Cureus Journal of Computer Science

Open Access Review Article

Early Heart Attack Detection Using Real-Time ECG Signals: A Systematic Survey

Pooja Ingle [1] , Sunil D. Kale [1] , Mahesh R. Shirole [1] , Ninad Shirsat [1]

1. Department of Computer Engineering & Information Technology, Veermata Jijabai Technological Institute, Mumbai, IND

Corresponding authors: Pooja Ingle, poojaingle815@gmail.com, Sunil D. Kale, kalesunild@gmail.com, Mahesh R. Shirole, mrshirole@it.vjti.ac.in

Review began 01/05/2025
Review ended 04/02/2025
Published 04/06/2025

DOI: https://doi.org/10.7759/s44389-024-02662-6

Abstract

Heart attacks remain one of the leading global health threats, making early detection a critical step in saving lives. Wearable devices, like smartwatches, are now playing a transformative role by offering real-time ECG monitoring and providing continuous tracking of heart activity. This allows individuals and healthcare providers to detect early warning signs, such as irregular heartbeats or abnormal ECG patterns, before they develop into serious emergencies. This survey explores the integration of real-time ECG monitoring into everyday devices, focusing on its growing importance in early heart attack detection. It reviews commonly used algorithms, such as convolutional neural networks and long short-term memory, as well as algorithms like support vector machines, random forests, and k-nearest neighbor networks. These algorithms analyze ECG data to detect cardiac anomalies with precision. The paper also discusses the benefits of early detection, challenges such as algorithm accuracy and device battery life, and the potential for future improvements in both wearable technology and machine learning models. These advancements could further enhance the reliability and accessibility of heart monitoring, leading to better outcomes for patients worldwide.

Categories: AI applications, Machine Learning (ML)
Keywords: convolutional neural network, early heart attack detection, ecg signal, machine learning, cardiovascular disease

Introduction And Background

Cardiovascular diseases (CVD), including heart attacks, remain the leading cause of mortality globally, accounting for a significant number of deaths annually. Early detection and timely intervention are crucial in improving outcomes for patients. With advancements in wearable technology, devices like smartwatches equipped with electrocardiogram (ECG) sensors are revolutionizing cardiac care by enabling continuous heart monitoring and providing real-time insights into heart health. These devices can detect early signs of abnormalities, such as arrhythmias, ST-segment deviations, and other cardiac irregularities, which are vital indicators of conditions like myocardial infarction and sudden cardiac arrest (SCA) [1].

Recent studies highlight the potential of smartwatches not only in detecting atrial fibrillation (AF) through irregular pulse notifications but also in identifying ST-elevation myocardial infarction (STEMI) and other critical cardiac events. For instance, a case report demonstrated how an Apple Watch identified STEMI in a patient, enabling timely medical intervention and a successful recovery [2]. Similarly, the Apple Heart Study showcased the effectiveness of wearable devices in detecting AF, emphasizing their role in preventive care and remote monitoring.

Innovative systems like ECG Alert have further expanded the horizon by integrating wearable ECG sensors, smartphone apps, and cloud-based servers to provide early warnings of potential heart attacks, potentially detecting them hours before their occurrence [3]. Additionally, research has shown that machine learning models, such as convolutional neural networks (CNNs), achieve high accuracy in analyzing ECG data for the early detection of heart attacks. Such systems represent a shift from traditional facility-based ECG testing to more accessible, real-time monitoring solutions [4].

In India, heart attacks cause nearly 25% of all deaths, mainly due to delayed symptom recognition and lack of early diagnosis. To address this, researchers are developing a real-time heart rate monitoring system that tracks ECG, heart rate, and blood pressure using multiple sensors. It also includes a symptom-based questionnaire and uses artificial intelligence - (AI)-driven algorithms, the Naive Bayes classifier, and the Framingham Risk Score - to assess heart attack risk. If a high-risk situation is detected, it sends instant alerts to patients and doctors [5].

An advanced smartwatch with ECG and photoplethysmogram (PPG) sensors detects early heart attack signs by monitoring heart rate and rhythm [6]. Using machine learning, it identifies abnormalities and alerts emergency contacts and medical services for swift response. It tracks vital signs in real time, analyzing data with a time series algorithm to detect cardiac distress. If irregularities occur, a mobile app relays the user's condition and location to emergency services. Beyond heart monitoring, smartwatches offer health tracking, safety features, and AI-driven personalized coaching for improved long-term wellness.

A study [7] compares artificial neural networks (ANNs) and CNNs for early heart attack detection using an ECG dataset. CNNs outperformed ANNs, achieving 98% accuracy versus 94%, thanks to their superior pattern recognition capabilities. The dataset, with 383 instances and 14 features, underwent preprocessing for better analysis. CNNs excelled in ECG signal classification, making them more effective for heart attack prediction. Future research aims to expand datasets, explore other machine learning models, and integrate real-time monitoring into smartwatches for instant risk assessment, highlighting AI's role in improving cardiac health.

Despite these advancements, challenges remain in ensuring the reliability and accuracy of these technologies, especially concerning false positives and compatibility with cardiac implantable devices [8]. This growing field underscores the need for further research, clinical trials, and algorithm enhancements to validate and optimize wearable ECG systems for widespread adoption in cardiac healthcare. By leveraging these cutting-edge technologies, we can potentially reduce the global burden of CVD, providing patients with timely and effective interventions.

Research also delves into the comparative performance of popular smartwatches in detecting AF, revealing variations in accuracy, sensitivity, and usability among models like the Apple Watch, Samsung Galaxy Watch, and Withings Move ECG. Beyond AF, these wearable devices are evolving to identify a broader spectrum of heart conditions, such as bradycardia, conduction disorders, and even signs of myocardial infarction. Furthermore, the integration of deep learning models with ECG monitoring systems has revolutionized heart health diagnostics. Studies have developed innovative algorithms, such as CNN-long short-term memory (LSTM) hybrid models and multi-lead CNNs to achieve high accuracy in detecting conditions like STEMI and identifying blocked coronary arteries.

Emerging machine learning techniques, such as those leveraging deep CNNs, have shown promise in detecting subtle changes in ECG signals that may indicate early stages of CVD. These advances underscore the potential of combining wearable devices and AI to enhance early detection, improve patient outcomes, and reduce the global burden of CVD. This paper explores these cutting-edge developments in wearable technology, deep learning, and their application in cardiovascular diagnostics, offering a comprehensive view of the current landscape and future possibilities in this critical field.

With smartwatches, this sophisticated analysis can happen in real time, allowing users to monitor their heart health continuously and receive notifications when potential issues are detected. This combination of ECG technology and CNN-powered analysis makes early detection more accessible and proactive, giving users more control over their heart health.

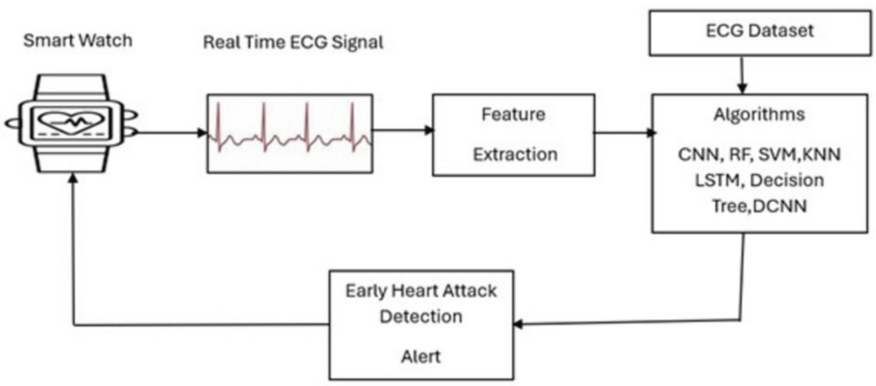

FIGURE 1: Framework of Early Heart Attack Detection Using ECG on Smartwatch

CNN, Convolutional Neural Network; RF, Random Forest; SVM, Support Vector Machine; KNN, K-Nearest Neighbor; LSTM, Long Short-Term Memory; DCNN: Deep CNN

Figure *1* represents the framework of early heart attack detection using ECG on smartwatch. It consists of different components working together to process ECG signals and detect potential heart attacks. These components are as follows:

1. Smart Watch: The smartwatch continuously records real-time ECG signals from the user's heart. It acts as the primary data source for heart monitoring.

2. Real-Time ECG Signal: The ECG waveform is captured and transmitted for further processing. It contains important heart activity data such as heart rate, P-wave, QRS complex, and T-wave.

3. Feature Extraction: Extracts meaningful features from the ECG signal (e.g., heart rate variability, waveform peaks, and intervals). Helps reduce data complexity and improve model performance.

4. Algorithms (Machine Learning and Deep Learning Models): The extracted features are fed into various machine learning and deep learning algorithms for classification:

a. CNN: CNN is a deep learning model designed to automatically detect patterns in ECG signals. It consists of convolutional layers that extract spatial and temporal features from ECG waveforms, such as QRS complexes, P-waves, and T-waves. CNNs are highly effective in classifying normal and abnormal heart rhythms due to their ability to recognize subtle waveform variations.

b. Random Forest (RF): RF is an ensemble learning algorithm that consists of multiple decision trees. Each tree is trained on different parts of the ECG dataset, and the final classification is determined through majority voting. RF is robust against overfitting and provides high accuracy in distinguishing between normal and abnormal ECG signals.

c. Support Vector Machine (SVM): SVM is a supervised learning algorithm used for binary classification (e.g., normal vs. abnormal ECG signals). It works by finding the optimal hyperplane that separates different classes in the feature space. SVM is particularly effective in classifying ECG signals with well-defined feature differences.

d. K-Nearest Neighbors (KNN): KNN is a non-parametric, instance-based learning algorithm that classifies new ECG samples based on their similarity to stored training samples. It calculates the distance between the new ECG reading and its nearest neighbors, assigning it to the most common class among them. KNN is simple and effective when the dataset is well structured.

e. LSTM: LSTM is a type of recurrent neural network designed for time-series data like ECG signals. It can capture long-term dependencies and remember past information, making it suitable for analyzing ECG recordings over time. LSTM is widely used for real-time heart monitoring and abnormality detection.

f. Decision Trees: Decision trees use a series of if-else rules to classify ECG signals. They split the data based on feature thresholds, such as heart rate variability or QRS duration, to determine whether an ECG is normal or abnormal. Although decision trees are simple and interpretable, they may not generalize well for complex ECG classifications.

g. Deep CNN (DCNN): DCNN is a deeper version of CNN, consisting of multiple convolutional and pooling layers. It is capable of learning complex ECG features with greater accuracy. DCNN is widely used for detection of arrhythmias, myocardial infarction, and AF from ECG signals.

These algorithms are trained on an ECG dataset containing both normal and abnormal heart rhythms.

5. ECG Dataset: A database of pre-recorded ECG signals is used to train and validate the machine learning model. It includes labeled ECG data of normal and abnormal heart conditions.

6. Early Heart Attack Detection and Alert: If an abnormal pattern is detected, the system triggers an alert. The alert can be sent to the user, a doctor, or emergency contacts. The smartwatch may also provide real-time warnings to the user.

This survey explores how real-time ECG signals are being used for early heart attack detection, examining the technologies and algorithms involved. We will look at the progress in this field, the challenges of working with wearable devices, and what the future might hold for improving the accuracy and reliability of these systems.

Review

Study selection process

Table *1* summarizes the study selection process, including inclusion/exclusion criteria and the search strategy. It offers a concise overview of the methodology used to select studies for this review.

Aspect	Details
Search Strategy	Systematic search across academic databases (PubMed, IEEE Xplore, Scopus, Google Scholar)
	Keywords: "ECG", "smartwatch", "heart attack detection", "ST-segment abnormalities", "wearable ECG", "cardiac monitoring"
	Filters: Peer-reviewed, clinical trials, case reports, systematic reviews, last 10 years
Inclusion Criteria	Focus on wearable ECG devices (e.g., smartwatches) for detecting heart conditions (e.g., heart attack, ST-segment abnormalities)
	Examined the effectiveness and accuracy of wearable ECG devices in detecting cardiac events
	Involved human participants or clinical data
	Utilized ECG as the primary diagnostic tool or monitored ECG alongside other health metrics
	Published in English, with clear methodology and statistical analysis
Exclusion Criteria	Studies not involving wearable ECG devices or smartwatches
	Focus on theoretical concepts or non-clinical applications of ECG monitoring
	Studies without human participants or clinical data
	No clear results related to ECG abnormalities or inadequate data/methodology
	Non-peer-reviewed publications or insufficient statistical analysis
Data Extraction	Type of wearable device (e.g., Apple Watch, ECGalert, etc.)
	Study population (age, health status, condition studied)
	Methodology (ECG monitoring, comparison to 12-lead ECG, etc.)
	Key findings (accuracy, sensitivity, specificity, clinical relevance)
	Conclusions and recommendations for future research
Quality Assessment	Used checklists for clinical studies and technology evaluations
	Evaluated sample size, statistical power, methodology rigor, and potential biases
Search Example	Search terms: "ECG wearable devices AND heart attack detection"
	Filters: Last 10 years, peer-reviewed, human studies
	Databases: PubMed, IEEE Xplore, Scopus

TABLE 1: Study Selection Process Including Inclusion/Exclusion Criteria

Kashou et al. [1] highlighted the importance of the ST segment on ECG in heart monitoring, as it represents the transition between the heart's ventricular depolarization (contraction) and the beginning of its repolarization (recovery) phase. It typically appears flat or isoelectric, and any deviations, such as elevation or depression, can signal significant heart issues like myocardial ischemia (restricted blood flow) or myocardial infarction (heart attack). ST segment abnormalities come in two main forms: ST elevation, which often indicates acute myocardial injury but can also arise from less serious conditions like early repolarization or left ventricular hypertrophy, and ST depression, commonly linked to ischemia or other factors like low potassium levels. Recognizing these variations, whether they slope up, down, or remain horizontal, is essential for accurately diagnosing and managing heart diseases, as they provide crucial insights into the heart's condition and the potential severity of cardiac events.

Stark et al. [2] discussed a case report on detecting STEMI using a smartwatch ECG. Advances in wearable technology, such as smartwatches, have enabled the recording of single-lead ECGs. This case report highlights how an Apple Watch helped diagnose a subacute ST-elevation myocardial infarction in a 61-year-old man without prior heart issues. The patient experienced mild chest pain and shortness of breath for three days, but initially thought his symptoms were muscular. After noticing unusual changes in his smartwatch ECG readings, he sought medical advice. His Apple Watch flagged abnormalities, prompting him to consult a doctor. At the doctor’s office, a 12-lead ECG confirmed ST-elevation indicative of a heart attack. A blockage in the left anterior descending artery was discovered by emergency coronary angiography and was effectively cleared with the implantation of a stent. The patient recovered well and was discharged just four days later, reporting no further symptoms during follow-up. This case underscores the potential of smartwatches in early detection of cardiac issues like STEMI. Although existing studies have focused on AF detection, this report suggests that smartwatch ECGs can also recognize signs of myocardial infarction. The quick identification of these changes could improve patient outcomes, especially for those who might ignore their symptoms. However, the rise of consumer-driven ECG monitoring raises concerns about the accuracy of self-diagnosis and the potential for false alarms, which could overwhelm healthcare providers. The authors advocate for larger clinical studies to better understand and validate the utility of smartwatches in detecting serious heart conditions like STEMI. By leveraging everyday technology, we can enhance early diagnosis and treatment of life-threatening conditions, but further research is crucial to ensure safety and effectiveness.

Gusev et al. [3] present a groundbreaking system called ECGalert, designed for early heart attack detection and notification. This system comprises a data center, smartphone applications, web applications, and a wireless mobile device, offering 24/7 remote healthcare support. The foundation of ECGalert is based on the ability to detect heart attacks at least two hours before they occur, enabling timely medical intervention that can greatly lower the possibility of death or serious tissue damage. Currently, no commercial products fully match ECGalert's goals and functionalities, despite the existence of various studies and similar devices that primarily focus on stress testing or personal fitness without adequate heart attack detection algorithms. With CVD being the leading cause of death globally, responsible for more than half of global fatalities and more than 40% of deaths in the European Union, addressing this issue is urgent, especially given the rising incidence of heart attacks in younger populations due to lifestyle changes. Traditional ECG tests often require inconvenient visits to medical facilities, while existing wearables tend to lack real-time alert systems essential for prompt intervention. The proposed ECGalert system includes a compact wearable ECG sensor that wirelessly connects to a smartphone app and a cloud-based server for real-time monitoring and alerts. If the sensor detects any abnormal heart activity, it notifies medical professionals, enabling them to provide immediate guidance or dispatch emergency services if necessary. The architecture of ECGalert combines a local processing smartphone with a cloud server, enhancing data processing capabilities while conserving battery life by operating in intervals rather than continuous monitoring. Targeting patients at risk of heart disease, ECGalert aims to offer early warnings of potential heart attacks, facilitating faster medical responses and improving patient outcomes. The authors are currently testing a prototype and refining the system for wider use. Ultimately, ECGalert seeks to leverage modern technology to transform heart disease monitoring and emergency response, making it more accessible and effective for those at risk.

Strik et al. [4] examine the potential of wearable devices, especially ECG-monitoring smartwatches, for identifying early indicators of heart conditions, including heart attacks. It highlights their accuracy in identifying cardiac irregularities like arrhythmias and their role in long-term monitoring, offering a convenient tracking solution for patients with implanted cardiac devices. Continuous monitoring through these devices can help detect potential issues early, ultimately preventing more severe conditions. The discussion also highlights the need for personalized assessments in patients with cardiac implantable electrical devices (CIEDs), stressing the importance of evaluating risks such as electromagnetic interference (EMI) that could impact device functionality. Research is recommended to ensure compatibility and safety when using ECG smartwatches with CIEDs. Additionally, the paper examines the use of smartwatches in patients undergoing left bundle branch area pacing, a new alternative to conventional biventricular pacing. While smartwatches show promise in monitoring these patients, there have been instances of technical issues, such as failure to record ECGs under certain conditions. The integration of ECG-enabled smartwatches marks a major advancement in cardiac care, enhancing patient engagement and enabling remote monitoring. While safety concerns regarding EMI and device malfunction are addressed demonstrating that smartwatches present minimal risk when used at safe distances, the paper underscores the immense potential of these devices in diagnosing and managing various challenges associated with CIEDs. Despite existing limitations, ongoing research and algorithm improvements may help resolve these issues, paving the way for the broader adoption of ECG smartwatches in cardiac care. Though extensive clinical trials are essential to validate their precision and dependability, advancements in technology indicate that these devices might revolutionize patient care by providing real-time, tailored cardiac monitoring.

Chandurkar et al. [5] highlight that in India, heart attacks contribute to approximately 25% of all deaths, mainly due to delays in recognizing symptoms or the lack of early diagnosis. To address this issue, researchers are developing a real-time heart rate monitoring system that can identify heart anomalies and potential heart attacks by tracking users' heart rates at early stages. The system provides ongoing tracking of vital signs, encompassing ECG, heart rate, and blood pressure, via a multisensor strategy that employs devices like the pulse sensor AMPED along with an ECG sensor. To enhance the accuracy of heart attack predictions, it includes a symptom-based questionnaire that asks users about common symptoms like chest pain and dizziness. If high-risk situations are detected, the system sends automated alerts to both patients and doctors. It utilizes two key algorithms: the naive Bayes classifier, which classifies risk levels based on clinical data and symptoms, and the Framingham risk score, which estimates heart attack probabilities by considering factors like blood pressure, age, and cholesterol levels. The system processes real-time data from sensors, gathers information on patient history, and classifies heart attack risk as high, medium, or low, providing immediate alerts and a comprehensive prediction report. Looking to the future, the system could incorporate facial recognition to detect physical distress signs, integrate additional sensors for metrics like blood oxygen levels, and employ advanced machine learning models to enhance prediction accuracy. Scalability and real-time cloud integration would allow for broader remote health monitoring, making this innovative solution a promising tool in the fight against CVDs.

Muthusundari et al. [6] present an innovative smartwatch equipped with ECG and PPG sensors, designed to detect early signs of heart attacks. By continuously monitoring the user's heart rate and rhythm, the smartwatch employs machine learning algorithms to identify abnormal patterns that may indicate a potential heart attack. When such patterns are detected, the device promptly alerts emergency contacts and connects with medical services to ensure swift assistance, thereby aiming to minimize response times and improve patient outcomes during cardiac events. The paper emphasizes the critical role of rapid response in enhancing survival rates from heart attacks, highlighting the urgent need for advanced solutions in this area. The smartwatch integrates multiple sensors to monitor essential physiological parameters in real time, and a time series analysis algorithm is employed to examine the collected data for indicators of cardiac distress. When any irregularities are detected, the smartwatch activates an immediate response via a dedicated mobile application that relays essential information, including the user’s condition and location, to emergency services. It also notifies predefined emergency contacts to ensure that help is on the way. In summary, smartwatches are becoming vital tools in healthcare, offering a wide range of monitoring features that empower users to take control of their health. These devices track various factors such as sleep patterns, physical activity, heart rate, and stress levels, providing valuable insights into overall health and lifestyle choices. Additionally, they assist with health management tasks like medication reminders and hydration tracking, while also offering safety features like fall detection and emergency SOS alerts for added peace of mind. Looking ahead, AI-powered assistants integrated into smartwatches could evolve into personalized health coaches, delivering tailored advice on nutrition, exercise, medication adherence, and overall wellness by leveraging extensive health data to support long-term health goals.

Kumar et al. [7] explore the early detection of heart attacks by utilizing machine learning and deep learning methods, with a particular focus on comparing ANNs and CNNs. Utilizing an ECG UCI Machine Learning Repository dataset, the study aimed to identify abnormal heart rhythms. CNNs, known for their ability to recognize patterns in images, achieved an impressive accuracy of 98%, outperforming ANN, which achieved 94%. The dataset included 383 instances with 14 features like as age, sex, cholesterol levels, blood pressure, and ECG results, with no missing values, facilitating seamless analysis. Data preprocessing involved normalizing the numerical features and encoding the categorical ones. Visualizations helped understand the distribution of features and their correlation with heart attack risks, using correlation matrices and feature distributions to highlight relevant variables. The CNN architecture comprised convolutional layers for pattern recognition, pooling layers for reducing dimensionality, and fully connected layers for making predictions. In contrast, the ANN, a more traditional neural network, served as a baseline for comparison. The results revealed that CNN outperformed ANN, achieving not only higher accuracy but also better precision and F-score metrics. The models produced binary classifications to indicate if a patient is at risk of a heart attack (1) or not (0). The study emphasizes that the CNN is a more effective model for heart attack detection, particularly for ECG signal classification, and suggests that future work could benefit from gathering more data to enhance model performance. The authors propose exploring comparisons with additional machine learning algorithms, such as RFs and decision trees, and implementing these models in real-time monitoring through wearable devices like smartwatches to provide immediate heart attack risk assessments. This research encourages continued exploration into the capabilities of CNNs and other machine learning approaches in the critical area of cardiac health monitoring.

Nasarre et al. [8] examine the potential of smartwatch ECGs, especially those in devices like the Apple Watch, to identify electrocardiographic irregularities associated with SCA in young adults. As smartwatches with ECG features become more popular, they enable individuals to record ECGs on their own, without the need for a doctor's prescription. However, the standard smartwatch typically records only lead I, and the study suggests that incorporating additional precordial leads could enhance cardiac screening. To improve detection, the researchers employed a multi-site recording approach that included the standard left wrist recording (AW-I) and additional precordial recordings from positions V1, V3, and V6 (AW-4). This method aimed to identify abnormalities that are typically detected on a comprehensive 12-lead ECG. The focus was on conditions associated with SCA, including Wolff-Parkinson-White syndrome, Brugada syndrome, hypertrophic cardiomyopathy (HCM), long QT syndrome, and arrhythmogenic right ventricular dysplasia/cardiomyopathy (ARVC/D). Participants in the study included healthy volunteers as well as patients with known cardiac conditions. Both smartwatch and 12-lead ECGs were recorded and analyzed independently by cardiologists unaware of the participants' statuses. The study utilized algorithms to compare the smartwatch ECGs against the gold-standard 12-lead ECG, employing statistical methods to evaluate sensitivity, specificity, and interobserver agreement. The findings revealed that while lead I (AW-I) has limitations in detecting certain abnormalities, such as Brugada patterns, the addition of precordial positions significantly improved diagnostic accuracy, particularly for conditions like HCM and ARVC/D. The study also reported high interobserver agreement for conditions like Brugada syndrome and ventricular pre-excitation. Looking ahead, the authors suggest enhancing detection accuracy through machine learning models or AI-based algorithms, which could facilitate real-time identification of SCA-related conditions. There is also potential for implementing smartwatch-based ECG screening programs for young adults at risk, especially among asymptomatic individuals. Integrating smartwatch ECG data into telehealth platforms could allow for seamless sharing with healthcare providers and trigger early interventions. Overall, the study highlights the promising feasibility of using smartwatches to detect cardiac abnormalities associated with SCA, particularly with the addition of precordial recordings. With advancements in AI and broader integration into healthcare systems, this technology could play a significant role in early diagnosis and prevention, ultimately reducing the incidence of SCA and related fatalities. Further research is necessary to validate these findings and explore the smartwatch ECGs' utility for other cardiac conditions.

Spaccarotella et al. [9] examine the use of commercially available smartwatches, particularly the Apple Watch Series 4, to record multichannel ECGs for detecting ST-segment changes linked to acute coronary syndromes. It compares the accuracy of smartwatch readings with standard 12-lead ECGs in diagnosing heart attacks. The study highlights the potential of this technology to enable earlier detection of life-threatening heart events. Participants included 100 individuals, with a mix of those suffering from STEMI, NSTEMI, and healthy controls. The Apple Watch recorded nine ECG leads from different body positions, and results were compared to standard 12-lead ECGs. The study found high agreement between the two methods, with sensitivity at 93% and specificity at 95% for detecting ST elevation, suggesting strong clinical reliability. However, limitations include the need for manual placement of the smartwatch and reliance on a cardiologist for ECG interpretation. The study used statistical tools like Cohen's kappa and Bland-Altman analysis to assess the agreement between smartwatch and standard ECG results. The authors propose future improvements, such as integrating AI for automated interpretation, developing smarter devices capable of recording full 12-lead ECGs without manual adjustment, and expanding the use of smartwatches for remote and emergency situations. This technology could enhance early detection of heart attacks and improve patient outcomes.

The researchers of the Apple Heart Study [10] investigated how smartwatches can assist in detecting AF through an irregular pulse notification algorithm. The study used the Apple Watch optical sensors to intermittently measure pulse intervals and notify users of irregular pulses, which could indicate AF. Participants who received notifications were given ECG patches to confirm the condition and were encouraged to consult healthcare providers through telemedicine. The study found that 84% of irregular pulse notifications were consistent with AF, highlighting the potential for smartwatches to aid in early detection. Future advancements could improve algorithm accuracy, enable continuous monitoring, and expand wearable technology's role in healthcare. This approach also demonstrates how remote monitoring and telemedicine can reduce costs and improve access to preventive care.

Goyal et al. [11] examined the portable heart attack detector, which is designed to continuously monitor a user's ECG and identify early signs of a heart attack, particularly through changes in the ST-segment. By providing real-time ECG monitoring, the device aims to reduce heart attack fatalities by sending instant alerts to caregivers or emergency services when abnormalities are detected. This portable, wearable device can be used 24/7 without disrupting daily activities and includes location tracking to ensure quick medical response. All data are stored in the cloud, allowing healthcare providers to review heart activity remotely. Future advancements could include machine learning for more accurate detection and integration with additional health metrics, further enhancing its life-saving potential. Kappiarukudil and Ramesh [12] focused on developing a wireless sensor network for real-time heart attack detection and monitoring CVD, particularly for patients in remote areas. The system uses a wearable wireless sensor to continuously monitor ECG signals and transmit them to a mobile phone. If an abnormality is detected, alerts are sent to the patient, doctor, family, and nearby hospitals. It also includes sensors for blood pressure and respiration to enhance detection accuracy. Data is transmitted through cellular or Wi-Fi networks, enabling continuous monitoring wherever the patient is. The system adjusts monitoring frequency based on the patient's health risk, storing data for doctors to review remotely. Future expansions aim to include monitoring for conditions like diabetes and respiratory issues, making it a scalable and cost-effective solution for remote healthcare, particularly in rural areas.

Abu-Alrub et al. [13] compared the effectiveness of three popular smartwatches - the Apple Watch Series 5, Samsung Galaxy Watch Active 3, and Withings Move ECG - in detecting AF. Researchers tested 200 patients, half with AF and half with normal heart rhythms, using both smartwatch ECGs and a traditional 12-lead ECG as the gold standard. The results showed that Apple and Samsung watches had higher accuracy in detecting AF, with 87-88% sensitivity and 81-86% specificity, while Withings produced more inconclusive results. However, doctors found the Apple and Withings ECGs easier to interpret than Samsung's. Although Samsung's ECG quality posed challenges for doctors, its automated software often outperformed manual interpretation. The study highlights that while smartwatches are effective tools for detecting AF, their ECG quality and diagnostic accuracy can vary across models.

Strik et al. [14] explore the expanding potential of smartwatches, which are now capable of recording single-lead ECGs, to detect various heart conditions beyond AF. While primarily designed for AF detection, smartwatches can also help identify heart attacks, bradycardia, and conduction disorders by capturing heart rate, rhythm, and other key data. Adjusting the watch's position can improve ECG readings, making it more useful for detecting heart attacks and slow heart rhythms. Additionally, smartwatch ECGs can help monitor the QT interval, important for preventing dangerous arrhythmias, and identify conditions linked to sudden cardiac death, like long QT syndrome and Brugada syndrome. Though designed for adults, they have also been successfully used in children to monitor congenital heart abnormalities. However, there are limitations, as single-lead ECGs cannot replace the detailed information from a 12 lead ECG, and users must be able to operate the device during critical moments. Future advancements in multi-lead recording and improved algorithms could significantly expand their diagnostic capabilities, making smartwatches even more valuable for heart health monitoring.

Akbar et al. [15] examine STEMI, which occurs when one or more coronary arteries become blocked, preventing blood flow to the heart muscle and leading to damage or death of the heart tissue. It is a medical emergency that requires prompt diagnosis and treatment to minimize damage. Symptoms include chest pain and shortness of breath, with risk factors like high blood pressure, diabetes, high cholesterol, smoking, and family history. Diagnosis is made through an ECG, which shows specific changes (ST-segment elevation), and confirmed by blood tests measuring troponin levels. Treatment aims to quickly restore blood flow, either through percutaneous coronary intervention to open the blocked artery or clot-busting medications if percutaneous coronary intervention is unavailable. Medications like beta-blockers, statins, aspirin, and antiplatelets are also administered. If untreated, STEMI can lead to severe complications such as heart wall rupture. Fast, coordinated care between EMS, emergency physicians, and cardiologists, particularly reducing the time from hospital arrival to artery opening, is vital for improving outcomes.

Wu et al. [16] investigate the development of deep learning models designed to detect STEMI and identify the blocked coronary artery using 12-lead ECGs. The study emphasizes the importance of early STEMI detection for improving treatment outcomes and survival rates. Researchers proposed three models: an LSTM network, CNN, and a hybrid CNN-LSTM model. Among these, the CNN-LSTM model performed best, achieving an impressive AUC of 0.99 for STEMI detection and 0.96 for identifying the left anterior descending artery involvement. Input data included 12-lead ECG recordings processed to remove noise and normalize signals, consisting of 883 cases (506 controls and 377 STEMI). The models provide two key outputs: a binary classification for STEMI detection and the identification of the blocked artery among the left anterior descending, right coronary artery, and left circumflex arteries. The algorithms utilized CNNs for feature extraction and LSTMs to capture the sequential nature of ECG signals. The paper suggests exciting future possibilities, such as real-time STEMI detection through wearable devices and the generalization of the models across diverse populations. Improving the models' accuracy in identifying complex multi-vessel disease cases and incorporating additional clinical data could enhance diagnostic precision. Furthermore, the potential to apply this technology to other cardiovascular conditions showcases the promise of deep learning in revolutionizing heart attack diagnosis, ultimately aiding healthcare professionals in critical decision-making.

Liu et al. [17] introduce a new algorithm for detecting myocardial infarction by applying CNN to multi-lead ECGs. The authors developed a beat segmentation algorithm to extract beats from the multi-lead ECG data, employing fuzzy information granulation for preprocessing. The heartbeats are then analyzed using a novel multi-lead-CNN model, which incorporates specialized two-dimensional (2D) convolutional layers and lead asymmetric pooling (LAP) layers. These LAP layers capture multiscale features from different ECG leads, allowing the model to leverage the unique characteristics of each lead while also considering the overall patterns across all leads. To evaluate the effectiveness of the algorithm, the researchers used real ECG datasets from the PTB diagnostic database, achieving impressive results: a sensitivity of 95.40%, specificity of 97.37%, and overall accuracy of 96.00%. The algorithm was developed with mobile healthcare applications in focus, showcasing its capability to perform real-time analysis on both MATLAB and ARM Cortex-A9 platforms. The average processing time per heartbeat was about 17.10 ms on MATLAB and 26.75 ms on the ARM platform, emphasizing the method's suitability for mobile healthcare environments.

Śmigiel et al. [18] highlight the essential role of analyzing and processing ECG signals in diagnosing CVDs, with classification methods increasingly being supported by machine learning algorithms. The research introduces a deep neural network designed for automatic classification of primary ECG signals, utilizing data from the PTB-XL database. Three distinct neural network architectures were examined: a convolutional network, one utilizing SincNet, and a convolutional network enhanced with entropy-based features. The dataset was divided into training, validation, and test sets in proportions of 70%, 15%, and 15%, respectively. Experiments were carried out to classify ECG signals into 2, 5, and 20 disease categories. Of the architectures tested, the convolutional network with entropy-based features produced the highest classification accuracy. The standard convolutional network, while slightly less accurate, was more computationally efficient due to its smaller number of neurons. Given that CVD remains the leading cause of death globally, accurately classifying heart conditions is essential for effective diagnosis and treatment. ECGs are a reliable, non-invasive diagnostic tool for heart diseases, but manual interpretation by cardiologists can be time-consuming and prone to errors, underscoring the need for automated solutions. Recent advances in machine learning, aided by the availability of large open-source ECG datasets, have facilitated the development of models capable of recognizing patterns in ECG data with high accuracy.

Deep learning, in particular, has proven to be a powerful approach in ECG signal classification. The PTB-XL database, used in this study, contains 21,837 clinical 12-lead ECGs from nearly 19,000 patients, providing a rich resource for training and validating classification models. The researcher's methodology involved filtering and normalizing the ECG data, followed by splitting it into training, validation, and test sets. This systematic approach enables a thorough evaluation of the neural networks' performance in classifying ECG signals across various conditions, contributing to enhanced diagnostic precision and improved patient outcomes in cardiovascular health.

Aarthy and Mazher Iqbal [19] discuss the challenge of diagnosing CVDs, which frequently develop without apparent symptoms until they reach more advanced stages. Many individuals may seem healthy and continue their daily routines, yet subtle signs of these diseases can be detected in their ECGs. These faint indicators, however, are frequently overlooked during routine assessments. Current machine learning models struggle to detect these subtle variations due to the complex and irregular nature of ECG patterns. This researchers introduces a novel deep learning approach aimed at identifying small changes in ECG signals by fine-tuning the learning rate of DCNN. The approach involves segmenting ECG signals into smaller parts, each of which is analyzed for unique central features. By using a clustering technique, the method successfully detects minor yet crucial variations in ECG characteristics. The model was trained using data from SRM College Hospital and Research Centre in Chennai, India, with the goal of predicting both typical and subtle changes in ECG patterns. These patterns were then compared to a pre-trained feature set for CVDs. The results show this method outperforms existing state-of-the-art techniques in detecting subtle ECG signal variations, potentially improving early detection of CVDs and offering a valuable tool for predictive medical diagnostics.

Alimbayeva et al. [20] discuss the persistent global impact of CVD, which remains a leading cause of death worldwide. This has led to renewed interest among healthcare professionals in wearable devices that monitor heart activity. The paper introduces an innovative ECG monitoring system that employs a single-lead ECG device enhanced with machine learning techniques. While the system primarily focuses on processing and analyzing ECG data, it also has the ability to predict potential heart diseases at an early stage. The wearable device is built on the ADS1298 chip and an STM32L151xD microcontroller. To ensure seamless communication, a REST API-based server module was developed to enable real-time data transfer from the microcontroller to the web interface, facilitating smooth interaction with the system's web component. Various algorithms were designed for ECG signal analysis, including techniques for artifact removal, K-means clustering for signal segmentation, and PQRST analysis. Machine learning techniques, such as isolation forests, were applied to detect anomalies in ECG readings. Additionally, the study performed a comparative analysis of different machine learning algorithms, including logistic regression, RF, SVM, eXtreme gradient boosting, decision forest, and CNNs, to predict the likelihood of CVDs. Among these, CNNs stood out, achieving an impressive accuracy of 92.6%, highlighting their effectiveness in processing ECG data.

Abubaker and Babayiğit [21] focus on detecting major heart conditions through ECG images using machine learning and deep learning methods. It compares deep learning models, such as AlexNet, SqueezeNet, and a proposed CNN architecture. The CNN model achieved high accuracy (98.23%) and improved even further (99.79%) when used for feature extraction with traditional machine learning models, like naïve Bayes. This research holds promise for enhancing AI-based diagnostic tools in healthcare, potentially integrating into internet of things ecosystems for more accessible cardiac monitoring. Anis and Sharma [22] proposed CNN-based ECG classification method that offers a fully automated solution for detecting heart diseases, eliminating the need for manual feature extraction. By categorizing heartbeats into five clinically significant groups, it adheres to the widely accepted Association for the Advancement of Medical Instrumentation (AAMI) standards, making it suitable for diverse medical applications. The model's superior performance on the MIT-BIH arrhythmia dataset shows its robustness and efficiency compared to older techniques. Looking ahead, the integration of this system into wearable devices could allow for continuous, personalized heart monitoring, enabling early diagnosis and preventative care for patients at risk of heart conditions.

Kurian and Thangam [23] present a deep CNN model that offers a practical solution for small healthcare facilities, providing an easy-to-use diagnostic tool that does not require extensive medical expertise. With ECG images taken via a smartphone, it simplifies the process of detecting critical heart conditions like myocardial infarction and arrhythmias. The remarkable 99% accuracy demonstrates its reliability, surpassing even advanced pre-trained models like ResNet and EfficientNet-B0. Future implementations could focus on integrating this model into mobile health applications, providing real-time heart monitoring and diagnosis in underserved areas, ultimately improving access to quality cardiac care worldwide. Aversano et al. [24] focused on the early detection of cardiac diseases using 2D CNN to analyze ECG images. Key features include waveform patterns reflecting heart conditions like arrhythmias and abnormalities. The input consists of ECG images from patients with various cardiac illnesses and healthy controls, while the output predicts the presence of heart disease. The CNN algorithm automatically extracts features and identifies disease markers. This innovative approach not only aims to enhance diagnostic accuracy but also seeks to empower patients by providing them with crucial health insights. Moreover, by leveraging advancements in technology, there is a potential to create user-friendly applications that make heart health monitoring accessible to everyone. In the future, expanding this method to larger datasets and integrating it with wearable technology could offer real-time, accessible heart disease monitoring and detection for early intervention.

Sambhaji and Tanajirao Bapuso [25] used a CNN classifier to diagnose non-STEMI heart disease from ECG signals using a Raspberry Pi. The process begins with acquiring ECG signal images from clinical sources. These images are preprocessed by resizing and converting them to grayscale for clearer analysis. The CNN then analyzes these images for heart disease diagnosis, providing timely insights that can make a significant difference in patient outcomes. The model achieved impressive accuracy (96%) and precision (97%), demonstrating its potential as a reliable diagnostic tool. By integrating this technology into user-friendly devices, we could empower healthcare professionals and patients alike, ensuring that critical heart health information is accessible anytime, anywhere. Future applications could see this technology integrated into portable, real-time devices for efficient heart disease monitoring in resource-limited environments.

Mahmoud et al. [26] present a new CNN architecture designed to predict heart disease by classifying ECG images. The model incorporates six convolutional layers, three max pooling layers for down sampling, and three fully connected layers, which enhances its ability to identify complex patterns in the data. The dataset used includes 928 ECG images categorized into four groups: normal, abnormal, and cases of past and current myocardial infarctions. The proposed model achieved an outstanding accuracy of 98%, surpassing other architectures such as VGG-19 and LeNet-5. Future improvements could target real-time clinical applications to further enhance patient outcomes. Banerjee et al. [27] present a hybrid CNN-LSTM architecture developed for detecting coronary artery disease (CAD) using ECG signals. The model leverages two important non-specific markers of CAD: abnormal ECG waveform morphology and irregular heart rate variability (HRV). The CNN module is responsible for extracting morphological features from ECG images, while the LSTM component captures the temporal dependencies within the HRV data. The architecture achieved classification accuracies of 93% and 88% on two different datasets. By focusing on both ECG waveform shape and heart rate fluctuations, the model effectively addresses two key factors in CAD detection. The high accuracy rates underscore its potential for clinical use, though further refinements could improve its performance in real-world applications. Future advancements may aim to enhance the model's efficiency for integration into wearable devices, making early CAD detection more accessible to a larger population. Additionally, future work could explore improvements in real-time monitoring and integration with affordable ECG devices to expand accessibility.

Arooj et al. [28] explore the use of DCNN for the early detection of heart disease. Using the UCI heart disease dataset, which includes 1,050 patients with 14 attributes, the model classifies cases as either healthy or indicative of cardiac disease. By leveraging deep learning, this approach aims to deliver faster and more accurate diagnoses, potentially saving lives and enhancing patient care. The model achieved a validation accuracy of 91.7%, highlighting the effectiveness of deep learning in medical image classification. These promising results showcase the potential of advanced technology in revolutionizing heart health management. Future efforts could focus on improving the model's real-time functionality and benchmarking it against other leading methods to further enhance diagnostic accuracy, making it an essential tool for healthcare providers in combating CVDs. Deng et al. [29] present a method for detecting AF using one-dimensional CNNs combined with time-domain features from ECG sequences. The input consists of filtered ECG signals segmented into heartbeats, from which eight time-domain features are extracted to create a feature vector. These features are combined with a one-hot encoded label to form a 10-dimensional input for the SVM classifier. The algorithm demonstrated high sensitivity (99.07%), specificity (97.05%), and total accuracy (98.03%), showcasing its potential as a dependable tool for early AF detection. By focusing on the intricacies of heartbeats, this method offers a glimpse into how technology can enhance our understanding of cardiovascular health. Future developments could focus on integrating this method into clinical settings for real-time monitoring and diagnosis, ultimately empowering healthcare professionals to make timely and informed decisions in patient care.

Nursalim et al. [30] focus on classifying five types of arrhythmias using deep learning models, specifically CNN architectures like AlexNet, ResNet-50, InceptionNet, and VGG-16, applied to ECG signals from the MIT-BIH database. The input consists of preprocessed ECG data, while the output is the classification of arrhythmias based on AAMI rules. The models achieved high classification accuracies, with AlexNet leading at 97.99%, highlighting the promise of AI in enhancing cardiac health diagnostics. By leveraging deep learning, this research opens the door to more accurate and efficient detection of arrhythmias, potentially saving lives through early intervention. Future developments may enhance these models' capabilities for real-time monitoring and improve clinical decision-making in cardiovascular care, making heart health management more accessible and effective for patients worldwide. Table *2* presents various studies on CVD classification and early heart attack detection using machine learning and deep learning techniques. It highlights diverse methodologies, including CNNs and SVMs, applied to various datasets, achieving high accuracy rates, often exceeding 90%. The table underscores the potential of these technologies for enhancing clinical decision-making and early intervention in heart health.

References	Author	Dataset	Purpose	Methods	Result
[7]	Kumar et al. (2022)	UCI ML Dataset	To predict early heart attacks using neural networks and evaluate the accuracy of different deep learning techniques.	Naïve Bayes, SVM, KNN, CNN, ANN	CNN accuracy 98% and ANN accuracy 94%.
[16]	Wu et al. (2022)	The dataset consists of 883 cases, including 506 control subjects and 377 STEMI patients, collected from external datasets, with confirmed results from CAG	To develop and evaluate three deep learning models for the accurate detection of ST-segment elevation STEMI and identification of the culprit vessel using 12-lead ECG.	CNN-LSTM	The CNN-LSTM deep learning model achieved an AUC of 0.99 in detecting STEMI, outperforming both traditional models and experienced physicians, while demonstrating comparable accuracy in predicting culprit vessels associated with myocardial infarction.
[17]	Liu et al. (2018)	PTB diagnostic database	To detect myocardial infarction using multilead ECG with a CNN-based algorithm.	Beat segmentation, fuzzy information granulation, multilead-CNN sub 2D convolution, lead asymmetric pooling, MATLAB, ARM Cortex-A9	Sensitivity 95.40%, specificity 97.37%, accuracy 96.00%, average processing time per heartbeat 17.10 ms (MATLAB) and 26.75 ms (ARM Cortex-A9).
[18]	Śmigiel et al. (2021)	PTB-XL database	To automatically classify ECG signals using deep learning techniques for cardiovascular disease diagnosis.	CNN, SincNet	The convolutional network with entropy-based features achieved the best classification result, while the standard convolutional network had the highest computational efficiency.
[19]	Aarthy and Mazher Iqbal (2024)	ECG signals from SRM College Hospital and Research Centre, Kattankulathur, Chennai, India	To develop a deep learning approach for early detection of cardiovascular diseases by identifying subtle variations in ECG signals using fine-tuned deep CNN.	CNN	The proposed method outperformed state-of-the-art approaches in detecting subtle and irregular ECG signal variations, improving early cardiovascular disease detection.
[20]	Alimbayeva et al. (2024)	Real-time ECG data from the wearable device	To monitor cardiac activity and predict potential heart disease using a wearable ECG device and machine learning techniques.	REST API, K-means clustering, logistic regression random forest, SVM, XGBoost, decision forest, CNN	CNNs achieved the highest accuracy of 0.926 for ECG anomaly detection and heart disease prediction.
[21]	Abubaker and Babayiğit (2023)	PhysioNet ECG Dataset	To develop a high-accuracy system for early detection and classification of cardiovascular diseases using machine learning and deep learning techniques, with a focus on lightweight models for integration into IoT health care systems.	SqueezeNet and AlexNet CNN, Naive Bayes	The proposed CNN model achieved a classification accuracy of 98.23%. When used as a feature extraction tool for traditional machine learning models, accuracy improved, reaching 99.79% with the Naïve Bayes algorithm.
[22]	Anis and Sharma (2022)	ECG signals classified according to AAMI standards	To develop a CNN-based model for classifying ECG signals into five heart disease categories, improving early detection of heart conditions.	CNN	The proposed method outperformed previous ECG signal classification techniques in terms of accuracy and computational efficiency.
[23]	Kurian and Thangam	12-lead ECG	To diagnose cardiac conditions (myocardial infarction, abnormal heartbeat, history of myocardial	CNN, ResNet,	Achieved 99% accuracy in diagnosing cardiac conditions from

	(2023)	images	infarction, normal heartbeat) using ECG images.	EfficientNet-B0	ECG images.
[24]	Aversano et al. (2023)	ECG images from cardiac patients with different heart-related illnesses and healthy controls	To predict heart disease using ECG images for early detection.	CNN-2D	Evaluation on a real-life dataset yielded promising results for heart disease prediction.
[25]	Sambhaji and Tanajirao Bapuso (2023)	Non-STEMI ECG signal images from clinical applications	To predict heart disease using ECG signal images for non-STEMI diagnosis.	CNN	Achieved 96% accuracy, 95% specificity, 97% precision, and 95% recall in predicting heart diseases.
[26]	Mahmoud et al. (2023)	MIT-BIH Arrhythmia Database	To predict heart disease using a newly proposed CNN architecture.	CNN	Achieved 98% accuracy, outperforming models like VGG-19, LeNet-5, and VGG-16.
[27]	Banerjee et al. (2020)	MIMIC II waveform dataset and an in-house noisy dataset recorded using a low-cost ECG sensor	To detect coronary artery disease using a hybrid CNN-LSTM architecture.	Hybrid CNN LSTM	Achieved 93% accuracy on MIMIC II Dataset and 88% accuracy on the in-house dataset.
[28]	Arooj et al. (2022)	UCI Heart Disease Data	To utilize a deep learning approach for early heart disease detection.	DCNN	Achieved a validation accuracy of 91.7%.
[29]	Deng et al. (2020)	MIT-BIH Atrial Fibrillation Database	To detect atrial fibrillation for clinical diagnosis using ECG data.	CNN, SVM	Achieved sensitivity of 99.07%, specificity of 97.05%, and total accuracy of 98.03%.
[30]	Nursalim et al. (2023)	MIT-BIH Arrhythmia Database	To classify five types of arrhythmia disorders for early treatment and accurate medical intervention.	CNN (AlexNet ResNet-50)	Achieved classification accuracy of 97.99% for AlexNet, 97.60% for ResNet-50, 97.59% for InceptionNet, and 97.55% for VGG-16.
[31]	Tasci et al. (2022)	Kaggle Psychiatry-ECG	To develop a novel ternary pattern-based classification model using ECG signals for the automatic detection of psychiatric disorders such as bipolar disorder, depression, and schizophrenia. This approach aims to enhance diagnostic accuracy and enable non-invasive, real-time mental health monitoring.	Multilevel discrete wavelet transform, iterative Chi2 algorithm, ANN	By applying the IMV algorithm, the overall classification accuracy significantly improved, reaching 96.25%.

TABLE 2: Early Heart Attack Detection: Different Methods With Obtained Results

STEMI, ST-Elevation Myocardial Infarction; CAG, Coronary Angiography; AAMI, Association for the Advancement of Medical Instrumentation; IoT, Internet of Things; SVM, Support Vector Machine; KNN, K-Nearest Neighbor; CNN, Convolutional Neural Network; ANN, Artificial Neural Network; LSTM, Long Short-Term Memory; API, Application Programming Interface; DCNN, Deep CNN; IMV, Iterative Majority Voting

Tasci et al. [31] highlight that psychiatric disorders such as bipolar disorder, depression, and schizophrenia have a significant impact on individuals' lives, often leading to disability. However, diagnosing these conditions remains a challenge due to the absence of definitive biological tests. Given the strong connection between the autonomic nervous system and the heart, ECG signals can serve as valuable biomarkers for identifying psychiatric conditions. This study introduces a novel ternary pattern-based classification model to automatically detect these disorders using ECG signals. The research is built on a newly collected dataset containing 3,570 ECG beats categorized into four groups: bipolar disorder, depression, schizophrenia, and healthy controls. Unlike deep learning-based feature extraction, this model relies on handcrafted feature engineering for efficient and accurate classification. The proposed methodology consists of four key phases: first, multilevel feature extraction is performed using multilevel discrete wavelet transform and a ternary pattern-based technique to enhance feature quality. Next, the most relevant features are selected using the iterative Chi2 algorithm, ensuring only the most discriminative data is used for classification. The refined feature set is then classified using ANN trained with tenfold cross-validation to ensure reliable and robust performance. To further enhance accuracy, an iterative majority voting (IMV) algorithm is applied, aggregating predictions from different ECG leads. The model demonstrated impressive performance, achieving lead-wise classification accuracy ranging from 73.67% to 89.19%, which was further improved to 96.25% using the IMV algorithm. These results confirm the effectiveness of the ternary pattern-based method in identifying psychiatric disorders using ECG signals. The potential applications of this research are vast, including wearable ECG devices for real-time psychiatric monitoring, clinical decision support tools to assist psychiatrists with objective diagnoses, and remote health monitoring systems to provide accessible mental healthcare. Future advancements could include integrating this model into smartwatches or fitness bands for real-time tracking, enhancing classification accuracy with multimodal data from EEG and HRV, and incorporating deep learning techniques for improved feature extraction. Expanding the dataset to include more diverse populations would also improve the model's generalizability. Ultimately, this study presents a groundbreaking approach to psychiatric disorder classification using ECG signals, paving the way for non-invasive, automated, and accurate mental health diagnostics that could significantly improve early detection and treatment.

Future scope

The future of wearable ECG devices holds great promise in enhancing cardiovascular health monitoring through several key advancements. One focus area is the refinement of machine learning and deep learning algorithms, particularly hybrid CNN-LSTM architectures, to improve the accuracy of heart attack detection by increasing sensitivity and specificity. These algorithms will need to be robust enough to handle noise and variations in ECG signals across diverse populations, ensuring consistent reliability. Another significant development is the integration of additional ECG leads and other physiological metrics, such as blood oxygen levels and blood pressure, to create more comprehensive diagnostic tools for wearable devices, which can improve the detection of cardiovascular risks.

Personalized monitoring is also poised for growth, with AI-driven models designed to adapt to an individual's health history and genetic factors, thus enhancing predictive accuracy and reducing false alarms. Real-time feedback is another priority, as future devices aim for faster processing to provide instant alerts, notifying emergency services and family members in critical situations to reduce response times. Clinical validation and large-scale trials will be essential for ensuring the efficacy and safety of wearable ECG devices, securing regulatory approval, and promoting widespread trust among healthcare providers and users.

Additionally, incorporating wearable ECG devices into telemedicine platforms will enable continuous remote monitoring, especially in rural and underserved areas, enhancing healthcare accessibility. To address the global burden of CVD, future devices must also be scalable and affordable, making them accessible to a wider population. Finally, AI-driven health coaching could offer personalized recommendations on lifestyle, medication adherence, and fitness, empowering users to maintain optimal heart health.

Conclusions

The advancements in wearable technology and real-time ECG signal processing have revolutionized the detection and prevention of heart attacks. Research highlights the significant role of devices like smartwatches and portable ECG monitors in continuously tracking cardiac health, identifying abnormalities, and providing early warnings of critical conditions such as STEMI or arrhythmias. Incorporating machine learning and deep learning techniques, including CNNs and hybrid architectures, has enhanced the accuracy and efficiency of ECG data analysis. These systems are proving invaluable in remote healthcare settings, reducing the burden on medical facilities, and enabling proactive interventions. Moreover, integration with cloud-based platforms allows for seamless data sharing and monitoring, facilitating timely medical responses and improved patient outcomes. Despite these achievements, challenges like false positives, device compatibility, and ensuring accessibility in low-resource settings persist.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sunil D. Kale, Mahesh R. Shirole, Pooja Ingle

Acquisition, analysis, or interpretation of data: Sunil D. Kale, Ninad Shirsat, Pooja Ingle

Drafting of the manuscript: Sunil D. Kale, Ninad Shirsat, Pooja Ingle

Critical review of the manuscript for important intellectual content: Mahesh R. Shirole, Ninad

Shirsat

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

References

1. Kashou AH, Basit H, Malik A: ST segment. StatPearls. (2023). Accessed: November 10, 2024: https://www.ncbi.nlm.nih.gov/books/NBK459364/.
2. Stark K, Czermak T, Massberg S, Orban M: Watch out for ST-elevation myocardial infarction: A case report of ST-elevation in single-lead electrocardiogram tracing of a smartwatch. European Heart Journal - Case Reports. 2020, 4:1-4. 10.1093/ehjcr/ytaa353
3. Gusev M, Stojmenski A, Guseva A: ECGalert: A heart attack alerting system. ICT Innovations 2017. ICT Innovations 2017. Communications in Computer and Information Science. Trajanov D, Bakeva V (ed): Springer, Cham; 2017. 778:27-36. 10.1007/978-3-319-67597-8_3
4. Strik M, Ploux S, Zande Jvd, et al.: The use of electrocardiogram smartwatches in patients with cardiac implantable electrical devices. Sensors. 2024, 24:527. 10.3390/s24020527
5. Chandurkar S, Arote S, Chaudhari S, Kakade V: The system for early detection of heart-attack. International Journal of Computer Applications. 2018, 182:30-33. 10.5120/ijca2018918108
6. Muthusundari S, Priyadharshii M, Preethi V, Priya K, Priyadharcini K: Smart watch for early heart attack detection and emergency assistance using IoT. LatIA. 2024, 2:109. 10.62486/latia2024109
7. Kumar A, Rathor K, Vaddi S, Patel D, Vanjarapu P, Maddi M: ECG based early heart attack prediction using neural networks. International Conference on Electronics and Sustainable Communication Systems (ICESC). 2022, 1080-1083. 10.1109/ICESC54411.2022.9885448
8. Nasarre M, Strik M, Ramirez FD, et al.: Using a smartwatch electrocardiogram to detect abnormalities associated with sudden cardiac arrest in young adults. EP Europace. 2022, 24:406-412. 10.1093/europace/euab192
9. Spaccarotella CAM, Polimeni A, Migliarino S, et al.: Multichannel electrocardiograms obtained by a smartwatch for the diagnosis of ST-segment changes. JAMA Cardiology. 2020, 5:1176-1176. 10.1001/jamacardio.2020.3994
10. Perez MV, Mahaffey KW, Hedlin H, et al.: Large-scale assessment of a smartwatch to identify atrial fibrillation. The New England Journal of Medicine. 2019, 381:1909-1917. 10.1056/NEJMoa1901183
11. Goyal A, Mittal S, Sawant R, Gidhwani A, Bagate J: Portable heart attack detector. 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT). 2017, 1-6. 10.1109/ICCCNT.2017.8203987
12. Kappiarukudil KJ, Ramesh MV: Real-time monitoring and detection of "heart attack" using wireless sensor networks. 2010 Fourth International Conference on Sensor Technologies and Applications. 2010, 632-636. 10.1109/SENSORCOMM.2010.99
13. Abu-Alrub S, Strik M, Ramirez FD, et al.: Smartwatch electrocardiograms for automated and manual diagnosis of atrial fibrillation: A comparative analysis of three models. Frontiers in Cardiovascular Medicine. 2022, 9:836375. 10.3389/fcvm.2022.836375
14. Strik M, Ploux S, Weigel D, et al.: The use of smartwatch electrocardiogram beyond arrhythmia detection. Trends in Cardiovascular Medicine. 2024, 34:174-180. 10.1016/j.tcm.2022.12.006
15. Akbar H, Foth C, Kahloon RA, Mountfort S: Acute ST-Segment Elevation Myocardial Infarction (STEMI). StatPearls Publishing, Treasure Island, FL; 2025.
16. Wu L, Huang G, Yu X, et al.: Deep learning networks accurately detect ST-segment elevation myocardial infarction and culprit vessel. Frontiers in Cardiovascular Medicine. 2022, 9:797207. 10.3389/fcvm.2022.797207
17. Liu W, Zhang M, Zhang Y, et al.: Real-time multilead convolutional neural network for myocardial infarction detection. IEEE Journal of Biomedical and Health Informatics. 2018, 22:1434-1444. 10.1109/jbhi.2017.2771768
18. Śmigiel S, Pałczyński K, Ledziński D: ECG signal classification using deep learning techniques based on the PTB-XL dataset. Entropy. 2021, 23:1121. 10.3390/e23091121
19. Aarthy ST, Mazher Iqbal JL: A novel deep learning approach for early detection of cardiovascular diseases from ECG signals. Medical Engineering & Physics. 2024, 125:104111. 10.1016/j.medengphy.2024.104111
20. Alimbayeva Z, Alimbayev C, Ozhikenov K, Bayanbay N, Ozhikenova A: Wearable ECG device and machine learning for heart monitoring. Sensors. 2024, 24:4201. 10.3390/s24134201
21. Abubaker MB, Babayiğit B: Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. IEEE Transactions on Artificial Intelligence. 2023, 4:373-382. 10.1109/tai.2022.3159505
22. Anis MT, Sharma V: Classification of ECG signal using CNN algorithm. International Conference on Electronic Systems and Intelligent Computing (ICESIC). 2022, 185-189. 10.1109/ICESIC53714.2022.9783598
23. Kurian T, Thangam S: Deep convolution neural network-based classification and diagnosis of heart disease using ElectroCardioGram (ECG) images. International Conference for Convergence in Technology. 2023, 4:373-382. 10.1109/I2CT57861.2023.10126473
24. Aversano L, Bernardi ML, Cimitile M, Montano D, Pecori R: Early diagnosis of cardiac diseases using ECG images and CNN-2D. Procedia Computer Science. 2023, 225:2866-2875. 10.1016/j.procs.2023.10.279
25. Sambhaji PS, Tanajirao Bapuso M-P: NSTEMI heart disease diagnosis and analysis using CNN classifier and Raspberry Pi. 2023 International Conference on Network, Multimedia and Information Technology (NMITCON). 2023, 1-9. 10.1109/NMITCON58196.2023.10276065

26. Mahmoud S, Gaber M, Farouk G, Keshk A: Prediction of heart disease using new proposed CNN model architecture. 2023 3rd International Conference on Electronic Engineering (ICEEM). 2023, 1-8. 10.1109/ICEEM58740.2023.10319589
27. Banerjee R, Ghose A, Muthana Mandana K: A hybrid CNN-LSTM architecture for detection of coronary artery disease from ECG. 2020 International Joint Conference on Neural Networks (IJCNN). 2020, 1-8. 10.1109/IJCNN48605.2020.9207044
28. Arooj S, Rehman S, Imran A, Almuhaimeed A, Alzahrani AK, Alzahrani A: A deep convolutional neural network for the early detection of heart disease. Biomedicines. 2022, 10:2796. 10.3390/biomedicines10112796
29. Deng M, Qiu L, Wang H, Shi W, Wang L: Atrial fibrillation classification using convolutional neural networks and time domain features of ECG sequence. 2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom). 2020, 1481-1485. 10.1109/TrustCom50675.2020.00201
30. Nursalim H, Bustamam A, Hermawan, Sarwinda D: Classification of electrocardiogram signal using deep learning models. 2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE). 2023, 767-772. 10.1109/ICCoSITE57641.2023.10127690
31. Tasci B, Tasci G, Dogan S, Tuncer T: A novel ternary pattern-based automatic psychiatric disorders classification using ECG signals. Cognitive Neurodynamics. 2022, 18:95-108. 10.1007/s11571-022-09918-8