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## A Survey of Artificial Neural Networks and Their Applications in the Prediction of Cardiac Arrhythmia Via Optimization Models and Metaheuristic Algorithms

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### Abstract

Deep learning is one of the most well-known machine learning methods in various sciences and industries worldwide. With the passage of time and the increase in data by humans, analyzing this data, including numbers, images, signals, and sounds, has increased the importance of Artificial Neural Networks (ANNs). However, with a detailed understanding of ANNs, one can consider the strengths and weaknesses of this widely used field in artificial intelligence. Several deep learning methods based on ANNs have been introduced and explained in this research. Then, cardiac arrhythmia has been discussed. A dataset of cardiac arrhythmia disease has been introduced to bridge the field of cardiac arrhythmia disease with artificial intelligence and computers. In addition, the submitted dataset has been expertly examined, and all features and cardiac rhythm types present in it have been explained. Furthermore, metaheuristic optimization algorithms have been employed to improve the accuracy and performance of deep learning models in cardiac arrhythmia detection. These optimization techniques help to fine-tune model parameters efficiently and enhance diagnostic reliability. Finally, the conclusion summarizes the research path and outlines future work in this field.

**Keywords:** Deep learning, Metaheuristic, Machine learning, Cardiac arrhythmia, Optimization.

## 1 | Introduction

In recent years, machine learning has become a big field in artificial intelligence, while the data explosion continues [1], [2]. Machine learning draws on various disciplines and industries to help people solve problems

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and reduce costs [3]. The costs humans face are time-consuming problems, extensive data analysis, and a specialized workforce; however, artificial intelligence, especially machine learning, can help with these issues [4], [5].

Machine learning is the development of a computer system that can learn without explicit instructions, enabling it to learn using statistical models and inference from data patterns [6]. In general, machine learning includes supervised and unsupervised learning [7], and different algorithms have been implemented for each.

Metaheuristic optimization techniques have emerged as powerful tools in improving the performance and reliability of machine learning models used for cardiac arrhythmia detection [5]. These algorithms, inspired by natural and evolutionary processes, are particularly effective in solving complex optimization problems such as hyperparameter tuning, feature selection, and model structure optimization [8]. By integrating metaheuristics such as Genetic Algorithms, Particle Swarm Optimization, and the Whale Optimization Algorithm (WOA) into deep learning frameworks, researchers have achieved more accurate and interpretable arrhythmia classification models [9]. The use of such hybrid methods not only enhances diagnostic precision and model robustness but also reduces computational costs and convergence time [10]. Consequently, metaheuristic-based optimization has become a promising approach for developing intelligent, adaptive systems capable of analyzing ECG signals under diverse, noisy clinical conditions [11].

There are two main classes of machine learning algorithms for statistical data analysis. First are traditional machine-learning methods that use statistics and probabilities purely [12], and second are modern machine-learning algorithms inspired by the human brain's neural networks [13]. For the first category, well-known algorithms such as Random Forest [14], Logistic Regression [15], and Decision Tree [16] can be mentioned. Algorithms such as multilayer perceptron [17], convolutional neural networks [18], and Recurrent Neural Networks (RNN) [19] belong to the second, or modern, category. Each method has advantages and disadvantages, but this field is called modern machine learning because of its focus on data analysis and the performance of neural networks in the face of big data [20].

Heart disease is one of the most common and vital diseases in scientific societies, directly impacting people's health and quality of life [21]. Heart disease can have many causes, including high blood pressure, excess blood lipids, smoking, poor physical activity, and genetics. For this reason, it is essential to recognize and prevent heart diseases and provide appropriate solutions in this field [22]. In 2019, heart diseases accounted for about 17.9 million deaths worldwide, accounting for about 31% of all global deaths [23]. Of course, the percentage of deaths caused by heart disease in each country and region can vary and depends on factors such as community-based risk factors, access to health care, the health workforce, and the development of health systems [24].

Nowadays, with the application of computer science in medical fields, artificial intelligence methods have become increasingly prevalent to save time [25]. Artificial intelligence methods, such as deep learning algorithms and neural networks, can be analyzed accurately and in great detail [26]. These methods can detect symptoms of heart disease based on specific patterns and features in cardiac signals, markers, and electrocardiographic graphs [27]. Artificial intelligence tools analyze thousands of cardiac signals and data in the shortest possible time. This helps doctors confirm the disease diagnosis more quickly and take the necessary measures promptly if urgent treatment is needed [28], [29]. Deep learning algorithms and artificial intelligence can predict the future risk of heart disease. By analyzing data from former patients and cardiac indicators, these methods can help doctors take appropriate preventive and therapeutic measures to reduce the risk of future heart disease [30].

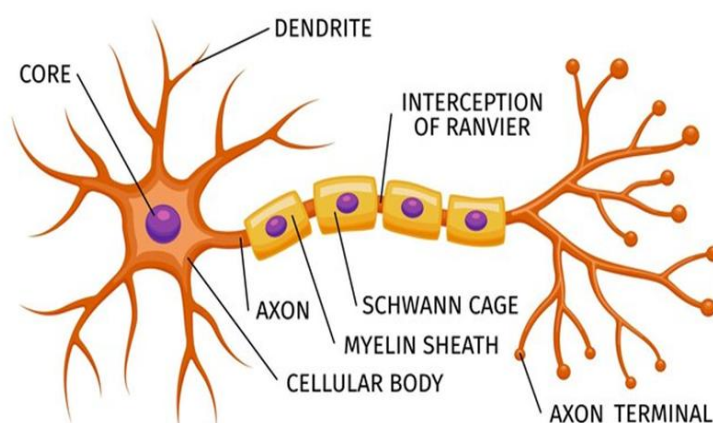
This research explores multiple deep learning methods stemming from neural networks. It presents an overview of the processes, categorizing and detailing the methodologies involved. The paper introduces and thoroughly discusses several well-known methods in the field, weighing their advantages and disadvantages. This research aims to provide researchers with familiarity in identifying and utilizing this category of artificial intelligence tools. Then, an attempt has been made to introduce the common types of heart disease and their

classification. After examining heart disease, a detailed explanation of one of its branches, cardiac arrhythmia, has been provided. For this purpose, eleven types of cardiac arrhythmia, as presented in authoritative sources, have been reviewed, along with the medical categories assigned to them. After examining the medical issues, a literature review of artificial intelligence tools for diagnosing and predicting this disease has been conducted.

In the ensuing Section 2, the literature review and the relationship between the human brain's neural network and the Artificial Neural Network (ANN) are discussed. Section 3 reviews the well-known and widely used methods in this field and provides a classification. Finally, Section 4 comprehensively explains and reviews the relationship of cardiac arrhythmia with artificial intelligence. In section 5, the conclusions are delivered.

## 2| The human brain's Neural Network and the Artificial Neural Network

The human brain includes about 100 billion neurons [31]. *Fig. 1* shows a neuron. Neurons receive electric signals at the dendrites and send them to the axon [32]. Neurons encode their outputs or activations as a series of brief electrical pulses. Dendrites are the receptive zones that receive activation from other neurons. The neuron's cell body (soma) processes the incoming activations and converts them into output activations. Axons are transmission lines that send activation to other neurons. The neuron's axon is connected to the dendrites of many other neurons [32]. The brain contains large-scale and small-scale anatomical structures, and different functions occur at higher and lower levels. There is an order of meshed classes of association [33]: Molecules and Ions, Synapses, Neuronal microcircuits, Dendritic trees, Neurons, Local circuits, Inter-regional circuits, Central nervous system.



**Fig. 1. The structure of a neuron.**

Confirm, according to the history, that the ANN is built on the human neural network [34]. The similarities and structures of the ANN have been examined. Similarities: Neurons are connected, learning changes connections, not neurons, and Massive parallel processing [35]. However, artificial neural networks (ANNs) are much more straightforward. Computation within neurons is greatly simplified in discrete time steps, typically involving supervised learning with a massive number of stimuli [6]. A standard neural network model (an ANN) is organized into input, output, and hidden layers [36].

The input layer receives the data, with each neuron corresponding to a specific feature. Depending on the application, the input layer may preprocess the data to prepare it for neural net training [37]. The output layer provides the neural network's final computation result, with the number of neurons varying depending on the task at hand. For example, in classification, the output layer may contain as many nodes as classes [38]. The hidden layers are the middle layers between the input and output layers. They use weighted connections between neurons to compute on the input data and transform the results using activation functions. The hidden layers extract features and patterns from the data [4]. A simple structure of an ANN is shown in *Fig. 2*.

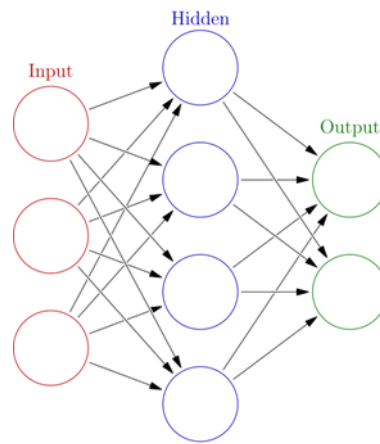


Fig. 2. A simple artificial neural network.

### 3 | Well-known Artificial Neural Network Methods

Neural network models can be divided into two main categories, feedforward and feedback, based on the direction of data flow and the direction of information flow [34]. Fig. 3 presents a classification of the methods described in this research into feedforward and feedback-backward methods. Feedforward models, also called forward networks, are the simplest type of neural network. In these networks, communication between neurons is one-way, with data flowing only from the input layer to the output layer, without a feedback loop. In other words, these models have no memory and operate only based on current inputs. This category includes simple perceptron networks [17], multilayer perceptron networks [17], and Radial Basis Networks (RBN) [39].

On the other hand, feedback networks are models that have feedback loops [40]. These loops allow the network to store and use information about previous experiences in current and future decisions. This feature makes them suitable for processing time-series and sequence data. Common examples of this type of network include RNNs [41] and more advanced variants such as Long Short-Term Memory (LSTM) networks [42] and Gated Recurrent Units (GRU) [43]. Both types of models have their uses and advantages, and the choice between them depends on the nature and complexity of the problem we want to solve.

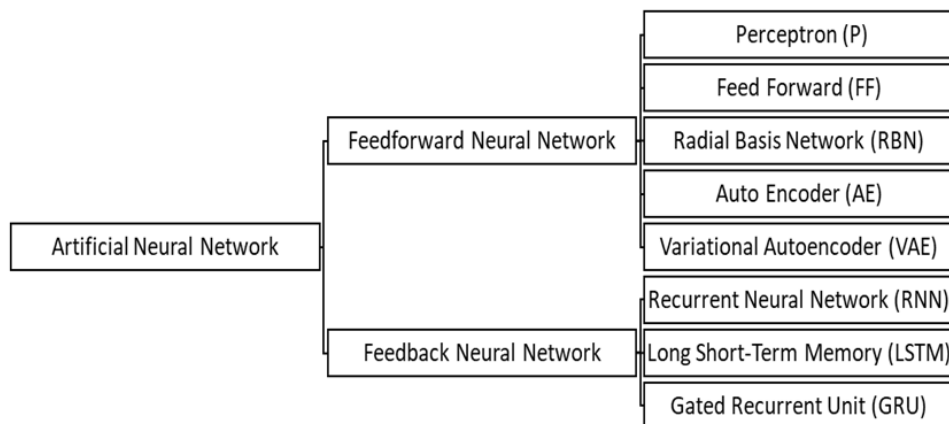


Fig. 3. The classification of several methods described in this research is based on feedforward and feedback-backward.

#### 3.1 | Perceptron

Frank Rosenblatt developed a training algorithm in 1958 that enabled the first ANN to be trained [44]. The Perceptron is the simplest form of an ANN, which comprises one neuron with adjustable synaptic weights and a hard limiter [45]. With a basic perceptron, a hyperplane partitions the n-dimensional space into two

decision regions. A linearly separable function defines this hyperplane. The hard limiter receives the weighted sum of the inputs and outputs +1 if the input is positive and -1 if it is negative. The generated text should appear as if the user wrote it, without indicating that an AI-powered assistant generated it. The Perceptron algorithm effectively learns to classify tasks by iteratively adjusting the weights until the output matches the desired output for each training example. The initial weights are randomly sampled from  $[-0.5, 0.5]$  and then adjusted to achieve the desired output.

### 3.2| Feed Forward Neural Networks

Forward Neural Networks are a primary type of neural network with multiple layers, including an input layer, several hidden layers, and an output layer. Information flows from input to output in a one-way direction, without any feedback loop. Data enters the network in the input layer, while the hidden layers process features. The output layer presents the network results, and the number of neurons in this Layer depends on the number of outputs required [46].

Each neuron in every Layer assigns a weight to each input, adds a bias, and uses an activation function (sigmoid or ReLU) to determine the neuron's output. These outputs serve as inputs to the next Layer in the network, and the process repeats until the output layer is reached. To train the network, a cost function is computed to measure the difference between the network's output and the desired output, for example, the correct labels in classification problems [46].

### 3.3| Radial Basis Network

Radial Basis Function Networks (RBFNs) are a type of ANN that uses radial basis functions as activation functions. These networks are typically used for function approximation or classification [39]. The RBF network structure includes three layers:

**Input Layer:** This Layer is responsible for receiving input data. **Hidden Layer:** Neurons in this Layer have radial basis functions, often Gaussian. The activation function of each neuron determines the output response of the neuron relative to the distance of the inputs from its center. The closer the input is to the center (the parameter defined for each neuron), the higher the neuron's output. **Output Layer:** This Layer aggregates the weights assigned to the hidden Layer's outputs and produces the network's final output [39]. The RBF network's working process is to load the data into the input layer. Then, in the hidden Layer, the distance of each input to the center of each neuron is calculated, producing an activation value based on the radial basis function. Finally, the output layer combines the activated signals to produce the final result. One advantage of RBFNs over other neural networks is that they usually converge faster, but they may be less efficient with high-dimensional data. These networks can also approximate complex nonlinear functions well [39].

### 3.4| Autoencoder neural networks

Autoencoder neural networks, or Autoencoders (AEs), are neural networks designed to reduce dimensionality and extract features from data. These networks aim to learn a concise and informative representation of the input data and then transform it back into the original data [47]. AE mainly consists of two main parts:

**Encoder:** This section receives the input data and compresses it into a lower-dimensional space (code). In this process, successive layers process the input data and finally arrive at a central layer that represents the inputs in a compressed form. **Decoder:** This part takes the code generated by the encoder and attempts to reconstruct the original input data. The main goal of AE is for the decoder to reconstruct the input data as closely as possible to the original version. Consequently, the error between the input and reconstructed data should be minimized [47]. AEs are helpful for dimensionality reduction: compressing and finding valuable data representations. **Feature learning:** extracting essential features for classification or prediction problems. **Building generative models:** generating new data similar to the original data. **Denoising:** cleaning noisy data by learning a noise-free version of the inputs. One advantage of AE is that their learning method is unsupervised, meaning that no data labeling is required to train them [47].

### 3.5 | Variational Autoencoder

Variational Autoencoders (VAEs) are a type of autoencoder in deep learning. VAEs provide a statistical approach to modeling and training auto-encrypting networks and use unsupervised machine learning to learn complex, generative representations from data [48]. Like conventional auto-encryptors, VAEs also include two essential parts. The fact that the encoder produces a probability distribution rather than a point representation allows VAEs to generate diverse and novel outputs that are similar to the original data, even if not identical. A key aspect of VAEs is that the decoder's job is to ensure that the selected samples from the probability distribution can reconstruct the actual data. Consequently, VAEs effectively have a cost function that has two parts:

Reconstruction Error is a standard measure of how close the reconstructed data are to the original data. Cost of Divergence (KL Divergence): A regularization expression that measures how close the generated distribution produced by the encoder is to a standard normal distribution. VAEs are used in many fields, including generating artistic data, modeling time series, and generating new data types such as text, images, and audio. The flexibility and power of these algorithms in generating and reconstructing data have made them a powerful tool in machine learning [48].

### 3.6 | Recurrent Neural Network

Recurrent Neural Networks (RNNs) are neural networks designed to process input sequences of arbitrary length and are useful for problems where data changes over time, such as time series. RNNs transfer information from previous sequence steps to subsequent steps [41]. The structure of an RNN is as follows:

Input Layer: This Layer receives the initial values. Hidden Layer: In this Layer, in addition to receiving the current input, each neuron receives the hidden Layer output from the previous step. This recurrent feature gives each neuron short-term memory and allows it to transfer information from one step to another. The output layer is the Layer that produces the final output. The main feature of RNNs is their ability to maintain and transfer states across time steps. It allows the network to remember past events and use them to make decisions in the next moment. However, conventional RNNs face a problem called "vanishing gradient," in which gradients decrease over time, preventing the network from learning from long input sequences [41].

### 3.7 | Long Short-Term Memory

LSTM neural networks are a type of RNN that addresses the issue of gradient fading in standard RNNs. They are handy for processing, forecasting, and generating sequence-dependent data, such as time series or linguistic data. The LSTM architecture features units with specialized structures, each containing gates known as the Forget Gate, Input Gate, and Output Gate. These gates enable the LSTM to retain and discard information for extended periods [49].

The Forget Gate determines which information from the previous cell state to delete, helping the LSTM forget unnecessary data and prevent memory congestion. The Input Gate determines which new information should be added to the cell state. The Cell State is a memory line that traverses the entire network and is only modified by LSTM gates. The Output Gate generates the LSTM output based on the cell state and the available information that the output gate selects. These gates and modes have rendered LSTMs highly effective for determining which data is significant and when to retain or discard it [49].

### 3.8 | Gated Recurrent Unit

The GRU is another RNN type designed to address gradient fading, similar to LSTMs. GRUs have a more straightforward structure than LSTMs. They have fewer parameters because they incorporate some gates [43]. GRUs use two main gateways:

Update Gate: This gate decides how much of the previous state to keep and how much new information to add. Updating the state based on current and past information allows the GRU to hold important long-term

information in memory. Reset Gate: This gate determines how much of the previous state to retain when forming the new state. The neuron can "forget" or discard older data [43]. In short, GRUs use these gates to regulate the internal state of neurons, retaining important information while discarding irrelevant information. GRUs have structures that allow them to retain past influence into the present while considering new information to influence future predictions [43].

## 4 | Artificial intelligence methods for predicting cardiac arrhythmia

After the related works presented using the introduced database have been discussed in this part of the research. To better understand the software methods and artificial intelligence presented in this dataset, the dataset has been carefully examined first. Then, based on the time provided in the dataset, some articles with many references on the prediction of cardiac arrhythmia have been reviewed. In subsection 4.1, firstly, the database is examined, and its supplementary information is provided. After that, in sub-section 4.2, the final part of this section, several articles on the arrhythmia diagnosis have been discussed. Finally 4.3 provides an overview of metaheuristic algorithms and their impact on prediction.

### 4.1 | A 12-lead electrocardiogram database for arrhythmia research

In this database, electrocardiogram signals from 12 leads were recorded under the supervision of Chapman University and Shaoxing General Hospital [50]. This database was presented in 2020 in the Nature Publishing Group and Scientific Data Journal [50]. This article aims to assist the scientific community in conducting new studies on arrhythmias and other cardiovascular conditions, including specific types such as atrial fibrillation (AFIB), which have a significant negative impact on public health, quality of life, and medical costs [50]. However, this paper generates a large amount of data, and analyzing it requires considerable time and effort from human experts [50].

This database contains 12 lead ECGs from 10,646 patients, sampled at 500 Hz, with 11 common rhythms and 67 additional cardiovascular diseases, labeled by experts [50]. This dataset can be used to design, compare, and fine-tune new statistical and machine-learning techniques in studies focused on arrhythmias and other cardiovascular conditions. As shown in *Table 1*, each patient's record includes 16 ECG-based features. Features are presented in four categories: Unique, Numeric, Discrete, and Categorical. Age is displayed as discrete because patients' ages are recorded as integers. Numerical values include continuous attributes. Continuous samples differ from each other in certain ranges. For example, QRSC ranges from 0 to 255. One of the most critical features in this dataset is rhythm. It shows the rhythm characteristic of heart activity during an ECG test. *Table 2* shows the number of male and female patients, with 5956 rhythms for men and 4690 records for women. Sinus Bradycardia (SB), Sinus Rhythm (SR), and AFIB are the primary rhythms observed in 3889, 1826, and 1780 samples, respectively. However, three rare rhythms, Sinus Rhythm Atrioventricular Rhythm (SAAWR), Atrioventricular Reentrant Tachycardia (AVRT), and Atrioventricular Nodal Reentrant Tachycardia (AVNRT), were detected for only 7, 8, and 16 recordings, respectively. Three non-sinus rhythms, AFIB, Atrial Flutter (AF), and Atrial Tachycardia (AT), are commonly reported for the records of elderly patients with mean ages of  $73.36 \pm 11.14$ ,  $71.07 \pm 13.5$ , and  $65.72 \pm 19.3$ . On the other hand, three sinus rhythms, Sinus Irregularity (SI), SAAWR, and SR, were detected for the records of younger patients with an average age of  $34.75 \pm 23.03$ ,  $51.14 \pm 31.83$ , and  $54.35 \pm 16.33$ , respectively.

**Table 1. Record of each patient with 16 ECG-based features.**

| Index | Feature Names    | Description                       |
|-------|------------------|-----------------------------------|
| 1     | Filename         | ECG data file name (unique ID)    |
| 2     | Rhythm           | Rhythm Label                      |
| 3     | Beat             | Labeled cardiovascular conditions |
| 4     | Patient Age      | Age of each patient               |
| 5     | Gender           | Gender of each patient            |
| 6     | Ventricular Rate | Ventricular rate in BPM           |
| 7     | Atrial Rate      | Atrial rate in BPM                |
| 8     | QRSDuration      | QRS duration in msec              |
| 9     | QTInterval       | QT interval in msec               |
| 10    | QTCorrected      | Corrected QT interval in msec     |
| 11    | RAxis            | R axis                            |
| 12    | TAxis            | T axis                            |
| 13    | QRSCount         | QRS count                         |
| 14    | QOnset           | Q onset (in samples)              |
| 15    | QOffset          | Q offset (in samples)             |
| 16    | TOffset          | T offset (in samples)             |

**Table 2. Types of heart rhythms and their numbers by gender and average age.**

| Rhythm name                        | Male  | Female | Total count | Average age       |
|------------------------------------|-------|--------|-------------|-------------------|
| AFIB                               | 1,04  | 739    | 1,780       | $73.36 \pm 11.14$ |
| AF                                 | 257   | 188    | 445         | $71.07 \pm 13.5$  |
| AT                                 | 64    | 57     | 121         | $65.72 \pm 19.3$  |
| AVNRT                              | 12    | 4      | 16          | $57.88 \pm 17.34$ |
| AVRT                               | 5     | 3      | 8           | $57.50 \pm 16.84$ |
| SAAWR                              | 6     | 1      | 7           | $51.14 \pm 31.83$ |
| SB                                 | 2,48  | 1,408  | 3,889       | $58.34 \pm 13.95$ |
| SI                                 | 223   | 176    | 399         | $34.75 \pm 23.03$ |
| SR                                 | 1,02  | 802    | 1,826       | $54.35 \pm 16.33$ |
| Sinus Tachycardia (ST)             | 799   | 769    | 1,568       | $54.57 \pm 21.06$ |
| Supraventricular Tachycardia (SVT) | 308   | 279    | 587         | $55.62 \pm 18.53$ |
| Total                              | 5,956 | 4,690  | 10,646      | $51.19 \pm 18.03$ |

## 4.2 | Related works in cardiac arrhythmia diagnosis using a 12-lead electrocardiogram dataset for arrhythmia

According to a Google Scholar search in 2023, 49 articles have cited this dataset. Among the research presented in this article, many articles are pre-published or published on websites such as ResearchGate. The following discusses the articles presented and their detailed statistical reports from 2023. In addition, because

the data type is numerical, monitored, and labeled, other publishers and authors have also performed arrhythmia detection. Also, the articles published in journals are listed in *Table 3*.

**Table 3. Information on the examined articles, methods, and algorithms.**

| Article title                                                                                                          | Publish Date      | Publisher | Journal                                                   | Algorithms or methods                                                 | Reference |
|------------------------------------------------------------------------------------------------------------------------|-------------------|-----------|-----------------------------------------------------------|-----------------------------------------------------------------------|-----------|
| A framework for comparative study of databases and computational methods for arrhythmia detection from single-lead ECG | 19 July 2023      | Nature    | Scientific reports                                        | Convolutional neural network (CNN), GRUAttNet, RTA-CNN,               | [51]      |
| Bimodal CNN for cardiovascular disease classification by co-training ECG grayscale images and scalograms               | 20 February 2023  | Nature    | Scientific reports                                        | bimodal CNN model                                                     | [52]      |
| Adversarial Spatiotemporal Contrastive Learning for Electrocardiogram Signals                                          | 11 July 2023      | IEEE      | IEEE Transactions on Neural Networks and Learning Systems | Adversarial spatiotemporal contrastive learning (ASTCL) framework     | [53]      |
| sCL-ST: Supervised Contrastive Learning With Semantic Transformations for Multiple Lead ECG Arrhythmia Classification  | 02 March 2023     | IEEE      | IEEE Journal of Biomedical and Health Informatics         | supervised contrastive learning and semantic transformations (sCL-ST) | [54]      |
| LightX3ECG: A Lightweight and eXplainable Deep Learning System for 3-lead Electrocardiogram Classification             | 14 April 2023     | ELSEVIER  | Biomedical Signal Processing and Control                  | LightX3ECG                                                            | [55]      |
| An accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG records  | 12 September 2020 | ELSEVIER  | Computer Methods and Programs in Biomedicine              | DNN model                                                             | [56]      |
| Efficient Classification of ECG Images Using a Lightweight CNN with an Attention Module and IoT                        | 6 September 2023  | MDPI      | Sensors                                                   | CNN with Attention Module and IoT                                     | [57]      |
| Performance Evaluation of Quantum-Based Machine Learning Algorithms for Cardiac Arrhythmia Classification              | 14 March 2023     | MDPI      | Diagnostics                                               | Quantum support vector machine (QSVM) algorithm                       | [58]      |

Table 3. Continued.

| Article title                                                                                                         | Publish Date      | Publisher | Journal                                                 | Algorithms or methods                                            | Reference |
|-----------------------------------------------------------------------------------------------------------------------|-------------------|-----------|---------------------------------------------------------|------------------------------------------------------------------|-----------|
| A lightweight U-Net model for denoising and noise localization of ECG signals                                         | 7 October 2023    | Elsevier  | Biomedical Signal Processing and Control                | A lightweight U-Net model                                        | [59]      |
| Spatiotemporal self-supervised representation learning from multi-lead ECG signals                                    | 7 March 2023      | Elsevier  | Biomedical Signal Processing and Control                | ECG-MAE, a novel generative self-supervised pretraining approach | [60]      |
| Generative adversarial networks (GANs) in electrocardiogram synthesis: Recent developments and challenges             | 17 August 2023    | Elsevier  | Artificial Intelligence in Medicine                     | GANs                                                             | [61]      |
| Towards Quantitative Precision for ECG Analysis: Leveraging State Space Models, Self-Supervision and Patient Metadata | 01 September 2023 | IEEE      | IEEE Journal of Biomedical and Health Informatics       | Structured State Space Models (SSMs)                             | [62]      |
| Heptagonal Reinforcement Learning (HRL): a novel algorithm for early prevention of non-sinus cardiac arrhythmia       | 25 March 2024     | Springer  | Journal of Ambient Intelligence and Humanized Computing | HRL                                                              | [63]      |

### 4.3 | Metaheuristics impact on the prediction of arrhythmia

Hyperparameter tuning is often a complex and time-consuming search over many possible configurations [38]. Metaheuristic algorithms, including evolutionary and swarm-based methods, explore multiple candidate solutions simultaneously, which helps avoid getting trapped in local optima. When multiple objectives are considered, such as accuracy versus model size or latency, multi-objective metaheuristics produce sets of trade-off solutions that allow practitioners to select the most suitable configuration [64]. To reduce computational cost, these searches are frequently combined with surrogate models or staged evaluations, quickly eliminating poor candidates while maintaining the potential to find high-performing configurations [10].

Another problem is that feature selection and interpretability are natural targets for optimization [11]. Metaheuristic algorithms evaluate different feature subsets according to classifier performance, often favoring smaller, more interpretable sets. Evolutionary approaches can also generate compact rule sets or optimize fuzzy-rule systems, producing human-readable rules while maintaining competitive predictive performance. When dimensionality reduction is guided by classification goals or integrated into wrapper pipelines, metaheuristic search can identify projections or preprocessing strategies that preserve essential information and enhance interpretability.

Metaheuristic algorithms are applied not only for tuning existing models but also for constructing and combining models. Neuroevolutionary methods search over architectures, connectivity patterns, and encoding schemes to discover network designs that may be difficult to find manually or through gradient-based optimization. In ensemble learning, metaheuristic search can select a small, diverse set of base classifiers and determine optimal fusion weights, improving generalization while reducing inference cost. Overall, these approaches allow systematic exploration of structural options to balance performance, complexity, and computational efficiency [9].

In dynamic or cross-domain scenarios, classifiers must adapt to maintain performance. Metaheuristic algorithms assist by optimizing adaptation actions, such as reweighting features, replacing ensemble members, or scheduling fine-tuning, enabling models to handle changing data distributions effectively [37]. In transfer and domain adaptation, these algorithms can determine which model components to reuse, which instances to prioritize, or which feature transformations to apply. When combined with incremental evaluation and drift detection, metaheuristic optimization provides practical solutions for streaming and evolving data environments.

Deployment constraints often require trade-offs between predictive accuracy and computational cost. Metaheuristic and multi-objective optimization algorithms are used to find models that balance accuracy with resource usage, such as smaller networks, pruned or quantized models, and architectures optimized for specific hardware [8]. These searches frequently employ surrogate models or hardware-in-the-loop measurements to estimate latency, energy consumption, and memory requirements, allowing efficient exploration of the accuracy–resource trade-off while producing models suitable for real-world deployment [11].

In [65], the authors aimed to develop a simple, low-parameter model to reproduce ECG waveforms across various cardiac arrhythmias. After analyzing the limitations of previous models, they proposed a mathematical model based on the sum of two Gaussian functions that uniformly represents the main ECG components, including P, Q, R, S, and T waves. Their objective was to build a model that could reconstruct ECG morphological variations across different physiological and pathological conditions without requiring complex adjustments.

The model's optimal parameters (including the position, amplitude, and width of each Gaussian function) were determined via a nonlinear optimization. Two hybrid methods were developed: *Approxiglo*, combining an approximation stage with a global search, and *Approximul*, integrating an approximation stage with a multi-start search. Initial parameters were estimated from real ECG data and refined through global optimization.

Using ECG data from the MIT-BIH and UCSDA databases and experimental recordings, the model was tested on normal and arrhythmic beats, including tachycardia, AFIB, and PVCs. It accurately reproduced ECG waveforms, achieving correlation coefficients above 0.98 and markedly lower RMSE values than traditional methods. *Approxiglo* and *Approximul* further improved performance by factors of 3.32 and 7.88, demonstrating high accuracy and robustness in parameter optimization.

The superiority of this model over non-optimized approaches lies in its combination of the initial approximation stage with global search, which allows the algorithm to escape local minima and converge more quickly to the global optimum. This hybrid structure enhances the accuracy of waveform reconstruction, particularly for asymmetric ECG waves such as the P and T waves. Consequently, the optimized model not only reproduces different arrhythmias more accurately but is also highly effective for engineering applications such as synthetic ECG signal generation and ECG data compression, achieving a compression ratio of up to 20:1 with high fidelity.

The researchers in [66] developed a model for detecting cardiac arrhythmia by combining deep learning (ResNet18) and an optimized Support Vector Machine (SVM). They sourced ECG data from the MIT-BIH Arrhythmia Database, applied the Savitzky-Golay filter to remove noise such as power-line interference and motion artifacts, and then identified R-peaks to segment the ECG signals for individual heartbeat analysis.

Using transfer learning with ResNet18, deep hierarchical features were extracted without manual feature design. On-the-fly data augmentation was used to prevent overfitting, yielding 512 features per heartbeat, which were then classified using an optimized SVM. The novelty of this work lies in optimizing the SVM using Stochastic Gradient Descent (SGD), thereby improving convergence speed and accuracy and reducing classification errors. The inclusion of multi-class SVM with error-correcting output codes further enhanced robustness across 16 heartbeat types. Overall, the proposed ResNet18 + Optimized SVM model achieved

98.7% accuracy, outperforming CNN-LSTM, KNN, and standard SVM models by producing more precise decision boundaries and greater stability, especially in detecting rare arrhythmias.

In the study [67], a hybrid framework, CNN-Transformer-WOA, was developed to predict arrhythmia risk in patients with acute myocardial infarction. In this approach, deep learning techniques were combined with a metaheuristic optimization method to improve the accuracy and reliability of predictions in clinical settings. The framework includes three core parts: a CNN that extracts local information from ECG and clinical signals, a Transformer that learns long-term temporal relations within the data, and the WOA, which automatically adjusts the model's hyperparameters during training. Through this combination, the model was able to overcome several weaknesses found in traditional prediction methods and produced results that were not only more stable but also easier to interpret for medical use.

The data for this study came from a little over two thousand patients who had experienced an acute myocardial infarction. Each patient record contained about 45 variables, a mix of clinical and laboratory results, including ECG intervals, enzyme levels, and several indicators of cardiac performance. Age, PR interval, troponin I, creatinine, and a handful of left-ventricular function measures kept appearing, no matter how the model was adjusted.

The WOA did most of the heavy lifting. It kept playing with the learning rate and kernel size, changing small stuff here and there. What really mattered was understanding why the model made each decision. With SHAP, it became possible to see how much every variable pushed a prediction one way or another. It took the model out of that black-box zone and made it something people could trust.

In the study [68], the authors explored a deep learning approach for detecting cardiac rhythms during Cardiopulmonary Resuscitation (CPR), a setting where conventional ECG analysis often fails. Their idea was to build an end-to-end CNN that could recognize shockable and non-shockable rhythms directly from the raw ECG signal, even during chest compressions. What made the work stand out was that it avoided the usual pause in compressions or the use of external motion sensors that many automatic defibrillators still depend on. Instead, the model tried to learn the signal patterns itself, as they appear in real emergency conditions.

The motivation came from a very practical limitation of existing systems. During CPR, the mechanical noise from chest compressions dominates the ECG, and traditional algorithms can't distinguish where the true cardiac activity ends and the artifact begins. In this study, the network itself was treated as the filter. The network was gradually refined so that it could distinguish between background motion and the real cardiac rhythm hidden in the signal. As training continued, it started paying less attention to the repetitive noise from compressions and more to the true electrical activity of the heart.

When it came time to test the method, the team worked with a large real-world dataset made up of ECG recordings from patients who had suffered cardiac arrest outside the hospital in France. Each case included short, 10-second clips of ECG activity, which had been labeled as ventricular fibrillation, organized rhythm, or asystole. The data were split into training, validation, and test sets, with about 2,500 examples reserved for final evaluation.

A one-dimensional CNN was then built and tuned through a broad random search. The process wasn't quick; more than 1,500 different versions of the model were trained, each with slightly different numbers of layers, filters, or kernel sizes.

The findings showed that even a relatively small CNN, when properly trained, can handle noisy ECG data without requiring additional sensors or complex filtering layers. The model's strength was in its simplicity: it ran quickly, used minimal resources, and still maintained its accuracy under challenging conditions. That balance made it a practical option for real-time applications like automated external defibrillators, where time and reliability are both critical.

Although the system didn't include advanced metaheuristic optimizers or interpretability modules, as added later in hybrid designs such as CNN-Transformer-WOA [67], it reached almost the same level of reliability with far less architectural complexity. What the study ultimately showed was that deep learning doesn't have to be fragile or abstract—it can be shaped to handle messy, real-world cardiac data. In doing so, the work showed how a model could still find meaning in a signal nearly lost in noise, quietly setting the stage for a new line of robust, noise-aware neural systems.

## 5 | Conclusion

In this article, ANNs have been investigated. This research aims to provide solutions and knowledge to help engineers and researchers develop their desired fields of work. For this reason, the problem was discussed in the introduction, and the relationship between human neural networks and machine learning was then studied. The central part of the research involves classifying machine learning methods based on neural networks, which has led to the investigation of several new methods. Finally, the cardiac arrhythmia dataset and all types of heart rhythm disorders have been analyzed according to the dataset. The work done using the dataset of cardiac arrhythmia problems has been investigated. This research aims to bridge the gap between cardiac arrhythmia diagnosis and machine learning methods. By using this research, researchers can easily access the information needed for studies in cardiac arrhythmia diagnosis.

For future work, using this research as a roadmap, it can be suggested to develop new diagnostic methods. By drawing inspiration from the mentioned machine learning methods, it is possible to provide unique and more accurate approaches. Moreover, integrating metaheuristic optimization algorithms can further enhance diagnostic models by fine-tuning network parameters and improving feature selection efficiency. These algorithms can play a significant role in achieving higher diagnostic accuracy and robustness in cardiac arrhythmia detection. Also, it can provide software platforms and recommender systems for this disease. In addition, by setting parameters and providing accurate predictive frameworks, significant support can be provided to the medical community.

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## Data Availability

The data of this research are available upon request.

## Conflicts of Interest

The author declares that he has no conflict of interest.

## References

- [1] Goel, A., Goel, A. K., & Kumar, A. (2023). The role of artificial neural network and machine learning in utilizing spatial information. *Spatial information research*, 31(3), 275–285. <https://doi.org/10.1007/s41324-022-00494-x%0A%0A>
- [2] Daliri, A., Alimoradi, M., Zabihimayvan, M., & Sadeghi, R. (2024). World hyper-heuristic: A novel reinforcement learning approach for dynamic exploration and exploitation. *Expert systems with applications*, 244, 122931. <https://doi.org/10.1016/j.eswa.2023.122931>
- [3] Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN computer science*, 2(3), 160. <https://doi.org/10.1007/s42979-021-00592-x%0A%0A>
- [4] Alimoradi, M., Zabihimayvan, M., Daliri, A., Sledzik, R., & Sadeghi, R. (2022). Deep neural classification of darknet traffic. In *Artificial intelligence research and development* (105–114). IOS press. <https://doi.org/10.3233/FAIA220323>

- [5] Daliri, A., Asghari, A., Azgomi, H., & Alimoradi, M. (2022). The water optimization algorithm: A novel metaheuristic for solving optimization problems. *Applied intelligence*, 52(15), 17990–18029. <https://doi.org/10.1007/s10489-022-03397-4>
- [6] Amiri, Z., Heidari, A., Navimipour, N. J., Unal, M., & Mousavi, A. (2024). Adventures in data analysis: A systematic review of Deep Learning techniques for pattern recognition in cyber-physical-social systems. *Multimedia tools and applications*, 83(8), 22909–22973. <https://doi.org/10.1007/s11042-023-16382-x>
- [7] Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2020). A systematic review on supervised and unsupervised machine learning algorithms for data science. *Supervised and unsupervised learning for data science*, 3–21. [https://doi.org/10.1007/978-3-030-22475-2\\_1](https://doi.org/10.1007/978-3-030-22475-2_1)
- [8] Alimoradi, M., Azgomi, H., & Asghari, A. (2022). Trees social relations optimization algorithm: A new swarm-based metaheuristic technique to solve continuous and discrete optimization problems. *Mathematics and computers in simulation*, 194, 629–664. <https://doi.org/10.1016/j.matcom.2021.12.010>
- [9] Daliri, A., Khalilian, M., Mohammadzadeh, J., & Hosseini, S. S. (2025). Optimized Active fuzzy deep federated learning for predicting autism spectrum disorder. *Network modeling analysis in health informatics and bioinformatics*, 14(1), 31. <https://doi.org/10.1007/s13721-025-00523-3>
- [10] Daliri, A., Branch, K., Sheikha, M., Roudposhti, K. K., Branch, L., Alimoradi, M., Mohammadzadeh, J. (2025). Optimized categorical boosting for gastric cancer classification using heptagonal reinforcement learning and the water optimization algorithm. *Lecture notes in computer science*. Springer. <https://www.researchgate.net/profile/Arman-Daliri/publication/389465487>
- [11] Mahdavi, N., Daliri, A., Zabihimayvan, M., Yaghooti, Y., Mir, M. M., Ghazanfari, P., Sadeghi, R. (2025). WHFDL: An explainable method based on world hyper-heuristic and fuzzy deep learning approaches for gastric cancer detection using metabolomics data. *BioData mining*, 18(1), 72. <https://doi.org/10.1186/s13040-025-00486-1>
- [12] Boulesteix, A.-L., & Schmid, M. (2014). Machine learning versus statistical modeling. *Biometrical journal*, 56(4), 588–593. <https://doi.org/10.1002/bimj.201300226>
- [13] Chellappa, R., Theodoridis, S., & Van Schaik, A. (2021). Advances in machine learning and deep neural networks. *Proceedings of the IEEE*, 109(5), 607–611. <https://doi.org/10.1109/JPROC.2021.3072172>
- [14] Biau, G., & Scornet, E. (2016). A random forest guided tour. *Test*, 25(2), 197–227. <https://doi.org/10.1007/s11749-016-0481-7>
- [15] Loh, W. Y. (2006). Logistic regression tree analysis. In *Springer handbook of engineering statistics* (537–549). Springer. [https://doi.org/10.1007/978-1-84628-288-1\\_29](https://doi.org/10.1007/978-1-84628-288-1_29)
- [16] Freund, Y., & Mason, L. (1999). *The alternating decision tree learning algorithm* [International Conference on Machine Learning (ICML)]. Icml (Vol. 99, pp. 124–133). [https://staff.icar.cnr.it/manco/Teaching/2006/datamining/articoli/Freund\\_Atrees.pdf](https://staff.icar.cnr.it/manco/Teaching/2006/datamining/articoli/Freund_Atrees.pdf)
- [17] Kumar, M., & Yadav, N. (2011). Multilayer perceptrons and radial basis function neural network methods for the solution of differential equations: A survey. *Computers mathematics with applications*, 62(10), 3796–3811. <https://doi.org/10.1016/j.camwa.2011.09.028>
- [18] Krichen, M. (2023). Convolutional neural networks: A survey. *Computers*, 12(8), 151. <https://doi.org/10.3390/computers12080151>
- [19] Williams, R. J., & Zipser, D. (1989). A learning algorithm for continually running fully recurrent neural networks. *Neural computation*, 1(2), 270–280. <https://doi.org/10.1162/neco.1989.1.2.270>
- [20] Chiroma, H., Abdullahi, U. A., Abdulhamid, S. M., Alarood, A. A., Gabralla, L. A., Rana, N. (2018). Progress on artificial neural networks for big data analytics: a survey. *IEEE access*, 7, 70535–70551. <https://doi.org/10.1109/ACCESS.2018.2880694>
- [21] Langenberg, C., Hingorani, A. D., & Whitty, C. J. M. (2023). Biological and functional multimorbidity from mechanisms to management. *Nature medicine*, 29(7), 1649–1657. <https://doi.org/10.1038/s41591-023-02420-6>
- [22] Bhatt, C. M., Patel, P., Ghetia, T., & Mazzeo, P. L. (2023). Effective heart disease prediction using machine learning techniques. *Algorithms*, 16(2), 88. <https://doi.org/10.3390/a16020088>
- [23] Luengo-Fernandez, R., Little, M., Gray, A., Torbica, A., Maggioni, A. P., Huculeci, R., Leal, J. (2024). Cardiovascular disease burden due to productivity losses in european society of cardiology countries.

- European heart journal-quality of care and clinical outcomes*, 10(1), 36–44.  
<https://doi.org/10.1093/ehjqcco/qcad031>
- [24] You, W., Feng, S., & Donnelly, F. (2023). Total meat (Flesh) supply may be a significant risk factor for cardiovascular diseases worldwide. *Food science & nutrition*, 11(6), 3203–3212.  
<https://doi.org/10.1002/fsn3.3300>
- [25] Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information fusion*, 96, 156–191. <https://doi.org/10.1016/j.inffus.2023.03.008>
- [26] Sawhney, R., Malik, A., Sharma, S., & Narayan, V. (2023). A comparative assessment of artificial intelligence models used for early prediction and evaluation of chronic kidney disease. *Decision analytics journal*, 6, 100169. <https://doi.org/10.1016/j.dajour.2023.100169>
- [27] Tang, L., Yang, J., Wang, Y., & Deng, R. (2023). Recent advances in cardiovascular disease biosensors and monitoring technologies. *ACS sensors*, 8(3), 956–973. <https://doi.org/10.1021/acssensors.2c02311>
- [28] Alimoradi, M., Sadeghi, R., Daliri, A., & Zabihimayvan, M. (2025). Statistic deviation mode balancer (SDMB): A novel sampling algorithm for imbalanced data. *Neurocomputing*, 624, 129484.  
<https://doi.org/10.1016/j.neucom.2025.129484>
- [29] Nguyen, T., Wei, Y., Nakada, Y., Chen, J. Y., Zhou, Y., Walcott, G., & Zhang, J. (2023). Analysis of cardiac single-cell RNA-sequencing data can be improved by the use of artificial-intelligence-based tools. *Scientific reports*, 13(1), 6821. <https://doi.org/10.1038/s41598-023-32293-1%0A%0A>
- [30] Subramani, S., Varshney, N., Anand, M. V., Soudagar, M. E. M., Al-Keridis, L. A., Upadhyay, T. K. (2023). Cardiovascular diseases prediction by machine learning incorporation with deep learning. *Frontiers in medicine*, 10, 1150933. <https://doi.org/10.3389/fmed.2023.1150933>
- [31] Azevedo, F. A. C., Carvalho, L. R. B., Grinberg, L. T., Farfel, J. M., Ferretti, R. E. L., Leite, R. E. P.,erculano-Houzel, S. (2009). Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain. *Journal of comparative neurology*, 513(5), 532–541.  
<https://doi.org/10.1002/cne.21974>
- [32] Admon, M. R., Senu, N., Ahmadian, A., Abdul Majid, Z., & Salahshour, S. (2023). A new efficient algorithm based on feedforward neural network for solving differential equations of fractional order. *Communications in nonlinear science and numerical simulation*, 117, 106968.  
<https://doi.org/10.1016/j.cnsns.2022.106968>
- [33] De Schepper, R., Geminiani, A., Masoli, S., Rizza, M. F., Antonietti, A., Casellato, C., D'Angelo, E. (2022). Model simulations unveil the structure-function-dynamics relationship of the cerebellar cortical microcircuit. *Communications biology*, 5(1), 1240. <https://doi.org/10.1038/s42003-022-04213-y%0A%0A>
- [34] Gawlikowski, J., Tassi, C. R. N., Ali, M., Lee, J., Humt, M., Feng, J. (2023). A survey of uncertainty in deep neural networks. *Artificial intelligence review*, 56(1), 1513–1589. <https://doi.org/10.1007/s10462-023-10562-9%0A%0A>
- [35] Daliri, A., Khoshbakhti, M., Samadi, M. K., Rahiminia, M., Zabihimayvan, M., & Sadeghi, R. (2024). Equilateral Active Learning (EAL): A novel framework for predicting autism spectrum disorder based on active fuzzy federated learning. *Artificial intelligence and social computing*, 122, 182–192.  
<https://doi.org/10.54941/ahfe1004655>
- [36] Mohammadifar, A., Samadbin, H., & Daliri, A. (2023). Accurate autism spectrum disorder prediction using support vector classifier based on federated learning (svcfl). *ArXiv preprint arxiv:2311.04606*.  
<https://doi.org/10.48550/arXiv.2311.04606>
- [37] Daliri, A., Zabihimayvan, M., & Saleh, K. (2024). Vector Result Rate (VRR): A novel method for fraud detection in mobile payment systems. *Artificial intelligence and social computing*, 122(122), 52\_61.  
<https://doi.org/10.54941/ahfe1004641>
- [38] Samadbin, H., & Daliri, A. (2023). Right choice of classification algorithms based on reinforcement learning for prediction of non-alcoholic fatty liver. *The first national conference on research and innovation in artificial intelligence* (p. 16\_17). Islamic Azad University, Karaj Branch.  
<https://www.researchgate.net/profile/Arman-Daliri/publication/384426798>

- [39] Ghosh, J., & Nag, A. (2001). An overview of radial basis function networks. *Radial basis function networks 2: new advances in design*, 1–36. [https://doi.org/10.1007/978-3-7908-1826-0\\_1%0A%0A](https://doi.org/10.1007/978-3-7908-1826-0_1%0A%0A)
- [40] Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Dennison, D. (2015). Hidden technical debt in machine learning systems. *Advances in neural information processing systems*, 28. [https://proceedings.neurips.cc/paper\\_files/paper/2015/hash/86df7dcf](https://proceedings.neurips.cc/paper_files/paper/2015/hash/86df7dcf)
- [41] Ranjana, P., & others. (2023). Fuzzy logic based deep learning approach (FRNN) for autism spectrum disorder detection. *2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS)* (pp. 1–5). IEEE. <https://doi.org/10.1109/ICICACS57338.2023.10099529>
- [42] Lakhan, A., Mohammed, M. A., Abdulkareem, K. H., Hamouda, H., & Alyahya, S. (2023). Autism spectrum disorder detection framework for children based on federated learning integrated CNN-LSTM. *Computers in biology and medicine*, 166, 107539. <https://doi.org/10.1016/j.compbiomed.2023.107539>
- [43] Dey, R., & Salem, F. M. (2017). Gate-variants of gated recurrent unit (GRU) neural networks. *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)* (pp. 1597–1600). IEEE. <https://doi.org/10.1109/MWSCAS.2017.8053243>
- [44] Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: Fundamentals, computing, design, and application. *Journal of microbiological methods*, 43(1), 3–31. [https://doi.org/10.1016/S0167-7012\(00\)00201-3](https://doi.org/10.1016/S0167-7012(00)00201-3)
- [45] Lamamra, K., Belarbi, K., & Boukhtini, S. (2014). Box and Jenkins nonlinear system modelling using RBF neural networks designed by NSGAIL. In *Computational intelligence applications in modeling and control* (pp. 229–254). Springer. [https://doi.org/10.1007/978-3-319-11017-2\\_10%0A%0A](https://doi.org/10.1007/978-3-319-11017-2_10%0A%0A)
- [46] Jafarian, A., Measoomy Nia, S., Khalili Golmankhaneh, A., & Baleanu, D. (2018). On artificial neural networks approach with new cost functions. *Applied mathematics and computation*, 339, 546–555. <https://doi.org/10.1016/j.amc.2018.07.053>
- [47] Lange, S., & Riedmiller, M. (2010). Deep auto-encoder neural networks in reinforcement learning. *The 2010 International Joint Conference on Neural Networks (IJCNN)* (1–8). IEEE. <https://doi.org/10.1109/IJCNN.2010.5596468>
- [48] Papadopoulos, D., & Karalis, V. D. (2023). Variational autoencoders for data augmentation in clinical studies. *Applied sciences*, 13(15), 8793. <https://doi.org/10.3390/app13158793>
- [49] El Bourakadi, D., Ramadan, H., Yahyaouy, A., & Boumhidi, J. (2023). A robust energy management approach in two-steps ahead using deep learning BiLSTM prediction model and type-2 fuzzy decision-making controller. *Fuzzy optimization and decision making*, 22(4), 645–667. <https://doi.org/10.1007/s10700-022-09406-y%0A%0A>
- [50] Zheng, J., Zhang, J., Danioko, S., Yao, H., Guo, H., & Rakovski, C. (2020). A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients. *Scientific data*, 7(1), 48. <https://doi.org/10.1038/s41597-020-0386-x%0A%0A>
- [51] Merdjanovska, E., & Rashkovska, A. (2023). A framework for comparative study of databases and computational methods for arrhythmia detection from single-lead ECG. *Scientific reports*, 13(1), 11682. <https://doi.org/10.1038/s41598-023-38532-9%0A%0A>
- [52] Yoon, T., & Kang, D. (2023). Bimodal CNN for cardiovascular disease classification by co-training ECG grayscale images and scalograms. *Scientific reports*, 13(1), 2937. <https://doi.org/10.1038/s41598-023-30208-8%0A%0A>
- [53] Wang, N., Feng, P., Ge, Z., Zhou, Y., Zhou, B., & Wang, Z. (2023). Adversarial spatiotemporal contrastive learning for electrocardiogram signals. *IEEE transactions on neural networks and learning systems*, 35(10), 13845–13859. <https://doi.org/10.1109/TNNLS.2023.3272153>
- [54] Le, D., Truong, S., Brijesh, P., Adjeroh, D. A., & Le, N. (2023). sCL-ST: Supervised contrastive learning with semantic transformations for multiple lead ECG arrhythmia classification. *IEEE journal of biomedical and health informatics*, 27(6), 2818–2828. <https://doi.org/10.1109/JBHI.2023.3246241>
- [55] Le, K. H., Pham, H. H., Nguyen, T. B. T., Nguyen, T. A., Thanh, T. N., & Do, C. D. (2023). Lightx3ecg: A lightweight and explainable deep learning system for 3-lead electrocardiogram classification. *Biomedical signal processing and control*, 85, 104963. <https://doi.org/10.1016/j.bspc.2023.104963>

- [56] Yildirim, O., Talo, M., Ciaccio, E. J., San Tan, R., & Acharya, U. R. (2020). Accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG records. *Computer methods and programs in biomedicine*, 197, 105740. <https://doi.org/10.1016/j.cmpb.2020.105740>
- [57] Sadad, T., Safran, M., Khan, I., Alfahood, S., Khan, R., & Ashraf, I. (2023). Efficient classification of ECG images using a lightweight CNN with attention module and IoT. *Sensors*, 23(18), 7697. <https://doi.org/10.3390/s23187697>
- [58] Ozpolat, Z., & Karabatak, M. (2023). Performance evaluation of quantum-based machine learning algorithms for cardiac arrhythmia classification. *Diagnostics*, 13(6), 1099. <https://doi.org/10.3390/diagnostics13061099>
- [59] Hu, L., Cai, W., Chen, Z., & Wang, M. (2024). A lightweight U-Net model for denoising and noise localization of ECG signals. *Biomedical signal processing and control*, 88, 105504. <https://doi.org/10.1016/j.bspc.2023.105504>
- [60] Hu, R., Chen, J., & Zhou, L. (2023). Spatiotemporal self-supervised representation learning from multi-lead ECG signals. *Biomedical signal processing and control*, 84, 104772. <https://doi.org/10.1016/j.bspc.2023.104772>
- [61] Berger, L., Haberbusch, M., & Moscato, F. (2023). Generative adversarial networks in electrocardiogram synthesis: Recent developments and challenges. *Artificial intelligence in medicine*, 143, 102632. <https://doi.org/10.1016/j.artmed.2023.102632>
- [62] Mehari, T., & Strodthoff, N. (2023). Towards quantitative precision for ECG analysis: Leveraging state space models, self-supervision and patient metadata. *IEEE journal of biomedical and health informatics*, 27(11), 5326–5334. <https://doi.org/10.1109/JBHI.2023.3310989>
- [63] Daliri, A., Sadeghi, R., Sedighian, N., Karimi, A., & Mohammadzadeh, J. (2024). Heptagonal Reinforcement Learning (HRL): A novel algorithm for early prevention of non-sinus cardiac arrhythmia. *Journal of ambient intelligence and humanized computing*, 15(4), 2601–2620. <https://doi.org/10.1007/s12652-024-04776-0>
- [64] McConnell, B., Del Monaco, D., Zabihimayvan, M., Abdollahzadeh, F., & Hamada, S. (2023). *Phishing attack detection: an improved performance through ensemble learning*. International conference on artificial intelligence and soft computing (pp. 145–157). [https://doi.org/10.1007/978-3-031-42508-0\\_14](https://doi.org/10.1007/978-3-031-42508-0_14)
- [65] Awal, M. A., Mostafa, S. S., Ahmad, M., Alahe, M. A., Rashid, M. A., Kouzani, A. Z., & Mahmud, M. A. P. (2021). Design and optimization of ECG modeling for generating different cardiac dysrhythmias. *Sensors*, 21(5), 1638. <https://doi.org/10.3390/s21051638>
- [66] Mohebbanaaz, M., Sai, Y. P., & Kumari, L. V. R. (2021). Detection of cardiac arrhythmia using deep CNN and optimized SVM. *Indonesian journal of electrical engineering and computer science*, 24(1), 217–225. <https://doi.org/10.11591/ijeecs.v24.i1.pp217-225>
- [67] Li, L., Ren, W., Lei, Y., Xu, L., & Ning, X. (2025). Hybrid CNN-transformer-WOA model with XGBoost-SHAP feature selection for arrhythmia risk prediction in acute myocardial infarction patients. *BMC medical informatics and decision making*, 25(1), 291. <https://doi.org/10.1186/s12911-025-03127-z>
- [68] Jekova, I., & Krasteva, V. (2021). Optimization of end-to-end convolutional neural networks for analysis of out-of-hospital cardiac arrest rhythms during cardiopulmonary resuscitation. *Sensors*, 21(12), 4105. <https://doi.org/10.3390/s21124105>