the signal [13]. Systems have also been developed to filter the signal and reduce the impact of muscle contractions or patient movement on the ECG recording. There are several types of signal filters:

- Low-Pass Filters.
- High-Pass Filters.
- Power-Line Filters.
- Anti-Aliasing Filters [14].

3.3. Limitations and Problems

Despite its ubiquity in clinical practice, errors in ECG interpretation are quite common. Data show that even one-third of reported ECGs contain errors, raising concerns about the accuracy and reliability of human ECG interpretation. Interpretation of a 12-lead resting ECG typically requires specialized knowledge of a physician such as an electrophysiologist, cardiologist, or primary care doctor. A

A meta-analysis published in 2020 showed that the median accuracy of ECG interpretation by physicians was only 54% [15].

4. Artificial Intelligence in ECG Analysis

4.1. Basic Concepts: Machine Learning vs. Deep Learning

The term machine learning refers to the capacity of artificial systems to acquire the ability to perform complex tasks and to enhance their performance through experience. As a subfield of artificial intelligence (AI), machine learning (ML) utilizes algorithms to empirically identify patterns within data. ML expands upon the capabilities of traditional statistical methods by detecting nonlinear relationships and high-order interactions among multiple variable patterns that may be difficult to capture using conventional statistical approaches. Although the concept and terminology of AI have been in use for over sixty years, their prevalence and practical application have increased dramatically over the past decade [16, 17, 18].

Deep learning (DL) has emerged as a highly effective approach within machine learning (ML), capitalizing on the availability of large-scale datasets and recent advancements in computational power to make accurate decisions based on complex data structures. It employs multi-layered artificial neural networks hence the term deep to learn mappings between input and output variables. The training process involves exposing the network to labeled datasets, allowing it to iteratively adjust internal weights in order to minimize an error function. This optimization continues until the model's outputs closely approximate the true values. A key advantage of deep neural networks lies in their capacity to autonomously discover complex and previously unknown patterns within the data, without relying on manually engineered features [17, 19].

4.2. Overview of commonly used machine learning algorithms in ECG:

Support Vector Machine (SVM)

The Support Vector Machine is one of the most widely used supervised learning algorithms, particularly effective for classifying complex, non-linear datasets. It functions by identifying a hyperplane that optimally separates data points belonging to different classes. SVMs can employ either linear or non-linear kernel functions, providing flexibility in handling diverse data structures. While SVMs are computationally efficient and adaptable through kernel selection, they can be challenging to interpret. Additionally, input features often require normalization and scaling to ensure optimal model performance [17, 18].

Random Forest

Random Forest is an ensemble learning technique that aggregates the outputs of multiple decision trees, arranged in a hierarchical structure. The final prediction is generated by averaging (for regression tasks) or taking the majority vote (for classification tasks) of individual tree predictions. This method is robust to noise and overfitting, even in the presence of high-dimensional data. It handles both continuous and categorical variables effectively and is capable of modeling complex variable interactions [17, 18].

Bayesian Networks

Graphical structures used to represent knowledge in uncertain domains. They represent variables and their probabilistic relationships [18].

Convolutional Neural Networks (CNNs)

The most widely used form of deep learning, an evolved form of deep neural networks with multiple hidden layers between input and output. Convolutional layers produce spatially dependent features for subsequent layers [18].

4.3. The Difference Between "Simple" and "Complex" AI Models

Depending on the complexity of the AI model understood in terms of its architecture, number of parameters, and computational requirements models can generally be categorized as either "simple" or "complex." The former category includes, for example, Support Vector Machines and Random Forests, while the latter encompasses models such as Convolutional Neural Networks [17, 18].

Simple models typically offer advantages such as lower computational demands and greater interpretability. In contrast, more complex models tend to perform better on large datasets and achieve higher predictive accuracy; however, they require substantial computational resources and access to large volumes of data [17, 18].

5. Simple AI Algorithms

5.1. Examples of Simple Algorithm Application

The literature extensively analyzes the effectiveness of various TML classifiers. The most commonly used include Support Vector Machines (SVM), Decision Trees (DT), and the k-Nearest Neighbor (k-NN) algorithm [20, 21].

Researchers pay particular attention to ensemble learning methods, which integrate the results of multiple weaker classifiers to improve overall prediction. Rao and Martis demonstrated that the Random Forest (RF) algorithm outperforms single classifiers such as C4.5 or ID3 [21]. Similar conclusions were drawn by Jahan et al., who, upon comparing different approaches, highlighted the high efficiency of gradient boosting algorithms, such as XGBoost and AdaBoost, in classifying short ECG segments [20]. Furthermore, Lown et al. successfully applied an SVM classifier based on Lorenz plot analysis for AF detection using data from inexpensive heart rate monitors [22].

5.2. Data Used in Research

Publicly available databases of physiological signals serve as the foundation for training and validating algorithms. The source most frequently cited in the analyzed works is the MIT-BIH Atrial Fibrillation Database (AFDB), which contains long-term ECG recordings [20, 22, 23]. Other key datasets include the MIT-BIH Arrhythmia Database and the PhysioNet Challenge 2017 database, the latter of which was used by Rao and Martis to evaluate algorithm effectiveness on a large sample of over 8,000 signals of varying lengths [21].

A significant methodological aspect is the use of data from mobile devices. For instance, the study by Lown et al. utilized RR interval data collected via a Polar-H7 chest strap, confirming the potential of simple algorithms in screening diagnostics outside the clinical environment [22]. A systematic review by Xie et al. indicates that using multiple datasets (both public and proprietary) allows for better model generalization [23].

5.3. Research Methodology: Pre-processing and Feature Extraction

A key stage in TML analysis is signal pre-processing and feature engineering. To remove noise and artifacts (e.g., baseline wander), techniques such as the Discrete Wavelet Transform (DWT) are employed [21].

AF detection in simple AI models relies primarily on the analysis of Heart Rate Variability (HRV) derived from RR intervals. The most commonly extracted features include statistical parameters such as the mean RR, RMSSD (Root Mean Square of Successive Differences), and Shannon entropy, which measures the degree of signal disorder [20, 21]. An alternative approach involves morphological analysis or visual data representation, such as the use of correlated Lorenz plots, which illustrate the rhythm irregularity characteristic of atrial fibrillation [22].

5.4. Results: Sensitivity, Specificity, Accuracy

Simple AI algorithms achieve impressive diagnostic results. The Random Forest (RF) model developed by Rao and Martis achieved an overall accuracy of 99.10% and an Area Under the Curve (AUC) of 0.998 [21]. In turn, the SVM algorithm applied by Lown et al. demonstrated 100% sensitivity and 97.6% specificity in identifying AF episodes during clinical validation [22].

In the study by Jahan et al., the AdaBoost algorithm for ECG segments of 60 heartbeats achieved a sensitivity of approximately 91.9% and a specificity of approximately 87.5%, surpassing the results obtained by single decision trees or SVM [20]. A meta-analysis conducted by Xie et al. indicates that the pooled sensitivity of machine learning algorithms in AF detection is approximately 97%, with traditional methods (TML) achieving an average sensitivity of 91.5% [23].

5.5. Comparison with Traditional ECG Analysis and More Complex AI Models

The application of AI in ECG analysis allows for the elimination of errors resulting from human factors, such as fatigue or differences in clinician experience. Research shows that AI can outperform physicians in measurement precision and the detection of subtle changes invisible to the naked eye [15].

When compared to more complex deep learning (DL) models, such as Convolutional Neural Networks (CNN), simple TML algorithms fall slightly behind in terms of sensitivity (91.5% for TML vs. 98.1% for DL) [23]. However, DL models require significantly greater computational power and large training datasets. Algorithms such as RF or SVM offer better interpretability of results and lower hardware requirements, making them more suitable for implementation in battery-operated devices and real-time systems [20, 21].

6. Challenges and Limitations of AI Algorithms in Arrhythmia Identification

6.1. Quality and Quantity of Training Data

The effectiveness of AI algorithms is fundamentally dependent on access to high-quality, labeled datasets. Training convolutional neural networks (CNNs) for ECG classification requires a massive number of annotated samples, the acquisition of which is a costly and time-consuming process requiring medical expert involvement [24]. Many publicly available ECG databases are relatively small, making it difficult to achieve the desired performance level without employing techniques such as transfer learning, which involves pretraining models on large datasets before adapting them to specific tasks [24].

Data heterogeneity presents another significant issue. ECG recordings obtained from remote monitoring devices are often characterized by lower signal quality, the presence of noise, and a drastic class imbalance resulting from the rare occurrence of cardiovascular events in the general population [24]. Furthermore, algorithms used in commercial wearable devices often operate as "black boxes," and the data used to train them remain undisclosed, preventing independent assessment of their quality and representativeness [25].

6.2. Transferability of Models to Different Populations

Generalizing AI models to populations different from those on which they were trained remains a critical challenge. Research indicates that consumer devices utilizing photoplethysmography (PPG) are adopted primarily by younger, tech-savvy populations, whereas older individuals who carry the highest risk of arrhythmias and thromboembolic complications may be underrepresented in validation studies [25]. For instance, the Apple Heart Study required participants to own their devices, potentially introducing selection bias towards a younger and healthier cohort with a lower risk of AF [26].

Moreover, models trained on high-quality ECG scans (e.g., from clinical databases) often lose accuracy when applied to the analysis of ECG images captured by smartphones in real-world settings. These photographs may contain artifacts, shadows, paper crumples, or perspective distortions that were not present in the training set [27]. To address this, advanced techniques such as domain adaptation are necessary to force the network to select features independent of the recording format [27].

6.3. Overfitting and Lack of Interpretability

The lack of transparency in the decision-making process of algorithms (the "black box" problem) constitutes one of the main obstacles to building physician trust in AI systems. Clinicians require justification for a diagnosis in medical terms, i.e., the identification of specific ECG features (e.g., absence of P-waves, irregular rhythm) that influenced the classification [27]. Existing interpretability methods, such as heatmaps (e.g., GRAD-CAM), are often not clinically precise enough; they may highlight the image background instead of the ECG signal or overlook small but crucial diagnostic features [27].

The phenomenon of overfitting is closely linked to the lack of interpretability. A model may learn to recognize features specific to a given domain (e.g., shadows in a photo) rather than the pathophysiological features of the arrhythmia. Novel approaches, utilizing methods such as Jacobian matrix analysis, aim to provide pixel-level interpretability, allowing for the precise indication of morphological and rhythmic arrhythmia features understandable to electrophysiologists [27].

6.4. Problems with Clinical Validation and Implementation

Despite the increasing number of FDA approvals for AI-based medical devices, the majority (over 50%) hold only an "assistive" status, meaning the final decision and responsibility rest with the physician [28]. An analysis of FDA approvals from 2021–2023 indicates a cautious regulatory approach, favoring technologies that support rather than replace human judgment [28].

AI implementation also faces difficulties regarding validation in real-world conditions. While

large-scale studies, such as the Huawei Heart Study or the Apple Heart Study, have demonstrated the feasibility of screening using mobile technology, concerns remain regarding false-positive results, which may lead to unnecessary burdens on the healthcare system [25, 26]. Furthermore, the lack of standard data exchange protocols from 12-lead devices and the variety of ECG printout formats pose barriers to integrating AI systems with hospital infrastructure [27]. Finally, the closed nature of many proprietary algorithms hinders external validation and the assessment of their reliability across diverse patient groups [25, 29].

7. Atrial Fibrillation Detection Using Artificial Intelligence: Applications in Wearable Devices and Telemedicine

Atrial fibrillation (AF) is one of the most common cardiac arrhythmias and is also a key risk factor for stroke, heart failure, and premature death [30]. Due to its often asymptomatic course and paroxysmal nature, early detection remains a significant diagnostic challenge. In response to this need, increasing attention is being paid to the use of simple, computationally efficient artificial intelligence (AI) algorithms that can be implemented not only in clinical settings but also in wearable devices and mobile applications [30].

7.1. Arrhythmia Detection with Simple AI Models

In a study by Zink et al., a handheld ECG device – MyDiagnostick – was used in a screening program involving over 7,000 patients aged 65 and older [30]. The initial analysis identified AF in 6.08% of cases, but the study's main contribution was the comparison between the performance of the device's conventional software and an algorithm based on deep neural networks. The AI model achieved an F1 score of 86%, outperforming the 81% achieved by the classical solution [30].

Notably, the implemented algorithm was radically simplified – the number of parameters was reduced by as much as 99% without significant loss of accuracy [30]. Such simplification paves the way for the deployment of these models in resource-limited devices such as smartwatches, smartphones, and health bands.

7.2. Wearable Devices as a Platform for AI

The ability to continuously monitor ECG at home using simple mobile devices is gaining increasing significance. AI models that can be easily integrated into wearable electronics offer a real opportunity to detect AF even in its paroxysmal form [30]. Moreover, the authors emphasized the importance of Explainable AI (XAI), which refers to tools that visualize which parts of the ECG recording were crucial for the classification, an approach that can help build physicians' trust in these systems [30].

7.3 Telemedicine as an Implementation Context

The development of simple AI algorithms should also be considered within the broader context of the digital transformation of healthcare. For example, a study by Goldim et al. showed that the implementation of over 50,000 remote consultations in one large hospital significantly reduced greenhouse gas emissions [31].

The authors highlighted that telemedicine may serve not only system efficiency but also the sustainable development of healthcare [31]. Its combination with AI algorithms that preliminarily analyze data and identify cases requiring further diagnostics may form the foundation of modern screening models [30, 31].

7.4. Acceptance of the Hybrid Model

Social acceptance is also crucial when implementing automated diagnostic systems. A qualitative study by Barratt and colleagues examined patient and physician opinions on transitioning to remote consultations particularly in the context of primary and specialist care [32]. Participants consistently emphasized the benefits of teleconsultations but also pointed to the need for continued access to in-person visits. A hybrid model combining both approaches appears to best meet the needs of both patients and clinicians [32].

7.5. Lessons Learned from the Pandemic

The COVID-19 pandemic played a significant role in accelerating the adoption of telemedicine. Data from a study conducted by Wiener et al. on the U.S. Veterans Health Administration showed that many centers not only increased the number of remote care planning conversations but also maintained these levels in the following years [33]. This indicates that once implemented, functional and effective solutions can permanently change how healthcare is organized [33].

8. Summary

Atrial fibrillation (AF) represents a growing cardiovascular epidemic, characterized by uncoordinated atrial activation and a significant increase in the risk of stroke, heart failure, and cognitive decline.

Despite its rising prevalence projected to triple in coming decades due to aging populations and lifestyle factors, early detection remains challenging. Conventional diagnostic methods, relying on 12-lead electrocardiograms (ECG) and manual interpretation by specialists, are resource-intensive and often fail to capture paroxysmal episodes. Consequently, there is an increasing clinical interest in leveraging artificial intelligence (AI) to automate arrhythmia detection, particularly through wearable technology and handheld devices.

This review critically assesses the utility of "simple" machine learning (ML) algorithms compared to more complex deep learning (DL) architectures. While deep learning models, such as Convolutional Neural Networks (CNNs), often achieve marginally higher sensitivity (e.g., 98.1%), they require massive annotated datasets and substantial computational power, making them less suitable for battery-operated portable devices. In contrast, simple algorithms specifically Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN) offer a compelling balance of efficiency and accuracy.

For instance, studies utilizing Random Forest classifiers on heart rate variability data have demonstrated accuracies as high as 99.1%, while SVM models applied to Lorenz plots have shown near-perfect sensitivity in clinical validation.

A significant advantage of these simpler models is their interpretability and lower hardware requirements, facilitating their integration into consumer wearables like smartwatches and handheld ECG recorders. In a screening study involving the MyDiagnostick device, a simplified neural network algorithm outperformed conventional software (F1 score of 86% vs. 81%) despite a 99% reduction in parameters. This efficiency is crucial for continuous, real-time monitoring outside the clinical environment.

However, the transition from research to clinical practice faces substantial hurdles. Key challenges include the "black box" nature of proprietary algorithms, which hinders physician trust, and the heterogeneity of real-world data, where noise and artifacts can degrade performance. Furthermore, regulatory bodies remain cautious; over half of FDA-approved AI devices are currently designated only as "assistive," leaving the final diagnostic responsibility with the clinician. The future of AF management likely lies in a hybrid model that combines the screening efficiency of explainable AI (XAI) with telemedicine infrastructure, ensuring that technological alerts are verified by human expertise to minimize false positives and alleviate the burden on healthcare systems.

Authors' contribution:
Conceptualization: Patryk Iglewski, Klaudia Brzoza, Michał Pietrasz
Methodology: Filip Matusiak, Michał Kociński, Michał Kociński
Investigation: Klaudia Brzoza, Filip Matusiak, Anna Komarczewska
Software: Patryk Iglewski, Michał Kociński, Michał Pietrasz
Formal analysis: Klaudia Brzoza, Michał Pietrasz, Anna Komarczewska
Writing- rough preparation: Klaudia Brzoza, Filip Matusiak, Anna Komarczewska
Writing- review and editing: Klaudia Brzoza, Patryk Iglewski, Filip Matusiak
Resources: Patryk Iglewski, Michał Kociński, Michał Pietrasz

All authors have read and agreed with the published version of the manuscript.
Funding statement: The study did not receive special funding.
Conflict of Interest Statement: The authors declare no conflict of interest.
Declaration on the use of AI: In preparing this work, the authors used Gemini for the purpose of improving language and readability, text formatting, and verification of bibliographic styles. After using this tool/service, the authors have reviewed and edited the content as needed and accept full responsibility for the substantive content of the publication.

REFERENCES

1. Schnabel, R. B., Yin, X., Gona, P., et al. (2015). Fifty-year trends in atrial fibrillation incidence, prevalence, risk factors, and mortality in the Framingham Heart Study: A cohort study. *The Lancet, 386*(9989), 154–162. https://doi.org/10.1016/S0140-6736(14)61774-8
2. Mou, L., Norby, F. L., Chen, L. Y., et al. (2018). Lifetime risk of atrial fibrillation by race and socioeconomic status: The ARIC (Atherosclerosis Risk in Communities) study. *Circulation: Arrhythmia and Electrophysiology, 11*(7), e006350. https://doi.org/10.1161/CIRCEP.118.006350
3. Staerk, L., Sherer, J. A., Ko, D., Benjamin, E. J., & Helm, R. H. (2017). Atrial fibrillation: Epidemiology, pathophysiology, and clinical outcomes. *Circulation Research, 120*(9), 1501–1517. https://doi.org/10.1161/CIRCRESAHA.117.309732
4. Anter, E., Jessup, M., & Callans, D. J. (2009). Atrial fibrillation and heart failure: Fire and fury. *Circulation, 119*(19), 2516–2525. https://doi.org/10.1161/CIRCULATIONAHA.108.821306
5. Wolf, P. A., Abbott, R. D., & Kannel, W. B. (1991). Atrial fibrillation as an independent risk factor for stroke: The Framingham Study. *Stroke, 22*(8), 983–988. https://doi.org/10.1161/01.STR.22.8.983
6. Bogun, F., Anh, D., Kalahasty, G., et al. (2004). Misdiagnosis of atrial fibrillation and its clinical consequences. *The American Journal of Medicine, 117*(9), 636–642. https://doi.org/10.1016/j.amjmed.2004.06.028
7. Lubitz, S. A., Faranesh, A. Z., Selvaggi, C., et al. (2022). Detection of atrial fibrillation in a large population using wearable devices: The Fitbit Heart Study. *Circulation, 146*(19), 1415–1424. https://doi.org/10.1161/CIRCULATIONAHA.122.060291
8. Saleh, K., & Haldar, S. (2023). Atrial fibrillation: A contemporary update. *Clinical Medicine, 23*(5), 437–441. https://doi.org/10.7861/clinmed.2023-23.5.Cardio2
9. Linz, D., Gawalko, M., Betz, K., et al. (2024). Atrial fibrillation: Epidemiology, screening and digital health. *The Lancet Regional Health – Europe, 37*, 100786. https://doi.org/10.1016/j.lanepe.2023.100786
10. German, D. M., Kabir, M. M., Dewland, T. A., Henrikson, C. A., & Tereshchenko, L. G. (2016). Atrial fibrillation predictors: Importance of the electrocardiogram. *Annals of Noninvasive Electrocardiology, 21*(1), 20–29. https://doi.org/10.1111/anec.12321
11. Yang, S. Y., Huang, M., Wang, A. L., et al. (2022). Atrial fibrillation burden and the risk of stroke: A systematic review and dose-response meta-analysis. *World Journal of Clinical Cases, 10*(3), 939–953. https://doi.org/10.12998/wjcc.v10.i3.939
12. Smulyan, H. (2019). The computerized ECG: Friend and foe. *The American Journal of Medicine, 132*(2), 153–160. https://doi.org/10.1016/j.amjmed.2018.08.025
13. Kraik, K., Dykiert, I. A., Niewiadomska, J., et al. (2025). The most common errors in automatic ECG interpretation. *Frontiers in Physiology, 16*, 1590170. https://doi.org/10.3389/fphys.2025.1590170
14. Venkatachalam, K. L., Herbrandson, J. E., & Asirvatham, S. J. (2011). Signals and signal processing for the electrophysiologist: Part I: Electrogram acquisition. *Circulation: Arrhythmia and Electrophysiology, 4*(6), 965–973. https://doi.org/10.1161/CIRCEP.111.964304
15. Muzammil, M. A., Javid, S., Afridi, A. K., Siddineni, R., et al. (2024). Artificial intelligence-enhanced electrocardiography for accurate diagnosis and management of cardiovascular diseases. *Journal of Electrocardiology, 83*, 30–40. https://doi.org/10.1016/j.jelectrocard.2024.01.006
16. Attia, Z. I., Harmon, D. M., Behr, E. R., et al. (2021). Application of artificial intelligence to the electrocardiogram. *European Heart Journal, 42*(46), 4717–4730. https://doi.org/10.1093/eurheartj/ehab649
17. Feeny, A. K., Chung, M. K., Madabhushi, A., et al. (2020). Artificial intelligence and machine learning in arrhythmias and cardiac electrophysiology. *Circulation: Arrhythmia and Electrophysiology, 13*(8), e007952. https://doi.org/10.1161/CIRCEP.119.007952
18. Nagarajan, V. D., Lee, S. L., Robertus, J. L., et al. (2021). Artificial intelligence in the diagnosis and management of arrhythmias. *European Heart Journal, 42*(38), 3904–3916. https://doi.org/10.1093/eurheartj/ehab544
19. Siontis, K. C., Noseworthy, P. A., Attia, Z. I., et al. (2021). Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nature Reviews Cardiology, 18*(7), 465–478. https://doi.org/10.1038/s41569-020-00503-2
20. Jahan, M. S., Mansourvar, M., Puthusserypady, S., Wiil, U. K., & Peimankar, A. (2022). Short-term atrial fibrillation detection using electrocardiograms: A comparison of machine learning approaches. *International Journal of Medical Informatics, 163*, 104790. https://doi.org/10.1016/j.ijmedinf.2022.104790
21. Rao, S. K. S., & Martis, R. J. (2023). RR interval-based atrial fibrillation detection using traditional and ensemble machine learning algorithms. *Journal of Medical Signals and Sensors, 13*, 224–232. https://doi.org/10.4103/jmss.jmss_4_22
22. Lown, M., Brown, M., Brown, C., et al. (2020). Machine learning detection of atrial fibrillation using wearable technology. *PLOS ONE, 15*(1), e0227401. https://doi.org/10.1371/journal.pone.0227401

23. Xie, C., Wang, Z., Yang, C., Liu, J., & Liang, H. (2024). Machine learning for detecting atrial fibrillation from ECGs: Systematic review and meta-analysis. *Reviews in Cardiovascular Medicine, 25*(1), 8. https://doi.org/10.31083/j.rcm2501008
24. Weimann, K., & Conrad, T. O. F. (2021). Transfer learning for ECG classification. *Scientific Reports, 11*, 5251. https://doi.org/10.1038/s41598-021-84374-8
25. Karakasis, P., Theofilis, P., Sagris, M., et al. (2025). Artificial intelligence in atrial fibrillation: From early detection to precision therapy. *Journal of Clinical Medicine, 14*, 2627. https://doi.org/10.3390/jcm14082627
26. Turakhia, M. P., Desai, M., Hedlin, H., et al. (2019). Rationale and design of a large-scale, app-based study to identify cardiac arrhythmias using a smartwatch: The Apple Heart Study. *American Heart Journal, 207*, 66–75. https://doi.org/10.1016/j.ahj.2018.09.002
27. Gliner, V., Levy, I., Tsutsui, K., et al. (2025). Clinically meaningful interpretability of an AI model for ECG classification. *npj Digital Medicine, 8*, 109. https://doi.org/10.1038/s41746-025-01467-8
28. Fernando, P., Lyell, D., Wang, Y., & Magrabi, F. (2025). Role of AI in clinical decision-making: An analysis of FDA medical device approvals. In M. S. Househ et al. (Eds.), *MEDINFO 2025: Healthcare Smart x Medicine Deep* (pp. 1019–1023). IOS Press. https://doi.org/10.3233/SHTI250993
29. Liang, H., Zhang, H., Wang, J., et al. (2024). The application of artificial intelligence in atrial fibrillation patients: From detection to treatment. *Reviews in Cardiovascular Medicine, 25*(7), 257. https://doi.org/10.31083/j.rcm2507257
30. Zink, M. D., Kuijpers, Y., Peeters, L., et al. (2025). Towards artificial intelligence-based decision support for large-scale screening for atrial fibrillation. *IEEE Journal of Biomedical and Health Informatics*. Advance online publication. https://doi.org/10.1109/JBHI.2025.3579621
31. Umpierre, R. N., Mattiello, R., Schmitz, C. A. A., et al. (2025). Greening healthcare and slashing carbon emissions through telemedicine: A cross-sectional study from over 50 thousand remote consults at a leading tertiary hospital. *Frontiers in Digital Health, 7*, 1497770. https://doi.org/10.3389/fdgth.2025.1497770
32. Barratt, H., Chaloner, C., Rainie, R., et al. (2025). What is the impact of a shift to remote consultations? A qualitative interview study in primary and secondary healthcare. *BMJ Open, 15*(6), e097633. https://doi.org/10.1136/bmjopen-2024-097633
33. Linsky, A. M., Canter, B. E., Glickman, M., et al. (2025). The COVID-19 pandemic and goals-of-care conversations in Veterans Health Administration clinics. *JAMA Network Open, 8*(6), e2515980. https://doi.org/10.1001/jamanetworkopen.2025.15980