

AI-Enabled Smart Watch Detection of Cardiac Arrest: A Review

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Abstract:

Cardiac arrest is a common cause of death, with a high mortality rate if it occurs outside of hospitals and does not receive immediate care. This paper explored the possibilities of using the widespread technology, smart watches, in the detection of cardiac arrest, with the assistance of AI and deep learning algorithms. After understanding cardiac arrest and the electrocardiogram (ECG) waves for diagnosis, current smart watch technology is more focused on other ECG readings, and despite its accuracy, it cannot support the detection of cardiac arrest. However, with the use of deep learning and generative AI, the potential of early onset cardiac arrest detection seems to be likely in the near future. Currently, smart watches are capable of capturing 3-lead ECG readings, as well as precordial ECG diagrams. With further research in AI training and hardware upgrades, early onset cardiac arrest detection is possible, and could help save many lives from cardiac arrest.

Keywords: Cardiac Arrest, AI, Smart Watches

1. Introduction

In modern days, public sanitization has increased, decreasing the incident of infections, contributing to the increase of the overall rates. As the average lifespan increased, chronic diseases became the leading causes of death [1]. Consequently, the detection and care for chronic diseases became an increasingly important topic for public health, as these conditions affect a growing number of individuals, and impair their health and quality of life. Yet, in the United States, people were often unaware of their risk to their health. Since 1921, heart disease is leading cause of death in the U.S. [2], and though not a heart disease itself, cardiac arrest is primarily caused by underlying cardiac diseases, like occlusive ischemic

coronary disease [3]. Cardiac arrest is an important health issue in the U.S., especially when 1000 Americans are affected each day outside of the hospital, claiming the lives of 9 out of 10 victims [4]. If help is received earlier, the survival rate can increase up to 50% [4]. Therefore, this calls for an urgent need for a better detection of cardiac arrest, and better monitoring of patients' health, enabling timely interventions, through both prompting bystanders' immediate actions, and earlier 911 activations.

This paper focuses on the potential of AI and deep learning for the early detection, especially when combined with monitoring from smart watches. Currently, about one-third of Americans use smart watches or bands, where 80% of device users would

share information with their doctor for health monitoring [5]. With such widespread use and acceptance of wearable devices, coupled with the sharing of data for health monitoring, it suggests that utilizing smart watches for the detection and tracking of cardiac arrest risks is plausible. Many studies today focus on employing deep learning to pick up patterns in vitals, such as ECG data or images, and utilize these patterns for the diagnosis of diseases. By applying similar technologies to the data from smart watches, it could result in accessible, real-time detection and diagnosis of cardiac problems, especially with early detection for signs of cardiac arrest. This would be immensely helpful in seeking early help for the onset of out-of-hospital cardiac arrest.

However, studies also showed that less than 25% of adults with cardiovascular disease risks use wearable devices, and only 38% of them use them regularly, compared to almost half of the adults who do have such risks. Additionally, income disparities exist, where individuals with higher household incomes and higher educational backgrounds are more likely to use wearable devices [5]. Therefore, strategies of promotion for utilizing wearable devices for patients with cardiovascular diseases, as well as measurements to make smart watches more accessible, should also be prioritized. Such measures could maximize the potential of smart watches for healthcare monitoring and cardiac arrest death prevention, while reducing disparities linked to socioeconomic status. These considerations are essential as our current technology pushes for the improvement of diagnosis and detection.

2. Background

2.1 . Cardiac Arrest

Cardiac arrest is a medical emergency when the heart stops pumping blood. The main cause of cardiac arrest is ventricular fibrillation (VF) or ventricular tachycardia (VT) [6], where the ventricles fail to function normally, either beating too fast, or are twitching instead of pumping the blood efficiently. Both conditions result in an inadequacy of blood being pumped from the left ventricle, which is the part of the heart that pushes freshly oxygenated blood from the lungs to the rest of the body. Therefore, without oxygenated blood, gas exchange would be inadequate in the brain and other vital organs, which would decrease the functions of these organs, and cause a medical emergency.

The risk factors for VF and VT are cardiac diseases, such as previous cardiac arrests, arrhythmia, or faulty genes. However, most people are unaware of their heart problems [6], which emphasizes the importance of a detecting tool

for civilian use. Early calls for help are crucial, especially in outside-of-hospital settings. It could reduce the mortality rate from 90% to 50% [4]. This calls for a tool for the identification of VF and VT.

2.2 . ECG and Smart Watches

The detection of both VF [7] and VT [8] is often diagnosed using an electrocardiogram (ECG), which places electrodes on the skin, and measures the electrical signals as they spread through the heart [9]. This can be detected on different areas of the skin [9]. Since the contraction of the heart muscle, which creates a heartbeat, is regulated by these electrical signals that start from the SA node, an ECG could effectively capture how the muscle contracts as the electrical signal spreads, and detect any abnormalities in contraction, such as VF and VT.

In September 2018, Apple was the first to introduce the FDA-approved ECG feature in its Apple Watch (AW) Series 4, as other smart watches have since then incorporated the technology as well, making ECG reading widely accessible to the public. Therefore, this paper focused on the AW series for smart watches. Both the AW series and other smart watches use a single-lead ECG, corresponding to lead I of the 12-lead ECG [10]. Their findings will be displayed as either atrial fibrillation (AF), sinus rhythm (SR), low or high heart rate, or inconclusive or poor reading in the notifications [10]. SR refers to the normal electrical activity of the heart. Currently, many studies have been focused on finding the accuracy of the smart watch, specifically in the detection of AF. It should be noted that smart watches do not have dedicated notifications for VF nor VT.

2.3 . Accuracy of Apple Watches

Most of the recent studies have indicated that AW has high diagnostic accuracy for detecting AF, comparing with the standard 12-lead ECG [11]. Though only using 1 lead, thus having a less comprehensive image than a 12-lead ECG data, it still provides valuable data that could be used for diagnosis, and the performance is dependable when detecting AF. This provides a cost-effective and accessible method for screening AF, as people with AW could screen without the need to utilize hospital resources, and monitor their health by contacting cardiologists, sending their graphs to them for further analysis.

However, the Apple Heart study (paper published in 2019), a collaborating study between Apple and American Heart Association shows that the population consisted of 68% of White population, 7.7% Black, and 12% Hispanic [12], while the U.S. census of 2020 showed that the population consisted of 61.6% White, 12.4% Black, and 18.7%

Hispanic [13]. This demonstrates that the algorithm and technology are pulling from a sample that does not accurately represent the country's population makeup, and risks propagating health disparities, where it may have increased inaccuracies for the disadvantaged populations, such as the Black and Hispanic populations [14].

2.4 . Current Deep Learning Applications

Studies have shown that with the application of a deep neural network (DNN) based algorithm, the sensitivity of AF detection would significantly increase, with nonsignificant increases in specificity [15]. This difference could be attributed to the difference in computing tools, where the DNN was utilizing the cloud-based algorithms for processing, while the smart watches operate on embedded algorithms on AW [15]. This provides technical restraints of the algorithm running on AW and is a limiting factor to the sensitivity of AF detection. Additionally, the limits of the AWs could also limit how DNN and other deep learning applications could be utilized, especially when balancing other factors such as battery, internet connection, etc. on the smart watches. Smart watches and their AF detection may be widely accessible, but when adding deep learning algorithms, there are many limiting factors that need to be taken into consideration.

With the increased sensitivity and specificity by utilizing DNN, it improves the accuracy of interpretation, when compared to traditional machine learning [16]. Studies have shown that with training, DNNs could perform on a similar accuracy, or even better, than certified cardiologists in AF screening [17]. There is great potential in the application of deep learning in diagnosis using the ECG signals, even if it were a single-lead ECG, and demonstrated with great accuracy when used to diagnose AF.

3. Current Potential for Smart Watch Cardiac Arrest Assistance

3.1 . Limits with VF and VT Detection

However, to diagnose cardiac arrest, smart watches like AW need to be able to detect VF and VT. Many studies have focused on the diagnosis of AF, as it is a feature of the AW. Some others have also explored how AW can detect other cardiac arrhythmias, such as VF and VT. Since sustained VT could lead to VF, most study cases focused on detecting VT, such as unintentional detection of VT [18], case studies [19], or dedicated studies for AW's effectiveness in diagnosing other cardiac arrhythmia other than AF [20]. Though studies have shown the ability for AWs to detect VT, some have pointed out that this detec-

tion was solely with nonsustained VT, while sustained VT was not detected at all [20]. This is a problem, as cardiac arrests are more at risk with sustained VT. Nonsustained VTs are more likely to resolve on their own.

There seemed to be a lack of studies about sustained VT and VF studies, which may be caused by the difference between the methods of diagnosing AF, VT, and VF. An ECG diagram includes the PQRST waves, like in Figure 1 [21]. Each wave corresponds to different electrical events in the heart, which indicate different movements in the cardiac muscles. The P waves show the depolarization of the atrium [21], meaning the contraction of both the left and the right atrium. The QRS Complex shows the depolarization of the ventricle [21], meaning the contraction of both the left and the right ventricle. The T wave shows the repolarization of the ventricle [21], or the relaxation of the left and right ventricles.

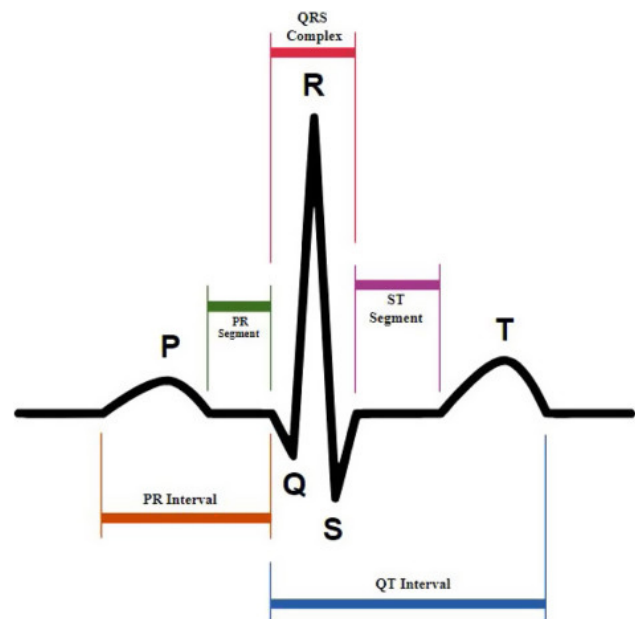


Figure 1: PQRST Waves in ECG diagrams. The figure is a demonstration of the standard heartbeat in an ECG diagram, labeled with the P wave, the QRS complex, the T wave, along with other identifiable markers such as the PR interval, the QT interval, the ST segment, etc.

Based on the current criteria of diagnosis, AF could be diagnosed if there are irregularly irregular RR intervals, absence of distinct repeating P waves, or irregular atrial activations in the ECG diagram [22], as proposed in the 2020 European Heart Journal. In contrast, according to Wellens' criteria, VT diagnosis requires specific patterns on the ECG waves for the QRS complexes [23]. This requires the ECG waves of the QRS complexes to be

captured from lead V1 and V6, which would be from a 12-lead ECG imaging [23]. This will help differentiate between VT and supraventricular tachycardia (SVT), where VT is always life-threatening, while SVT is a broad spectrum that can include AF and is rarely life-threatening [24]. This shows that with the current technology used in smart watches like AW, it is not yet possible to detect VT and VF, unless they have increased the number of leads for ECG detection. However, if multiple leads could be utilized, AW and other smart watches could detect early signs of cardiac arrest through VT and VF ECG waves.

3.2 . Multiple Leads with Smart Watches

Though designed to be a single-lead ECG with only one positive and one negative electrode, researchers have found ways to utilize AW as a multi-lead tool. For example, leads II and III could be acquired by placing the watch on the left lower abdomen. Placing the right index finger on the crown of the watch will record data for lead II, and the left index finger in the same way will record for lead III [25]. Studies have shown the data obtained

through these methods are accurate and comparable to the standard 12-lead ECG results, thus suitable for diagnosis [25]. However, it should be noted that these studies focused on the diagnosis of myocardial infarction (MI), and effectiveness of these method's data in cardiac arrest detection has not been evaluated yet.

Researchers also found ways of using AW to obtain the precordial leads (V1-V6) of a standard 12-lead ECG, which is what Wellens' criteria require for VT diagnosis. This requires the patient to place the AW on different parts of the chest, corresponding to the location of the V1-V6 leads on a standard 12-lead ECG, using the right finger to touch the crown, as demonstrated in Figure 2 [25]. This would result in a reading that corresponds to V1-V6 leads in the standard 12-lead ECG [25]. However, like the measuring methods for lead II and III, this method was developed with a focus on the measurement for MI detection, using different parts of the PQRST wave, and not with cardiac arrest detection in mind. No studies have shown if these methods are effective in detecting VT, VF, or the early onset of cardiac rest yet.

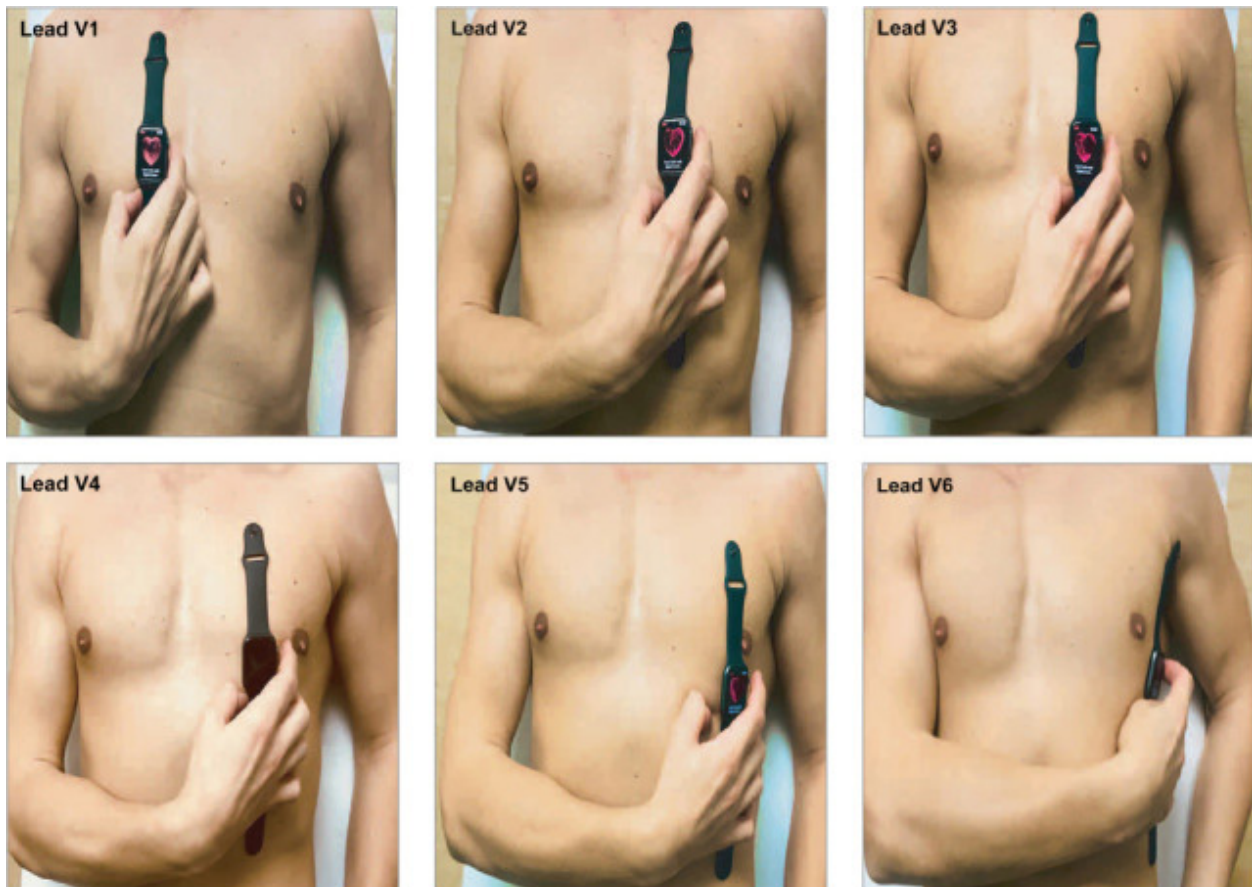


Figure 2: Taking precordial electrodiagrams using Apple Watches. The figure is a demonstration of how precordial electrodiagrams of a standard 12-lead ECG (Lead V1-V6) could be taken using an Apple Watch.

4. Discussion

There are few studies that focused on the potential of single-lead ECG diagnosis of VT and VF using AW, even fewer that focused on the multi-lead potential for AW, let alone the application of DNN onto this technology. However, with the example of how precordial electrodiagrams can aid with MI diagnosis, similar technologies should be explored for the detection of early-onset cardiac arrest.

With the application of deep learning, readings with fewer leads, such as 3-lead readings, can be reconstructed into a 12-lead reading, aiding in early diagnosis. Studies have shown this possible, where the V1-V6 (excluding V2) leads could be reconstructed, using the three leads I, II, and V2 using neural network models, U-shaped networks, and generative models for AI. Though the reconstructions for V1-V6 leads (excluding V2) were less satisfactory [26], with further improvement, they could achieve better accuracy in reconstruction. This requires further training of the AI, further research on the topic, and, most importantly, further improvement of the smart watches. With the current technology, the single-lead ECG that smart watches use cannot be able to identify and recognize VT and VF, therefore unable to provide aid consistently as a feature. To obtain a 3-lead ECG, it would either require further coaching of the population on how to obtain the 3-lead, which would be unrealistic in times of emergency, or it could be established with more accessories that come along with the smart watches.

Beyond further improvement of both the hardware and the software, there are still many improvements with the smart watch's detection of cardiac arrest. Compatibility with different population demographics, such as children, adults, and the elderly, could be further specified with future studies and developments. Additionally, early treatments and early calls for help upon development could also be implemented with the improved technology, such as calling emergency services upon early detection, notifications to nearby users for help if one were to experience cardiac arrest, or delivery of shock when applicable. There are many possibilities in the technology, ones that could save many lives from cardiac arrests, which require further exploration, development, improvements, and break through the current limitations on AI reconstruction for 12-lead, detection of early cardiac arrest signs, and smart watches' limitations on using a single-lead ECG.

5. Conclusion

Though with little studies' exploration, the detection of cardiac arrest using smart watches would be immensely helpful in saving many patients, especially due to the low

survival rate out-of-hospital without immediate bystander care. With the current single-lead ECG model of smart watches, this does not seem like a goal, despite its high accuracy with AF. The detection of early onset cardiac arrest requires identification of VF and VT, which requires a more comprehensive view of the heart, and cannot be supported by the single-lead ECG. However, it is not to say that with the current technology that smart watches hold, it is not reachable. Researchers have found that smart watches can capture 3-lead and precordial ECG data, with high accuracy, if placing the watch on different places other than the wrist, and only parts of the body like the chest. These demonstrated potential for VF and VT detection. Additionally, though still in progress, researchers have been exploring ways to reconstruct standard 12-lead ECG data using 3-lead ECG data, with the help of deep learning AI and generative AI. Since 3-lead ECG data could be obtained using smart watches, it provides a more accessible method of identifying VF and VT. Still, this requires much more training, as the results so far have not been the most satisfactory. For the convenience of the patients, upgrades in hardware could also help make it more accessible, such as the addition of accessories or a 3-lead ECG in the watch. With such an addition, it no longer requires conscious checking and placement of the watch on different body locations for diagnosis, but it could be monitoring the health of the user while they perform daily tasks. These are future outlooks that could be continued explored, and if researchers break through the limits, it will provide a life-saving tool that monitors people's health and help people in cardiac arrest cases as early as possible.

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