*Artificial Intelligence in Electrocardiogram for Classifying Arrhythmia: Review

***Mr. Ragavan Veerarajan [1*], Dr. Vanitha V [2]**

[*1] Research Scholar, Sri Ramachandra Faculty of engineering and Technology, Sri Ramachandra Institute of Higher Education and Research; ragavanveerarajan24@gmail.com (Orcid-ID- 0009-0003-1880-1228)

[2] Associate Professor, Sri Ramachandra Faculty of engineering and Technology, Sri Ramachandra Institute of Higher Education and Research; vanithav@sret.edu.in (Orcid-ID - 0000-0003-1010-3241)

* Correspondence: ragavanveerarajan24@gmail.com)

Cite this paper as: Mr. Ragavan Veerarajan , Dr. Vanitha V (2025) Artificial Intelligence in Electrocardiogram for Classifying Arrhythmia: Review. *Frontiers in Health Informatics, 14* (1), 227-240

***Abstract:** In recent years, artificial intelligence has been developing rapidly in terms of software algorithms such as machine learning, deep learning, reinforcement learning, and hardware implementations like IoT, embedded systems, and sensor network systems. Arrhythmia is a medical condition that occurs when the normal pumping mechanism of the human heart becomes irregular. Detecting arrhythmia types is one of the essential steps in diagnosing the condition, and it can help cardiologists make decisions. This paper summarizes the latest developments in artificial intelligence for electrocardiogram-based arrhythmia type classification problems. This review aims to keep track of new medical and computer science accomplishments in recent years. This study will also help understand the workspace available in cardiology with artificial intelligence and inspire naive researchers using the recent research findings. Furthermore, this paper presents a systematic review of artificial intelligence, data mining, machine learning, and deep learning with feature extraction methods for building the AI model for cardiological data.

***Keywords:** Arrhythmia, artificial intelligence, feature extraction

1. *Introduction

Cardiology is a branch of medical science that deals with disorders of the heart and some parts of the circulatory system. Cardiologists diagnose and treat conditions such as congenital heart defects, coronary artery disease, electrophysiology, heart failure, and valvular heart disease. In most cases, cardiologists use an electrocardiogram (ECG) as a diagnostic tool. An ECG captures the physiological activities of the heart over a period. ECG charts help cardiologists understand the behavior of patients' hearts. Cardiologists easily find abnormalities of the heart such as atrial fibrillation (AF), premature atrial contraction (PAC), premature ventricle contraction (PVC), myocardial infarction (MI), and congestive heart failure (CHF). Generally, the heart signals are referred to by P, Q, R, S, and T waves [1]. A P wave occurs during atrial depolarization, a QRS complex wave during ventricular depolarization, and a T wave occurs during ventricular repolarization. One cardiac cycle starts from the P wave to the T wave, as shown in Figure 1.

1.1 Atrial fibrillation (AF):

Humans' dangerous situations are blood clots, strokes, heart failure, and other heart-related complications. This happens due to an irregular heartbeat (arrhythmia) called A-Fib, or Atrial Fibrillation. The human heart comprises four chambers (two atrial chambers and two ventricle chambers), two upper chambers called atria, and two lower chambers called ventricles. Within the upper right chamber of the human heart (right atrium) is a group of cells called the sinus node. This is the human heart's natural pacemaker. Each heartbeat starts with the signal produced by the heart's sinus node. The signal travels through the two upper heart chambers and through a connecting pathway between the upper and lower chambers called the atrioventricular (AV) node. Because of the signal movements, the heart squeezes (contracts), sending blood to your heart and body [1]. Usually, the human heart contracts and relaxes to a regular beat. In atrial fibrillation, the atrial part of the heart (upper chambers of the heart) beats irregularly instead of effectively moving blood into the ventricles. A stroke results if a clot breaks off, enters the bloodstream, and lodges in an artery leading to the brain. This heart arrhythmia affects approximately 15–20 percent of stroke patients. Even though untreated atrial fibrillation doubles the risk of heart-related deaths and is associated with a 5-fold increased risk of stroke, many patients are unaware that A-Fib is a serious condition [2].

1.2 Premature atrial contraction (PAC):

Premature atrial contractions (PACs) are contractions of the atria that are triggered by the atrial myocardium but have not originated from the sinoatrial node (SA node). PACs are commonly referred to as atrial premature complexes (APCs), premature supraventricular complexes (PSVs), premature supraventricular beats, and premature atrial beats. This phenomenon can be caused by an assortment of medical diseases, structural abnormalities, pharmaceuticals, and non-regulated compounds. [3].

1.3 Myocardial infarction (MI):

A heart attack is medically called a myocardial infarction (MI). The heart's blood flow decreases or stops at a part of the heart that causes this myocardial infarction. The most common symptom is chest pain or discomfort, which may travel into the shoulder, arm, back, neck, or jaw. Myocardial infarctions are one of the leading causes of death in the developed world, with a prevalence approaching three million people worldwide and more than one million deaths in the United States annually. This activity reviews the presentation, evaluation, and management of patients with myocardial infarctions and highlights the role of the interprofessional team in caring for these patients. [4].

1.4 Congestive heart failure (CHF):

Congestive heart failure (CHF) is a chronic, progressive condition affecting the heart muscle's pumping power. While often referred to simply as heart failure, CHF specifically refers to the stage in which fluid builds up within the heart and causes it to pump inefficiently. CHF develops when the ventricles can't pump enough blood volume to the body. Eventually, blood and other fluids can back up inside human parts: the lungs, abdomen, liver, and lower body. CHF can be life-threatening. In today's era, the rising volume of patients is driven by these heart problems. Traditional health care models and software are insufficient to deal with affected people with timely and high-quality outcomes. Therefore, healthcare experts, medical scientists, and researchers focus on a new, intelligent patient and data-oriented approach. Artificial intelligence, machine learning, deep learning, natural language processing, reinforcement learning, IoT, and robotic medical systems are promising areas in medical fields. They thus could help diagnose heart failure patients efficiently [5]. The next part of cardiology is monitoring and measuring the heart's health. The two major measuring tools are echocardiography and electrocardiography (ECG). An echocardiogram is a live imaging test that doctors use to monitor heart activity. The principle of echocardiography is echoing. (For example, when we seek into a well, the echo returns a fraction of a second later because our sound wave reflects off a surface.) the same principle is applied to cardiac ultrasound. Echo generates cardio images using high-pitched sound waves. Echocardiograms can help physicians view live feeds of a beating heart to get important functional data about heart health [6]. An ECG is a medical device. Doctors usually use ECG to understand the electrical activity of a patient's heart. An electrocardiogram charts the electrical rhythm of a patient's heart in the form of waves. Waves that are inconsistent, irregular, or non-standard can be a sign of heart disease. The purpose of an electrocardiogram is to help the doctor understand the heart's health and check for abnormalities [7]. Heart Echo and ECG provide different kinds of heart measurement results to doctors. Even though two devices give suitable measurement parameters, doctors still need time to select the treatment method. In recent days, deep learning and AI-based algorithms have the highly accurate capability of interpreting the echo and ECG results, classifying heart problems, and deciding on further treatments [8]. In the upcoming sections of this paper, we will discuss how artificial intelligence helps cardiologists from the perspective of measuring devices like echo and ECG, heart problems like A-fib, CHF, MCI, and others.

2. ECG INTERPRETATION:

Arrhythmias are frequently detected through electrocardiogram monitoring. Because of aging populations, the availability of simple-to-use wearable devices and the quantity of ECG recordings are growing [9]. The initial step in ECG analysis is capturing the QRS complex wave pattern from the ECG data. The various QRS complex wave shapes cause the majority of arrhythmias. In other words, arrhythmias are described using the QRS waveform structure. QRS detection techniques are divided into four groups: There are four approaches: (i) syntactic approaches, (ii) non-syntactic approaches, (iii) hybrid approaches, and (iv) transformational approaches [10]. QRS detection methods based on pattern recognition are used in the syntactic approach. Non-syntactic techniques use digital filters to eliminate extraneous components from ECG data and output just the QRS waves. Non-syntactic techniques are commonly employed. The hybrid technique combines syntactic and non-syntactic approaches to detect the QRS complex. These are not often used. The transformative techniques used include Fourier Transform, Cosine Transform, Pole–Zero Transform, Differentiator Transform, Hilbert Transform, and Wavelet Transform to detect the QRS complex patterns [11].

3. NEURAL NETWORK

With the advent of big data, tremendous opportunities have emerged to develop AI systems that are more efficient, supporting not just clinicians but also countries in providing better healthcare to their residents [12]. Deep learning relies heavily on artificial neural networks (ANNs). They are adaptable, robust, and scalable, making them suitable for large-scale, high-complexity machine learning applications like classifying billions of photos, enabling voice recognition, identifying arrhythmias, and segmenting tumors. Surprisingly, ANNs have been around for a long time;

Warren McCulloch, a neurophysiologist, and Walter Pitts, a mathematician, initially presented them in 1943 in their seminal work. [13].McCulloch and Pitts offered a simple computational model of how biological neurons in animal brains may work together to accomplish complicated computations using propositional logic. The first artificial neural network architecture was created in this way. A neural network is a highly complicated structure composed of interconnected neurons that offers exciting alternative solutions for complex problem solving and other applications. In today's computer science field, researchers from various disciplines are developing artificial neural networks to solve problems like pattern recognition, prediction, optimization, associative memory, and control [14]. We will start with the biological neuron before moving on to the artificial neurons.

The biological neuron in Figure 2 is made up of a cell body that contains the nucleus and most of the cell's complicated components, as well as multiple branching extensions called dendrites and one very long extension called the axon. The axon's length can range from a few millimeters to tens of thousands of millimeters, longer than the cell body. The axon divides into multiple branches termed telocentric towards its extremities. At the tips of these branches are microscopic structures known as synaptic terminals (or) synapses, which are linked to the dendrites (or) directly to the cell bodies of other neurons. These synapses allow biological neurons to receive brief electrical impulses called "messages" (signals) from other neurons. When a neuron briefly gets adequate messages (signals) from other neurons, it fires its own signals. Individual biological neurons appear simple, but they are arranged in a massive network of billions of neurons, with each neuron often linked to thousands of other neurons. A vast network of relatively primary neurons may conduct highly complicated calculations, just like a sophisticated anthill can grow from the joint efforts of simple ants. In 1957, Frank Rosenblatt invented the Perceptron model shown in Figure 3. one of the simplest ANN architectures. It is built on an artificial neuron that was a little unusual. Numbers are used as inputs and outputs. Each input connection has a weight associated with it. The perceptron calculates the weighted sum of its input using the formula $y = w_1x_1 + w_2x_2 + \cdots + w_nx_n = X^T.W$, then applies a step function to them and outputs the result $h_w(x) = step\ (y), where\ \ y = X^T.W$.

As we will see in this chapter, many additional architectures have been developed since then. There are several reasons to believe that this AI wave will be different and will have a far greater influence on our lives: (i)there is a greater volume of data available, (ii)higher processing power, and (iii)incredible AI-based technologies consistently make headline news [15].

3.1. CNN

Deep learning has several advantages over traditional machine learning techniques, including the ability to find meaningful characteristics in high-dimensional data independently of a simple neural network. CNN has evolved as a popular approach for classifying objects based on their environment. It has a tremendous capacity to absorb contextual information and, as a result, has solved the challenges of pixel-by-pixel categorization. It greatly reduces the number of parameters necessary [16]. A convolutional neural network is made up of three layers: convolution layers, pooling layers, and fully connected layers, and it learns spatial hierarchies of data automatically and adaptively using a backpropagation method. The first two layers, convolution, and pooling extract feature, while the third, a fully connected layer, transfers the collected features into a final output, such as classification. A convolution layer is an integral part of CNN, comprising a stack of mathematical operations like convolution and a specific linear operation. As previous layers feed their outcomes to the next layer, the extracted characteristics can grow in-depth in a hierarchical manner, which is shown in figure 4. The iterative process of achieving a good result is called training. Model training reduces the difference between output and labels through optimization algorithms such as gradient descent and backpropagation [17]. The ability to extract features varies depending on the CNN structure. The classification performance of the CNN classifier will improve as the convolutional layer is deepened. However, when the convolutional layer extends to a given depth, the classifier's performance deteriorates, and the training time increases. [18].

3.2. RNN

Recurrent neural networks are intended to comprehend temporal or sequential data. These networks use other data points in a sequence to create better predictions. They do this by accepting input and exploiting the activations of previous or later nodes in the sequence to impact the output. Because ECG data are essentially sequential time series data, RNN structures are well suited to learning hidden patterns from ECG signals. CNN is a feed-forward artificial neural network that employs multilayer perceptron with little pre-processing. RNNs, unlike feed-forward neural networks, can handle arbitrary sequences of inputs using their internal memory. Recurrent neural networks were created because of their highly dynamic activity, whereas multilayer feed-forward networks have static mappings. RNNs have been employed in a variety of applications, including associative memory, optimization, and generalization. [19]. Another important RNN architecture is the long short-term memory (LSTM) network, a form of RNN commonly employed for time series analysis. It can successfully remember previous knowledge and realize long-term text reliance learning. It has been used in various applications, including natural language processing and speech recognition. LSTM is also utilized to identify ECG arrhythmias. Recent research shows LSTMs are highly capable of classifying ECG signals, producing 99.74% average accuracy for ECG classification problems [20].figure 5 depicts the general RNN architecture for the classification problems.

3.3. GAN

A Generative Adversarial Network (GAN) comprises two neural networks, one generator and one discriminator, and each network competes with the other. The generator network learns to map a noise vector to the data distribution it wishes to create. The generator's purpose is to generate data samples comparable to the samples in the original dataset. The discriminator network, on the other hand, gets data samples from either created (fake) or genuine (real) samples and is responsible for identifying whether the received samples are real or false [21]. GAN-based ECG Classification models are best suited for real-time ECG monitoring, where they can perform reliably and effectively. Generally, GAN models support the dual learning task of synthesizing adversarial ECG signals while classifying the signal category [22].

4. ECG DATA SOURCES

The collection of ECG data frequently necessitates using costly hardware, a medical specialist's assistance, and the target patients' consent. As a result, to improve ECG-centric research for numerous applications, one of which is AF, researchers have created public databases such as physionet. The availability of such information brings up many options for experimenting with various feature extraction and ML approaches in building machine learning-driven solutions [23]. ECG annotations are frequently expensive to gather, limiting the size of many ECG data sets and preventing the collection of a vast ECG database that reflects the heterogeneity of ECG data. The optimal solution to the arrhythmia classification problem is to investigate unsupervised and self-supervised (i.e., labels are created automatically) algorithms for larger datasets[24]. Table 1 provides the major Physionet ECG databases with specifications.

Thanks again to Physionet for donating the ECG digital data registries. Physionet challenges are another reason why ECG-based arrhythmia classification is more acceptable. Many well-known healthcare companies are launching conceptual framework gathering events on AI-based cardiac issues using the physionet challenges platform. Table 2 lists the most popular Physionet cardiac challenges from 2010 to 2021.

The number of users and researchers participating in physionet challenges has grown in recent years. Figure 6 depicts the performance of the physionet tasks during the last few years. In Table 2, from 2010 to 2014, the information about the arrhythmia classification challenges is taken from the components of a new research resource for a complex physiologic signals database [28].

5. ARTIFICIAL INTELLIGENCE APPROACH TO CLASSIFY THE ECG SIGNALS:

Artificial intelligence (AI) is a broad field of computer science that focuses on creating intelligent computers that can accomplish activities that normally require human intelligence. Although ECG has long provided useful insights into cardiac and non-cardiac health and illness, interpreting it requires significant human ability. The use of AI in the ECG is an important phenomenon. Advanced AI technologies, like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short Term Memory (LSTM) Architecture, and Generalized Adversarial networks (GAN), have enabled quick, human-like ECG interpretation. In contrast, multilayer AI networks can identify signals and patterns that are essentially incomprehensible to human interpreters, making the ECG a strong, non-invasive diagnostic. The AI models for detecting arrhythmias like left ventricular dysfunction, atrial fibrillation, and hypertrophic cardiomyopathy, as well as determining a person's age, sex, and race, among other phenotypes, have been developed using large sets of digital ECGs linked to rich clinical data. With the fast development in the availability of mobile and wearable ECG devices, AI-based ECG phenotyping's clinical and population-level implications are still being discovered. [37]. Using 91,232 single-lead ECGs from 53,549 individuals who used a single-lead ambulatory ECG monitoring equipment, a deep neural network (DNN) was able to classify 12 rhythm classes (atrial fibrillation and flutter, AVB (*atrioventricular block*), Bigeminy, EAR (*ectopic atrial rhythm*), IVR (*idioventricular rhythm*), Junctional rhythm, noise, sinus rhythm, SVT (*supraventricular tachycardia*), Trigeminy, Ventricular tachycardia, Wenckebach). For every 256 input samples, the network receives raw ECG data (sampled at 200 Hz or 200 samples per second) and produces a prediction of one of 12 potential rhythm classes. By effectively training or emphasizing the most critical problems, this strategy might lower the rate of misdiagnosed automated ECG readings and enhance the efficiency of expert human ECG interpretation [38]. In 2018, Pawel Plawiak and UR Acharya [39] demonstrated that a complex machine learning architecture could achieve 99.37 percent accuracy for a 17-class electrocardiogram classification problem. They created a 48 + 4 + 1 Genetic Algorithmic architecture that uses the MIT Arrhythmia database to classify 17 ECG classes ("*Normal sinus rhythm, Atrial premature beat, Atrial flutter, Atrial fibrillation, Supraventricular tachycardia, Pre-excitation (WPW), Premature ventricular contraction, Ventricular bigeminy,* *Ventricular trigeminy, Ventricular tachycardia, Idioventricular rhythm, Ventricular flutter, Fusion of ventricular and normal beat, Left bundle branch block beat, Right bundle branch block beat, Second-degree heart block, Pacemaker rhythm.")* from 29 patients' records. The architecture is made up of three layers: the first layer has 48 models (*12 SVM (Support Vector Machine) + 12 KNN (K-Nearest Neighbour) + 12 PNN (Probabilistic Neural Network + 12 RBFNN*), and the second layer contains four SVM models. The final layer contains one SVM model with robust ensembling features. This model can be used in cloud computing or mobile devices to quickly assess cardiac health with the highest specificity score (99.6 percent). Bahareh Pourbabaee, Mehrsan Javan Roshtkhar, and Khashayar Khorasani [40] experimented with five deep learning architectures to detect arrhythmias in an ECG signal. They employ two segments: the first extracts the essential features from the input ECG signals, and the second classifies the arrhythmia using filtered signals. They make use of the PAF Prediction Challenge Database v1.0.0 [41]. Table 3 displays their experimental details along with their f1 score. The feature extraction tasks are dominated by the KNN and Gaussian SVM models. Compared to handcrafted features, experimental results confirm the effectiveness of the learned features for patient screening. F1 Score is calculated using the formula F1 Score=2*(Precision*Recall) Precision+ Recall.

3.2. Figures, Tables and Schemes

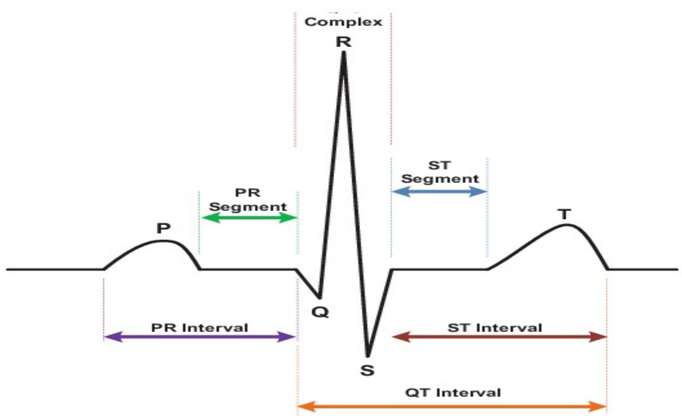

Figure 1. One cardiac cycle Waves

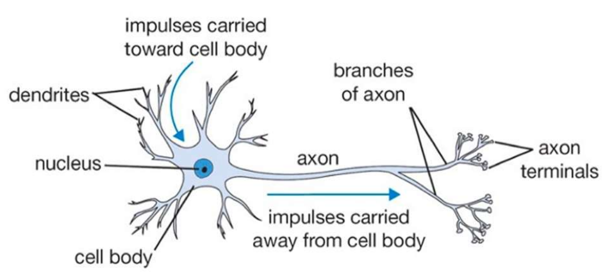

Figure 2. Biological Neuron

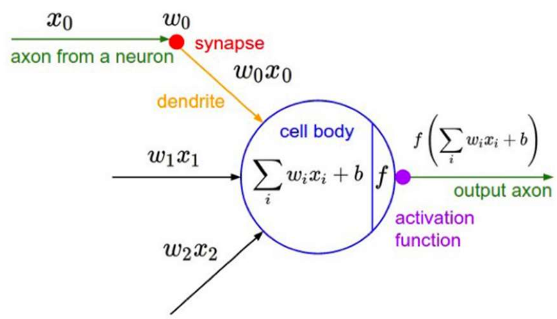

Figure 3. Perceptron Model

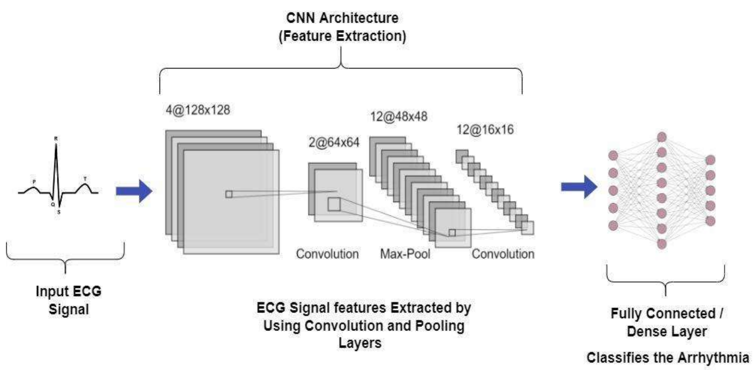

Figure 4. General CNN Architecture for Arrhythmia Classification

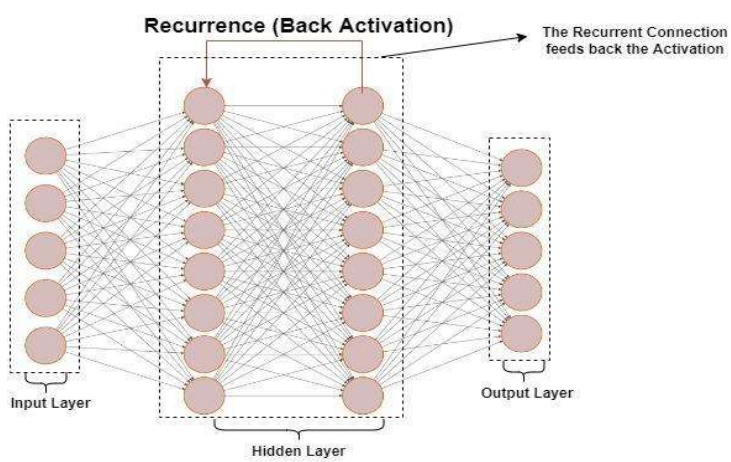

Figure 5. General RNN Architecture

Figure 6. Performance of Physionet cardiac challenges

Table 1. ECG Data Registries for Arrhythmia Classifications

S.No	Physionet Challenges	Specifications	ECG Record details
1	MIT-BIH: The Massachusetts Institute of Technology – Beth Israel Hospital Arrhythmia Database [25].	The MIT-BIH Arrhythmia Database comprises 48 half-hour snippets of two-channel ambulatory ECG recordings acquired from the BIH Arrhythmia Laboratory's 47 patients.	48 records of 30 min each
2	EDB: The European Society of Cardiology ST-T Database [26].	The European ST-T Database evaluates algorithms for analyzing ST and T-wave variations.	90 records of 2 hours each
3	NST: The Noise Stress Test Database [27].	This collection contains 12 half-hour ECG recordings and three half-hour noisy recordings typical of ambulatory ECG recordings. The noise recordings were made with physically active volunteers and conventional ECG recorders, leads, and electrodes; the electrodes were positioned on the individuals' limbs in areas where the ECGs could not be seen.	12 records of ECG of 30 min each, plus three records with noise excess
4	Intracardiac Atrial Fibrillation Database [28].	This collection contains endocardial recordings from the right atria of eight atrial fibrillation patients. The database has four records for each of the eight patients (one for each placement). Each record's name	8 Records of ECG Sampled at 1Khz frequency

		identifies the patient (iaf1, iaf2,... iaf8) and the catheter placement (svc, ivc, tva, afw). Each record has eight signals (intracardiac: CS12-CS90, or ECG: I, II, V1, aVF). Each signal is sampled at 1 kHz with a 14-bit resolution, and the amplitudes are uncalibrated.	
5	Long Term AF Database [29].	This database contains 84 long-term ECG recordings from patients with paroxysmal or persistent atrial fibrillation (AF). Each record comprises two ECG signals collected concurrently at 128 Hz with 12-bit resolution across a 20 mV range; record lengths vary but are generally 24 to 25 hours.	84 long-term Records up to 24 to 25 hours

Table 2. Physionet challenges and year wise research outcomes

Year	**Physionet Challenge Name**	**Number of Resultant Publications**	**Source Code Availability**
2021	Will Two Do? Varying Dimensions in Electrocardiography: The PhysioNet/Computing in Cardiology Challenge 2021 [30].	60	Still not Accessible
2020	Classification of 12-lead ECGs: The PhysioNet/Computing in Cardiology Challenge 2020 [31].	62	Still not Accessible
2019	Early Prediction of Sepsis from Clinical Data: The PhysioNet/Computing in Cardiology Challenge 2019 [32].	55	90
2018	You Snooze You Win: The PhysioNet/Computing in Cardiology Challenge 2018 [33].	32	18
2017	AF Classification from a Short Single Lead ECG Recording: The PhysioNet/Computing in Cardiology Challenge 2017 [34].	44	68
2016	Classification of Heart Sound Recordings: The PhysioNet/Computing in Cardiology Challenge 2016 [35].	13	47

2015	Reducing False Arrhythmia Alarms in the ICU: The PhysioNet/Computing in Cardiology Challenge 2015 [36].	20	27
2014	Robust Detection of Heart Beats in Multimodal Data: The PhysioNet/Computing in Cardiology Challenge 2014.	15	34
2013	Non-invasive Fetal ECG: The PhysioNet/Computing in Cardiology Challenge 2013.	29	24
2012	Predicting Mortality of ICU Patients: The PhysioNet/Computing in Cardiology Challenge 2012.	17	15
2011	Improving the Quality of ECGs Collected using Mobile Phones: The PhysioNet/Computing in Cardiology Challenge 2011.	17	6
2010	Mind the Gap: The PhysioNet/Computing in Cardiology Challenge 2010.	12	4

Table 3. Performance Indices for the Combination of Feature Extraction and Classification Architecture

Experiment Number	Feature Extraction Method	Classification Method	Precision	Recall	F1 Score
1	CNN	CNN	93.60	76.47	84.17
2	KNN	CNN	90.79	90.20	90.49
3	Linear SVM	CNN	87.58	87.58	87.58
4	Gaussian SVM	CNN	92.96	86.27	89.49
5	Multi-Layer Perceptron	CNN	90.65	82.35	86.30

6. CONCLUSION

In this study, we have discussed the different types of heart arrhythmias, the importance of detecting the arrhythmia, and the challenges available in the ECG monitoring and arrhythmia detection process. We also reviewed the various artificial intelligence methodologies already used for the arrhythmia classification problem. The AI methods involve feature extraction and classification steps for this classification problem. This study aimed to investigate efficient feature extraction and neural network methods for the arrhythmia classification problem. It is also concluded that using a proper combination of feature extraction and classification network can improve the performance of the arrhythmia classifier.

Funding: This research received no external funding

*References

1. Amin, A., Houmsse, A., Ishola, A., Tyler, J., Houmsse, M. The current approach of atrial fibrillation management. Avicenna journal of medicine. 2016; 6(01): 8-16.
2. Heaton, J., Yandrapalli, S. Premature atrial contractions. StatPearls [Internet]: StatPearls Publishing; 2020.
3. Mechanic, O. J., Gavin, M., Grossman, S. A., Ziegler, K. Acute Myocardial Infarction (Nursing). StatPearls [Internet]: StatPearls Publishing; 2021.
4. Ntiloudi, D., Gatzoulis, M. A., Arvanitaki, A., Karvounis, H., Giannakoulas, G. Adult congenital heart disease: looking back, moving forward. International Journal of Cardiology Congenital Heart Disease. 2021; 2: 100076.
5. Malik, A., Brito, D., Vaqar, S., Chhabra, L. Congestive Heart Failure. StatPearls. Treasure Island (FL): StatPearls Publishing Copyright © 2022, StatPearls Publishing LLC.; 2022.
6. Joshi, A. K., Tomar, A., Tomar, M. A review paper on analysis of electrocardiograph (ECG) signal for the detection of arrhythmia abnormalities. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering. 2014; 3(10): 12466-12475.
7. Barrett, M., Boyne, J., Brandts, J., Rocca, B.-L., De Maesschalck, L., De Wit, K.*, et al.,* Artificial intelligence supported patient self-care in chronic heart failure: a paradigm shift from reactive to predictive, preventive and personalised care. Epma Journal. 2019; 10(4): 445-464.
8. Pană, M.-A., Busnatu, Ș.-S., Serbanoiu, L.-I., Vasilescu, E., Popescu, N., Andrei, C.*, et al.,* Reducing the Heart Failure Burden in Romania by Predicting Congestive Heart Failure Using Artificial Intelligence: Proof of Concept. Applied Sciences. 2021; 11(24): 11728.
9. Hatala, R., Norman, G. R., Brooks, L. R. Impact of a clinical scenario on accuracy of electrocardiogram interpretation. Journal of general internal medicine. 1999; 14(2): 126-129.
10. Drezner, J. A., Asif, I. M., Owens, D. S., Prutkin, J. M., Salerno, J. C., Fean, R.*, et al.,* Accuracy of ECG interpretation in competitive athletes: the impact of using standardised ECG criteria. British journal of sports medicine. 2012; 46(5): 335-340.
11. Breen, C., Kelly, G., Kernohan, W. ECG interpretation skill acquisition: A review of learning, teaching and assessment. Journal of electrocardiology. 2019.
12. Hayman, S., editor The mcculloch-pitts model. IJCNN'99 International Joint Conference on Neural Networks Proceedings (Cat No 99CH36339); 1999: IEEE.
13. Pooja Patidar, P. S., Priyanka Mangal Artificial Neural Network. IJERT. 2018; NCETECE – 2014 (Volume 2 – Issue 10)(Issue 10).

14. Indolia, S., Goswami, A. K., Mishra, S. P., Asopa, P. Conceptual understanding of convolutional neural network-a deep learning approach. Procedia computer science. 2018; 132: 679-688.
15. Géron, A. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems: " O'Reilly Media, Inc."; 2019.
16. Yamashita, R., Nishio, M., Do, R. K. G., Togashi, K. Convolutional neural networks: an overview and application in radiology. Insights into imaging. 2018; 9(4): 611-629.
17. Yao, G., Mao, X., Li, N., Xu, H., Xu, X., Jiao, Y.*, et al.,* Interpretation of electrocardiogram heartbeat by CNN and GRU. Computational and Mathematical Methods in Medicine. 2021; 2021.
18. Shaker, A. M., Tantawi, M., Shedeed, H. A., Tolba, M. F. Generalization of convolutional neural networks for ECG classification using generative adversarial networks. IEEE Access. 2020; 8: 35592-35605.
19. Singh, S., Pandey, S. K., Pawar, U., Janghel, R. R. Classification of ECG arrhythmia using recurrent neural networks. Procedia computer science. 2018; 132: 1290-1297.
20. Hou, B., Yang, J., Wang, P., Yan, R. LSTM-based auto-encoder model for ECG arrhythmias classification. IEEE Transactions on Instrumentation and Measurement. 2019; 69(4): 1232-1240.
21. Hossain, K. F., Kamran, S. A., Tavakkoli, A., Pan, L., Ma, X., Rajasegarar, S.*, et al.,*, editors. ECG-Adv-GAN: Detecting ECG Adversarial Examples with Conditional Generative Adversarial Networks. 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA); 2021: IEEE.
22. Zhou, Z., Zhai, X., Tin, C. Fully automatic electrocardiogram classification system based on generative adversarial network with auxiliary classifier. Expert Systems with Applications. 2021; 174: 114809.
23. Rizwan, A., Zoha, A., Mabrouk, I. B., Sabbour, H. M., Al-Sumaiti, A. S., Alomainy, A.*, et al.,* A review on the state of the art in atrial fibrillation detection enabled by machine learning. IEEE reviews in biomedical engineering. 2020; 14: 219-239.
24. Weimann, K., Conrad, T. O. Transfer learning for ECG classification. Scientific reports. 2021; 11(1): 1-12.
25. Moody, G. B., Mark, R. G. The impact of the MIT-BIH arrhythmia database. IEEE Engineering in Medicine and Biology Magazine. 2001; 20(3): 45-50.
26. Taddei, A., Distante, G., Emdin, M., Pisani, P., Moody, G., Zeelenberg, C.*, et al.,* The European ST-T database: standard for evaluating systems for the analysis of ST-T changes in ambulatory electrocardiography. European heart journal. 1992; 13(9): 1164-1172.
27. Moody, G. B., Muldrow, W., Mark, R. G. A noise stress test for arrhythmia detectors. Computers in cardiology. 1984; 11(3): 381-384.
28. Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G.*, et al.,* PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. circulation. 2000; 101(23): e215-e220.
29. Petrutiu, S., Sahakian, A. V., Swiryn, S. Abrupt changes in fibrillatory wave characteristics at the termination of paroxysmal atrial fibrillation Ghassemi, M. M., Moody, B. E., Lehman, L.-W. H., Song, C., Li, Q., Sun, H.*, et al.,*, editors. You snooze, you win: the physionet/computing in cardiology challenge 2018. 2018 Computing in Cardiology Conference (CinC); 2018: IEEE.in humans. Europace. 2007; 9(7): 466-470.

30. Reyna, M. A., Sadr, N., Alday, E. A. P., Gu, A., Shah, A. J., Robichaux, C.*, et al.,*, editors. Will two do? Varying dimensions in electrocardiography: the PhysioNet/Computing in Cardiology Challenge 2021. 2021 Computing in Cardiology (CinC); 2021: IEEE.
31. Perez Alday, E. A., Gu, A., Shah, A., Liu, C., Sharma, A., Seyedi, S., Bahrami Rad, A., Reyna, M., & Clifford, G. D. Classification of 12-lead ECGs: The PhysioNet/Computing in Cardiology Challenge 2020 (version 1.0.1). PhysioNet. 2020. doi: https://doi.org/10.13026/f4ab-0814.
32. Reyna, M. A., Josef, C., Seyedi, S., Jeter, R., Shashikumar, S. P., Westover, M. B.*, et al.,*, editors. Early prediction of sepsis from clinical data: the PhysioNet/Computing in Cardiology Challenge 2019. 2019 Computing in Cardiology (CinC); 2019: IEEE.
33. Ghassemi, M. M., Moody, B. E., Lehman, L.-W. H., Song, C., Li, Q., Sun, H.*, et al.,*, editors. You snooze, you win: the physionet/computing in cardiology challenge 2018. 2018 Computing in Cardiology Conference (CinC); 2018: IEEE.
34. Clifford, G. D., Liu, C., Moody, B., Li-wei, H. L., Silva, I., Li, Q.*, et al.,*, editors. AF classification from a short single lead ECG recording: The PhysioNet/computing in cardiology challenge 2017. 2017 Computing in Cardiology (CinC); 2017: IEEE.
35. Liu, C., Springer, D., Li, Q., Moody, B., Juan, R. A., Chorro, F. J.*, et al.,* An open access database for the evaluation of heart sound algorithms. Physiological Measurement. 2016; 37(12): 2181.
36. Clifford, G. D., Silva, I., Moody, B., Li, Q., Kella, D., Shahin, A.*, et al.,*, editors. The PhysioNet/computing in cardiology challenge 2015: reducing false arrhythmia alarms in the ICU. 2015 Computing in Cardiology Conference (CinC); 2015: IEEE.
37. Siontis, K. C., Noseworthy, P. A., Attia, Z. I., Friedman, P. A. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nature Reviews Cardiology. 2021; 18(7): 465-478.
38. Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P.*, et al.,* Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature medicine. 2019; 25(1): 65-69.
39. Pławiak, P., Acharya, U. R. Novel deep genetic ensemble of classifiers for arrhythmia detection using ECG signals. Neural Computing and Applications. 2020; 32(15): 11137-11161.
40. Pourbabaee, B., Roshtkhari, M. J., Khorasani, K. Deep convolutional neural networks and learning ECG features for screening paroxysmal atrial fibrillation patients. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2018; 48(12): 2095-2104.
41. Moody, G., Goldberger, A., McClennen, S., Swiryn, S., editors. Predicting the onset of paroxysmal atrial fibrillation: The Computers in Cardiology Challenge 2001. Computers in Cardiology 2001 Vol 28 (Cat No 01CH37287); 2001: IEEE.