

## Classification of Cardiovascular Arrhythmia Using Deep Learning Techniques: A Review

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### Abstract

Deep Learning (DL), an offshoot of Machine Learning (ML) has emerged as a powerful and feasible solution for medical image analysis due to advancements in robust computer software and hardware technologies. It plays a key role in Cardiovascular disease (CVD) diagnosis by detecting anomalies in Electrocardiogram (ECG) signals. Cardiac arrhythmia, which refers to irregular heartbeat, may signal an early symptom of CVD and can lead to mortality if ignored. Accurate detection of arrhythmias is very strenuous even for experts to distinguish between acute and chronic conditions in ECG readings. This triggered the focus of researchers to explore the application of Artificial Intelligence for ECG classification. Traditional machine learning methods use handcrafted features that require domain knowledge. The new era in DL makes the automatic detection of Cardio Vascular Disease (CVD) possible. In this paper, an exhaustive review of DL-based techniques for ECG classification has been presented. Research findings in this survey indicate the challenges and issues with arrhythmia detection, such as single lead and multiple lead ECG signals, choice of the size of the training data set, and the number of arrhythmia classes, etc. The study also signifies that there is great scope for improving the performance of the arrhythmia prediction models by employing hybrid ensemble learning, time series analysis using Recurrent Neural Network architectures and identification of unexplored classes of arrhythmia.

**Keywords:** Arrhythmia, Cardiovascular Disease, CNN, Deep Learning, Electrocardiogram

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### 1. Introduction

Cardiovascular Disease is one of the major chronic diseases that lead to death around the world. It is not a disease caused by a single reason but it occurs due to a cluster of pathologies, which affects the cardiovascular system. It includes coronary heart disease, heart and blood vessel disorder, rheumatic heart disease, angina, stroke, aortic aneurysm cerebrovascular disease, and other less common cardiovascular diseases [1]. CVD is an epidemic, according to the report submitted by the Chronic Diseases Collaborating Group to the Lancet [2]. Nearly 17.9 million people face their deaths every year. Out of five, four people die due to heart attacks and strokes, and one-third of premature deaths occur in the age of below 70. CVD

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accounts for 31% of mortality; most of this is in the form of coronary heart disease and cerebrovascular accident [3]. However, there is betterment in scientific research for diagnosing CVD, as it persists to be the preceding reason for premature death around the planet [4]. Cardiovascular diagnosis is not a simple procedure as it involves a long and exorbitant process, and has to be interpreted by the experts alone [5].

Generally, the most popular method for early screening of CVD is done by the analysis of ECG signals. Energy signals generated by the heart are electrical waves produced from depolarization and re-polarisation of some blood cells [6]. ECG is considered to be an invasive method for recording the electrical exertion of the human heart using single or multiple-lead detections. It is very useful for clinically diagnosing cardiac diseases. It plays a significant part in analyzing and identifying various arrhythmias using P, QRS, and T waves [7]. The three main challenges in detecting Arrhythmia using ECG signals are 1) Different waveforms for different patients 2) Waviness in ECG signal due to change in heart rate 3) observation noise [57]. ECG beats are categorized as Ventricular ectopic beat (VEB), Supra Ventricular ectopic beat (SVEB), Left bundle branch (LBBB), Paced (P), Unknown (Q), Right bundle branch (RBBB), Fusion (F), and Normal (N) as shown in figure 1 [8].

Cardiovascular disease is easily detected and diagnosed by classifying ECG signals [9]. A review of DL methods used in the classification of the ECG signal is presented in this paper and the remaining section of this paper is organized as follows Section 2. describes the ECG Classification process and the deep learning architectures used for ECG Classification, Section 3. presents the review of literature on DL based ECG Classification, Section 4. discusses the experimental results and future directions of research, and Section 5. presents the Conclusions.

## 2. ECG Classification using Deep Learning

ECG classification process categorizes the signal as an abnormal and normal signal, based on the intervals in PR, RR, and QRS width in ECG signal [10]. A Normal Sinus Rhythm is shown in Fig 1. Generally, ECG classification involves three important phases;

- (i) Preprocessing,
- (ii) Feature learning,
- (iii) Classification [11].

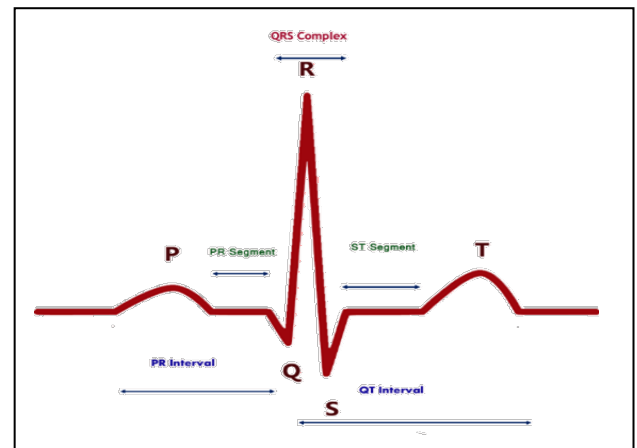


Figure 1. Normal Sinus Rhythm

Acquired ECG Signal will have noises not only from the ECG signal acquiring devices but also from transferring medium, and the storage medium. To achieve accuracy and reliability, noise should be removed in the signal by eliminating high and low frequencies. Preprocessing is a primary process to eliminate various categories of noise and artifacts in the ECG signal before annotating the ECG signal. Removal of noise before classification may eliminate false classification and false diagnosis [12, 13]. It reinforces the raw ECG signal's quality by removing noise, which is classified into five primary categories: baseline wander, electrode contact noise, powerline interference, muscle contractions, and electrode motion artifacts [14]. Resampling and denoising are performed in the data preprocessing procedure, by applying noise specific filters, to the ECG signal [15].

Segmented heartbeat waveforms are obtained after filtering the ECG signal [16]. Every ECG signal is acquired uniquely, and some may take several hours to record the signal.

In the recording, tags are pointing to a particular location known as ECG annotations which represents the event at that particular location. The standard set of annotation code described for ECG includes both beat annotation and non-beat annotation. Every instance in the annotation can have up to six attributes [17]. It may be time-consuming for recording the signal as well as for the technicians to annotate the signals. Hence, automatic interpretation of the ECG signal will aid the physicians in fast diagnosis [15]. Generally, for extraction of features in ML based ECG classification, few techniques such as PCA (Principal Component Analysis), ICA (Independent Component Analysis), LDA (Linear Discriminate Analysis), and DWT (Discrete wavelet transform) are widely used [18, 19].

The focus of research on DL based methods is due to feature learning, a special feature of DL that learns data representations automatically [22]. The major reason behind DL benefit with all the domains is automatic feature

extraction and this makes ECG interpretation achieve greater performance leading to accurate diagnosis [23].

Lastly, feature classification is done to classify the abnormal and normal beats using standard classifiers like Artificial Neural Network (ANN), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) [19-21].

## 2.1. Deep Learning Architecture for ECG Classification

Deep Learning algorithms are found to be extremely robust and accurate in recent years in the automatic interpretation of medical images such as Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) [24,25]. It is also extensively applied in the analysis of Coronary Angiography, Echocardiography, and ECG signals [26]. DL follows the behavioral approach of the human brain [27]. And it is capable of unfolding complicated data patterns efficiently [22].

The architecture of a deep learning model is built as a collection of modules arranged in stack organization particularly designed for handling Tensor data [28]. DL methods are classified as deep discriminative models such as DNN, CNN, RNN, etc., and unsupervised models such as RBM, DBM, Autoencoders, etc., [29-31].

### CNN

CNN has strongly placed its footprint in health informatics [32]. The name convolution is coined from the operation discrete convolution on the function with real-valued arguments created by the feature map while filtering is applied [33]. It is a multilayer perceptron, in which convolutional layers are made to learn features on patches that are sampled randomly from the large image [34].

A simplified CNN architecture has three types of layers: The convolutional layer, the pooling layer, and the fully connected layer, as shown in Fig 2. [35]. A convolutional layer is a collection of feature maps with different weight vectors such that in every location, multiple features can be extracted [36]. Convolutional layers reduce the complexity of the model by optimization of its output [35]. The feature of the image can be calculated by convolving the feature map with the image at a particular point. The feature map is designed to perform this operation in various positions of the image. Subsampling layers are used to eliminate irrelevant features to avoid computing complexity and overfitting [34]. The pooling layer performs downsampling with the input using spatial dimensionality to reduce the parameters when the images are big. A fully connected layer converts the feature maps to vectors [35]. The features extracted by the convolutional layer are fed to a fully connected layer for the classification of input signals [37-39].

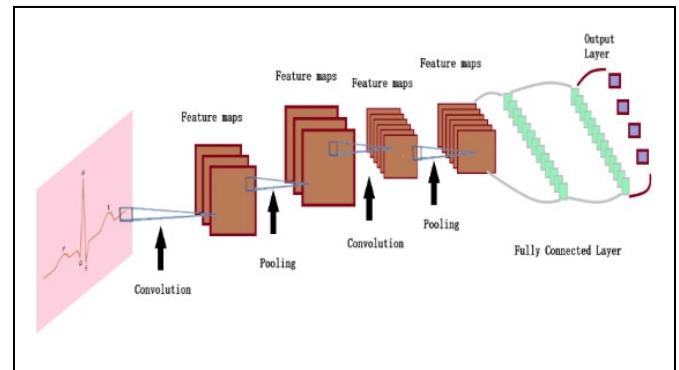


Figure 2. A Simple CNN Architecture

### RNN

A recurrent neural network is structured to handle a variable-length sequence of inputs and it is a prolongation of a conventional feed-forward neural network [40]. RNNs have sequentially connected feed-back networks which is a more powerful mechanism compared to feedforward neural networks. It helps the network to do temporal processing and learn sequences [41]. The model learns itself from the data on how to represent memory [42]. RNNs store the information from the previous iteration in the neurons for future prediction, which makes it different from CNN [43]. It can cluster, classify, and predict especially text and time-series data [44].

### LSTM

LSTM is a restructured architecture of RNN, which reduces the time taken to handle a long data sequence [44]. The recurrent hidden layer consists of memory blocks in LSTM, which is made up of memory cells where the connection is cyclic. These memory cells are responsible for storing data. Gates circuit is used to control the information flow. LSTM is a peculiar type of RNN that handles temporal data [41]. Three types of gates are arranged in this structure: Forget gate, input gate, and output. Every memory block has an input and output gate. Forget gate is responsible for removing the unwanted information that is not needed for further processing [45].

Multiple inputs and output gate units are used to secure the information in the memory from hassle [46]. A self-connected linear unit is present in the core of every memory cell, which is known as a Constant Error Carousel (CEC) [47]. It provides a short-term memory for a long period [48]. LSTM keeps vanishing gradient problems by using Gating functions [49, 50].

### 3. Related Works

Totally 100 publications were retrieved for study and out of which 28 were chosen for investigation based on the relevance and up-to-date publications.

Kiranyaz et al. (2015) developed an automatic monitoring system for precise electrocardiogram classification by applying an adaptive one-dimensional Convolutional Neural Network (1D-CNN). The algorithm design is too simple to adapt for any dataset because of the unvarying parameters used in the model and combining feature extraction and classification in a single learning phase. It achieves superior performance in classification when compared with comparative methods used in spotting SVEB and VEB. Hence, it has been adapted widely in a real-time cardiac monitoring system [51].

Rajpurkar et al. (2017) developed a novel methodology for diagnosing cardiac arrhythmias from ECG signals recorded from the single-lead wearable monitor. The proposed system worked with a real-time dataset. The algorithm has experimented on a gold standard test set that was annotated by the cardiologist's Committees, and it exceeds the performance of six cardiologists on the committee board in both Precision(Positive Predictive Value) and recall (Sensitivity) [52].

Hong et al. (2017) introduced a novel algorithm for the classification of ECG by combining Deep Neural Network (DNN) and expert features. This algorithm finds the untold illustrative wave (centerwave) within the long ECG record, and features were extracted within this centerwave. These extracted features, expert features, and deep features are amalgamated with an ensemble classifier for further classification of cardiovascular disease. This framework exhibits better performance [53].

Pyakillya et al. (2017) had developed a model for ECG signal classification with the architecture of 1D convolutional layers and FCN layers, and the accuracy obtained during validation is 86%. The proposed work can be tested with unstructured and unbalanced data. Moreover, it is interpreted as a 1D time series that is used in single-lead ECG portable devices. The proposed work can classify ECG recordings even without experts [54].

Andreotti et al. (2017) proposed a classification of ECG signals, especially the short segments present in the signals, by augmenting the database. The proposed algorithm attained an F1 score of 72.1% for the training set and 83% for the testing set gradually. Furthermore, the authors have proved that classification is possible even with the short recording in ECG when Deep Learning is applied [55].

Xiang et al. (2018) had developed an absolute model for QRS Complex detection which extracts both fine-grained and coarse-grained morphological features using attention-based two-level 1-D CNN. This method achieved a good score with a Positive Predictivity Rate (PPR) of 99.91%, a sensitivity of 99.77%, and a Detection Error Rate (DER) of 0.32%. [56].

Goodfellow et al. (2018) developed a new method for the classification of a single lead ECG waveform as Atrial

Fibrillation, Normal Sinus Rhythm, or other rhythms. This method uses a deep convolutional network for training which generates a classifier in the first phase and extraction of class activation mapping in the second phase. The model attains an average score of 0.84 and 0.88 as F1 Score, and accuracy respectively for all rhythms in the validation dataset. The class activation mapping permits for visualization of regions of the waveform in the model which helps the clinicians for making better classification decisions [57].

Ochiai et al. (2018) introduced a new method to identify arrhythmia in ECG in which the classifier is built by fusing CNN with a denoising encoder. This classifier achieves good performance with an accuracy of 0.947 in 1D CNN, 0.966 in 2D CNN for ventricular ectopic beat(VEB) and it also achieves an accuracy of 0.947 in 1D, 0.966 in 2D for supraventricular ectopic beats (SVEB). This method proves to be a potential non-patient-specific way for arrhythmia detection especially, in VEB. Beyond the work, the proposed algorithm is extended to 12-lead ECG [58].

Yildirim et al. (2018) discussed a new methodology for diagnosing arrhythmia, which is built on long-duration ECG signals. It performs arrhythmia classification for 17 classes by depleting 1D-CNN. The deep learning approach distinguished pacemaker rhythm, normal sinus rhythm, and 15 other rhythmic disorders accurately with long-duration (10s) ECG signals and reached an accuracy of 91.33%. The major advantage is that this model is less complex, which can assist clinicians in a fast and efficient way, yielding a high score. [59].

Anwar et al. (2018) developed a new technique for ECG classification by blending morphological and dynamic features. Morphological features are acquired by applying, Discrete Wavelet Transform (DWT) on every heartbeat. The hybrid features with twelve ICA projection DWT coefficient, RR interval features, and Teager energy values are amalgamated and fed into a neural network for ECG Classification. This model outperforms existing methods with a maximum accuracy of 99.84% for both class-oriented and subject-oriented schemes with three-fold validation. [60].

Ribeiro et al. (2018) had designed a model by using a short-duration 12-lead ECG for diagnosing abnormalities in the electrocardiogram (ECG) and the performance of the model was measured by F1 scores which shows greater than 80% and specificity reached 99%. This tool can detect false-positive diagnoses and improve accuracy [61].

Li et al. (2018) proposed a CNN model to detect arrhythmia or irregular heartbeats using automatic feature extraction from a 2D ECG signal converted from the 1D signal. This model forms a two-dimensional information vector combining heartbeats and the morphology which is then processed by CNN with different learning rates and bias. This model achieved good performance when compared with standard methods for the categories of five and eight heartbeats with an average accuracy of 99.1%. The proposed classifier includes both biased dropout algorithms and ADADELTA to enhance performance and

it is suitable for the effectuation in portable devices for ECG monitoring for diagnosing CVD [62].

Xu et al. (2018) find a new methodology with the alignment of signal in raw ECG for end-to-end classification of various types of arrhythmia. Consecutive vectors and sample points are extracted from the ECG time domain. Every vector poses a P wave, a T wave, and a QRS complex. The proposed method converts the raw signal into aligned heartbeats that are beat-by-beat classified with the aid of DNN. [63].

Chen et al. (2018) put forward a unique methodology to detect types of cardiovascular arrhythmia disease. The proposed method applies denoising and filtering methods to annihilate the baseline drift and myoelectric interference. The signal after the filtering process was converted into heartbeats. Both the spatial domain and the time-frequency domain features can be extracted implicitly by the algorithm with no need for a manual process of extracting it. The novel method identifies four types of arrhythmia disorder using CNN which reached the highest accuracy of 99%. The comparative performance was assessed with the algorithm SVM and achieved an accuracy of 73.54% [64].

Kim et al. (2019) introduced an algorithm for the classification of ECG heartbeats using GoogLeNet architecture. They made slight changes in the kernel size of the convolution layers and tested with three and five ECG segments that reached an accuracy of 95.94%, and 98.31% respectively. The proposed algorithm can categorize five distinct heartbeats namely, RBBB, LBBB, Normal Sinus Rhythm (NSR), Premature Ventricular Contraction (PVC), and Atrial Premature Contraction (APC) with high accuracy [65].

Ji et al. (2019) developed an algorithm for the betterment and effectuation of ECG classification which is built using Faster Regions CNN (F-R-CNN). This model can classify cardiovascular arrhythmia disease into five categories with an accuracy of 99.21%. The comparative performance was tested using the One Versus Rest Support Vector Machine (OVR SVM), and it is observed that the accuracy is elevated by 2.59%. The developed model can be used in healthcare Robots for detecting arrhythmia and cardiovascular disease diagnosis [66].

Rajkumar et al. (2019) have developed an erudition algorithm to examine the patient with different arrhythmia diseases and classify them with ECG signals. The algorithm is designed based on CNN with the RELU activation function. The designed model hikes its performance to 93.6% by classifying most of the common arrhythmia with accurate results. The result is analyzed by implementing different activation layers and found RELU to be ELU has ranged high in these comparative results [67].

Kaouter et al. (2019) introduced a model that classifies three types of ECG signals in patients as normal heartbeats Congestive Heart Failure and Arrhythmia. The work has been carried out with three databases and achieved an accuracy of 93.75% while comparing it with other standard

methods. CNN used in the developed model is too simple to be constructed with only four convolutional layers and separated into two blocks which are used to classify the ECG signal. The model reduces the computational resources by reducing the size of the architecture compared with some of the other DL models. [68].

Zhang et al. (2019) had invented a unique cascaded-CNN (C-CNN) for distinct noise level classification in dynamic ECG signals. It classifies five dynamic ECG signals such as severe motion artifacts, severe myoelectrical noise, low interference, mild motion artifacts, and mild myoelectrical noise. ECG signals are split into three categories severe, mild, and low in this study, with cascaded CNN which satisfies the clinical requirements and reached an accuracy of 91.8% on a public dataset and 92.7% on a private dataset [69].

Moskalenko et al. (2019) had discovered a model for the segmentation of ECG signals automatically. The Qualitative segmenting technique used to list offsets and onsets of P and T waves was designed by applying U-Net. The performance of the proposed algorithm appeared to be superior when compared with other stand-of-art segmentation algorithms, and it achieves F1-measures of 97.8% for P wave, 99.5% for T wave, and 99.9% for QRS Complex [70].

Zheng et al. (2020) developed a methodology for classifying arrhythmia by blending Long Short Term Memory (LSTM) and CNN. The classifier does not need any preprocessing such as feature extraction or denoising methods and it can detect eight ECG signals, inclusive of normal sinus rhythm. The developed method has proved its accuracy by 99.01%, specificity by 99.57%, and sensitivity by 97.67%. It can directly assist experts, and it can be used for medical robots and other medical monitors for diagnostic treatments [71].

Tung et al. (2020) had implemented a channel-wise attention mechanism in a new architectural framework for the classification of the ECG efficiently. This model has been designed with multi-lead ECG for diagnosing cardiovascular disease, and it is used for ECG tracking in real-time for Holter and other wearable devices. Resnet is structured using three models [72].

Vijayarangan et al. (2020) introduced a structure constructed with the combination of LSTM and CNN for ECG signals. Gradient weighted Class Activation Map is implemented as a primary step to exhibit the prominence of the CNN model. As the next method, by training the input deletion mask prominence is attained in the LSTM model [73].

Malik et al. (2020) proposed a revised new algorithm for the QRS complexes with two novel features. In the amplitude of the signal, local estimates are applied first. The second feature applies a technique that fits the heart rate modification. The developed model competes with other standard algorithms that use short-term ECG recordings. And the developed model obtains a PPR of 99.73% and a sensitivity of 99.90%. The novel method is

efficient and the exactness of the algorithm is suitable for health care in mobile applications, with ultra-long-term and pathological ECG recordings [74].

Ribeiro et al. (2020) probed the automatic classification of ECG which is being tested in 12-lead ECG signals by implementing a Deep Neural Network. The model diagnoses ECG abnormalities into six types such as RBBB, Atrial Fibrillation (AF), Sinus Bradycardia (SB), LBBB, Sinus Tachycardia (ST), and 1st degree AV block (1dAVb) even in the short duration 12-lead ECG recordings. It is compared with similar algorithms for detecting AF which took part in 2017 the Physionet Challenge, for single-lead ECGs in an open dataset. The Performance of the model was measured by using F1 scores and Specificity which reaches above 80% and 99% respectively [75].

Smigiel et al. (2021) suggested three neural network architectures: a convolutional network-based architecture, a SincNet-based architecture, and a convolutional network-based with extra entropy-based features. Studies for 2, 5, and 20 classes of disease were carried out. The best classification was obtained by the CNN with entropy features. Due to the drastically reduced number of neurons, the convolutional network without entropy-based features produced a slightly less favourable outcome but had the maximum processing efficiency [76].

Rahman et al. (2022) developed a comparison and accuracy analysis of several transfer learning methodologies employing ECG classification for detecting arrhythmia (CAA-TL). Real-time data from healthy and unhealthy datasets have been added, enhanced, and combined with the dataset. By utilising various techniques such as ResNet50, AlexNet, and SqueezeNet, the CAA-TL improved the accuracy of cardiac disease identification. When dealing with multi-classification using a large dataset of ECG data, the comparison of various deep learning algorithms with respect to layers broadens the research and increases clarity and accuracy, but also time-consuming. Implementing the suggested method revealed accuracy for AlexNet, SqueezeNet, and ResNet50 of 98.8%, 90.08%, and 91%, respectively [77].

Khan et al. (2023) presented a study on a CNN-based DL method for classifying ECG signals found in the PhysioNet MIT-BIH Arrhythmia database. The suggested method uses a 1-D convolutional deep residual neural network (ResNet) model to extract features from the input heartbeats. For training, the Synthetic Minority Oversampling Approach (SMOTE), which addresses the class imbalance problem is applied and it successfully categorises the five heartbeat types. Accuracy, precision, sensitivity, F1-score, and kappa are used in ten-fold cross-validation to assess the performance of the classifier. The results show an average of 98.63% accuracy, 92.86% precision, 92.41% sensitivity, and 99.06% specificity. The average F1-score attained was 92.63%, and the Kappa was 95.5%. The research indicates that the suggested ResNet achieves high accuracy [78].

From the literature survey, it is observed that mostly MIT/BIH arrhythmia (Beth Israel Hospital) dataset is used for performance evaluation [79].

## 4. Results

Cardiovascular disease diagnosis is a crucial process to reduce the mortality rate. It is an umbrella term, covering several CVD disorders including cardiovascular arrhythmia. Rigorous research has been reported on the classification of arrhythmia through ECG signals using deep learning techniques. The proposed methods can classify at least two to five classes of arrhythmia. The database mostly used in these research works were collected from the MIT-BIH arrhythmia dataset. Moreover, this research works used single Lead or multi Leads depending on the types of arrhythmia classes. ECG lead records the electrical activity of the heart in the form of a graph through multiple electrodes placed at different locations in the body.

Single Lead is used for detecting preliminary heart monitoring to check various arrhythmias or for simple educational research purposes. Compared with a single Lead, Lead-II is more efficient in detecting arrhythmia since this Lead is very closer to the cardiac axis. With the advancement in technology, the number of leads has also increased. The use of 12-Leads shows better performance in effectively predicting arrhythmia when compared with less number of Leads. It is observed that the majority of the research articles reviewed in this paper have worked with 12-Leads and few have worked with Lead-I and Lead-II.

ECG being one-dimensional time series data it should be converted into two dimensional form before applying deep learning algorithms. The review of the literature clearly reveals that noise removal is an important step that is carried out before classification in the preprocessing phase so as to improve accuracy.

The performance of the DL-based techniques is evaluated using the performance metrics given in Table I.

Table 1. Performance Metrics for ECG Classification

Metrics	Formula
Accuracy	$\frac{TP + TN}{TP + FP + FN + TN}$
F1-Score	$\frac{2 * (\text{precision} * \text{recall})}{(\text{precision} + \text{recall})}$
Recall/Sensitivity	$\frac{TP}{TP + FN}$
Specificity	$\frac{TN + FP}{TN + FP + TP}$
Precision	$\frac{TP}{TP + FP}$

Table II presents the summary of the DL algorithms discussed in the Literature survey section.

Table 2. Summary of Deep Learning Algorithms for ECG Classification

Author & Year of Publication	Techniques used	Performance Metrics	Dataset
Kiranyaz et al. (2015) [51].	CNN	VEB: Accuracy - 99%, SVEB: Accuracy - 97.6%	MIT-BIH Arrhythmia Benchmark Database (Lead II)
Rajpurkar et al. (2017) [52].	CNN	Sequence level Accuracy: F1-score : 0.776 Set level Accuracy : F1-score : 0.809	Annotated Dataset(Lead I)
Hong et al. (2017) [53].	Ensemble Classifier	F1-score: 0.84	The Physionet computing in cardiology challenge: AF classification from a short single lead ECG recording(Lead I)
Pyakillya et al. (2017) [54].	FCN layers and 1D convolutional layers.	Validation data Accuracy: 86%	Preprocessed time-series data. (Lead I)
Andreotti et al. (2017) [55].	CNN	Augmented database F1 score: 72.1% and test set F1 score: 83%	(INCART-DB, LTAFFDB, AFDB). (Lead I)
Xiang et al. (2018) [56].	1D-CNN	Sensitivity: 99.77%, Precision: 99.91%, and DER: 0.32%.	St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (INCART) database and MIT-BIH arrhythmia (MIT-BIH-AR) database.
Goodfellow et al. (2018) [57].	CNN	Recall=0.85, F1=0.84, Precision=0.84, and Accuracy=0.88.	AF Classification Challenge 2017 database from PhysioNet (Lead I)
Ochiai et al. (2018) [58].	CNN with Denoising AutoEncoder	VEB: Accuracy - 1D : 0.951, 2D : 0.957, SVEB : Accuracy - 1D : 0.947, 2D : 0.966	MIT-BIH Arrhythmia Database(Lead II)
Yildirima et al. (2018) [59].	1D-CNN	Accuracy:91.33% - classification time/single sample of 0.015 sec.	MIT-BIH Arrhythmia Database (Lead I)
Anwar et al. (2018) [60].	DWT	Accuracy: 99.75%	MIT-BIH Supraventricular Arrhythmia Database and MIT-BIH arrhythmia Database. TNMG (12 lead)
Ribeiro et.al (2018) [61].	CNN	F1 Score > 80% and Specificity: 99%.	
Li et al. (2018) [62].	CNN	Accuracy: 99.1%	MIT-BIH Arrhythmia Database. (Lead II)
Xu, et al. (2018) [63].	DNN	Accuracy: 99.70%	MIT-BIH Arrhythmia Database. (Lead II)
Chen et al. (2018) [64].	CNN	Accuracy: 98.15%	St.Petersburg Institute of Cardiological Technics 12-Lead Arrhythmia Database

Author & Year of Publication	Techniques used	Performance Metrics	Dataset
Kim et al. (2019) [65].	GoogLeNet with Convolution layers	3 ECG segments – Accuracy: 98.31%	MIT-BIH Arrhythmia Benchmark Database.
Ji et al. (2019) [66].	Faster R-CNN	Accuracy : 99.21%, 2.59% higher than OVR SVM	MIT-BIH Arrhythmia Database.
Rajkumar et al. (2019) [67].	CNN with ELU activation function	Accuracy : 93.6%	MIT-BIH Arrhythmia Database.
Kaouter et al. (2019) [68].	CNN	Accuracy : 93.75%	162 recordings - Physionet databases: 30- (BIDMC) congestive heart failure database, 36-(MIT-BIH) Normal Sinus Rhythm Database, and 96-(MIT-BIH) Arrhythmia Database
Zhang et al. (2019) [69].	C-CNN	Overall Recognition Rate: Private Dataset - 92.7% and Public Dataset -91.8%	MIT-BIH Arrhythmia Database.(12-Lead)
Moskalenko et al. (2019) [70].	U-Net	F1-measures - P wave: 97.8%, T wave: 99.5%, and QRS complex: 99.9%.	Lobachevsky University Electrocardiography Database(LUDB) (12-Lead)
Zheng et al. (2020) [71].	CNN with LSTM	Accuracy : 99.01%, Specificity : 99.57%, and Sensitivity : 97.67%	MIT-BIH Arrhythmia Database.(Lead II)
Tung et al. (2020) [72].	CNN	VEB: Accuracy – 98.9%, SVEB: Accuracy - 97.6%	MIT-BIH Arrhythmia Database.(Multi lead)
Vijayarangan et al. (2020) [73].	CNN & LSTM	Recall: 0.97, Accuracy: 0.97, Precision: 0.98, and F1-Score: 0.97.	MIT-BIH Long-Term Database (LTDB), MIT-BIH Arrhythmia Database (MITDB), Long-Term Atrial Fibrillation Database (LTAfDB), combined. Lead II alone extracted. (Lead II)
Malik et al. (2020) [74].	QRS detection algorithm	Sensitivity : 99.90% and Precision : 99.73%	Eleven Annotated Databases at Physionet(short-term ECG recordings) (Lead I)
Ribeiro et al. (2020) [75].	DNN	F1 scores > 80% and Specificity: 99%.	2 million labels - TNMG's ECG system (12-Lead)
Smigiel et al. (2021) [76].	SineNet	Accuracy:89.2%	PTB-XL dataset
Rahman et al. (2022) [77].	CAA-TL	Accuracy of AlexNet: 98.8%, SqueezeNet: 90.08%, and ResNet50:91%	MIT-BIH Arrhythmia Database.(Lead II)
Khan et al. (2023) [78].	ResNet	Accuracy: 98.63%	MIT-BIH Arrhythmia Database.(Lead II)



It is obvious from Table 2 that the accuracy of the algorithms almost reached 99% accuracy and are being applied in real-time health monitoring systems to assist clinicians. It is also worth noting that the following DNN models such as CNN, Ensemble Classifier, Denoising encoder, GoogLeNet, Faster-R-CNN, U-Net, Autoencoder, and LSTM are applied at different stages of the ECG Classification process for diagnosing different classes of arrhythmia.

## 5. Discussions

Though DL algorithms have proved its efficiency in the detection of Cardiac Arrhythmia detection, there is still a lot of scope for furthering research in improving the performance. So far, the existing methods can detect two to five classes of Arrhythmia which motivates us to investigate the detection of other classes of Arrhythmia and Ventricular Flutter or Fibrillation as well.

Challenges are also involved in choosing the appropriate size of training data set for arrhythmia detection especially diagnosing SVEB without compromise on accuracy and should be tested for single and multiple ECG leads. The performance of the classifiers can also be enhanced by building new and hybrid models using ensemble learning. Apart from specific parameters, other patient parameters can also be included for accurate diagnosis of CVD. Researchers are also thriving to reduce the ratio of false positives and false negatives in ECG abnormality detection.

Furthermore, the time-series nature of the ECG signal prompts the replacement of DL classifiers with LSTM as it is capable of learning long-term dependencies which may help to unfold new classes of Arrhythmias. The use of RNNs and its variants for long-term ECG signals are also explored for effective diagnosis.

Research can also focus on model compression to reduce the complexity during the deployment phase in the health monitoring system and medical robots.

## 6. Conclusion

Deep Learning has mostly spread its roots in all fields, mostly in medical imaging for accurate diagnosis and precision medicine that made the healthcare system qualitative. The primary objective of cardiovascular detection is to prevent premature morbidity and mortality. Deep learning provides a powerful platform for integrating clinical and medical imaging. This article discussed the various deep learning techniques implemented in the workflow pipeline right from the process of denoising ECG signals to the classification of cardiovascular Arrhythmia. It also analysed the performance of different architectures and has given great insights into the data sets used for arrhythmia detection. As research continues to evolve, this article will serve as an eye-opener for budding researchers in this domain for exploring novel and effective solutions.

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