# A SURVEY OF ECG AND LESION-BASED SEGMENTATION AND DETECTION OF CARDIOVASCULAR DISEASES USING DEEP LEARNING

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***ABSTRACT***

*In the entire world, cardiovascular diseases (CVDs) are the main cause of death. In order to improve patient outcomes, early and precise diagnosis of CVDs is essential. A non-invasive and frequently used diagnostic method for finding different cardiovascular problems is electrocardiogram-ECG analysis. The interest in creating automated systems for ECG-based segmentation and identification of cardiovascular disorders has increased as deep learning methods have advanced. This study examines current developments in deep learning-based techniques for ECG segmentation and cardiovascular disease detection, highlighting both their advantages and disadvantages.*

***KEYWORDS****— Cardiovascular diseases (CVDs), ECG, Deep Neural Networks, Classification model*

## 1. INTRODUCTION

An enormous worldwide medical concern, heart diseases (CVDs) cause a sizable portion of fatalities globally. Effective prevention has the potential to substantially enhance the lives of patients and reduce death rates, making prompt and precise detection of CVDs essential for efficient management and treatment. Analysing electrocardiograms (ECGs) is a popular non-invasive diagnostic technique that offers insightful information about the electrical activity of the heart. ECG signals provide important details on the morphology, heart rhythm, and numerous anomalies linked to cardiovascular illnesses.

Traditional methods for interpreting ECG signals require manual examination by experienced clinicians, which can be time-consuming and subject to inter-observer variability. Furthermore, the increasing volume of ECG data generated due to advancements in digital health technologies poses a challenge for healthcare providers to efficiently analyze and diagnose cardiovascular conditions. To address these challenges, there has been a surge of interest in leveraging deep learning techniques to develop automated systems for ECG-based segmentation and detection of cardiovascular diseases [18].

Deep learning, a subfield of machine learning, has demonstrated remarkable success in various domains, including computer vision, natural language processing, and medical image analysis [1]. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have the ability to learn complex patterns and features directly from raw data, making them well-suited for ECG analysis. By exploiting the inherent hierarchical structures in ECG signals, deep learning models can automatically extract relevant features and identify subtle abnormalities that may be indicative of underlying cardiovascular pathologies.

The objective of this research paper is to provide a comprehensive review of recent advancements in deep learning-based methods for ECG-based segmentation and detection of cardiovascular diseases.

We aim to explore the potential of these techniques in improving diagnostic accuracy, facilitating early detection, and enabling personalized treatment strategies.

## 2. DEEP LEARNING IN ECG ANALYSIS

An advance version of machine learning called deep learning uses artificial neural networks with several layers to learn structured information representations. Due to its capability of automatically obtaining pertinent characteristics straight from raw input without requiring for explicit design of features, it has attracted considerable attention in recent years [2,3]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two types of models developed using deep learning, have achieved outstanding results in a number of fields, including computer vision, natural language processing, and medical picture analysis [11].

In the context of ECG analysis, deep learning models offer the potential to extract complex patterns and relationships from ECG signals, enabling accurate diagnosis and detection of cardiovascular abnormalities. By learning hierarchical representations, these models can capture both local and global dependencies within the ECG data, improving their ability to identify subtle abnormalities and discriminate between different cardiac conditions.

### 2.1 Deep Learning Architectures for ECG Analysis

Deep learning architectures have been widely explored for ECG analysis, leveraging their unique capabilities to handle the temporal nature of ECG signals. Some commonly employed architectures include:

a. Convolutional Neural Networks (CNNs): CNNs excel in capturing spatial dependencies and have been successfully applied to ECG analysis tasks such as heartbeat classification and arrhythmia detection. By applying convolutional filters to ECG segments, CNNs can automatically learn relevant features, such as waveform morphology, amplitude variations, and temporal patterns.

b. Recurrent Neural Networks (RNNs): RNNs are designed to process sequential data and have been effective in capturing temporal dependencies in ECG signals. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are popular RNN variants used in ECG analysis[9]. They can model the sequential nature of ECG signals, making them suitable for tasks such as arrhythmia detection, heart rate prediction, and abnormality detection.

c. Hybrid Architectures: Hybrid architectures that combine CNNs and RNNs have been proposed to leverage the advantages of both models[6]. These architectures allow for the extraction of spatial features by CNNs, followed by capturing temporal dependencies using RNNs. Such models have demonstrated improved performance in tasks like heartbeat classification and anomaly detection.

### 2.2 Preprocessing and Feature Extraction Techniques

Preprocessing and feature extraction are crucial steps in ECG analysis, aimed at enhancing the quality of the input data and extracting informative features for deep learning models. Some common techniques include:

a. Baseline Wander Removal: Baseline wander refers to low-frequency variations in the ECG signal caused by patient movement or electrode placement. Filtering techniques, such as high-pass filters or wavelet denoising, are commonly employed to remove baseline wander and enhance signal quality.

b. Noise Reduction: ECG signals can be contaminated by various sources of noise, such as power line interference or muscle artifacts. Techniques like band-pass filtering, adaptive filtering, or wavelet denoising can be applied to reduce noise and improve the signal-to-noise ratio.

c. Feature Extraction: Deep learning models can learn features directly from raw data. However, in some cases, explicit feature extraction techniques can be beneficial. Time-domain features (e.g., mean, variance), frequency-domain features (e.g., spectral energy), or wavelet-based features (e.g., wavelet coefficients) are commonly extracted from ECG signals to provide relevant information to the deep learning models.

### 2.3 Training and Evaluation Strategies:

Training deep learning models for ECG analysis requires careful consideration of various factors. Some key strategies include:

Dataset Preparation: Building a comprehensive and representative dataset is essential for training deep learning models. ECG data should cover a diverse range of cardiac conditions and incorporate a sufficient number of samples. Annotation of ECG data by experts is crucial to create reliable ground truth labels.

Training Strategies: Deep learning models for ECG analysis are trained using large datasets through an iterative optimization process. Common training strategies include:

c. Model Evaluation: Proper evaluation of deep learning models is crucial to assess their performance. Evaluation strategies include:

Performance Metrics: Metrics such as accuracy, sensitivity, specificity, precision, recall, and F1-score are commonly used to measure the model's performance in ECG analysis tasks. Additionally, area under the receiver operating characteristic curve (AUC-ROC) is often employed to evaluate the model's discriminatory power.

Cross-Validation: Cross-validation techniques, such as k-fold cross-validation or stratified cross-validation, can be used to assess the model's performance on multiple subsets of the dataset and mitigate issues related to dataset bias and generalization.

External Validation: To assess the generalizability of deep learning models, external validation on independent datasets is crucial. Models should be tested on data from different sources or populations to evaluate their performance in real-world scenarios.

## 3. ECG SEGMENTATION

ECG segmentation is a critical step in the analysis of electrocardiogram (ECG) signals, aimed at identifying and delineating specific components of the cardiac cycle. Accurate segmentation enables the extraction of relevant features and facilitates the detection and diagnosis of various cardiovascular abnormalities. This section explores different aspects of ECG segmentation, including R-peak detection, QRS complex detection, P and T wave detection, and ST-segment detection [20].

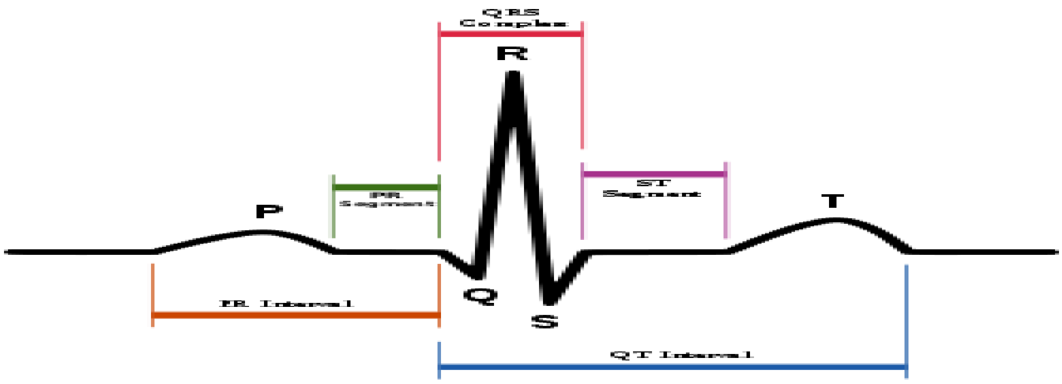


**FIG. 1.** *ECG Wave*

### 3.1R-Peak Detection:

R-peak detection is a fundamental step in ECG segmentation, as it identifies the peak of the QRS complex, which represents the main depolarization of the ventricles. Accurate detection of R-peaks is essential for various ECG analysis tasks, such as heart rate calculation, arrhythmia detection, and abnormality diagnosis. Deep learning techniques have been employed for robust and automated R-peak detection, offering advantages over traditional methods that rely on heuristics or signal processing techniques [21].

Deep learning models, such as CNNs and RNNs, can be trained to learn discriminative features directly from the raw ECG signal or its transformed representations. Various approaches have been proposed for R-peak detection using deep learning, including single-lead models, multi-lead models, and models that incorporate contextual information from neighboring ECG segments. These models are trained on labeled datasets, where expert annotations indicate the R-peak locations, enabling the model to learn to identify the characteristic features associated with R-peaks.

### 3.2 QRS Complex Detection:

In the ECG waveform, the ventricles' depolarization is represented by the QRS complex. For various clinical applications, such as the classification of arrhythmias, the diagnosis of ischemia, and the extraction of QRS-based features, accurate identification of the complex of QRS signals is essential. Deep learning techniques have been used to automatically identify the QRS complex in ECG readings, doing away with the requirement for complicated signal processing techniques or manual annotation.
DL models can learn discriminative features from the ECG signal, capturing the unique morphological characteristics of the QRS complex. By training on labeled datasets with annotated QRS complex locations, the models can identify and localize the QRS complex accurately. The use of deep learning-based QRS complex detection allows for improved accuracy, robustness to noise and artifacts, and potential scalability to large-scale datasets.

### 3.3 P and T Wave Detection:

The P wave represents the atrial depolarization, while the T wave reflects ventricular repolarization in the ECG signal. Detection of the P and T waves is crucial for assessing cardiac health, diagnosing arrhythmias, and analyzing the effects of medication on cardiac repolarization. Deep learning approaches have been explored for automated detection of P and T waves, offering potential advantages over traditional methods that rely on manual annotation or complex signal processing techniques.
Deep learning models, particularly CNNs and RNNs, can learn to identify the distinct morphological characteristics of P and T waves directly from the ECG signal. By training on labeled datasets with expert annotations indicating the locations of P and T waves, the models can learn to detect these waves accurately. The deep learning-based detection of P and T waves provides the opportunity for automated and objective analysis of cardiac repolarization, aiding in the diagnosis and monitoring of cardiovascular diseases.

### 3.4 ST-Segment Detection:

The ECG waveform's ST section corresponds to the interval between ventricular depolarization and repolarization. The segment of the ST may change if there has been ischemia of the myocardium or damage [12]. For the accurate identification of ischemic coronary artery disease and for the tracking of individuals at risk, the ST segment must be accurately detected. Automated ST-segment detection has been implemented using deep learning techniques, allowing for effective and impartial analysis [13].
Deep learning models can be trained to identify the ST segment based on its distinct morphology and location in the ECG signal. By training on labelled datasets with annotated ST segment positions, these models can learn to detect and localize the ST segment accurately. Deep learning-based ST-segment detection provides a valuable tool for timely identification of ischemic changes, assisting clinicians in making accurate diagnoses and enabling prompt interventions for patients at risk of cardiovascular complications.

## 4. CARDIOVASCULAR DISEASE DETECTION

The examination and evaluation of numerous clinical data, such as medical history, medical examination, test results, radiology investigations, and cardiovascular diagnostic procedures like electrocardiograms (ECG), are necessary for the identification of cardiovascular illness. Eechocardiography, stress tests, cardiac MRI, and coronary angiography. These diagnostic methods provide valuable information about the structure, function, and electrical activity of the heart, allowing healthcare professionals to assess cardiovascular health, identify abnormalities, and make accurate diagnoses.

### 4.1 Ischemic Heart Disease:

It is a disease marked by a decreased blood supply to the heart muscle as a result of an artery constriction or obstruction. ECG analysis plays a vital role in the detection and diagnosis of IHD. Deep learning techniques have been employed to develop automated systems for IHD detection, aiding in the identification of ECG patterns associated with myocardial ischemia or infarction.

Deep learning models can be trained on large datasets of ECG recordings, including both normal and IHD cases. By learning the distinctive features and patterns present in ischemic ECG signals, these models can accurately classify ECG segments or entire recordings as indicative of IHD. The integration of deep learning-based IHD detection systems can assist healthcare providers in early diagnosis, risk stratification, and timely intervention for patients at risk of ischemic events.

### 4.2 Arrhythmia Detection:

Early stage detection of arrhythmias is crucial for appropriate management and prevention of potentially life-threatening events. Deep learning approaches have been explored for automated arrhythmia detection and classification, offering improved accuracy and efficiency compared to traditional methods.

By training deep learning models on diverse arrhythmia datasets, these models can learn to distinguish between different arrhythmia types, such as atrial fibrillation, ventricular tachycardia, or bradycardia. The models can analyze ECG features, including waveform morphology, RR intervals, and temporal patterns, to detect abnormal rhythm patterns. Deep learning-based arrhythmia detection systems provide valuable support to clinicians in the identification and management of arrhythmias, aiding in appropriate treatment decisions and enhancing patient outcomes.

### 4.3 Congestive Heart Failure:

Congestive heart failure (CHF) occurs when the heart is unable to pump blood efficiently, leading to fluid buildup in the lungs and other tissues. ECG analysis plays a significant role in assessing cardiac function and identifying ECG patterns associated with CHF. Deep learning techniques have been applied to develop automated systems for CHF detection, assisting in early diagnosis and monitoring of disease progression.

Deep learning models can be trained on ECG datasets from patients with CHF, capturing the characteristic features of ECG signals in CHF cases. These models can learn to identify abnormalities such as reduced QRS amplitude, prolonged QRS duration, or ST-segment changes indicative of CHF. By integrating deep learning-based CHF detection systems into clinical practice, healthcare providers can improve early detection, risk stratification, and management strategies for patients with CHF.

### 4.4 Other Cardiovascular Diseases:

In addition to ischemic heart disease, arrhythmias, and congestive heart failure, deep learning techniques have been explored for the detection and diagnosis of various other cardiovascular diseases. These include but are not limited to:

Valvular heart diseases: Deep learning models have been employed to identify ECG patterns associated with valvular abnormalities, such as stenosis or regurgitation, aiding in early detection and management decisions.

Cardiomyopathies: Deep learning-based approaches have shown potential in distinguishing different types of cardiomyopathies based on ECG features, facilitating personalized treatment strategies.

Cardiac conduction abnormalities: Deep learning models can analyze ECG signals to detect conduction abnormalities, such as bundle branch blocks or atrioventricular blockages, providing insights into the underlying pathophysiology.

Hypertrophic cardiomyopathy: Deep learning techniques have been employed to identify ECG patterns indicative of hypertrophic cardiomyopathy, enabling early detection and risk stratification for this condition.
By leveraging deep learning-based approaches, healthcare providers can improve the detection, diagnosis, and management of various cardiovascular diseases, ultimately leading to better patient outcomes.

## 5. DEEP LEARNING NEURAL NETWORK

Artificial neural networks are trained to perform tasks like speech recognition, natural language processing, and image recognition using a process called deep learning. These networks use interconnected nodes to process and interpret data in a manner that mimics the structure and operation of the human brain.
DL is providing the significant changes in the development of GPUs in computers and the accessibility of enormous datasets for develop the NNs have made deep learning possible.
Self-driving cars, facial recognition, voice assistants, recommendation systems, and many other technologies use deep learning. Deep learning is additionally

### 5.1 Feed-Forward Neural Networks

One variety of artificial neural network is the FFN networks that features a single-layer architecture with input and output layers. Even when applying nonlinear activation functions at the output layer, this network's linear approach restricts its capacity to handle complex data patterns.
Deep neural networks with more than two layers have been created to address this problem. Neural networks enable training on less datasets and can minimise the number of trainable parameters by approximating complex functions with fewer units.
The use of perceptron, or modified perceptron with multiple output units (Figure 1), in jobs involving complex data patterns is prohibited because they are considered to be linear models.

### 5.2 Recurrent Neural Networks (RNNs)

The outputs from the LSTM can be given as inputs to the current phase of recurrent neural networks in part because of linkages that create steered loops. The final result of the LSTM may recall previous inputs because of its internal memory[4], which is used as an intake in the current stage of operation. The usual applications of RNNs include automatic translation, identification of handwriting, statistical analysis, and the processing of natural languages.

These neural networks with more than two layers have been designed to overcome this issue, with a loose assumption on the activation function. Neural networks enable training on less datasets and can minimise the number of trainable parameters by approximating complex functions with fewer units.

### *5.3 Convolutional Neural Networks*

The structural information between nearby pixels or voxels is crucial for (medical) images, however vectorization invariably removes this type of configural and structural information. These models are frequently employed for image-based tasks. These networks use convolutional and pooling layers with 2D or 3D images as input to better utilise spatial and configural information. As in a typical multilayer neural network, fully linked layers are immediately after CNNs. In contrast to a deep neural network, a CNN uses three techniques that significantly minimise the degrees of freedom in a model: a local receptive field, weight sharing, and subsampling (Figure 1).
Deep neural networks face difficulties with over-fitting and processing time. Advanced features that speed up calculation include batching processes. To prevent overfitting in deep neural networks, a few parameters are taken into account, such as initial weights, learning rate, and size. Regularisation techniques like transfer learning, drop out, data augmentation, and early stopping are also used.

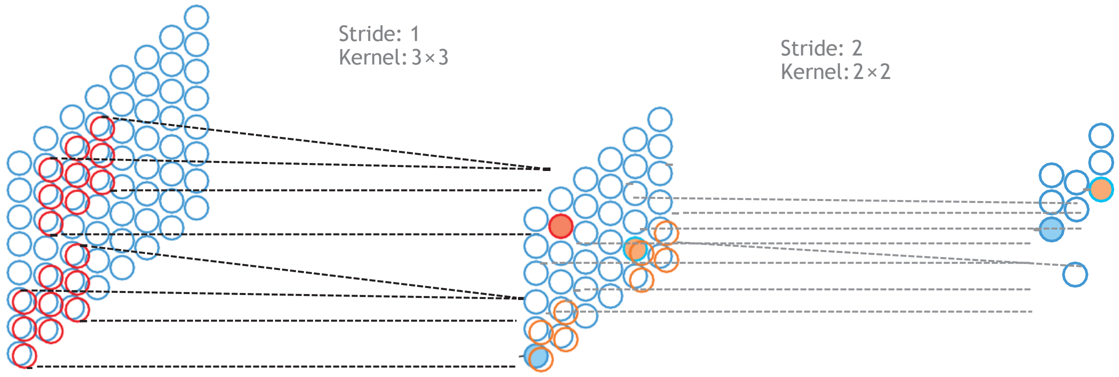


**Fig 2:** The 3 main techniques of CNN processes

## 6. Attributes Selection and Risk Prediction

Pre-processing, Feature Extraction, and Classification are the three main stages of the suggested approach for heart disease prediction utilising ECG signals. Heartbeat detection and the filtering process are both carried out in the initial stage. Following preliminary processing, feature acquisition will take place, and the best features will then be chosen using a new algorithm. The best features will next go through a classification procedure, where the existence of cardiovascular disease will be predicted using an Optimised Neural Network (NN)[7]. Additionally, the suggested approach will be used to train the NN by choosing the best weight, increasing the accuracy of the model that makes predictions. The conventional approach mainly focuses on the static mutation process, however the suggested improved algorithm also takes into account the adaptive mutation process.
The leading cause of death is now cardiovascular heart disease, and prompt diagnosis is crucial. Angiography can provide an accurate diagnosis, but it is quite expensive and has numerous negative effects. Patients' data was acquired using a variety of existing procedures, which were then implemented using a variety of mining algorithms to obtain high accuracy with minimal expense and downsides. According to the current medical literature, the characteristics taken into account in this database are likely indicators of CAD. Feature creation is a method used to sanitise the datasets. To gauge the effectiveness of prediction, the parameters increase and confidence is measured.
Python will be used for implementing the experimental study and the suggested ECG-based cardiovascular disease forecasting system. The suggested model will be compared to many cutting-edge models using Type 1 measurements and Type 2 measurements for the performance study. Precision, The degree of sensitivity Particularity, accuracy, A False negative rate (FNR), and False Discovery Rate (FDR) are examples of Type II measures, which are unfavourable measures.

**Table 1** Results of individual articles of deep learning and ECG based CVD Prediction

| S.no. | Method | Dataset/Data reference | Outcome |
|---|---|---|---|
| 1 | 1D-CNN | MIT-BIH, St.-Petersberg, PTB databases | accuracy was 98, , and selectivity was 98.[19] |
| 2 | DL-CCANet and TL-CCANet | MIT-BIH, database, INCART database | DL-CCANet, Reached 95.30 and 94.10, the TL-CCANet 95.[20] |
| 3 | Deep Learning algo-rithm | Mayo clinic ECG laboratory in September 2018 | The precision was 87, sensibility of 83.0, and specificity of 87.0 were attained.[21] |
| 4 | CNN | PhysioNet database | 0.85 total F1[21] |
| 5 | CNN | PhysioNet database | 0.82 total F1 |
| 6 | convolutional neural network | MIT - BIH Arrhythmia database | With a score of 91.33 with a 1-sample detection time of 0.015.[22] |
| 7 | Transfer learning | Physio net/CinC Challenge 2017 dataset | The method achieved F1F1 score of 0.89 and 0.86.[23] |

| | | | |
|---|---|---|---|
| 8 | RNN | Physio net/CinC Challenge 2017 dataset | Achieved the maximum accuracy of 79[24] |

## 7. CONCLUSION

Analysis has been done on the effectiveness of several categorization algorithms for predicting the presence or likelihood of developing heart disease. On 303 domains, a review enquiry was carried out. We compared the effectiveness of decision trees, artificial neural networks, and logistic regression. The experimentation comprised 13 patient characteristics. By graphical comparisons, classification method performances were compared. The ANN gained a larger area in the baseline and curve, it is discovered. The error rate for the decision tree is 0.21, the error rate for the logistic regression is 0.22, and the error rate for the ANN is 0.198. It has been determined that the ANN, which provides the lowest error rate and highest accuracy, is the best method for classifying the records.
This study looked at research publications on ECG-based coronary artery disease prediction using deep learning techniques. the publicly accessible ECG datasets from the Physionet, MIT-BIH, INCART[18][21], and Kaggle databases. Despite the size of the medical industry and the amount of data it produces every second, an environment is in place for storing all the information and keep it safe and accessible. The results of this study make it clear that Conventional Neural Networks, a deep learning technique, have an elevated precision level on massive data sets.

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Furthermore, he has contributed significantly to research by publishing 15 patents (both national and international) and copyrights, primarily in the field of Computer Science and Engineering, with the intention of benefiting the nation. Dr. Raghuvanshi has authored and co-authored over 45 papers in esteemed international journals that are recognized by SCI, SCOPUS, and UGC Care, as well as presented his work at various international and national conferences.