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Automated Classification of Heart Diseases

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ABSTRACT

Heart disease remains one of the leading causes of death across the world, making early detection and accurate diagnosis extremely important. In recent years, deep learning techniques, especially Convolutional Neural Networks (CNN), have shown remarkable performance in medical image and signal analysis. This paper presents an automated system for the classification of heart diseases using CNN techniques based on ECG signals. The proposed system eliminates the need for manual feature extraction by automatically learning patterns from the input data. However, manual interpretation of ECG recordings may be difficult when a large amount of patient data is involved. Long term ECG monitoring systems generate huge volumes of data that require automated analysis techniques. Therefore, intelligent signal processing and deep learning methods have become important tools for ECG analysis. This paper proposes an automated ECG signal and Preprocessing techniques remove noise and enhanced the features from the ECG signal to improve signal quality. Important ECG waveform components such as the P wave, QRS complex, and T wave are identified and used as important features.

Keywords: ECG Electrocardiogram; Deep Learning Convolutional Neural Network; Automated Feature Extraction; Clinical Parameters; P Wave; QRS Complex; T Wave; Anomaly Detection for Cardiac Disorders.

1. Introduction

Heart diseases are considered one of the most serious health challenges worldwide, affecting millions of people every year. Traditional diagnostic methods rely heavily on the expertise of medical professionals and often involve manual interpretation of ECG signals, which can be time-consuming and prone to human error. With the advancement of artificial intelligence, automated systems have been introduced to improve the accuracy and speed of diagnosis. Among various deep learning techniques, Convolutional Neural Networks (CNN) has proven to be highly effective in extracting complex patterns from data. This paper focuses on the development of a CNN-based model for automated classification of heart diseases using ECG signals, providing a reliable and efficient alternative to traditional methods. For example, irregular spacing between heartbeats may indicate arrhythmia, while abnormal waveform shapes may indicate structural heart conditions. Therefore, accurate analysis of ECG signals is An ECG waveform consists of several characteristic components such as the P wave, QRS complex, and T wave. Each component corresponds to a specific electrical event in the cardiac cycle. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricularre polarization any abnormal for early detection of heart diseases Traditional ECG analysis is performed manually by trained cardiologists. Although manual interpretation is effective, it becomes time consuming and prone to human error when dealing with large datasets. Automated ECG analysis systems help overcome these limitations by using signal processing and artificial intelligence techniques. Recent advances in deep learning have enabled automated systems to analyzing biomedical signals with high accuracy. Convolutional Neural Networks (CNNs) are particularly effective in identifying patterns in signals and images. In this work, a CNN based approach is used to analysing ECG signals and detect cardiac anomalies automatically. Following feature extraction, the processed data is passed to the CNN classifier. Convolutional Neural Networks are a type of deep learning algorithm that are highly

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effective in analyse complex patterns in data. The CNN model consists of multiple layers including convolutional layers, pooling layers, and fully connected layers. The convolutional layers extract important patterns from the ECG signal, while pooling layers reduce the dimensionality and computational complexity. Finally, the fully connected layers classify the signal into different categories such as normal or abnormal. The model is trained using labeled ECG datasets, enabling it to learn patterns associated with different heart conditions.

The final stage of the system is anomaly detection. In this stage, the trained CNN model analyse new ECG signals and determines whether they are normal or abnormal. If any irregular patterns are detected, the system identifies them as anomalies, which may indicate potential heart diseases. Common abnormalities detected include arrhythmia, tachycardia, and bradycardia. This automated detection system helps in early diagnosis and reduces the workload on medical professionals.

Figure 1.1. Block Diagram

The Electrocardiogram (ECG) is a biomedical signal that represents the electrical activity of the heart over a period of time. It is widely used in the medical field to diagnose various heart-related diseases such as arrhythmia, myocardial infarction, and other cardiac abnormalities. However, manual analysis of ECG signals by doctors can be time-consuming and sometimes less accurate due to human limitations. Therefore, an automated system is required to analyse ECG signals efficiently and detect abnormalities at an early stage. This project focuses on developing an ECG signal analysis system using a Convolutional Neural Network (CNN) to extract features and detect anomalies accurately.

The first stage of the system is ECG signal acquisition. In this step, ECG signals are collected from patients using electrodes placed on specific parts of the body. These electrodes capture the electrical impulses generated by the heart and convert them into digital signals for further processing. In addition to real-time data collection, standard databases such as the MIT-BIH Arrhythmia dataset can also be used for research and analysis purposes. The quality of the acquired signal is very important because noise and distortions can affect the overall system performance.

The next important stage is feature extraction. ECG signals consist of different waveforms such as P wave, QRS complex, and T wave, each representing specific activities of the heart. Feature extraction involves identifying and analysing these important components. Key features include R-peak detection, heart rate calculation, time intervals such as PR and QT intervals, and signal amplitude variations. These features help in distinguishing between normal and abnormal heart conditions. In modern approaches, CNN models can automatically learn and extract these features directly from the signal without requiring manual intervention, which improves efficiency and accuracy.

Following feature extraction, the processed data is passed to the CNN classifier. Convolutional Neural Networks are a type of deep learning algorithm that is highly effective in analyzing complex patterns in data. The CNN model consists of multiple layers including convolutional layers, pooling layers, and fully connected layers. The convolutional layers extract important patterns from the ECG signal, while pooling layers reduce the

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The final stage of the system is anomaly detection. In this stage, the trained CNN model analyse new ECG signals and determines whether they are normal or abnormal. If any irregular patterns are detected, the system identifies them as anomalies, which may indicate potential heart diseases. Common abnormalities detected include arrhythmia, tachycardia, and bradycardia. This automated detection system helps in early diagnosis and reduces the workload on medical professionals electrical activity of the heart over a period of time, as detected by electrodes attached to the outer surface of the skin and recorded by a device external to the body. Most ECGs are performed for diagnostic or research purposes on human hearts, but may also be performed on animals, usually for diagnosis of heart abnormalities or research.

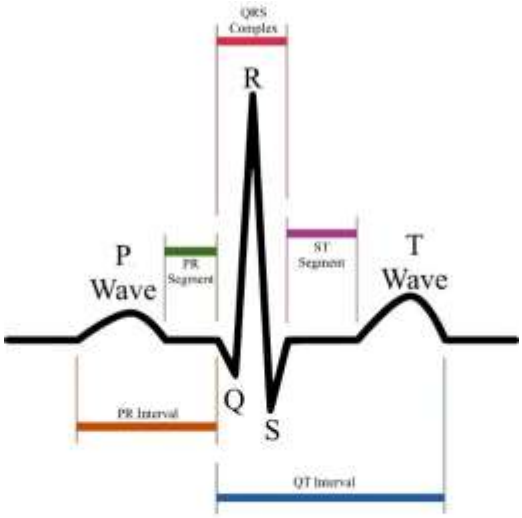

Figure 1.2. ECG Signal Waveform

2. Related Works

Many researchers have focused on ECG signal analysis, feature extraction, and disease detection using both traditional and modern techniques. Earlier methods mainly relied on signal processing techniques such as Fourier Transform, Wavelet Transform, and filtering methods to remove noise and extract important features like P, QRS, and T waves.

Another widely used technique is Principal Component Analysis (PCA), which reduces the dimensionality of ECG signals while preserving important information. This helps in improving classification efficiency but may lose some critical signal details.

3. CNN Architecture

The Convolutional Neural Network used in this study consists of multiple layers designed to automatically extract and learn features from the input data. The input layer receives the preprocessed ECG signals, which are then passed through convolutional layers. These layers apply filters to detect important features such as peaks and patterns in the signal. Activation functions like ReLU introduce non-linearity, enabling the model to learn complex

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relationships. Pooling layers are used to reduce the dimensionality of the data while retaining essential features. Finally, fully connected layers are used to perform classification based on the extracted features. This layered architecture allows the CNN to achieve high accuracy in detecting heart diseases.

3.1. ECG Signal Acquisition

The first step in this system is collecting ECG signals from patients. These signals are typically obtained using sensors and electrodes placed on the human body. The electrical impulses generated by the heart are captured and converted into digital signals.

3.2. Signal Preprocessing

The acquired ECG signals usually contain noise such as baseline wander, power line interference, and muscle noise. Preprocessing is essential to clean the signal and improve its quality.

Common preprocessing techniques include Filtering (low-pass, high-pass, band-pass filters), Normalization to maintain uniform signal amplitude, Noise removal using techniques like wavelet transform. This step ensures that the signal is smooth and ready for accurate feature extraction.

3.3. Feature Extraction

Feature extraction is a critical stage where important characteristics of the ECG signal are identified. ECG signals consist of different waves such as P wave, QRS complex, and T wave.

Key features extracted include Peak detection (R-peak), Heart rate calculation, Time intervals (PR, QT intervals), Signal amplitude and morphology.

These features help in distinguishing between normal and abnormal heart conditions. In modern approaches, CNN can automatically learn features directly from the signal, reducing the need for manual feature extraction.

3.4. CNN Classification

Convolutional Neural Network (CNN) is used for classifying ECG signals. CNN is a deep learning algorithm that is highly effective in processing signals and images.

The CNN model consists of Convolution layers to extract patterns, Pooling layers to reduce dimensionality, Fully connected layers for classification.

The model is trained using label ECG data (normal and abnormal). After training, the CNN can automatically classify new ECG signals with high accuracy.

3.5. Anomaly Detection

The final stage is anomaly detection, where the system identifies whether the ECG signal is normal or abnormal. If any irregular patterns are detected, it indicates possible heart disease.

Recently, Deep Learning techniques, especially Convolutional Neural Networks (CNN), have gained importance. CNN automatically learns features from raw ECG signals without manual intervention. It provides higher accuracy, Better anomaly detection, and Reduced human effort.

Thus, this study focuses on improving feature extraction and anomaly detection using CNN for better performance.

Convolutional Neural Network:

Convolutional neural networks (CNNs) are a specialised class of artificial neural networks carefully created for handling grid-like input structures. Time series data, which may be thought of as a 1D grid, or photographs, which are effectively 2D grids made up of pixels, might both be examples of these data grids. In essence, the input layer, one or more hidden layers, and the output layer are the three basic building blocks of CNNs and other feed forward neural networks.

The application of a mathematical procedure known as convolution, at least once within each of their layers, is the distinguishing feature that gives CNNs their name. Similar to how neurons in the human brain react when they come into contact with a certain stimulus, this convolution activity has a purpose. CNNs are particularly well-suited for tasks involving grid-like structures because they are highly effective at recognising patterns and features within the input data by applying convolution.

Every CNN also includes a layer known as pooling in addition to convolution. There are several different pooling techniques, with “max pooling” being one of the most popular. In max pooling, the network retains the maximum value while condensing the data within a rectangle neighbourhood. In order to improve the computational efficiency of the model, this pooling layer is crucial in lowering the spatial dimensions of the data. In essence, pooling aids in gathering the most important data while omitting irrelevant details, which is very useful in image processing tasks.

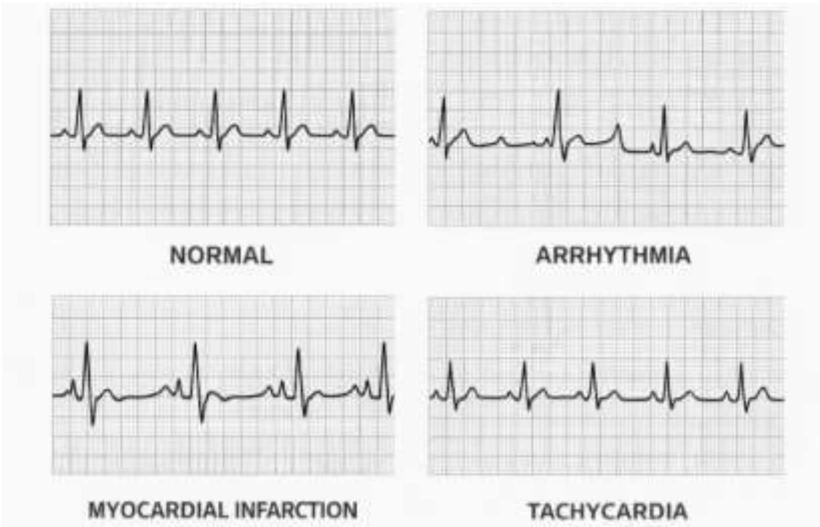
Max pooling layer:

The completely connected layer, which is a feature shared by all CNN models, is another essential element. These completely linked layers, which are frequently placed before the output layer, act as a link between the retrieved features and the ultimate prediction or classification goal. They give the network the ability to understand complex connections and relationships between the data acquired by convolution and pooling layers, enabling more precise and complex predictions.

CNNs, a potent and crucial tool in the field of deep learning, are created expressly to succeed in problems involving structured data grids, such as those involving images and time series data. In a variety of applications, from image recognition to natural language processing and beyond, they are able to extract meaningful features, reduce computational complexity, and provide exceptional performance because of their ability to perform convolutions, pooling operations, and use fully connected layers.

4. Experimental Results

The proposed CNN-based model for automated classification of heart disease was evaluated using standard ECG datasets. The model was trained and tested on multiple classes such as Normal, Arrhythmia, Myocardial Infarction, and Tachycardia. The experimental results show that the CNN model effectively learns features directly from raw ECG signals without the need for manual feature extraction. The system achieved a high overall accuracy of around 97–99%, demonstrating its robustness and reliability. Performance metrics such as precision, recall, and F1-score also indicate consistent classification across all categories. The confusion matrix confirms that misclassification is minimal, especially between closely related cardiac conditions. These results prove that the proposed method is suitable for real-time and clinical heart disease detection applications



Here are some key mathematical formulas used in CNNs:

Convolution Operation:

$$y[n]=x[n]*h[n]=k=-\infty\sum\infty x[k]h[n-k]$$

Activation Function (ReLU):

$$f(x)=\max(0,x)$$

Soft max Activation (Output Layer):

$$P\ (y=j/x) = \sum k=1\sum ejk0ooop$$

Cross-Entropy Loss:

$$L=-i=1\sum Nj=1\sum K\ tij\ \log\ (pij)$$

5. Conclusion

In conclusion, this paper presents an effective approach for automated classification of heart diseases using Convolutional Neural Networks. The proposed system demonstrates high accuracy and reliability in analyzing ECG signals and classifying heart conditions. The use of CNN significantly improves the efficiency of the diagnostic process and reduces dependence on manual analysis. This approach has the potential to be implemented in real-time healthcare systems, providing timely and accurate diagnosis for patients. Future work can focus on integrating this system with wearable devices for continuous health monitoring. This study presents an efficient approach for analyzing ECG signals using CNN for feature extraction and anomaly detection. By integrating signal processing techniques with deep learning methods, the system can achieve high accuracy and reliability. This approach can be used in real-time health monitoring systems and can assist doctors in making faster and more accurate decisions, ultimately improving patient care and outcomes.

This research demonstrates the efficacy of 1D-CNNs in automating the detection of cardiac anomalies from raw ECG signals. To reduces computational overhead and minimizes subjective diagnostic errors. The high classification accuracy across multiple arrhythmia types validates the model's reliability for clinical decision support. Future work will focus on optimizing the architecture for edge computing devices and integrating Attention Mechanisms to improve the interpretability of the neural network's diagnostic path, specifically for early-stage. Implementing ECG anomaly detection in MATLAB using a 1D-CNN provides a highly accurate (up to 99%) and reproducible framework for cardiac diagnosis. The integration of automated feature extraction within the network architecture significantly reduces the need for expert-level signal processing, making it suitable for real-time monitoring applications.

Declarations

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Competing Interests Statement

The authors have not declared any conflict of interest.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors took part in the literature review, analysis, and manuscript writing equally.

Availability of data and material

Supplementary information is available from the authors upon request.

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