Received: 13 September 2024 | Revised: 11 December 2024 | Accepted: 31 December 2024 | Published online: 14 January 2025

REVIEW

Medinformatics
2025, Vol. 00(00) 1–14
DOI: 10.47852/bonviewMEDIN52024336

BON VIEW PUBLISHING

Machine Learning Enabled In-Home ECG: A Review

Aqsa Bibi[1] and Jawwad Sami Ur Rahman[1,*]

[1]*Department of Biomedical Engineering, Riphah International University, Pakistan*

Abstract: Machine learning (ML)-based in-home electrocardiogram (ECG) systems have emerged as transformative tools, advancing beyond traditional cardiology methods by offering innovative techniques for cardiac care. These systems enable sustained data collection, real-time monitoring of cardiac status, and individualized treatment plans, all while minimizing the need for frequent clinic visits. By leveraging advanced analytics and ML algorithms, in-home ECG systems analyze large-scale datasets to detect patterns and anomalies that might otherwise go unnoticed, providing early alerts and improving patient outcomes. This review examines the latest trends in ML-enhanced in-home ECG technology, emphasizing its functionality in anomaly detection, continuous monitoring, and decision-making processes. The integration of ML not only enhances diagnostic precision but also opens avenues for scalable, personalized, and remote healthcare solutions. Despite these advancements, significant challenges remain, including issues related to data privacy, algorithmic biases, and the reliability of real-world implementations. Addressing these challenges is essential for optimizing the performance and ethical use of these systems. This review also explores opportunities for future research, particularly in improving algorithm robustness and addressing biases to ensure equitable and accurate cardiac care for diverse populations. By integrating state-of-the-art ML techniques, in-home ECG systems are poised to revolutionize contemporary cardiology, reducing healthcare costs and enabling a progressive shift toward accessible, patient-centered care. This comprehensive exploration highlights the potential of ML-based in-home ECG systems to redefine cardiac monitoring and treatment, contributing to the broader transformation of modern healthcare.

Keywords: machine learning, remote monitoring, electrocardiogram, in-home ECG, advanced ML algorithms

1. Introduction

Machine learning (ML) is a subfield of artificial intelligence (AI) in which an endeavor is made to design model that help the computer to learn from the data to make prediction or decisions [1]. It involves allowing systems to expose themselves to a certain type of task in order that they themselves learn how to enhance their performance in that area without more programming. This is done by using big datasets in which the phenomena's algorithms learn and make predictions by developing their models with regard to more data in the processes, as they occur. In the healthcare domain, ML has proven to be a useful technology, especially when it comes to computation as well as interpretation of large amounts of medical data. An electrocardiogram (ECG) is a medical procedure that measures electrical activity of the heart over a period of time [2]. This diagnostic tool is useful in managing and diagnosing the different types of heart diseases, for example, arrhythmias, ischemic heart disease, and any conditions that affects the electrical conduction in the heart. The ECG produces data in form of a graph that depicts timing and duration of each electrical phase in heart cycle with help of which we diagnose. However, with clinical ECG monitoring, the patient needs to visit the healthcare facilities frequently as a lot of data are collected, and this may be costly for the patient, especially where the patient requires long-term monitoring [3]. To overcome these drawbacks, in-home ECG monitoring system have been designed. These systems enable tracking of the heart activity of a patient without the need to be in a clinical setting, hence making it convenient and noninvasive to a patient. Some of the in-home ECG devices can be worn and are portable and easy to use thus requiring the patient to collect ECG data for a longer duration [4]. This data can then be transmitted to physicians for analysis or in more and more cases can be analyzed using ML algorithms built in where any potential for a cardiac event is flagged for patient attention immediately.

The healthcare sector has changed because of new technologies and the need for more personalized, easy to reach, and effective healthcare solutions. One of these improvements is the expansion of in-home medical devices that help people with long-term illnesses like cardiovascular diseases (CVDs) manage their conditions. Heart diseases and strokes are still the leading causes of death in the world, affecting 17.9 million people each year [5]. This scary number shows how important it is to keep an eye on heart health and act quickly when problems arise. ECGs have been very helpful in identifying and treating heart problems for a long time. On the other hand, these ECGs were mostly only useful in hospital settings where healthcare professionals could read those [6]. ECGs have gotten a lot better since ML technology emerged out. This has led to the creation of home tracking devices that could change the way cardiac care is performed forever. Converging medical expertise with AI, home

*__Corresponding author:__ Jawwad Sami Ur Rahman, Department of Biomedical Engineering, Riphah International University, Pakistan. Email: jawwad.sami@riphah.edu.pk

ECGs enabled with ML offer improved diagnostics that surpass long-established techniques [7]. This means they keep a close look on cardiac activities, analyzing huge amounts of data in real-time to identify deviations from normalcy, predict possible heart issues, and make immediate observations. On the other hand, ML algorithms are used to integrate these technologies as this helps detect complex patterns in ECG signals that may not be seen using standard analysis [8]. This has the advantage of not only improving accuracy of diagnosis but also early detection of cardiovascular conditions hence better patient management and reduced cases of adverse heart events. Switching to in-home ECG monitoring from clinic-based comes with several advantages associated with accessibility and patient empowerment. In addition, home-based ML-driven ECG machines allow for continuous noninvasive monitoring while in comfort zones and hence reduce clinic visits for patients' convenience and lighten up pressure on healthcare systems [9]. Furthermore, individuals get to control their heart health by managing it themselves through such tools thereby making them more involved in their own care. Apart from the fact that it improves patients' conditions, ML-facilitated ECG systems at home may provide a way out of this predicament as they can be implemented on a large scale. As people get older and older, there is an increase in chronic diseases while healthcare resources are limited. Therefore, this gives rise to the need for new ideas aimed at reducing the load on global healthcare facilities [8]. These systems could minimize chances of emergency hospitalization and improve general healthcare efficiency when used continuously.

Nevertheless, implementing ML-enabled in-home ECGs comes with challenges. Data privacy issues, algorithmic biases, and proper integration into existing healthcare infrastructure are some of the main concerns to be addressed [10]. Similarly, it is fundamental that clinical investigations and trials are conducted extensively to establish its reliability within widespread populations and efficacy under real-life conditions. Generalizability of these systems depends greatly on teaching ML algorithms using diverse representative datasets to ensure no biases exist towards certain groups or individuals which lead to unequal delivery of care. The objective here is to give a detailed account of what the current in-home ECG ML-enabled technology looks like. This research therefore tries to explain how ML is used to enhance home-based ECG monitoring that would have implications for the future healthcare system at large.

Contributions of this review: To provide clarity and emphasize the focus of this article, the contributions of this review are outlined as follows:

1) Analyzing the latest trends and advancements in ML-enabled in-home ECG monitoring systems.
2) Comparing various ML algorithms used for in-home ECG data processing in terms of accuracy, scalability, and real-world applicability.
3) Identifying the challenges and limitations, including algorithmic biases, data privacy, and implementation issues.
4) Proposing future directions for research to enhance the robustness, equity, and effectiveness of in-home ECG systems.
5) Highlighting the role of ML in transforming traditional cardiac care into remote, patient-centered, and cost-effective solutions.

2. Methodology

Similar to most systematic reviews, a systematic approach was used to identify relevant articles for this review by considering the application of ML in supporting ECG monitoring at home. This approach to the research strategy was intended to capture all the important and recent studies related to the subject. The first research question was to identify how ML could be used to improve ECG monitoring systems that are used at home. Secondary research questions were also developed so as to gain a deeper insight of the specific area of the discussion. These arose in regard to the kind of ML algorithms employed in this domain, the efficiency of these algorithms in the identification of cardiac concerns, the issues that characterize the application of ML in ECG tracking, and the differences between home-based ECG monitoring and clinical ECG systems. It was also necessary not only to use index terms recommended by the TPB but to apply the correspondent free-text search terms also. Such a twofold search strategy proved the most effective in terms of retrieving the maximum amount of data pertaining to the subject both in its totality and in its detailed aspects. Some of the words and phrases used in the search included "machine learning" "in-home monitoring" "electrocardiogram" "wearable ECG systems" and "remote cardiac monitoring". Boolean operators like AND, OR, NOT were employed to perform search and filter the obtained results so that they were relevant to the research questions. The search strategy used for the articles was geared towards the interdisciplinary nature of the research area with an emphasis on medicine and technology. This review also focused on including articles in the databases from different disciplines in order to gather multicategory articles concerning in-home ECG monitoring and the utilization of ML for enhancing such systems. The search covered medical and engineering libraries as well as computer science to get all kinds of researches and modern developments in the topic area. Because of this, several databases that include medical research, technological innovation, and general academic sources were chosen for a review of in-home ECG monitoring using ML. Clinical databases including PubMed and Cochrane Library were useful in identifying articles and perspectives on clinical use and evidence of the ECG systems. The use of databases associated with Engineering and computer science including IEEE Xplore, ACM digital library, and Springer link help to makeup information on the modern ML algorithms and technologies applied to ECG monitoring. The general academic databases Google Scholar Web of Science, and Scopus further expanded the search scope for interdisciplinary and future trends.

These criteria limited the search results from the present till the year 2024 to contribute only the recent developments in the ML-aided ECG systems. Incorporated papers had to be published in scientific journals or conference proceedings wherein the major concern was to focus on the ML approaches in in-home or remote ECG monitoring, technical and clinical issues, and the ethical issues such as privacy concerns and fairness of algorithm. The papers excluded were those which did not use ML in their research or were published prior to 2015, unless the Technique was medically historic.

Two sets of inclusion criteria were employed: an initial title and abstract screening to determine relevance of the studies found in the search and subsequent full-text review to extract data relating to the ML algorithms used, the accuracy of the identified algorithms, and benefits of in-home ECG systems that are powered by ML. The recruited papers were analyzed to contrast and compare various ML models and explore their applicability to clinical practice, as well as to define the directions for further development. The use of this systematic search strategy guaranteed that the review provided a diverse and complete view of the studies available in this area of research and find out some of the issues and/or

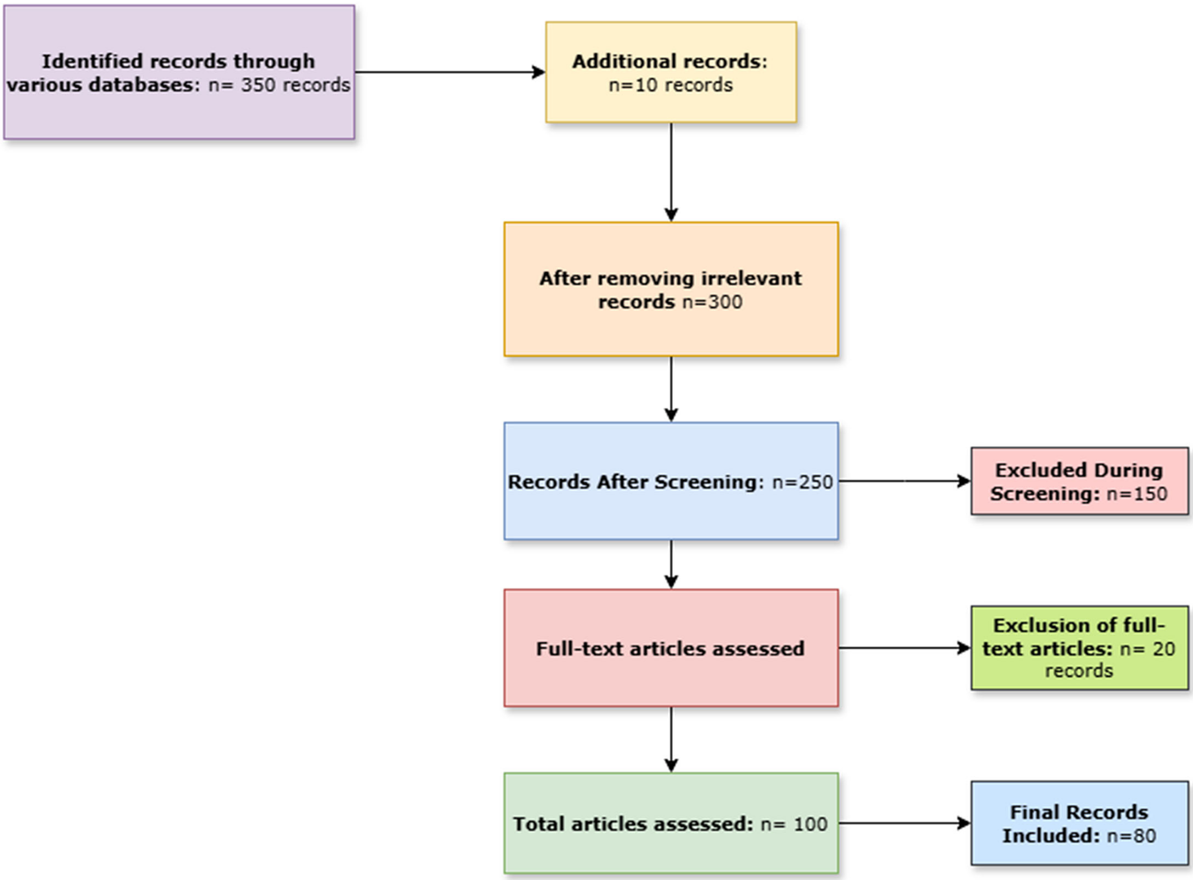

Figure 1. Research strategy flow diagram

progress that have been made in this area of research. Figure 1 represents complete flow of search strategy.

3. Notable Datasets in In-Home ECG Research

Datasets play a crucial role in the development and validation of ML models for in-home ECG monitoring, enabling accurate anomaly detection and classification. Among the most widely used datasets, the MIT-BIH Arrhythmia Database stands out as a gold standard in ECG signal analysis, with over 48 half-hour recordings from 47 subjects, capturing a variety of arrhythmias and cardiac conditions. Similarly, Physio Net provides a series of challenge datasets that include multi-lead ECG recordings annotated for arrhythmias, noise, and other anomalies, making them invaluable for evaluating ML algorithms in real-world scenarios. The ECG5000 dataset, a reduced version of a larger Physio Net database, is popular for multi-class classification and anomaly detection tasks, offering 5,000 labeled ECG samples across five categories. Additionally, the Chapman-Shaoxing and Ningbo Database comprises over 10,000 12-lead ECG recordings collected from diverse populations, providing an opportunity to train models that generalize across different demographics. Another important resource is the St. Petersburg INCART Database, which contains 75 annotated 12-lead ECG recordings, enabling researchers to test the robustness of algorithms for detecting complex cardiac events. The PTB Diagnostic ECG Database, with 549 records from 290 subjects, includes high-resolution signals from 15 leads, making it ideal for evaluating multi-lead ECG analysis and diagnostic precision. Together, these datasets provide the diversity, annotation quality, and real-world relevance needed to develop robust and scalable ML models for in-home ECG systems, ensuring they meet the diverse and complex needs of cardiac care.

4. Rise of Wearable and Portable ECG Devices

In the last few years, portable and wearable ECG devices have become increasingly popular part of life especially when it comes to monitoring heart health in absence of clinical environment [11]. Previously, ECG monitoring could only be done within clinics where patients had to go for tests at set intervals. However, with the need of having constant monitoring of heart conditions and real-time monitoring due to other factors such as chronic heart disorders, wearable ECG monitoring devices provide a breakthrough both in the realms of preventive and precision medicine. Modern smartwatches, chest patches, and some types of fitness trackers are now capable of capturing ECG signals and recording them with the subjects' continuous activity [12]. It is worth noting that these devices are fitted with sensors that can pick and record the electrical activity of the heart and relay such data to the mobile apps or cloud for real-time digestion. This continuous data stream allows identifying cardiac abnormalities, including arrhythmia or atrial fibrillation (AFib) that may be undiagnosed between visits.

The mobility of such devices also assists the patients to be in control of their heart health without having to travel to hospital so often. By contrast, CGM eliminates the need for frequent finger prick measurements confirming that another advantage of wearable ECG devices is real-time feedback [13]. When combined with algorithms based on ML, these devices can interpret the data as it is being recorded, and warn patients and doctors about emerging problems. The real-time analysis is particularly useful when trying to monitor transient or sporadic pathologies afflicting the heart since they will not manifest during normal physical assessments. Additionally, wearable ECG systems help in delivering personalized healthcare since the monitoring is done depending on individual patient's health state, his or her heart rhythm, and patterns that may be obtained as time progresses [14]. Another unique healthcare service that has cropped up because of in-home wearing devices is the ECG monitoring that has also been propelled by the culture of preventive health checkups. Through the constant monitoring of activity in the heart these devices enable timely management of potential life-threatening episodes like heart attacks or stroke. Wearable ECG technology has one of its major advantages in shifting from a reactive form of healthcare to a proactive one because patients can be monitored even when their conditions are not yet critical. In addition, the size and functionality of these devices have been reduced and optimized and hence have been adopted by persons with chronic conditions, and other persons who want or need to monitor their health status. As wireless communication systems and cloud-based platforms are incorporated with the wearable ECG devices, the collected data can be easily transmitted to physicians and other healthcare providers to manage the patients via telemedicine [15]. Therefore, the emergence of the portable and wearable ECG devices has made cardiac care less facility-bound and more frequent, consistent, and patient-tailored. These devices are a clear step-up from previous devices established in the United States' health industries and can potentially enhance benefits for patients through the identification and treatment of the disease in its early stages. Figure 2 shows how ML based in-home ECG is enhancing the cardiac care by providing the essential features.

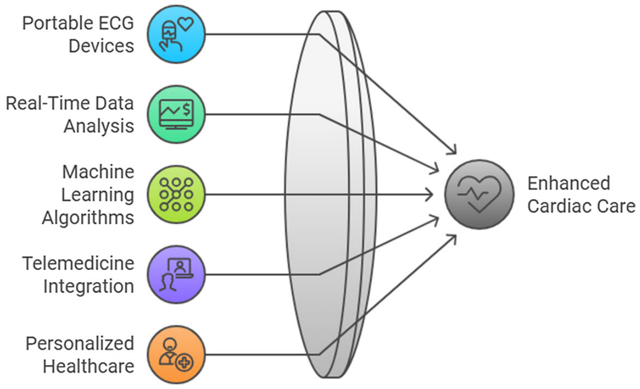

Figure 2. Revolutionizing heart health monitoring

5. ECG Monitoring

ECG is the most common and easy cardiac diagnostic test, with over 300 million recorded annually [16]. ECG tracking can be categorized into short-term and long-term monitoring. Long-term recording involves using bedside monitors in ICUs or Holter monitors for monitoring patients. Short-term ECG tracking can be done through medical-grade ECG recordings or hand-held wearable devices. Body surface ECG is a biosignal used in consumer and medically recommended monitors, while ambulatory ECG monitors have three or more chest electrodes linked to an external recording or patch monitor [17]. Implantable or insertable loop recorders provide long-term ECG monitoring for months or years. Devices like the Reveal LINQ system from Medtronic, Confirm Rx insertable heart monitor from Abbott, and Bio-Monitor from Biotronik are examples of these devices [18]. They are placed under the skin over the chest or under the collarbone to improve ECG readings. Implantable loop recorders offer benefits like uniform ECG wave shapes and can detect atrial arrhythmias. However, they may not be suitable for finding rhythms that last only a few seconds or minutes. Early adopting wearable ECG devices like Apple Watch and KardiaMobile can help provide constant ECG data [19]. As wearable tech becomes more flexible as shown in Figure 3 [5], it will be easier for doctors to use these technologies when needed as Figure 1 shows the innovative wearable technologies.

6. ML Based In-Home ECG

ML-based in-home ECG has become an innovative leap in the field of cardiology as it allows real-time, home-based cardiac health check [20]. For almost all heart issues, ECG has been part of the standard diagnosis and a component of the management plan, although with a need for clinical visits and professional interpretations. The ECG acquisition system is shown in Figure 4 [3]. The integration of the ML has transformed the growth of ECG systems towards the one that focusses on sophisticated intelligent systems which can diagnose the cardiac disorders, predict the probable occurrence heart-related incidences, and respond to it without having to consult a doctor repeatedly. In-home ECG systems improve with the help of ML algorithms as they can process large amounts of data in real time and find trends in data that will signify cardiovascular disorders early [21]. The continuous monitoring capability addresses issues associated with transient events that patients with cardiac problems may experience but which will go unnoticed during standard clinical checkups. The key aspect is ensuring that a diagnosis of these conditions occurs early, thus decreasing the probability of severe cardiac events and a resulting rise in the load on healthcare facilities and the overall improvement in the conditions for patients [22]. In-home ML-enabled ECG systems also help the patients by enabling them to be more proactive about their health care. These systems help to enhance responsibility and follow patient's treatment plans closer since they allow individuals to keep track of their cardiac health on their own [23]. Moreover, the large volumes of data that may be accumulated over time could be utilized to deliver more sensitive patient healthcare in the ability to target most of the different individuals specifically. An up-to-date ML approach of ECG monitoring at home through the development in technology has yet shown great potential to transform cardiovascular care and medicine by making it more personalized, accessible, effective care.

In-home ECG systems provide continuous cardiac monitoring in non-clinical environments, reducing the need for frequent hospital visits. These systems are widely used for the early detection of cardiac conditions such as arrhythmias. Devices such as portable ECG monitors and wearable sensors are integrated with ML

Figure 3. Innovative and current wearable technologies

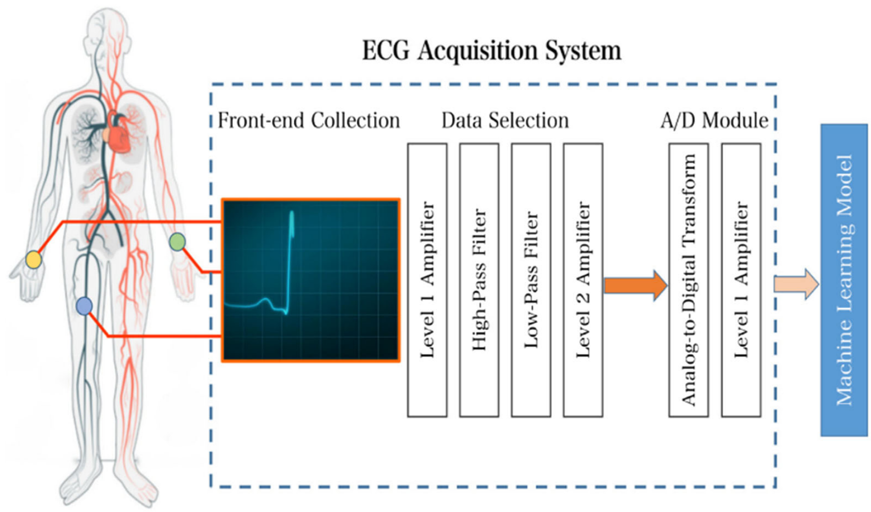

Figure 4. ECG acquisition system

models to ensure accurate analysis and real-time feedback [24]. ML has significantly enhanced ECG signal processing, enabling accurate anomaly detection and noise filtering. Convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) are commonly employed for these tasks due to their ability to process sequential and high-dimensional data effectively. CNNs, for instance, are extensively used for feature extraction and classification, with studies showing accuracy improvements of up to 92% in specific datasets [25]. The collaboration of wearable ECG devices and ML algorithms facilitates the efficient processing of large-scale ECG datasets. Devices equipped with hybrid CNN-LSTM models have shown remarkable performance, with some achieving high sensitivity and specificity rates. For instance, the integration of these models into wearable devices has reduced latency and improved power efficiency [26]. Despite their success, these systems face challenges such as data variability, model generalization across diverse populations, and data privacy issues. Addressing these issues will require further research into robust training methodologies and the development of lightweight ML models optimized for resource-constrained environments.

7. ML Algorithm Testing for Utilization in ECG Monitoring

Many ML methods have been examined for improving the clinical management of cardiovascular ailments with the aid of ECG monitoring. A recently published international study known as LINK-HF compared the efficacy of an ML algorithm functioning on a smartphone and cloud-based infrastructure in estimating the rehospitalization risk of patients with HF [27]. The sample size was 100 and used data collected from a wearable patch that recorded a number of physiological indexes including temperature, physical activity level, and ECG. The algorithm was given up to 88% sensitivity in predicting the need for hospitalization similar to the implantable devices, which has been used for traditional heart failure monitoring. Another study is underway to evaluate the possibility of this method for avoiding rehospitalization in HF patients, which is a major advancement in applying ML for at-home ECG devices [28]. Since mobile tracking devices will be providing large volumes of data, there is need for automated and efficient systems that can help doctors in arriving at fast decisions. To this, ML responds with flexible, Historical techniques to review the clinical information are labor-intensive and cumbersome, which make it impractical for large population [29]. Computerized analysis of data that can greatly facilitate mobile tracking to identify emergent conditions such as the exacerbation of heart failure, early stages of coronary syndrome, or the onset of actual cardiac arrest. With the help of ML analysis, such events can be spotted earlier, and doctors can take action, while at the same time, the system can provide feedback and statistics on milder situations. Previously, the mobile monitoring systems mainly depended on some simple biosignals monitoring, including simple rules of heart rate and rhythm of the heart and so on [30]. Some of these methods proved to be imprecise and, with no clinical involvement, brought a set of small errors into the analysis. Machine Learning (ML) has shown potential in cardiovascular medicine by identifying patterns in large datasets. For instance, studies have shown that using ML, it is possible to diagnose myocardial ischemia from the cardiac CT images and also categorize the types of human arrhythmias based on data recorded by wearable ECG monitors. This is because the analysis of biosensor data from several sensors using ML algorithms to predict the effects of heart failure, arrhythmias, or other cardiac illness will eventually help in foster care without lengthy rule making and testing. This automation is critical especially for continuous monitoring of patients' ECG while at home since timely response is vital to protect the patients and manage them appropriately.

In ECG monitoring, the flows are used in conjunction with ML and rule-based expert systems for the automated interpretation of ECGs and the rapid exclusion of amenable diagnoses without the need for intervention by a human expert [31]. Thanks to new wireless ECG monitors, one can turn to actual-time, remote heart monitoring in a home environment, relying on the ML algorithms able to analyze ECG signals. Most prominent on this last subset, deep learning (DL), a subfield of ML, exhibits tremendous prowess in classifying ECG signals with high accuracy by extracting features from the raw data. DL measures which preceded CNNs include SAE and DBN. In a similar manner, CNNs that are popular in image recognition are also used in ECG signal and have been developed from advanced DL ventures [32]. Also, the recurrent neural network (RNN), one of which is LSTM, is beneficial in analyzing time series data and then making it suitable for ECG classification [33]. There have been significant advances in the application of DL in ECG signal classification as well as feature extraction. SAE and DBN are used for the unsupervised coding of ECG segments while CNN and RNN architectures can process the ECG data in one of the two forms which is as a one-dimensional time series signal or in image form [34]. Other hybrid networks that include CNN and RNN models have been found to improve the training of spatial and temporal features, hence improving the classification of ECG signals. Incorporation of DL in ECG has also greatly eliminated the need for manual interpretation thereby leading to more important tasks being attended to by the healthcare professionals. But at the same time, DL models are very sensitive to the input data quality and can be faced with issues in the case of unbalanced datasets especially in case of less frequent types of heartbeats. In addition, DL models are computationally expensive, which is a challenge when it comes to integration of the technology into Wearable devices that have either limited processing powers and or limited battery capacity. In ECG monitoring, the application of DL has proven to produce better results than the traditional approach, with least interference by human beings [35]. However, there are some issues that still have to be addressed as follows; real-world data often contains noisy data and the model should not be very computationally expensive. For future work, the focus should be on designing models that are stronger, lighter, and requiring less parameters to be trained for the purpose of broadened usage of the ML algorithms in the context of wearable devices. However, the application of DL algorithm for diagnosing ECG has a vast potential, which has been progressing through research studies in recent years. Although previous studies have reviewed the subject of using ML in ECG monitoring in different perspectives, to the best of the authors' knowledge, the literature does not encompass a systematic review on the application of DL in the ECG diagnosis. This review aims to bridge the existing knowledge gap by providing a systematic and comprehensive overview of machine learning based methods currently implemented in ECG diagnostics. It describes their features, potential improvements, and the unresolved issues that need to be addressed to enhance the integration of these approaches into clinical practice. ML has become the key factor in the current ECG monitoring techniques expanding the possibilities of home and remote cardiac management. It has been argued that by incorporating advanced ML algorithms in such systems, they are also able to provide real-time analysis and increase diagnostic accuracies besides aiding in early identification of potential dangerous cardiac incidents. It enhances the quality of care of the patients and the experience of care for cardiac health that has the potential to shift the paradigms of care for heart diseases outside the formal clinical settings.

Limited studies have attempted to use different ML techniques to improve outcomes attained from in-home ECG monitoring. The international LINK-HF trial assessed the capability of a machine learning model, developed using smartphone and cloud technologies, to predict hospital readmissions in heart failure patients by analyzing data from a wearable patch [36]. The algorithm used in this study was found to have 88% [28] accuracy in determining the need for a hospitalization, effectiveness that is as good as implantable devices that are normally used in clinical settings. This result also emphasizes the fact that even a non-clinical population of HF patients can build a strong foundation for early detection and intervention via using ML situated in household environments.

This is rather important since the in-home ECG monitoring creates a significant amount of data. It has been seen that manual review of the data is a tedious process which not only takes a lot of time, cost a lot of money, but is scarcely scalable as well. ML-based systems provide this solution by analyzing the ECG data in the real time and provide alerts for both critical and non-critical situations such as the onset of worsening heart failure, or any changes in the type and rate of the arrhythmias. While the earlier concepts and implementations of mobile monitoring included the basic rules as well as the HRV, the systems based on ML can better interpret the biosignal data without constant supervision of the clinicians. Specifically, the component of ML known as DL has shown great potential to analyze ECG signals with high accuracy; therefore, they are very suitable for home monitoring [37]. For instance, CNN and RNN have been applied in the classification of ECG signals, detection of arrhythmias, and forecasting of possible cardiologic disorders. CNNs which originally are good in image recognition have been utilized in analyzing ECG signals where the signals are transformed into time series or even images [38]. In particular, RNNs involve the LSTM networks that are especially used in processing the sequential data such as ECG to identify long-term relationships in the heart rhythms.

8. Existing Work on ML-Enabled In-Home ECG

Over the past few years, some research works have sought to incorporate ML into in-home ECG monitoring systems to change the way cardiac disorders are diagnosed and managed outside healthcare facilities. Notable here has been the potential of ML in improving diagnostic accuracy of ECG data; several authors have presented a host of models and algorithms touching on the hurdles of in-home monitoring. Among the first studies in this field was an experiment which decided to design the deep neural network (DNN) to determine the presence of arrhythmias based on 91 218 single-lead records made with ambulatory ECGs [39]. In their work, the authors exposed that the DNN in question reached the equivalent diagnostic performance with no supervised cardiologists at identifying various forms of the arrhythmia and therefore the incorporation of ML into ECG analysis in non-clinical settings can be considered as effective. This work went far to help shed more light on the possibility of using ML in designing in-home ECG systems that do not necessarily require supervision or monitoring from the professors in real time.

In the same vein, another study [40] utilized CNNs to diagnose AF based on data gathered from wearable ECG devises. Their model was able to detect AF in asymptomatic patients which was to explain the preventive nature of the ML algorithms in in-home ECG monitoring. The authors found out that with the help of ML, cardiac disorders could be diagnosed before the symptoms are manifested themselves clinically and appropriate treatment measures can be taken. This is even more the case in home monitoring where constant data transmission and nearly real-time analysis are required for identifying paroxysmal or episodic ECG abnormalities that may not necessarily manifest during in-clinic evaluations. Another important contribution was made by researcher by putting forward a new small-sized CNN model for the detection of arrhythmia using MIT-BIH Arrhythmia Database. In their study, they obtained result of 91% from their model which actually surpassed Google Net a complex model, and it was appropriate use in wearable ECG devices [41]. Due to this, it was suitable for contexts with limited resources like portable and wearable gadgets, thus showing the need for designing model that does not heavily drain the resources of in-home monitoring systems. This research was very important in showing that even with more simplified models' high levels of accuracy were achievable and hence more practical in Wearable devices that are in the market for continuous ECG monitoring.

Other developments in this area where they focused on the use of wearable ECG devices combined with arrhythmia detection by using AI algorithms. They used CNNs and the LSTM networks in their study to analyze ECG but in a real-time manner, making heart monitoring possible all the time [42]. The above strategy enhanced the possibility of identifying arrhythmias beyond the hospital setting especially for individuals who need close monitoring of their hearts. DL models used in this context allowed to have a stable and almost real-time analysis of the data recorded by the devices so as to detect, for instance, arrhythmias or other kinds of disturbances which suggest an urgent action. Such real-time feedback is crucial especially in home setting because timely interventions that aim at averting serious heart-related problems can be facilitated. Further, the researcher improved the above methodology by proposing a new model, which integrates CNN and LSTM for ECG examination [43]. Another advantage for their model was the outstanding features of identifying arrhythmias, being designed for home use – the increased diagnostic performance and the real-time signal processing. Specifically, integrating the advantages of CNNs and LSTMs in this manner allowed this hybrid model to obtain both the spatial and the temporal information from ECG signals, thereby improving its predictive accuracy [43]. Their work helped to understand how it is possible to achieve better performance of in-home ECG monitoring with the help of integration of different ML methods. A significant contribution is inculcated by study [44], in their study where they proposed the Parallel GRNN for classifications of ECG signals in in-home monitoring systems. Using the GRNN, they were able to get heartbeat classification with an accuracy of 95% which enhances the possibility of the model to be applied at home. Different authors' work is summarized in Table 1. That is why the high performance and simplicity of the construction of the GRNN model made it possible to use the developed approach to real-time ECG analysis in portable devices. This study also reaffirmed the possibilities of employing more basic but equally efficient models in such contexts as wearable ECG devices.

Apart from classification, two functionalities of noise reduction and signal enhancement have been two vital applications of ML in in-home ECG monitoring. CNNs-based noise reduction model was proposed [45] to enhance the ECG signals recorded through wearable devices. In this method, they employed nonlocal means for denoising, and thus, they obtained high-quality ECG data to feed the ML algorithms. This step is essential in the in-home environment because wearable devices are liable to noise and motion artifacts to a significant extent. The quality of the signal was boosted which positively impacted the precision and adroit performance of functional diagnostics and ML analysis of ECG.

Another important field where great attention has been devoted is feature selection and feature optimization methods. The methods of SVM combined with PSO in classification of ECG signals are utilized [46]. Their approach enhanced the classification of ECG signal for wearable technology making it appropriate for home use. PSO type of concepts assists to fine-tune the optimization of the models, ML to achieve the optimum results given the limited resources in portable and wearable ECG devices [47]. Altogether, these papers prove the increasing role of ML to develop in-home ECG monitoring. Recent studies have demonstrated that the

Table 1. Summary of previous work on the ML-enabled in-home ECG monitoring

Author	Technology utilized	Features	ECG signal lead number	ML algorithm	No. of patients	Accuracy
Katal et al. [56]	ECG signal analysis	Time and frequency analysis	2 to 12 leads	Long short-term memory and convolutional neural networks (CNN)	162	Up to 93% in analyzing the ECG signal & determination of arrhythmias
Madan et al. [57]	ECG signal to scalogram images	Dimensional scalogram images	12 leads	Two-dimensional convolutional neural network and long short-term memory	126	98.7% (ARR) and 99% (NSR)
Hannun et al. [40]	Ambulatory ECG	Analysis of time series	Single lead	Deep neural network (DNN)	9,132 Records of ECG	Up to or comparable to cardiologists
Chang et al. [58]	ECG signal analysis	Morphological features	Multiple leads	Support vector machine (SVM), Convolutional neural network (CNN)	Combination of different records	Approx. 90%
Somani et al. [59]	ECG signal Analysis	Time and frequency domain,	morphological features	12 leads	Recurrent neural network,	Convolutional neural network
774,783	Comparable to cardiologist					
Xiao et al. [60]	Processing of ECG signals	RR intervals and QRS complex	12 leads	Convolutional neural network, Deep learning model with multi-structure	126,526	Up to 99% with variability in interpatient performance
Sattar et al. [61]	Classification of ECG signal after digitization of these signals	Wavelet transform features, Digitized ECG signal features	Single lead (Lead II)	Convolutional neural network, Self-supervised learning (SSL)	2914	Approx. 92%
Adasuriya and Haldar [62]	ECG signal analysis	PQRST wave detection intervals	12 leads	Convolutional neural network, support vector machine, decision tree	53549	High accuracy with variability in numbers
Al'Aref et al. [63]	ECG Classification	Wavelet transform features.	12 leads	Convolutional neural network, Hybrid Machine Learning models	67,001	Accuracy is high in different cardiac conditions
Vu et al. [64]	ECG signal classification	Time domain features	1–3 leads	Convolutional neural network	21,241	97.5%
Singh et al. [65]	Remote ECG monitoring	RR intervals	1–12 leads	Convolutional neural network	12,186	95%
Dıker et al. [66]	Classification of ECG signals	Waveform characteristics	3–12 leads	Support vector machine,	1000	94%
Ansari et al. [67]	Classification and augmentation of ECG data	Augmented features of ECG	Single lead (II leads)	Convolutional neural network	38,241	99%
Abubaker et al. [68]	Processing of ECG Signals	PCA feature selection	1–12 leads	Convolutional neural network, Random Forest	66,321	93%
Sraitih et al. [69]	Classification of ECG Data	Analysis of ST segment, HRV	12 leads	Convolutional neural network and multi-layer perceptron	16,385	97.9%

application of ML algorithms in analyzing ECG signals has proven to be highly effective in real-time monitoring of patient's atrial and ventricular arrhythmias and other pathological conditions. The combination with wearable ECG devices increases the chances of accurate diagnosis using ML [48], which in the same breath makes the monitoring continuous and independent from several visits to clinical facilities. As these technologies become more advanced, this means that even more detailed models, that offer patients real-time individualized recommendations of cardiac health, will be developed, thus dissolving the traditional boundaries between the patient and the traditional medical approach to the prevention of cardiac diseases outside of the clinic. Altogether these works draw attention to progress in the use of ML in conjunction with in-home ECG. Thus, they highlight the ever-evolving possibilities of ML to offer timely, accurate, and contactless cardiac examination for moving from disease-centered to risk-centered care. Constant research works will breed better models and the refinement of the existing models in enhancing the efficiency of in-home ECG monitoring rendering the management of CVDs even more crucial.

9. Real-World Case Studies of ML-Enabled Home ECG Devices

AliveCor's KardiaMobile is a portable, FDA-approved ECG device that uses ML to detect heart conditions like AFib. The device works by capturing ECG signals and sending them to a smartphone app, where ML algorithms analyze the data in real time. These algorithms compare the user's ECG signal to patterns of normal and abnormal heart rhythms, alerting users if any irregularities are detected [49]. This real-time feedback allows for early detection and intervention, providing users with peace of mind and reducing the risk of undiagnosed heart issues. However, one challenge is ensuring the device's accuracy, particularly when noise or interference affects the ECG signal, requiring ongoing updates to the ML models.

The Apple Watch with its ECG functionality is another prominent example of a wearable ECG device that uses ML for heart health monitoring. The watch captures ECG signals and processes them using ML models to identify conditions like AFib and normal sinus rhythm. By analyzing the data in real-time, the device provides immediate feedback to users, which can be sent to healthcare providers for further review [50]. The Apple Watch is a powerful tool for continuous health monitoring, offering users the ability to track their heart health easily. However, ensuring accurate readings during physical activity, where motion artifacts can distort the ECG signal, remains a challenge for the device. Figure 5 illustrates the application of machine learning in various ECG devices. It specifically highlights three devices: AliveCor's KardiaMobile, the Apple Watch ECG, and Biobeat's wearable device, indicating how each integrates machine learning technology to enhance cardiovascular diagnostics.

Biobeat's wearable device combines ECG and blood pressure monitoring in one compact design, making it an effective tool for continuous cardiovascular health monitoring. This device uses ML to process both ECG and blood pressure data in real time, detecting irregular heart rhythms and changes in blood pressure that may indicate cardiovascular risks. By offering timely alerts, Biobeat enables users and healthcare providers to take action before problems escalate [51]. However, like other wearable ECG devices, the challenge lies in ensuring accurate readings during physical activity and managing battery life while processing data continuously. Despite these challenges, Biobeat's device is paving the way for more advanced, comprehensive home health monitoring.

10. Future Prospect

The future of ML in home ECG monitoring shown in Figure 6, holds immense potential for advancing personalized healthcare, but several challenges must be addressed to fully realize its benefits [52]. One critical issue is the limited battery life of wearable ECG devices, which constrains their long-term usability. Future research should focus on developing energy-efficient hardware and algorithms that minimize computational overhead without compromising accuracy. For instance, lightweight ML models, such as pruned or quantized neural networks, could significantly reduce the power consumption of on-device processing. Another pressing challenge is computational overhead, particularly for real-time anomaly detection in resource-constrained environments. Deploying ML algorithms on embedded systems requires optimization techniques such as model compression, knowledge distillation, and edge AI integration. These approaches could enhance the performance of in-home ECG systems, making them more scalable and practical for widespread use.

Data privacy and security concerns also pose significant barriers to adoption [53]. As in-home ECG systems collect and transmit sensitive medical data, ensuring compliance with regulations such as GDPR and HIPAA is paramount. Future developments could explore decentralized storage solutions, such as blockchain technology, and advanced encryption methods to safeguard patient data [54]. Improvement directions also include advanced data augmentation techniques to address the issue of limited and imbalanced datasets. Synthetic data generation using generative adversarial networks or domain adaptation techniques could help create diverse training datasets, improving the robustness and

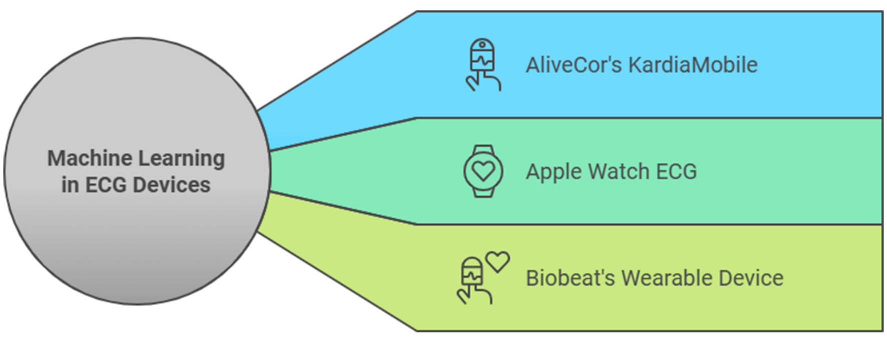

Figure 5. Machine learning in ECG devices

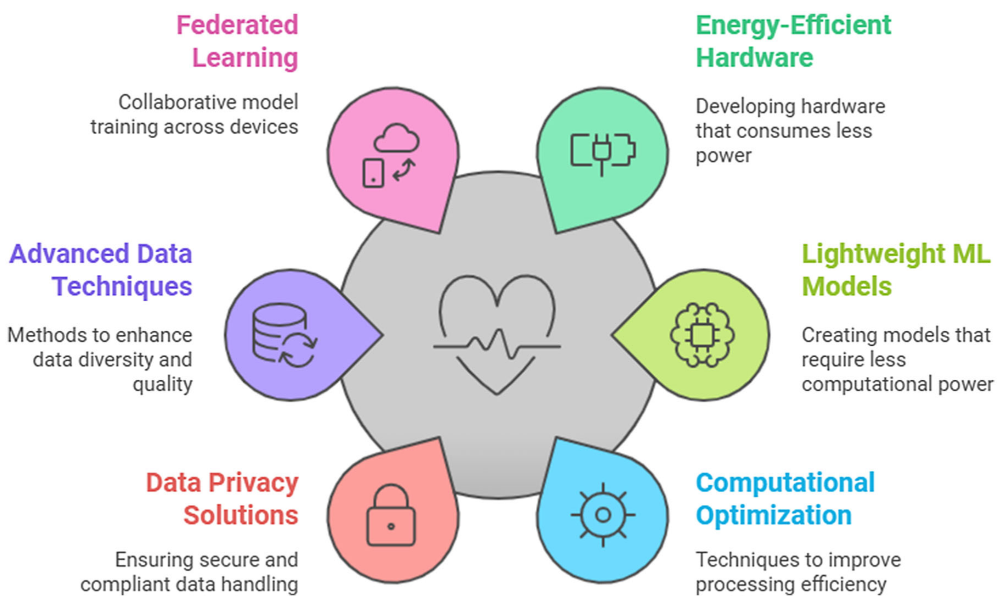

Figure 6. Advancing ML in-home ECG monitoring

generalizability of ML models. Additionally, fairness-aware algorithms must be developed to mitigate biases in predictions, ensuring equitable care for all demographic groups. Looking ahead, ML applications in home medical devices are expected to expand significantly over the next 5–10 years [55]. Emerging technologies such as federated learning could enable collaborative model training across multiple devices without compromising patient privacy. Real-time health monitoring systems powered by explainable AI may also enhance trust and adoption by providing interpretable diagnostic feedback to patients and clinicians. Furthermore, integration with other wearable devices, such as smartwatches and fitness trackers, could pave the way for comprehensive, multi-modal health monitoring ecosystems. By addressing these challenges and pursuing these improvement directions, ML-enabled in-home ECG systems can revolutionize cardiac care, providing accessible, efficient, and personalized solutions for a wide range of patients.

11. Discussion

This review summarizes the significant achievements and unresolved challenges related to ML-supported in-home ECG monitoring systems. AI has demonstrated its ability to enhance diagnostic precision, enable real-time evaluation, and optimize the early detection of potential cardiac pathologies in a home setting. These advancements have contributed to the development of preventive medicine, where patients' cardiac health can be closely monitored without requiring frequent intervention from healthcare professionals. Among the trends identified, the use of DL models, particularly CNNs and RNNs, for interpreting ECG data was found to be the most promising [35]. These models have shown remarkable performance in identifying arrhythmias, heart failure, and other cardiac abnormalities, making them highly suitable for home use. For instance, DNNs have achieved diagnostic accuracy comparable to expert cardiologists in detecting arrhythmias, underscoring the potential of ML-enabled ECG systems to provide independent monitoring [70]. This capability, which supports early warning systems, plays a crucial role in the timely detection of critical events. Despite these advancements, there are several challenges that need to be addressed for the widespread deployment of ML-enabled in-home ECG systems. One of the primary concerns is the quality and source of data collected from wearable devices. Wearable ECG devices often capture noisy signals with motion artifacts [71] and unpredictable signal quality due to user movements. To address these issues, researchers have employed signal enhancement techniques. While current methods have shown improvements in reducing noise and interference, further advancements are required to produce cleaner and more reliable ECG signals for accurate interpretation.

Another critical challenge is the generalization of ML models across diverse populations. Many ML models are trained on datasets that lack representation from different demographic groups, which can lead to biased diagnoses and inequitable healthcare outcomes. Ensuring equity in healthcare requires training ML algorithms on datasets that encompass diverse populations, including different ages, genders, and ethnic groups. Such an approach would help reduce bias and improve the broader applicability of ML-enabled ECG systems [72]. Achieving this goal will necessitate close collaboration between hardware developers, medical practitioners, and regulatory authorities to establish standardized data collection formats and ethical guidelines for the use of in-home monitoring systems with ML models. To summarize, the integration of ML with in-home ECG monitoring has brought significant benefits [4]. However, key issues such as data quality, model generalization, and integration with the existing healthcare system remain unresolved and require further improvement. Addressing these challenges will enable ML-enabled ECG systems to become the foundation for real-time, personalized cardiac care in homes and other out-of-hospital settings.

12. Conclusion

ML has revolutionized electrocardiography (ECG), enabling more accurate diagnostics, early detection of cardiovascular conditions, and personalized risk assessments. In-home electrocardiograph (ECG) systems powered by ML provide a convenient, noninvasive solution for continuous cardiac monitoring, reducing the need for frequent healthcare visits. DL models, particularly convolutional and RNNs, have shown exceptional performance in real-time arrhythmia detection and myocardial infarction classification, proving highly effective in both clinical and non-clinical environments. However, challenges such as data privacy, algorithmic biases, and the need for diverse training datasets must be addressed to ensure equitable and reliable healthcare delivery. As advancements in ML algorithms and wearable technologies continue, ML-enabled ECG systems have the potential to transform cardiovascular care, making personalized and preventive medicine more accessible and efficient.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Aqsa Bibi: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Jawwad Sami Ur Rahman:** Methodology, Validation, Investigation, Resources, Writing – review & editing, Supervision, Project administration.

References

[1] Nath, M. P., Pandey, P., Somu, K., & Amalraj, P. (2018). Artificial intelligence & machine learning: The emerging milestones in software development. *International Journal of Research and Scientific Innovation*, *5*(9), 36–44.

[2] Ware, W. A., Bonagura, J. D., & Scansen, B. A. (2022). Electrocardiography. In W. A. Ware & J. D. Bonagura (Eds.), *Cardiovascular disease in companion animals: Dog, cat and horse* (pp. 135–166). CRC Press. https://doi.org/10.1201/9780429186639-6

[3] Teijeiro, T., Félix, P., Presedo, J., & Castro, D. (2018). Heartbeat classification using abstract features from the abductive interpretation of the ECG. *IEEE Journal of Biomedical and Health Informatics*, *22*(2), 409–420. https://doi.org/10.1109/JBHI.2016.2631247

[4] Dey, N., Ashour, A. S., Shi, F., Fong, S. J., & Sherratt, R. S. (2017). Developing residential wireless sensor networks for ECG healthcare monitoring. *IEEE Transactions on Consumer Electronics*, *63*(4), 442–449. https://doi.org/10.1109/TCE.2017.015063

[5] Bai, W., Sinclair, M., Tarroni, G., Oktay, O., Rajchl, M., Vaillant, G., . . . , & Rueckert, D. (2018). Automated cardiovascular magnetic resonance image analysis with fully convolutional networks. *Journal of Cardiovascular Magnetic Resonance*, *20*(1), 65. https://doi.org/10.1186/s12968-018-0471-x

[6] Liu, X., Wang, H., Li, Z., & Qin, L. (2021). Deep learning in ECG diagnosis: A review. *Knowledge-Based Systems*, *227*, 107187. https://doi.org/10.1016/j.knosys.2021.107187

[7] Liu, W., Huang, Q., Chang, S., Wang, H., & He, J. (2018). Multiple-feature-branch convolutional neural network for myocardial infarction diagnosis using electrocardiogram. *Biomedical Signal Processing and Control*, *45*, 22–32. https://doi.org/10.1016/j.bspc.2018.05.013

[8] Baloglu, U. B., Talo, M., Yildirim, O., San Tan, R. S., & Acharya, U. R. (2019). Classification of myocardial infarction with multi-lead ECG signals and deep CNN. *Pattern Recognition Letters*, *122*, 23–30. https://doi.org/10.1016/j.patrec.2019.02.016

[9] Romdhane, T. F., Alhichri, H., Ouni, R., & Atri, M. (2020). Electrocardiogram heartbeat classification based on a deep convolutional neural network and focal loss. *Computers in Biology and Medicine*, *123*, 103866. https://doi.org/10.1016/j.compbiomed.2020.103866

[10] Tan, J. H., Hagiwara, Y., Pang, W., Lim, I., Oh, S. L., Adam, M., . . . , & Acharya, U. R. (2018). Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals. *Computers in Biology and Medicine*, *94*, 19–26. https://doi.org/10.1016/j.compbiomed.2017.12.023

[11] Soh, P. J., Vandenbosch, G. A. E., Mercuri, M., & Schreurs, D. M. M. P. (2015). Wearable wireless health monitoring: Current developments, challenges, and future trends. *IEEE Microwave Magazine*, *16*(4), 55–70. https://doi.org/10.1109/MMM.2015.2394021

[12] Chukwunweike, J. N., Michael, S., Mbamalu, M. I., & Emeh, C. (2024). Artificial intelligence and electrocardiography: A modern approach to heart rate monitoring. *World Journal of Advanced Research and Reviews*, *23*(1), 1385–1414. https://doi.org/10.30574/wjarr.2024.23.1.2162

[13] Witt, D. R., Kellogg, R. A., Snyder, M. P., & Dunn, J. (2019). Windows into human health through wearables data analytics. *Current Opinion in Biomedical Engineering*, *9*, 28–46. https://doi.org/10.1016/j.cobme.2019.01.001

[14] Walinjkar, A., & Woods, J. (2017). ECG classification and prognostic approach towards personalized healthcare. In *2017 International Conference on Social Media, Wearable and Web Analytics (Social Media)*, 1–8. https://doi.org/10.1109/SOCIALMEDIA.2017.8057360

[15] Prajitha, C., Sridhar, K. P., & Baskar, S. (2022). ECG diagnosis for arrhythmia detection with a cloud-based service and a wearable sensor network in a smart city environment. *Frontiers in Sustainable Cities*, *4*, 1073486. https://doi.org/10.3389/frsc.2022.1073486

[16] Krittanawong, C., Rogers, A. J., Johnson, K. W., Wang, Z., Turakhia, M. P., Halperin, J. L., & Narayan, S. M. (2021). Integration of novel monitoring devices with machine learning technology for scalable cardiovascular management. *Nature Reviews Cardiology*, *18*(2), 75–91. https://doi.org/10.1038/s41569-020-00445-9

[17] Periyaswamy, T., & Balasubramanian, M. (2019). Ambulatory cardiac bio-signals: From mirage to clinical reality through a decade of progress. *International Journal of Medical Informatics*, *130*, 103928. https://doi.org/10.1016/j.ijmedinf.2019.07.007

[18] Sakhi, R., Theuns, D. A. M. J., Szili-Torok, T., & Yap, S. C. (2019). Insertable cardiac monitors: Current indications and devices. *Expert Review of Medical Devices*, *16*(1), 45–55. https://doi.org/10.1080/17434440.2018.1557046

[19] Al-Alusi, M. A., Ding, E., McManus, D. D., & Lubitz, S. A. (2019). Wearing your heart on your sleeve: The future of cardiac rhythm monitoring. *Current Cardiology Reports*, *21*(12), 158. https://doi.org/10.1007/s11886-019-1223-8

[20] Chen, J., Wang, W., Fang, B., Liu, Y., Yu, K., Leung, V. C. M., & Hu, X. (2023). Digital twin empowered wireless healthcare monitoring for smart home. *IEEE Journal on Selected Areas in Communications*, *41*(11), 3662–3676. https://doi.org/10.1109/JSAC.2023.3310097

[21] Keikhosrokiani, P., & Kamaruddin, N. S. A. B. (2022). IoT-Based in-hospital-in-home heart disease remote monitoring system with machine learning features for decision making. In S. Mishra, A. González-Briones, A. K. Bhoi, P. K. Mallick & J. M. Corchado (Eds.), *Connected e-Health: Integrated IoT and cloud computing* (pp. 349–369). Springer International Publishing. https://doi.org/10.1007/978-3-030-97929-4_16

[22] Balogh, E. P., Miller, B. T., & Ball, J. R. (2015). *Improving diagnosis in health care*. USA: The National Academies Press. https://doi.org/10.17226/21794

[23] da Costa, C. A., Zeiser, F. A., da Rosa Righi, R., Antunes, R. S., Alegretti, A. P., Bertoni, A. P., . . . , & Rigo, S. J. (2024). Internet of things and machine learning for smart healthcare. In S. Namasudra (Ed.), *IoT and ML for information management: A smart healthcare perspective* (pp. 95–133). Springer. https://doi.org/10.1007/978-981-97-5624-7_3

[24] Cosoli, G., Spinsante, S., Scardulla, F., D'Acquisto, L., & Scalise, L. (2021). Wireless ECG and cardiac monitoring systems: State of the art, available commercial devices and useful electronic components. *Measurement*, *177*, 109243. https://doi.org/10.1016/j.measurement.2021.109243

[25] Andrysiak, T. (2016). Machine learning techniques applied to data analysis and anomaly detection in ECG signals. *Applied Artificial Intelligence*, *30*(6), 610–634. https://doi.org/10.1080/08839514.2016.1193720

[26] Nazir, A., He, J., Zhu, N., Qureshi, S. S., Qureshi, S. U., Ullah, F., . . . , & Pathan, M. S. (2024). A deep learning-based novel hybrid CNN-LSTM architecture for efficient detection of threats in the IoT ecosystem. *Ain Shams Engineering Journal*, *15*(7), 102777. https://doi.org/10.1016/j.asej.2024.102777

[27] Mincholé, A., Jager, F., & Laguna, P. (2010). Discrimination between ischemic and artifactual ST segment events in Holter recordings. *Biomedical Signal Processing and Control*, *5*(1), 21–31. https://doi.org/10.1016/j.bspc.2009.09.001

[28] Faragli, A., Abawi, D., Quinn, C., Cvetkovic, M., Schlabs, T., Tahirovic, E., . . . , & Alogna, A. (2021). The role of non-invasive devices for the telemonitoring of heart failure patients. *Heart Failure Reviews*, *26*, 1063–1080. https://doi.org/10.1007/s10741-020-09963-7

[29] Liang, J., Li, Y., Zhang, Z., Shen, D., Xu, J., Yu, G., . . . , & Lei, J. (2020). Evaluating the applications of health information technologies in China during the past 11 years: Consecutive survey data analysis. *JMIR Medical Informatics*, *8*(2), e17006. https://doi.org/10.2196/17006

[30] Dias, D., & Paulo Silva Cunha, J. (2018). Wearable health devices—Vital sign monitoring, systems and technologies. *Sensors*, *18*(8), 2414. https://doi.org/10.3390/s18082414

[31] Armoundas, A. A., Narayan, S. M., Arnett, D. K., Spector-Bagdady, K., Bennett, D. A., Celi, L. A., . . . , & Al-Zaiti, S. S. (2024). Use of artificial intelligence in improving outcomes in heart disease: A scientific statement from the American heart association. *Circulation*, *149*(14), e1028–e1050. https://doi.org/10.1161/CIR.0000000000001201

[32] Rouast, P. V. (2020). *Using deep learning to detect food intake behavior from video*. PhD Thesis, University of Newcastle.

[33] Chauhan, S., & Vig, L. (2015). Anomaly detection in ECG time signals via deep long short-term memory networks. In *2015 IEEE International Conference on Data Science and Advanced Analytics*, 1–7. https://doi.org/10.1109/DSAA.2015.7344872

[34] Musa, N., Gital, A. Y., Aljojo, N., Chiroma, H., Adewole, K. S., Mojeed, H. A., . . . , & Katb, I. (2023). A systematic review and meta-data analysis on the applications of deep learning in electrocardiogram. *Journal of Ambient Intelligence and Humanized Computing*, *14*(7), 9677–9750. https://doi.org/10.1007/s12652-022-03868-z

[35] Murat, F., Yildirim, O., Talo, M., Baloglu, U. B., Demir, Y., & Acharya, U. R. (2020). Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review. *Computers in Biology and Medicine*, *120*, 103726. https://doi.org/10.1016/j.compbiomed.2020.103726

[36] Singhal, A., & Cowie, M. R. (2021). Digital health: Implications for heart failure management. *Cardiac Failure Review*, *7*, e08. https://doi.org/10.15420/cfr.2020.28

[37] Lih, O. S., Jahmunah, V., San, T. R., Ciaccio, E. J., Yamakawa, T., Tanabe, M., . . . , & Acharya, U. R. (2020). Comprehensive electrocardiographic diagnosis based on deep learning. *Artificial Intelligence in Medicine*, *103*, 101789. https://doi.org/10.1016/j.artmed.2019.101789

[38] Pandey, S. K., Shukla, A., Bhatia, S., Gadekallu, T. R., Kumar, A., Mashat, A., . . . , & Janghel, R. R. (2023). Detection of arrhythmia heartbeats from ECG signal using wavelet transform-based CNN model. *International Journal of Computational Intelligence Systems*, *16*(1), 80. https://doi.org/10.1007/s44196-023-00256-z

[39] Raj, S., & Ray, K. C. (2017). ECG signal analysis using DCT-based DOST and PSO optimized SVM. *IEEE Transactions on Instrumentation and Measurement*, *66*(3), 470–478. https://doi.org/10.1109/TIM.2016.2642758

[40] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature Medicine*, *25*(1), 65–69. https://doi.org/10.1038/s41591-018-0268-3

[41] Dang, H., Sun, M., Zhang, G., Qi, X., Zhou, X., & Chang, Q. (2019). A novel deep arrhythmia-diagnosis network for atrial fibrillation classification using electrocardiogram signals. *IEEE Access*, *7*, 75577–75590. https://doi.org/10.1109/ACCESS.2019.2918792

[42] Petmezas, G., Haris, K., Stefanopoulos, L., Kilintzis, V., Tzavelis, A., Rogers, J. A., . . . , & Maglaveras, N. (2021). Automated atrial fibrillation detection using a hybrid CNN-LSTM network on imbalanced ECG datasets. *Biomedical Signal Processing and Control*, *63*, 102194. https://doi.org/10.1016/j.bspc.2020.102194

[43] Dey, M., Omar, N., & Ullah, M. A. (2021). Temporal feature-based classification into myocardial infarction and other CVDs merging CNN and Bi-LSTM from ECG signal. *IEEE Sensors Journal*, *21*(19), 21688–21695. https://doi.org/10.1109/JSEN.2021.3079241

[44] Yadav, H., Shah, P., Gandhi, N., Vyas, T., Nair, A., Desai, S., . . . , & Raboaca, M. S. (2023). CNN and bidirectional GRU-based heartbeat sound classification architecture for elderly people. *Mathematics*, *11*(6), 1365. https://doi.org/10.3390/math11061365

[45] Jin, L., Zhang, W., Ma, G., & Song, E. (2019). Learning deep CNNs for impulse noise removal in images. *Journal of Visual Communication and Image Representation*, *62*, 193–205. https://doi.org/10.1016/j.jvcir.2019.05.005

[46] Li, W., Li, B., Guo, H. L., Fang, Y. X., Qiao, F. J., & Zhou, S. W. (2020). The ECG signal classification based on ensemble learning of PSO-ELM algorithm. *Neural Network World*, *30*(4), 265–279. https://doi.org/10.14311/NNW.2020.30.018

[47] Abdolrasol, M. G. M., Hussain, S. M. S., Ustun, T. S., Sarker, M. R., Hannan, M. A., Mohamed, R., . . . , & Milad, A. (2021). Artificial neural networks based optimization techniques: A review. *Electronics*, *10*(21), 2689. https://doi.org/10.3390/electronics10212689

[48] Wang, Y. C., Xu, X., Hajra, A., Apple, S., Kharawala, A., Duarte, G., . . . , & Faillace, R. T. (2022). Current advancement in diagnosing atrial fibrillation by utilizing wearable devices and artificial intelligence: A review study. *Diagnostics*, *12*(3), 689. https://doi.org/10.3390/diagnostics12030689

[49] Shankar, S. V., Oikonomou, E. K., & Khera, R. (2023). CarDS-Plus ECG platform: Development and feasibility evaluation of a multiplatform artificial intelligence toolkit for portable and wearable device electrocardiograms. *medRxiv*. https://doi.org/10.1101/2023.10.02.23296404

[50] Velmovitsky, P. E., Alencar, P., Leatherdale, S. T., Cowan, D., & Morita, P. P. (2022). Using apple watch ECG data for heart rate variability monitoring and stress prediction: A pilot study. *Frontiers in Digital Health*, *4*, 1058826. https://doi.org/10.3389/fdgth.2022.1058826

[51] Iqbal, S. M. A., Leavitt, M. A., Mahgoub, I., & Asghar, W. (2024). Advances in cardiovascular wearable devices. *Biosensors*, *14*(11), 525. https://doi.org/10.3390/bios14110525

[52] Damaševičius, R., Jagatheesaperumal, S. K., Kandala, R. N. V. P. S., Hussain, S., Alizadehsani, R., & Gorriz, J. M. (2024). Deep learning for personalized health monitoring and prediction: A review. *Computational Intelligence*, *40*(3), e12682. https://doi.org/10.1111/coin.12682

[53] Tyagi, A. K., Kumari, S., & Tiwari, S. (2024). Internet of things for smart healthcare: A survey. In A. K. Sharma, N. Chanderwal, S. Tyagi & P. Upadhyay (Eds.), *Future of AI in medical imaging* (pp. 19–41). IGI Global. https://doi.org/10.4018/979-8-3693-2359-5.ch002

[54] Tamilselvi, M. (2024). A novel privacy enabled human health and safety monitoring system using IoT with smart wearable device. In *2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems*, 1021–1027. https://doi.org/10.1109/ICSSAS64001.2024.10760484

[55] Haleem, A., Javaid, M., Singh, R. P., & Suman, R. (2022). Medical 4.0 technologies for healthcare: Features, capabilities, and applications. *Internet of Things and Cyber-Physical Systems*, *2*, 12–30. https://doi.org/10.1016/j.iotcps.2022.04.001

[56] Katal, N., Gupta, S., Verma, P., & Sharma, B. (2023). Deep-learning-based arrhythmia detection using ECG signals: A comparative study and performance evaluation. *Diagnostics*, *13*(24), 3605. https://doi.org/10.3390/diagnostics13243605

[57] Madan, P., Singh, V., Singh, D. P., Diwakar, M., Pant, B., & Kishor, A. (2022). A hybrid deep learning approach for ECG-based arrhythmia classification. *Bioengineering*, *9*(4), 152. https://doi.org/10.3390/bioengineering9040152

[58] Chang, A., Cadaret, L. M., & Liu, K. (2020). Machine learning in electrocardiography and echocardiography: Technological advances in clinical cardiology. *Current Cardiology Reports*, *22*(12), 161. https://doi.org/10.1007/s11886-020-01416-9

[59] Somani, S., Russak, A. J., Richter, F., Zhao, S., Vaid, A., Chaudhry, F., . . . , & Glicksberg, B. S. (2021). Deep learning and the electrocardiogram: Review of the current state-of-the-art. *EP Europace*, *23*(8), 1179–1191. https://doi.org/10.1093/europace/euaa377

[60] Xiao, Q., Lee, K., Mokhtar, S. A., Ismail, I., Pauzi, A. L. B. M., Zhang, Q., & Lim, P. Y. (2023). Deep learning-based ECG arrhythmia classification: A systematic review. *Applied Sciences*, *13*(8), 4964. https://doi.org/10.3390/app13084964

[61] Sattar, S., Mumtaz, R., Qadir, M., Mumtaz, S., Khan, M. A., de Waele, T., . . . , & Shahid, A. (2024). Cardiac arrhythmia classification using advanced deep learning techniques on digitized ECG datasets. *Sensors*, *24*(8), 2484. https://doi.org/10.3390/s24082484

[62] Adasuriya, G., & Haldar, S. (2023). Next generation ECG: The impact of artificial intelligence and machine learning. *Current Cardiovascular Risk Reports*, *17*(8), 143–154. https://doi.org/10.1007/s12170-023-00723-4

[63] Al'Aref, S. J., Anchouche, K., Singh, G., Slomka, P. J., Kolli, K. K., Kumar, A., . . . , & Min, J. K. (2019). Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging. *European Heart Journal*, *40*(24), 1975–1986. https://doi.org/10.1093/eurheartj/ehy404

[64] Vu, T., Petty, T., Yakut, K., Usman, M., Xue, W., Haas, F. M., . . . , & Zhao, X. (2023). Real-time arrhythmia detection using convolutional neural networks. *Frontiers in Big Data*, *6*, 1270756. https://doi.org/10.3389/fdata.2023.1270756

[65] Singh, S., Chaudhary, R., Bliden, K. P., Tantry, U. S., Gurbel, P. A., Visweswaran, S., & Harinstein, M. E. (2024). Meta-analysis of the performance of AI-driven ECG interpretation in the diagnosis of valvular heart diseases. *The American Journal of Cardiology*, *213*, 126–131. https://doi.org/10.1016/j.amjcard.2023.12.015

[66] Dıker, A., Avci, E., Cömert, Z., Avci, D., Kacar, E., & Serhatlioğlu, İ. (2018). Classification of ECG signal by using machine learning methods. In *2018 26th Signal Processing and Communications Applications Conference*, 1–4. https://doi.org/10.1109/SIU.2018.8404298

[67] Abubaker, M. B., & Babayiğit, B. (2023). Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. *IEEE Transactions on Artificial Intelligence*, *4*(2), 373–382. https://doi.org/10.1109/TAI.2022.3159505

[68] Chen, C. Y., Lin, Y. T., Lee, S. J., Tsai, W. C., Huang, T. C., Liu, Y. H., . . . , & Dai, C. Y. (2022). Automated ECG classification based on 1D deep learning network. *Methods*, *202*, 127–135. https://doi.org/10.1016/j.ymeth.2021.04.021

[69] Sraitih, M., Jabrane, Y., & Hajjam El Hassani, A. (2021). An automated system for ECG arrhythmia detection using machine learning techniques. *Journal of Clinical Medicine*, *10*(22), 5450. https://doi.org/10.3390/jcm10225450

[70] Miao, K. H., & Miao, J. H. (2018). Coronary heart disease diagnosis using deep neural networks. *International Journal*

of Advanced Computer Science and Applications, *9*(10), 1–8. https://doi.org/10.14569/IJACSA.2018.091001

[71] Zou, C., Qin, Y., Sun, C., Li, W., & Chen, W. (2017). Motion artifact removal based on periodical property for ECG monitoring with wearable systems. *Pervasive and Mobile Computing*, *40*, 267–278. https://doi.org/10.1016/j.pmcj.2017.06.026

[72] Satu, M. S., Moni, M. A., Kaiser, M. S., & Arefin, M. S. (2023). *Machine intelligence and emerging technologies: First international conference*. Switzerland: Springer. https://doi.org/10.1007/978-3-031-34619-4

How to Cite: Bibi, A., & Sami Ur Rahman, J. (2025). Machine Learning Enabled In-Home ECG: A Review. *Medinformatics*. https://doi.org/10.47852/bonviewMEDIN52024336