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# EXPLORING THE POTENTIAL OF MACHINE LEARNING FOR DIAGNOSIS OF ATRIAL FIBRILLATION

**Mohsin Imam*1, Sufiyan Adam*2**

*1,2Department Of Computer Science, Atma Ram Sanatan Dharma College, University Of Delhi New Delhi, India, 110021.

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## ABSTRACT

The most prevalent type of arrhythmia (Greek a-, loss + rhythmos, rhythm = loss of rhythm) that results in hospitalisation in the United States is called atrial fibrillation (AF). Although atrial fibrillation can occasionally go unnoticed, it is linked to a higher risk of heart failure and stroke in individuals, as well as a lower quality of life in terms of overall health (HRQOL). The yearly cost of treating AF is estimated to be between $6.0 to $26 billion for the American healthcare system [1]. Early detection of atrial fibrillation (AF) and therapeutic intervention can help patients have fewer symptoms and have better health-related quality of life (HRQOL), all while saving money on medical expenses. However, an electrocardiogram (ECG) that was only recorded at one moment in time is used as the standard test for identifying atrial fibrillation (AF). This approach provides no information on the relationship between the symptoms and AF or cardiac rhythm. Due to the democratisation of health monitoring [2] and the introduction of powerful computers in the last ten years, Machine Learning algorithms have been demonstrated to be helpful in identifying AF from the ECG of patients. The symptoms of atrial fibrillation (AF), its diagnosis, and the possibility for further study on the subject are all summarised in this article.

## I. INTRODUCTION

The top chambers of the heart (atria) pulse more quickly and irregularly than the heart's lower chambers, a condition known as atrial fibrillation (ventricles). Breathlessness, palpitations, and weakness are typical symptoms. Although AF by itself is not fatal, it increases the risk of heart failure, stroke, and other side effects. Some people may have recurrent AF episodes, whilst others may experience persistent AF episodes that necessitate medical intervention. In AF, the development of clots in the atria is a serious issue. These clots may spread to other organs and prevent blood from getting to them. To restore normal electrical activity of the heart, AF is treated with medication and other procedures.

### 1 Atrial Fibrillation Mechanistic Elements

Without atrial fibrillation, the electrical system of the heart controls how quickly each of the heart's chambers contracts. The sinoatrial (SA) node is a group of specialised cells in the right atrium of the heart that is in charge of producing electrical impulses at a regular rate that fluctuates according to the degree of physical activity being experienced by the subject (rate is greater during running compared to sleeping). The atria contract, forcing blood into the ventricles, after the impulses have travelled via a series of conducting cells, or "pathways." Finally, the atrioventricular (AV) node conducts the impulses to the ventricles. The His-Purkinje Network also helps the impulses spread out throughout the ventricles. The ventricles constrict as a result, pushing blood to the lungs and the rest of the body. At rest, a typical human heart beats between 60 and 100 times per minute.

Fast and disorganised impulses are generated by the SA node in individuals with AF. Because of the irregular rhythm of their contractions, the atria are unable to efficiently pump blood to the ventricles. Multiple competing impulses reach the ventricles via the AV node, disrupting the normal, orderly flow of impulses. The AV node is a filter, letting only certain impulses through. These factors lead to irregular and discordant ventricular contractions in relation to the atria. Depending on the individual, the heart's atria and ventricles may beat at various speeds, resulting in a pulse rate anywhere from 300 to 600 per minute.

## II. FORMS OF ATRIAL FIBRILLATION

Due to its therapeutic importance, the American Heart Association advises categorising AF into four subtypes depending on the temporal rhythm: first detection, paroxysmal, persistent, and permanent.

### 2.1 First Detection Atrial Fibrillation

First Detection, regardless of how long an episode lasts, AF refers to the first time it is seen in a person. It could be a sign or not. Due to the fact that it is only useful when significant symptoms are present, the conventional approach of diagnosing AF based on the patient's ECG is not now favoured.

### 2.2 Paroxysmal Atrial Fibrillation

A kind of aberrant cardiac rhythm known as paroxysmal atrial fibrillation (AF) is characterised by erratic and fast atrioventricular contractions (the upper chambers of the heart). Due to the fact that it happens intermittently rather than continually, it is referred to as "paroxysmal".

Atria contracts irregularly and create aberrant electrical activity in the heart, which results in AF. In paroxysmal AF, these episodes of abnormal heart rhythm can come on suddenly and may last for a few minutes to a few days. They may occur frequently or infrequently, and they may be triggered by various factors such as stress, alcohol consumption, or exercise.

### 2.3 Persistent Atrial Fibrillation

An abnormal cardiac rhythm known as persistent atrial fibrillation (AF) is characterised by the atria contracting quickly and irregularly (the upper chambers of the heart). Being continuous rather than happening in brief bursts or episodes qualifies it as "persistent.". In persistent AF, the abnormal heart rhythm is continuous and may last for days, weeks, or even longer. It may be more difficult to treat than paroxysmal AF (AF that occurs in short bursts or episodes) because it is more persistent and may require more aggressive treatment.

### 2.4 Permanent Atrial Fibrillation

A kind of abnormal cardiac rhythm known as permanent atrial fibrillation (AF) is characterised by erratic and brisk atria contractions (the upper chambers of the heart). It is classified as "permanent" because it is continuous and does not resolve on its own, unlike paroxysmal AF which occurs in short bursts or episodes. In permanent AF, these abnormal heart rhythms are continuous and do not resolve spontaneously. Underlying cardiac diseases such coronary artery disease, hypertension, or issues with the heart valves may contribute to permanent AF.

## III. SYMPTOMS OF ATRIAL FIBRILLATION

There is a lack of information on the precise symptoms of atrial fibrillation as a result of the common paradigm of diagnosing atrial fibrillation based on the ECG recorded at a single point in time rather than in real-time matching to the observation of the symptoms. Atrial fibrillation often manifests as variations in sympathetic nervous system activity, inadequate myocardial perfusion, reduced cardiac output, and impaired ventricular diastolic filling. [4,5]. The effectiveness of AF treatment methods, such as cardioversion ablation and the Cox-Maze procedure, is typically assessed by tracking the occurrence of symptoms in between clinic visits or by obtaining an ECG or limited Holter monitor recordings at the patient's subsequent clinic visit to get a better understanding of heart rhythm after the procedure. These methods are unable to provide information on asymptomatic episodes of atrial fibrillation, which continue to carry a risk of deep vein thrombosis, pulmonary embolism, and stroke [6]. Studies using wearable heart rate monitors (such as smartwatches) and implanted cardiac monitoring systems have shed insight on the actual recurrence of atrial fibrillation (AF). In patients with symptomatic paroxysmal AF observed for 12 months, Page et al. found that asymptomatic atrial tachyarrhythmia recurred 12 times more frequently than symptomatic atrial tachyarrhythmia [7, 8]. Later research found that individuals with diverse clinical diseases experienced silent AF significantly more frequently, which accounted for 54–94% of all AF arrhythmias [10, 11]. Asymptomatic AF is more prevalent in patients who have undergone an interventional clinical treatment to treat atrial fibrillation. According to Verma and colleagues [7], the ratio of asymptomatic to symptomatic AF cases rose from 1.1 to 3.7 after catheter ablation of the patient. We are now able to attempt to link reported symptoms with heart rhythms in addition to detecting asymptomatic atrial fibrillation thanks to the introduction of implanted cardiac monitoring devices. A figure between 17 and 21% was discovered by two separate experiments that sought to investigate the predictive significance of reported symptoms in connection to cardiac rhythm [10, 13]. When there was no episode of paroxysmal atrial fibrillation that could be verified by a device, 45-79% of all symptom reports were

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reported [10, 12, 13]. There are still unresolved underlying explanations for four non-AF arrhythmic symptoms. Symptom assessment and management remain the goal of treating AF, regardless of the actual heart rhythm at the time of symptom onset.

## IV. CURRENT CLINICAL DIAGNOSIS TECHNIQUES OF ATRIAL FIBRILLATION

It is important for individuals with AF to receive regular medical care to manage their condition and reduce the risk of complications. Treatment options for AF may include medications to control the heart rate and rhythm, lifestyle changes, and procedures such as cardioversion (a cardiac electrical shock to reestablish a regular beat) or ablation (a procedure to destroy abnormal electrical pathways in the heart). Atrial fibrillation is now identified by the patient's electrocardiogram (ECG) (AF). The ECG shows how voltage varies with respect to time, which illustrates how the heart muscles depolarize and then repolarize with each pulse. A succession of waves make up the ECG graph of a typical heartbeat (shown in Figure 1): a V-wave for atrial depolarization, a WXY complex for ventricular depolarization, and a Z-wave for ventricular repolarization. The VX, YZ, and WZ intervals are additional signal components.

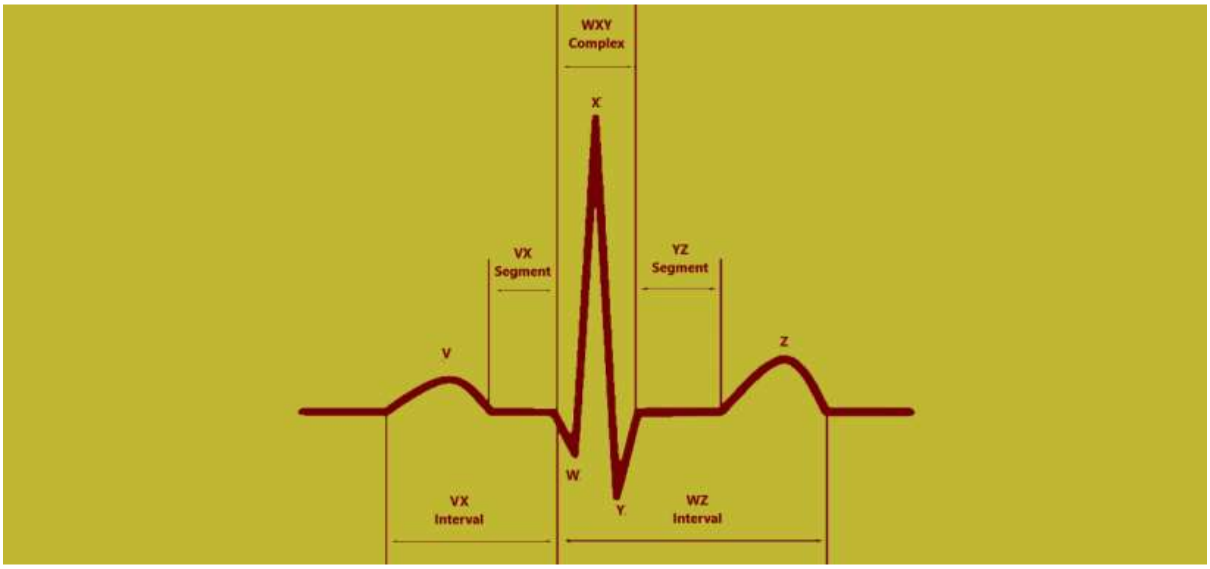


**Figure 1:** Normal Heartbeat ECG

In addition to ECG, Holter monitoring, which is a portable ECG device that is worn for a period of time (typically 24 to 48 hours) to continuously monitor the heart's electrical activity. It can detect intermittent episodes of AF that may not be detectable during a single ECG recording [15]. Additionally Echocardiography, which is a test that uses ultrasound waves to produce images of the heart. By identifying aberrant cardiac rhythms, it may be used to diagnose AF and evaluate the anatomy and function of the heart. Ambulatory blood pressure monitoring is also a technique in which a test is conducted that measures blood pressure at regular intervals over a period of time (typically 24 hours). It can be used to detect AF by detecting abnormal heart rhythms during blood pressure readings.

## V. APPLICATION OF MACHINE LEARNING TO ATRIAL FIBRILLATION

Computers can learn from data thanks to the discipline of artificial intelligence known as machine learning. A subfield of machine learning called deep learning uses several layers of neurons as its computational components. A deep learning model must be exposed to several samples of the sort of data it needs learn before it can establish the relationship between inputs and outputs. The deep learning model takes the input and calculates the output after witnessing an example, starting with random weights for the function it is attempting to learn. Then, it uses a loss function to determine how much the calculated output deviates from the anticipated output, and it updates the weights by back propagating the loss across the layers of neurons [14].

Machine learning models relied on people to choose the attributes from which they would learn throughout the early stages of their use. For example, in ECG analysis, morphological and temporal data would be the model's inputs, while the outputs to be predicted would be the ECG rhythm, serum potassium level, or LV ejection percent (LVEF). The issue with this system was that humans depended on their knowledge and experience, which varied and were inconsistent among individuals, to choose features. As a result, during training in deep learning, the model itself chooses the features. A convolutional neural network is the most used AI-ECG model (CNN). It chooses the features to look at while predicting the result by using convolutions as filters. Each component of the input matrix (an image, an ECG, or other 2D-representable data) makes a different contribution to predicting the output depending on the weights of the convolutional layers. The neural network can be thought of as a collection of mathematical layers (such as pooling layers, rectified linear units, dropout, etc.), which receive the features selected by an extraction layer and carry out the associated operations to produce an output. These mathematical layers include the convolutional layers. Intuition and trial-and-error are used by the network designer to determine the configuration, number, and shape of the convolutional layers [16].

The ECG data shows voltage along the vertical axis and time along the horizontal axis. As a result, convolution can be 2D and accept both time and voltage information from all leads across all time points, or it can be vertical and accept voltage values from all leads, horizontal and accept voltage values from a single lead over all time points. Due to the lack of some information available to individuals, deep learning enables the network to choose characteristics and train from them without human influence or limits. The problem can now be solved most effectively using this agnostic approach, although it does encompass the neural network's inner workings. It is impossible for humans to understand why a network is analysing a certain piece of data and coming up with a particular forecast. Medical specialists are concerned about this procedure since it is a "black box" [17]. Therefore, researchers and doctors continue to see promise in less agnostic models like logistic regression, reinforcement learning, and random forest. Machine learning's reinforcement learning area rewards the model based on how well it predicts the outcome [16]. The model determines the actions required to maximise the reward. Building a number of decision trees is part of the random forest execution process. The outcome that the highest number of trees predicted ultimately matches the actual result. Another drawback of the CNN architecture is that it uses supervised learning.

In contrast to semi-supervised and unsupervised learning methods, every training data for a CNN model must be labelled. This requires a lot of time. Clustering algorithms are an example of an unsupervised learning technique that aims to learn the characteristics shared by inputs that all fall into the same class [18]. Therefore, the model can be trained with data that has not been labelled.

Additional input, such as natural language processing to process text such as prescriptions, medical records, and symptom descriptions, may be added to the neural networks described above [19]. Topic modelling using rules, text vectorization, and word patterns are all examples of these techniques. The combined results of all the networks can then be used to make an accurate prediction.

### 5.1 Mobile electrocardiogram and other wearable monitoring devices

AI and ML algorithms can be implemented on mobile and wearable devices to facilitate diagnosis at the point-of-care. Algorithms are used on single-lead [20], despite the fact that most are built for 12-lead ECG data. These algorithms are not limited to the analysis of electrocardiogram data. Photo plethysmography signals are used for passive detection of atrial fibrillation in devices like the Apple watch [10]. A single-lead ECG can also be used to estimate blood potassium levels and diagnose hypertrophic cardiomyopathy (HCM) [20, 21]. The Apple Watch uses electrophysiological data from a single bipolar vector in more recent models to detect the presence of AF [10].

### 5.2 Advantages and drawbacks of using machine learning to diagnose atrial fibrillation.

The diagnosis accuracy and workflow efficiency of AI models are superior to those of human diagnosticians. ECG data is ideal for training algorithms for machine learning due to their simplicity and minimal memory requirements. Due to researchers' access to enormous databanks and the sophisticated characteristics of contemporary computers, machine learning algorithms now outperform humans. [22] Machine learning algorithms are able to recognise incredibly weak ECG irregularities that enable them to detect AF even when the patient is not having an episode of AF. These patterns can be used to identify atrial fibrillation (AF) in addition to other cardiac conditions such hypertrophic cardiomyopathy (HCM), silent AF, and left ventricular

(LV) systolic dysfunction, as well as systemic physiology like a particular gender, age, or plasma potassium levels [20].

For machine learning algorithms to be trained and perform to acceptable standards, large amounts of data are necessary. The gathering of precise data is primarily responsible for the challenges in the widespread application of these algorithms. A model that performs well for one population but poorly for others may be produced by the data collected from one population and used to train the model. Furthermore, statistics for a particular population may change over time as a result of environmental factors. It's possible that individuals who created the model overlooked something that might have improved performance. It is obvious that the introduction of AI-related applications in the healthcare context raises a new set of problems that were previously unforeseen.

## VI. CONCLUSION

In conclusion, this research paper explored the potential of machine learning for the diagnosis of atrial fibrillation. We discussed the mechanistic elements of atrial fibrillation and various forms of the condition. We also examined the current clinical diagnosis techniques for atrial fibrillation and the role that machine learning can play in this process, including the use of mobile electrocardiograms and other wearable monitoring devices.

The advantages of using machine learning for the diagnosis of atrial fibrillation include the ability to analyse large amounts of data quickly and accurately, as well as the potential to identify patterns and trends that may not be apparent to human analysts. However, there are also drawbacks to this approach, including the potential for bias in the data used to train machine learning algorithms and the need for careful monitoring to ensure that the algorithms are performing accurately.

Overall, machine learning and deep learning have the potential to revolutionize the diagnosis of atrial fibrillation and other medical conditions. However, it is important to carefully consider the limitations of these approaches and to ensure that they are used in a responsible and ethical manner.

## VII. FUTURE WORK

Numerous studies are now being conducted with the goal of creating better, more efficient AI models. Researchers now have access to more diverse datasets that help to lessen bias in their models as the world becomes more linked and technology becomes more widely available to the general people. As a result, the application of artificial intelligence to ECG data processing (henceforth referred to as AI-ECG) will more effectively function on ECGs from a variety of populations and images with a wide range of picture quality. To acquire public confidence, like with other medical uses of artificial intelligence, models' ability to be explained is essential.

AI-interdisciplinary ECG's poses its own issues. It is imperative that those creating the technology make it sufficiently intuitive so that businesses can easily acquaint their employees with the new technology and equip them to use it efficiently in order to make the switch from conventional diagnosis to AI-ECG. The broad use of AI-ECG would be significantly hampered by regulatory clearances. Before being used, AI-ECG must be examined, confirmed, and validated, just like any other medical procedure. It might be challenging to decide what inquiries to make in order to obtain regulatory permission when we venture into new areas. It would be essential for businesses and governments to collaborate closely.

## VIII. REFERENCES

[1] Sanna, T., Diener, H.C., Passman, R.S., Di Lazzaro, V., Bernstein, R.A., Morillo, C.A., Rymer, M.M., Thijs, V., Rogers, T., Beckers, F. and Lindborg, K., 2014. Cryptogenic stroke and underlying atrial fibrillation. New England Journal of Medicine, 370(26), pp.2478-2486.

[2] Tison, G.H., Sanchez, J.M., Ballinger, B., Singh, A., Olgin, J.E., Pletcher, M.J., Vittinghoff, E., Lee, E.S., Fan, S.M., Gladstone, R.A. and Mikell, C., 2018. Passive detection of atrial fibrillation using a commercially available smartwatch. JAMA cardiology, 3(5), pp.409-416.

[3] Kochiadakis, G.E., Skalidis, E.I., Kalebubas, M.D., Igoumenidis, N.E., Chrysostomakis, S.I., Kanoupakis, E.M., Simantirakis, E.N. and Vardas, P.E., 2002. Effect of acute atrial fibrillation on phasic coronary blood flow pattern and flow reserve in humans. European heart journal, 23(9), pp.734-741.

[4] Range, F.T., Schäfers, M., Acil, T., Schäfers, K.P., Kies, P., Paul, M., Hermann, S., Brisse, B., Breithardt, G., Schober, O. and Wichter, T., 2007. Impaired myocardial perfusion and perfusion reserve associated with increased coronary resistance in persistent idiopathic atrial fibrillation. European heart journal, 28(18), pp.2223-2230.

[5] Skinner Jr, N.S., Mitchell, J.H., Wallace, A.G. and Sarnoff, S.J., 1964. Hemodynamic consequences of atrial fibrillation at constant ventricular rates. The American journal of medicine, 36(3), pp.342-350.

[6] Dorian, P., Guerra, P.G., Kerr, C.R., O'Donnell, S.S., Crystal, E., Gillis, A.M., Mitchell, L.B., Roy, D., Skanes, A.C., Rose, M.S. and Wyse, D.G., 2009. Validation of a new simple scale to measure symptoms in atrial fibrillation: the Canadian Cardiovascular Society Severity in Atrial Fibrillation scale. Circulation: Arrhythmia and Electrophysiology, 2(3), pp.218-224.

[7] Daoud, E.G., Bogun, F., Goyal, R., Harvey, M., Man, K.C., Strickberger, S.A. and Morady, F., 1996. Effect of atrial fibrillation on atrial refractoriness in humans. Circulation, 94(7), pp.1600-1606.

[8] Page, R.L., Wilkinson, W.E., Clair, W.K., McCarthy, E.A. and Pritchett, E.L., 1994. Asymptomatic arrhythmias in patients with symptomatic paroxysmal atrial fibrillation and paroxysmal supraventricular tachycardia. Circulation, 89(1), pp.224-227.

[9] Strickberger, S.A., Ip, J., Saksena, S., Curry, K., Bahnson, T.D. and Ziegler, P.D., 2005. Relationship between atrial tachyarrhythmias and symptoms. Heart Rhythm, 2(2), pp.125-131.

[10] Patten, M., Maas, R., Karim, A., MÜLLER, H.W., Simonovsky, R. and Meinertz, T., 2006. Event-recorder monitoring in the diagnosis of atrial fibrillation in symptomatic patients: Subanalysis of the SOPAT trial. Journal of cardiovascular electrophysiology, 17(11), pp.1216-1220.

[11] Patten, M., Maas, R., Karim, A., MÜLLER, H.W., Simonovsky, R. and Meinertz, T., 2006. Event-recorder monitoring in the diagnosis of atrial fibrillation in symptomatic patients: Subanalysis of the SOPAT trial. Journal of cardiovascular electrophysiology, 17(11), pp.1216-1220.

[12] Orlov, M.V., Ghali, J.K., ARAGHI-NIKNAM, M.O.H.S.E.N., Sherfesee, L.O.U., Sahr, D., Hettrick, D.A. and Atrial High Rate Trial Investigators, 2007. Asymptomatic atrial fibrillation in pacemaker recipients: incidence, progression, and determinants based on the atrial high rate trial. Pacing and clinical electrophysiology, 30(3), pp.404-411.

[13] Rumelhart, D.E., Hinton, G.E. and Williams, R.J., 1986. Learning representations by back-propagating errors. nature, 323(6088), pp.533-536.

[14] Todorov, T., Bogdanova, G., Noev, N. and Sabev, N., 2019. Data management in a Holter monitoring system. Tem Journal, 8(3), pp.801-805.

[15] LeCun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W. and Jackel, L.D., 1989. Backpropagation applied to handwritten zip code recognition. Neural computation, 1(4), pp.541-551.

[16] Rudin, C., 2019. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), pp.206-215.

[17] Alashwal, H., El Halaby, M., Crouse, J.J., Abdalla, A. and Moustafa, A.A., 2019. The application of unsupervised clustering methods to Alzheimer's disease. Frontiers in computational neuroscience, 13, p.31.

[18] Chary, M., Parikh, S., Manini, A.F., Boyer, E.W. and Radeos, M., 2019. A review of natural language processing in medical education. Western Journal of Emergency Medicine, 20(1), p.78.

[19] Ko, W.Y., Siontis, K.C., Attia, Z.I., Carter, R.E., Kapa, S., Ommen, S.R., Demuth, S.J., Ackerman, M.J., Gersh, B.J., Arruda-Olson, A.M. and Geske, J.B., 2020. Detection of hypertrophic cardiomyopathy using a convolutional neural network-enabled electrocardiogram. Journal of the American College of Cardiology, 75(7), pp.722-733.

[20] Yasin, O.Z., Attia, Z., Dillon, J.J., DeSimone, C.V., Sapir, Y., Dugan, J., Somers, V.K., Ackerman, M.J., Asirvatham, S.J., Scott, C.G. and Bennet, K.E., 2017. Noninvasive blood potassium measurement using signal-processed, single-lead ecg acquired from a handheld smartphone. Journal of electrocardiology, 50(5), pp.620-625.

[21] Siontis, K.C., Noseworthy, P.A., Attia, Z.I. and Friedman, P.A., 2021. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nature Reviews Cardiology, 18(7), pp. 465-478.