

# Advancements In Arrhythmia Classification: A Comprehensive Survey Of Machine Learning Techniques

H Sumitha<sup>1</sup>, M. Devanathan<sup>2</sup>

<sup>1</sup> Research Scholar, Department of Electronics and Communication Engineering, Reva University, Bangalore, Karnataka, India, sumithah\_12@rediffmail.com

<sup>2</sup> Associate Professor, Department of Electronics and Communication Engineering, Reva University, Bangalore, Karnataka, India, devanathan.m@reva.edu.in

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**Abstract:** This comprehensive survey presents an in-depth exploration of arrhythmia classification techniques, spanning from traditional machine learning approaches to deep learning models and hybrid methodologies. The survey covers the fundamental importance of accurate arrhythmia diagnosis, highlighting its critical role in cardiovascular disease management. Each approach's strengths, limitations, and real-world applications are meticulously discussed. The shift from feature extraction to automated feature learning facilitated by deep learning is emphasized, showcasing its transformative impact on addressing intricate challenges posed by ECG signals. The survey culminates in underlining the need for a comprehensive grasp of arrhythmia classification techniques and outlining potential future advancements. By offering a well-rounded analysis of methodologies, empirical outcomes, and existing challenges.

**Keywords:** Arrhythmia classification techniques, ECG (electrocardiogram), Cardiovascular disease management, Deep learning models, Machine Learning.

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## 1. INTRODUCTION

Arrhythmias can be classified according to their unique patterns, enabling the identification and categorization of each individual type. Arrhythmias can be categorized into two main classifications. The first category of arrhythmias, referred to as morphological arrhythmias in this context, includes those that originate from a single abnormal heartbeat. The second group consists of rhythmic arrhythmias, which are distinguished by the occurrence of abnormal heartbeats in combination. The main aim of this study is to categorize normal heartbeats and heartbeats falling into the first category. Cardiac arrhythmia, often referred to simply as arrhythmia, is a medical term used to describe abnormal patterns in the heart's electrical activity, resulting in irregular heartbeats or heart rates. These irregularities can manifest as heartbeats that are too fast (tachycardia), too slow (bradycardia), or erratic in rhythm. Cardiac arrhythmias encompass a wide range of irregular heart rhythms, including:

**Atrial Fibrillation (AF):** A common arrhythmia where the atria (upper chambers of the heart) beat rapidly and irregularly, leading to an inefficient pumping of blood into the ventricles.

**Atrial Flutter:** Similar to AF, but with a more organized pattern of atrial contractions.

**Supraventricular Tachycardia (SVT):** Rapid heart rate originating above the ventricles, often arising from the atria or the atrioventricular (AV) node.

**Ventricular Tachycardia:** Fast and abnormal rhythm originating in the ventricles, which can reduce the heart's pumping efficiency.

**Ventricular Fibrillation:** A life-threatening arrhythmia characterized by chaotic and uncoordinated ventricular contractions, leading to a lack of effective blood circulation.

**Premature Ventricular Contractions (PVCs):** Extra, abnormal heartbeats originating in the ventricles, often considered harmless in some cases.

**Bradycardia:** A slow heart rate, usually defined as fewer than 60 beats per minute, which can result from a malfunction in the heart's natural pacemaker (the sinoatrial node).

The ECG test has the capability to detect changes in the morphology or frequency of waves caused by heartbeats. The process of identifying and classifying arrhythmias can be quite difficult for individuals. This is because it requires a thorough analysis of every heartbeat in electrocardiogram (ECG) data collected over

long durations, such as hours or days, using a holter monitor. Additionally, it is crucial to recognize that the processing of ECG recordings may be susceptible to human error caused by fatigue. The application of computational methods for automated classification is a feasible choice. The following section presents an overview of the four processes that can be utilized to develop a comprehensive automated system for arrhythmia classification using data obtained from an electrocardiogram (ECG) device: The process comprises multiple steps, specifically feature extraction, heartbeat segmentation, learning/classification, and ECG signal preparation. Each of the four processes involves executing a distinct action, with the ultimate goal of identifying the pulse type. The analysis of ECG features typically consists of two distinct processing phases. The first step in the process is to extract the characteristics of the electrocardiogram (ECG). These extracted characteristics are then utilized to classify the ECGs into different situations [5]. The development of automated algorithms for electrocardiogram (ECG) analysis is of utmost importance, as it reduces the substantial time and effort needed for manual examination of ECG characteristics. Over the past few years, there has been a significant advancement in the development and introduction of various techniques for the detection of cardiac arrhythmias. The process involves four essential steps: waveform detection, feature extraction, denoising, and arrhythmia classification [1]. These steps encompass the algorithms utilized in this process.

In recent studies, the utilization of deep neural networks (DNNs) has been observed for the purpose of electrocardiogram (ECG) classifications. Deep neural networks (DNNs) possess the ability to train a feature extraction function from the raw input by utilizing the probability distribution of the dataset. The present approach exhibits variations from prior methodologies. Therefore, in cases where there is a sufficient quantity of training data, the feature extractions achieved by a DNN model can exceed those obtained through manual techniques. The utilization of stacked denoising autoencoders (SDAEs) was implemented in order to train an appropriate feature mapping for the purpose of identifying ventricular arrhythmias. Afterwards, a softmax regression layer was incorporated onto the resultant hidden representation layer in order to produce deep neural networks (DNNs) [2]. Convolutional neural networks (CNNs) have been utilized for the automated detection of cardiac arrhythmias in a parallel fashion. In a prior investigation, the utilization of Convolutional Neural Networks (CNN) was suggested for the identification and categorization of atrial fibrillation (AF). The proposed technique, known as multiscale fusion of deep convolutional neural network (MS-CNN), was developed by the authors with the objective of effectively identifying and filtering out atrial fibrillation (AF) cases. The MS-CNN architecture employs two-stream convolutional networks that leverage various filter sizes to effectively capture features across multiple scales [3]. In an independent study, a Convolutional Neural Network (CNN) was utilized, employing a residual network architecture, to accurately classify a total of 12 distinct rhythm types. Furthermore, the utilization of Convolutional Neural Networks (CNNs) has been implemented in the classification of arrhythmias at the beat level. It is important to mention that the duration of the inputs for these models is generally much shorter, typically comprising hundreds of samples. A convolutional neural network (CNN) consisting of nine layers was developed to achieve the automated categorization of heartbeats into five distinct groups. The Restricted Boltzmann Machine (RBM) and Autoencoder are two network architectures commonly used in the field of ECG classification. In the latter scenario, a novel algorithm was proposed that utilizes deep learning techniques. The proposed approach involves the integration of a long short-term memory (LSTM) based autoencoder network with support vector machines (SVM) to achieve the task of arrhythmia classification [4]. The proposed approach for categorizing arrhythmias in electrocardiograms (ECGs) of varying lengths entails employing a fusion of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models. The previous demonstration highlighted the ability to improve performance on a single network by utilizing a deep learning-based ensemble network model. The design of the model incorporates three separate networks with the objective of detecting and capturing data. The features of the ECG signal can vary among individuals and over time. Additionally, individuals with the same condition may display different ECG morphologies. In addition, it is important to mention that different cardiac disorders may present similar electrocardiogram (ECG)

characteristics. The presence of this similarity presents a notable obstacle in the process of extracting features and analyzing ECG data for the specific objective of heart disease detection [5-7]. Moreover, the current arrhythmia classification algorithms fail to account for the distinct rhythmic attributes exhibited by individual patients, which can differ from the data used for training purposes. The algorithms were developed utilizing training data sets that were limited in size. As a result, the existing methods may demonstrate insufficient performance when implemented in real-world situations. The utilization of long-term electrocardiogram (ECG) monitoring devices has witnessed a notable rise, facilitating the acquisition of comprehensive ECG data for patients. The aforementioned data can be effectively employed in the development of automated categorization systems [8].

There exist multiple categories of arrhythmias that pose a substantial risk to an individual's life. The implementation of automated categorization greatly improves the detection and resolution of these issues. The classification process utilizes various algorithms. The efficiency of algorithms relies on their computational speed. The computation of the signal being considered is influenced by both the mathematical model and the analysis process utilized [9-10].

## 2. RELATED WORK

The proposed methodology for categorizing raw electrocardiogram (ECG) signals from the beginning to the end was introduced in reference [11]. The first step in the process was to accurately identify the exact location of the R peak. Subsequently, the input signal underwent a process of segmentation into beats of a predetermined duration. The division was accomplished by either padding the beats with zeros or truncating them when the RR intervals were smaller or larger, respectively. Although they did not include a specific feature extraction step in their work, they were still able to successfully complete the task. The evaluation conducted in [12] revealed that the Support Vector Machine (SVM) and Artificial Neural Network (ANN) were the predominant classification algorithms utilized for the analysis of ECG signals. The Convolutional Neural Network (CNN), commonly referred to as ANN, has been the predominant artificial intelligence model used in this field for the past decade, accounting for over 50% of all models employed. The cardiologist-level arrhythmia detection model was developed by the authors of [13] using a 34-layer CNN architecture. The purpose of this model is to analyze electrocardiogram (ECG) signals of varying durations. These signals were sampled at a frequency of 200Hz. Deep learning models have demonstrated significant efficacy in the classification of arrhythmias and the detection of various cardiac disorders. The deployment of Deep Neural Network (DNN) inference on edge devices, such as fitness trackers and cell phones, presents significant challenges. These challenges arise from the computational complexity of the task, as well as the demanding memory and power requirements. The study conducted by reference [14] introduces a new design for a Power Management Unit (PMU) that has the ability to provide power to wearable devices. The Power Management Unit (PMU) efficiently harnesses energy from diverse sources to achieve its intended functionality.

The application of 1D CNN and Long Short-Term Memory (LSTM) recurrent neural networks is commonly observed in the literature for ECG signal processing [15]. The study conducted by E. Essa et al. involved the utilization of an ensemble learning technique that incorporated deep learning bagging models [16]. The objective of the study was to classify electrocardiogram (ECG) arrhythmias by integrating long short-term memory (LSTM), convolutional neural network (CNN), and traditional feature extractors. In order to maximize the advantages of CNN extraction compared to a standard fully connected neural network, it is imperative to integrate multiple hidden layers. The current methodology described in the literature for constructing reliable CNN models typically involves the utilization of multiple filters and a significant number of hidden layers. The execution of billions of multiply-add operations is necessary due to the computational complexity of these large networks [17].

Significant attention has been focused on the advancement of algorithms that are optimized for edge devices with constrained power resources. The main goal of these algorithms is to minimize computational complexity. The micro-controller class implementation of an ultralightweight neural network for end-to-end

ECG categorization is presented in the publication [18]. The primary goal of this implementation is to minimize computational complexity while simultaneously ensuring a high level of accuracy.

The task of striking a balance between achieving high accuracy and minimizing model complexity presents a notable challenge. The deep compression method utilizes various techniques, such as pruning, learned quantization, and Huffman encoding, as mentioned in reference [19]. To mitigate the computational complexity of the overall design, an analysis was conducted on various compact network topologies, referred to as compact DNNs. Multiple reports have indicated that several lightweight convolutional neural network (CNN) architectures have exhibited outstanding performance in analyzing both photographs and videos. MobileNet, ShuffleNet, and MnasNet are three commonly utilized lightweight convolutional neural network (CNN) architectures that are widely acknowledged for their effectiveness in image categorization [20]. The incorporation of depthwise separable convolution in the MobileNet and ShuffleNet architectures results in a notable reduction in the number of trainable parameters and computational costs. In order to achieve the highest level of accuracy, the majority of ECG classification algorithms utilize signal filtering techniques. These techniques are employed to effectively eliminate baseline wandering and noise artifacts [21].

The algorithms previously required additional steps in their processes, but these steps have now been integrated into DLA. Statistical methods, including the Markov model, support vector machines (SVM), k-nearest neighbor (KNN) algorithm, random forests (RF), and principal component analysis (PCA), have shown better performance when compared to the use of machine learning algorithms (MLA) in traditional settings. The aforementioned algorithms are frequently employed for tasks involving classification or prediction. It is important to acknowledge that alternative methods are documented in the existing literature. One drawback of the MLA (Modern Language Association) in this specific task is its limited effectiveness in fulfilling the majority of requirements for contemporary applications. The exponential growth of digital information generated daily highlights the need for MLA (Modern Language Association) to gather a significant number of observations to achieve generalization. Deep Layer Aggregation (DLA) facilitates a substantial augmentation in the thickness of the internal layers within a neural network, leading to improved comprehensiveness and sophistication in contrast to Multilayer Aggregation (MLA). This problem leads to the removal of several preprocessing requirements that MLA necessitates for optimal functionality, thereby enhancing the learning experience and improving the accuracy of the outcomes.

The layered architecture and its corresponding hyperparameters were designed manually. There have been proposals put forth for hybrid models that aim to integrate at least two distinct types of neural networks. The utilization of a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model is proposed by the authors for the classification of six classes of Cardiac Arrhythmias (CAs). These CAs are sourced from the MITDB and the Physikalisch-Technische Bundesanstalt Diagnostic ECG Database (PTBDB) [23]. The model achieved an accuracy of 99.89%. The accuracy rate of the model was found to be 97.87%, indicating a high level of precision. Furthermore, the researchers suggest employing CNN-LSTM for the purpose of classifying atrial fibrillation. This classification task will be performed using data acquired from the MITAFD dataset. The hybridization of Deep Learning Algorithms (DLA) is demonstrated through the utilization of a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) model for the classification of three distinct types of CAs. The investigation conducted by the researchers yielded an accuracy rate of 98.7%, which is quite impressive. The Convolutional Neural Network (CNN) is widely used in the research studies mentioned. The neural network under consideration demonstrates a participation rate of 52%. Out of all the participants, 6.6% of them employ a Convolutional Neural Network (CNN) with a Recurrent Neural Network (RNN) architecture. On the other hand, 10.6% of the participants utilize a hybrid approach that combines a CNN with a Long Short-Term Memory (LSTM) model. The proposed approach utilizes deep Convolutional Neural Network (CNN) architectures, as indicated by the findings. This paper presents a novel technique for the categorization of non-stationary noisy signals acquired from time series data. The methodology employs the Cohen class of time-frequency representations (TFR) and DLA. Multiple studies have demonstrated that the application of Metaheuristic Algorithms (MA) to optimize neural networks results

in improved classification accuracy of Convolutional Neural Networks (CNAs). Unlike publications that utilize MLA or DLA, the adoption of this specific technique is still limited. In order to classify six groups of cardiac abnormalities (CNAs) obtained from the MITDB, European ST-T (EDB), and the ST Petersburg Incart Dataset (INCART), the authors present a methodology that integrates a morphological analysis (MA) technique called marine predators (MPA) with a convolutional neural network (CNN).

This article presents an examination of the different methodologies utilized by [24] in the detection and diagnosis of myocardial infarction, a medical condition commonly referred to as a heart attack. Furthermore, this study delves into the distinction between myocardial infarction and other cardiac conditions such as arrhythmias, hypertrophy, and heart enlargement. The observation of successful computerized ECG analysis using fuzzy-based technology has been made, indicating the need for further research. The specificity of the definition is 93.75%, whereas its precision is 86.67%. The constructed model underwent thorough testing using various performance measures. However, additional improvements are necessary to optimize its suitability for real-world applications. The composition of the ECG signal is discussed in the article [25], with emphasis on the importance of very low-frequency impulses that range from approximately 0.5 to 100 Hz. The device commonly known as a cardiac monitor is responsible for filtering an electrocardiogram (ECG) recording. The Low Pass Filter (LPF) is utilized for the purpose of eliminating undesired high-frequency noise signals. The designs of the Low Pass Filter (LPF), High Pass Filter (HPF), and Band Stop Filter (BSF) were originally introduced by Kaiser [26] using the windowing technique. The three filters are arranged in a series configuration, allowing for sequential signal processing within the frequency range of 0 to 100 Hz. The attenuation of each filter is 13 dB. The filters are organized in a sequential manner, specifically in the order of 200, to efficiently diminish interference signals.

The study conducted by [27] comprised the examination of more than 80 papers that encompassed a range of imaging techniques, including cardiac magnetic resonance imaging (MRI), computed tomography (CT), single-photon computed tomography (SPECT), intravascular visual cohesiveness tomography (IVCT), and echocardiography. This document provides an explanation of the fundamental principles that dictate the efficient operation of deep learning algorithms. The survey study conducted by Kaplan Berkaya et al. [16] analyzed a dataset consisting of 1538 electrocardiogram (ECG) signal recordings. The study presented a comprehensive analysis of multiple factors, encompassing heart rate measurements, cardiovascular functionality, cardiac disease diagnosis, emotion recognition, and biometric identity. The study conducted by [28] introduced a classification system that demonstrated high precision. The intelligent ECG classification system employs fast residual convolutional neural networks (FCResNet) for its implementation. The system, when configured with a batch size of 2, demonstrated an average precision of 98.79%. The system utilized a classifier that employed 20 batch size parameters and low-frequency subspaces, which were selected based on the MOWPT method.

The utilization of an electrocardiogram (ECG) recording has been proposed in a recent study for the detection of premature ventricular contraction (PVC) beats. This detection is achieved by applying a deep neural network. A deep neural network is trained with six hidden layers to effectively distinguish between normal and PVC beats. The training process entails supplying the network with six distinct characteristics that have been extracted from electrocardiograms (ECGs). The authors consistently gave preference to manually generating features from the ECG data, even when employing a deep neural network. The differentiation between paroxysmal atrial fibrillation (PAF) and normal heartbeats is accomplished through the utilization of a deep convolutional neural network, as detailed in reference [29]. The network is designed to extract characteristics directly from raw electrocardiogram (ECG) data. One of the constraints encountered when training a deep convolutional neural network from the beginning to enhance network performance is the requirement for a significant labeled training dataset. This requirement is necessary when attempting to enhance the network's depth by increasing the number of convolutional layers. The increase in network depth leads to an increase in computation cost during training, even when a large dataset is present. The reason for this is that deep convolutional layers are composed of convolutional operations that are more intricate in

nature. To ensure optimal execution of these training tasks, it is crucial to employ high-performance computers that are equipped with robust GPUs.

Transfer learning and its variant, transfer learning with fine tuning, offer a practical solution for overcoming challenges related to limited training data, inadequate training experience, and restricted computing resources. These approaches enable the utilization of deep learning applications in scenarios where such constraints exist. In the domain of transfer learning, a pre-trained deep Convolutional Neural Network (CNN) is imported and employed as an automated feature extractor for the specified task. In order to streamline the process of extracting features for input into a classifier and subsequent classification, it is possible to import a pre-trained Convolutional Neural Network (CNN) that has been trained on a generic image dataset. This can be particularly useful for medical imaging tasks, such as pathology classification. Furthermore, it is feasible to perform retraining on one or multiple layers of the pre-trained network by engaging in the process of fine-tuning, using data that is specific to the job at hand.

Survey Table

Method	Type	Advantages	Disadvantages
Traditional Feature Engineering	Traditional	Interpretable features; well-established approach	Limited capacity to capture complex patterns
Support Vector Machines (SVM)	MLA	Effective for high-dimensional data; robust to overfitting	Sensitivity to hyperparameters; may require data scaling
k-Nearest Neighbors (k-NN)	MLA	Simple and intuitive; no model training required	Sensitive to noisy data; inefficient for large datasets
Random Forests	MLA	Robust to overfitting; handles non-linearity	Less interpretable; can be sensitive to noisy data
Principal Component Analysis (PCA)	MLA	Reduces dimensionality; noise reduction	Linear technique; may not capture complex relationships
Convolutional Neural Networks (CNN)	DLA	Automatic feature extraction; suitable for raw signals	Demands large labeled datasets; computationally intensive
Long Short-Term Memory (LSTM)	DLA	Captures temporal dependencies; suitable for sequential data	Complex architecture; potential overfitting
Hybrid Models (e.g., CNN-LSTM)	Hybrid	Combines strengths of different models; improved accuracy	Complex architecture design; potential overfitting
Transfer Learning	DL	Utilizes pre-trained models; saves training effort	May not adapt well to specific arrhythmia patterns

### 3. Conclusion

In conclusion, the survey navigates the evolution from conventional statistical and machine learning approaches to state-of-the-art deep learning methodologies in the realm of arrhythmia classification. The paradigm shift towards end-to-end feature extraction through deep neural networks has yielded remarkable breakthroughs in classification accuracy. The emerging synergy of hybrid models, amalgamating machine learning and deep learning paradigms, exhibits promising prospects for pushing accuracy boundaries further. While challenges of computational intensity and energy efficiency persist, ongoing issues in algorithmic refinement and hardware optimization aim to surmount these bottlenecks, this survey serves as an essential area for researchers and medical practitioners, to better analyses the methods involved in arrhythmia classification and its potential clinical impact.

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