Automated ECG Classification for Myocardial Infarction Diagnosis using CNN and Wavelet Transform

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Abstract.

In this study, this study proposes a methodology for classifying electrocardiogram (ECG) signals into normal and myocardial infarction (MI) classes. The methodology consists of three main steps: pre-processing, segmentation, and classification. ECG signals obtained from the PTB database are initially subjected to pre-processing using the Daubechies wavelet transform to filter out noise and enhance signal quality. Subsequently, the signals are segmented into 651-sample segments and further reduced to 500 samples per segment for dimensionality reduction. These segmented signals serve as input data for a convolutional neural network (CNN) model, which extracts relevant features and performs the classification task. The proposed methodology achieves an impressive classification accuracy of 97.8% for ECG signals. These findings highlight the effectiveness of our approach in accurately distinguishing between normal and MI ECG patterns.

Keywords: electrocardiogram (ECG) · myocardial infarction (MI) · convolutional neural network (CNN) · Daubechies wavelet transform.

1 Introduction

Artificial Intelligence (AI) has revolutionized various domains of healthcare, and one area that greatly benefits from AI advancements is the classification and diagnosis of heart diseases. Electrocardiogram (ECG) signals, which represent the electrical activity of the heart, play a crucial role in understanding cardiac health and detecting abnormalities.

ECG signals are recorded by placing electrodes on the patient's body, and they provide valuable information about the heart's rhythm, rate, and overall functioning.

The interpretation of ECG signals has traditionally relied on manual analysis by healthcare professionals, which can be time-consuming and subjective. However, with the advancements in AI and deep learning techniques, it is now possible to automate the analysis of ECG signals and improve the accuracy and efficiency of heart disease diagnosis.

In this paper, this study aims to leverage AI algorithms, such as deep neural networks, to develop a system that can automatically process and interpret ECG signals.

By extracting relevant features and patterns from the signals, the AI model can classify different types of heart diseases with a high level of accuracy. This AI-based approach eliminates the subjectivity and variability associated with manual analysis, providing consistent and reliable results.

By harnessing the power of AI, this study can not only enhance the accuracy of heart disease diagnosis but also enable faster and more efficient analysis, allowing healthcare professionals to make informed decisions promptly. The automated classification and diagnosis of heart diseases using ECG signals have the potential to improve patient outcomes, facilitate timely interventions, and optimize the utilization of healthcare resources.

Through the utilization of comprehensive datasets, advanced deep learning models, and rigorous evaluation, this project aims to contribute to the ongoing efforts in leveraging AI for improving cardiovascular care. By developing a robust and accurate AI system for ECG signal analysis, this study can augment the capabilities of healthcare professionals, enhance patient care, and ultimately save lives.

2 Related Work

In recent times, substantial advancements have been made in the developmentof deep neural networks (DNNs), leading to significant improvements in the ac- curacy of classifying various clinical tasks [1]. Among the methods used for analyzing biomedical signals, the convolutional neural network (CNN) has become increasingly popular in this field [7]. Numerous techniques have been proposed to overcome the limitations of manual electrocardiogram (ECG) analysis, with a particular focus on extracting meaningful information directly from the rawdata. Effective feature extraction is achieved through techniques like wavelet transform (WT) [10]. Moreover, reduction methods such as principal component analysis (PCA) and meta-heuristic algorithms like particle swarm optimization (PSO) [11] are employed. The classification step involves various techniques suchas neural networks (NN) [9], support vector machine (SVM) [10], and k-nearest neighbor (KNN) [9].

While these methods have shown promising performances, they do come with certain drawbacks. First, the inclusion of additional feature extraction and selection algorithms leads to increased computational complexity. Second, external factors such as age, sex, and pathological changes in myocardial infarctions (MIs) can influence ECG patterns, resulting in dynamic changes in explicit or implicit features. Predefined handcrafted features struggle to maintain generalization abilities in such cases. To effectively leverage information from different layers, Rajpurkar et al. [8] developed a 34-layer CNN to diagnose irregular heart rhythms based on single-lead ECG, achieving a maximum accuracy of 90.80% and surpassing cardiologists' performance. Similarly, Acharya et al. [7] proposed an 11-layer 1-D CNN for detecting MIs using lead II ECG signals, attaining a maximum accuracy of 95.22. In our proposed method, based on the aforementioned papers, this study has incorporated a preprocessing step to denoise the signal and utilized the same CNN model. As a result, our method outperforms other existing methods and achieves an impressive accuracy of 97.8%.

3 Methodology

3.1 Method Overview

Our approach to effectively categorizing ECG signals into two classes, normaland MI, consists of three main steps: pre-processing, segmentation, and classification. To evaluate our method, this study suggests utilizing the PTB database, which comprises 448 recordings. In order to mitigate signal noise, this study apply the Daubechies wavelet transform with 6 to 10 levels for signal filtering. Each recording is then divided into multiple segments, with each segment containing 651 samples. To reduce dimensionality, this study further truncates the segments to 500 samples before initiating model training. These processed samples are directly fed into a CNN model for feature extraction and ECG signal classification. For a sual representation of our proposed approach, please refer to Figure 1

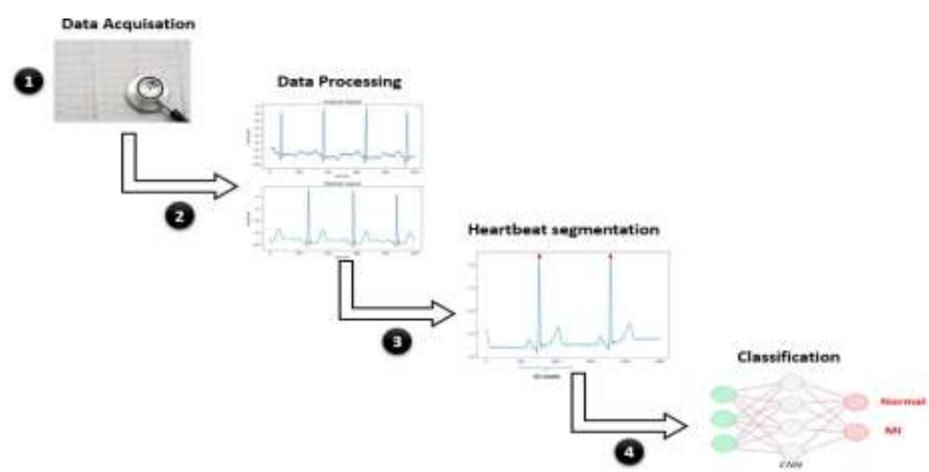

Fig. 1. Diagram of model structure

3.2 Data Acquisition

The PTB Diagnostic ECG Database holds a prestigious reputation as a care-fully curated collection of electrocardiograms (ECG) recordings, recognized internationally. It serves as a vital standard resource for research and diagnosis,

enabling the development of advanced algorithms and methods to analyze and classify ECG signals. This comprehensive database encompasses various ECG recordings, featuring both normal cases and data related to specific cardiac conditions, such as myocardial infarction (MI). Its impact on cardiovascular research and the improvement of heart-related disorder diagnosis and treatment is significant.

In the realm of MI diagnosis algorithms [1], the PTB Diagnostic ECG Databaseholds a distinguished position as the most extensively utilized resource. It com-prises 549 12-lead records sampled at 1000 Hz, gathered from 290 patients. Among these records are 368 cases of MI from 148 patients and 80 records from 52 healthy control (HC) patients. Our research specifically focuses on the investigation of lead II records. The detailed characteristics of the PTB database, presented in Table 1, underscore its crucial role as a valuable asset in our work and the broader scientific community.

Table 1. The attributes of the electrocardiogram (ECG) data acquired from the PTB database.

	Normal	Mi
Minimum age	17	36
Maximum age	81	86
Average age	43.43	60.37
Number of males	39	110
Number of females	13	38

Our data was split into two sets: the training set, which comprised 80% of the data with 40,581 instances, and the test set, which comprised 20% of the data with 10,146 instances.

3.3 Data Processing

Precise identification and categorization of heart diseases based on electrocardiogram (ECG) readings are crucial. However, the ECG signal is susceptible to weaknesses and interference noises during acquisition, resulting from factors like equipment limitations, patient movements, or breathing. These noises present a significant challenge in analyzing the ECG signal, making a preprocessing step necessary for dependable classification. In this research, this study adopt the Daubechies 6 wavelet transform with 10 levels of decomposition [7] to effectively remove noise from the ECG signal. The wavelet transform enables the identification of high-frequency coefficients, which indicate the presence of noise in the signal. Subsequently, this study employs a threshold processing technique to eliminate unwant

noise components, such as electromyography (EMG) noise and power line interference. Figure 2 illustrates the ECG beat signals before and after the denoising process, highlighting the effectiveness of our denoising approach

3.4 Heartbeat Segmentation

According to [8], the wavelet transformation method proves to be highly effective in detecting R peaks in electrocardiogram (ECG) signals when compared with the Tompkins algorithm. This approach offers superior performance in accurately identifying the significant points in the ECG waveform known as R peaks, which indicate the contraction of the ventricles.

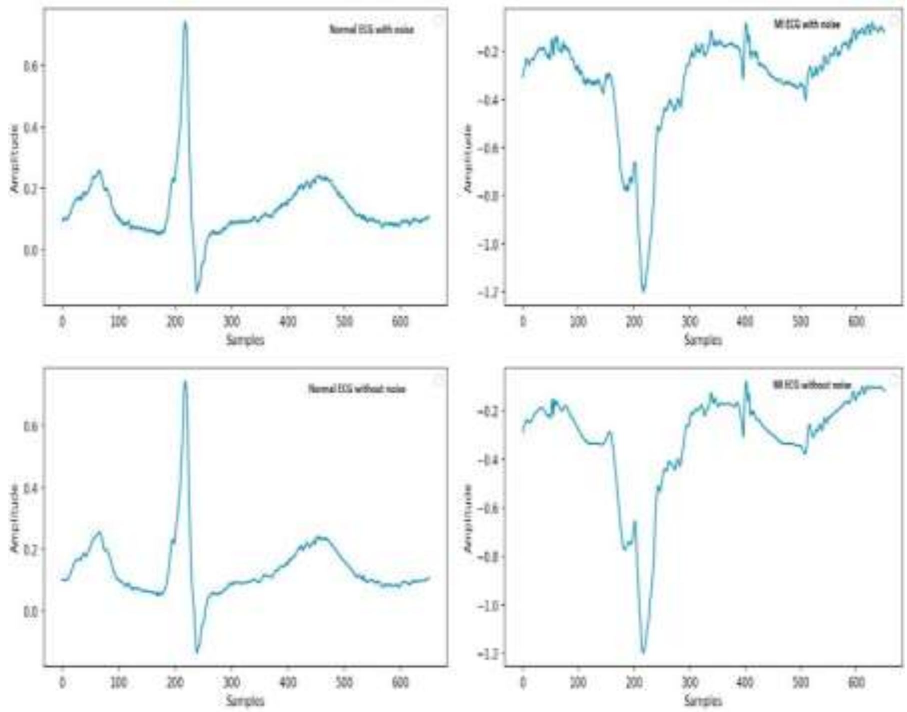

Fig. 2. The diagram of the denoising effect

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To visually demonstrate this, Figure 3 depicts the segmentation process using the 2-level Daubechies 3 wavelet transform. Each segment of an ECG beat consists of 651 samples, with 250 samples captured before the R peak and 400 samples taken after the R peak.

The wavelet transform successfully captures the distinct features of the ECG waveform, enabling precise detection of the R peak locations. By segmenting the ECG signal in this manner, the analysis can focus on specific regions of interestaround the R peaks, thereby facilitating further examination and diagnosis of cardiac abnormalities.

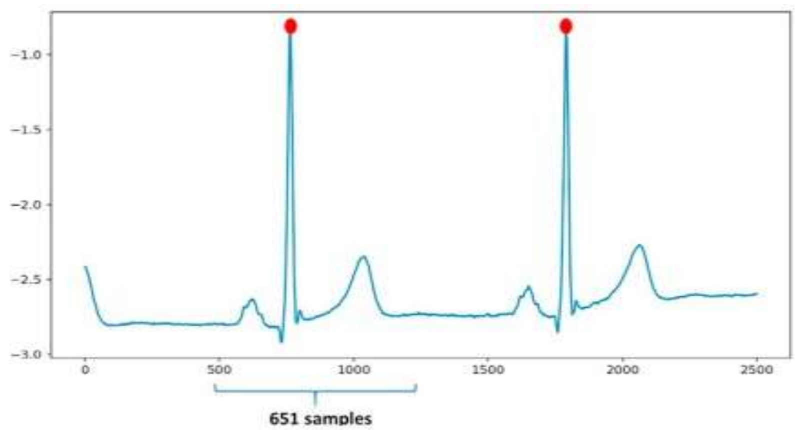

Fig. 3. Heartbeat Segmentation

3.5 CNN architecture

In Figure 4, it can be observed that a Convolutional Neural Network (CNN) typically comprises three main layers: the convolution layer, pooling layer, and fully connected layer. The CNN uses a fixed-sized filter matrix to convolve an input series of feature maps, thereby extracting high-level features. The pooling operation reduces the size of the feature maps while retaining important information. Additionally, it effectively captures dominant features that remain consistent regardless of rotation or position.

The fully connected layer employs a multi-layer perceptron (MLP) and operates on the flattened input after multiple convolutions and pooling operations, connecting each input to all neurons.

The model in this figure is composed of four convolution layers, four max- pooling layers, and three fully connected layers. The convolution layer uses a stride of 1, and the pooling layer uses a stride of 2. Max-pooling is performedafter each convolution operation. Finally, the fully connected layer connects the neurons from the preceding layers to create a probability distribution over two classes: normal and MI (Myocardial Infarction). The initial layer (layer 0) undergoes convolution with a 102-sized filter, leading to the formation of the first layer (layer 1). Then, a max-pooling operation with a size of 2 is performed on each feature map, resulting in layer 2. This max-pooling reduces the number of neurons from 399 x 3 to 199 x 3.

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x 3 to 199 x 3. Next, the feature maps of layer 2 are convolved with a 24-sized filter, generating layer 3. Another max-pooling operation is then applied to each feature map, producing layer 4. Subsequently, layer 4's feature map is convolved with an 11-sized filter, creating layer 5. Afterward, a max-pooling operation is performed on each feature map, reducing the number of neurons to 39 x 10 in layer 6.

Layer 6's feature map is convolved with a 9-sized filter, creating layer 7. Following this, a subsequent max-pooling operation is applied, resulting in layer 8. Notably, layer 8 is fully connected to layer 9, which consists of 30 neurons. Layer 9 is further connected to layer 10, containing 10 neurons, and finally,to the output layer, which has 2 neurons representing the "normal" and "MI" (Myocardial Infarction) categories.

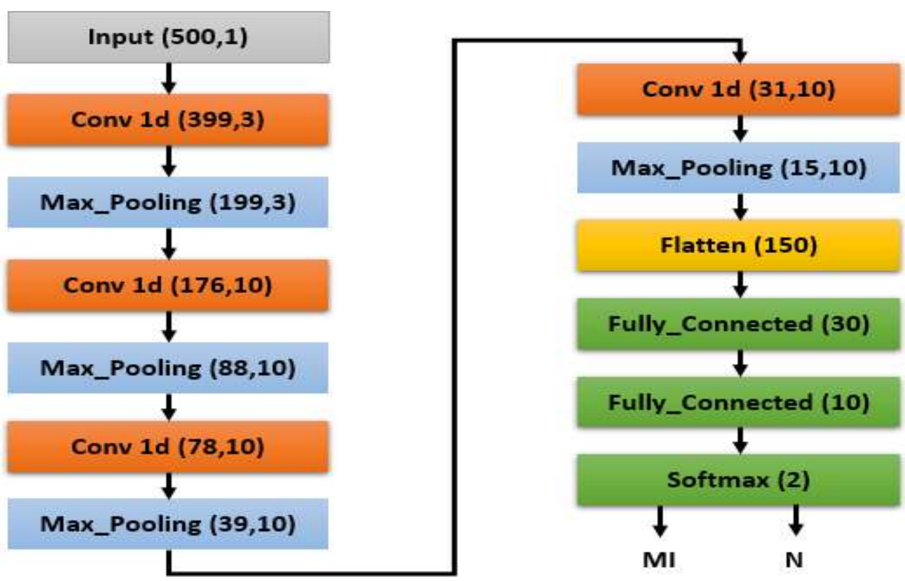

Fig. 4. Architecture of the proposed CNN model

In the Convolutional Neural Network (CNN), the activation function plays a crucial role in determining whether a neuron should be activated or not in response to a signal.

It acts as a mathematical function that governs signal processing. One widely used activation function is the Rectified Linear Unit (ReLU), which sets negative results to zero. Mathematically, the ReLU function can be expressed as: $f(x) = max(0, x)$. In this study, the ReLU activation function is applied to layers 1, 3, 5, 7, 9, and 10. Additionally, the softmax function is used in layer 11 (the final layer) to provide a probability distribution for classification.

4 Experimental Results

Our model was trained on a workstation equipped with an Intel(R) Core(TM) i5 6200U CPU running at 2.30GHz and 8GB of RAM. The experimental data used for training and testing was sourced from the widely recognized and precise MIT-BIH ECG database. This database is a standard resource in ECG research, providing comprehensive expert annotations. To split the data for training and testing, this study divided it into two sets, allocating 80% for training and 20% for testing. During the training process, this study utilized 300 epochs, with each epoch consisting of a batch size of 32. This batch size was applied to the entire input data.

For optimization, a learning rate of 0.001 was employed to control the update step size during the training process. Additionally, before training, this study performed signal rescaling to normalize the data and ensure it falls within the range of [-1, 1]. This normalization step proved beneficial as it improved the accuracy of the model compared to training without normalization.

Figure 6 illustrates the accuracy and loss curves for both the training and validation stages of our model. These curves provide insights into the performance and progress of the model during the training process.

To evaluate the effectiveness of our model, this study employed several metrics: accuracy, specificity, and sensitivity. These metrics play a crucial role in assessing the model's performance in classifying ECG signals.

In the experimental verification, our proposed CNN model achieved out- standing results. The accuracy obtained was 97.8%, indicating the percentage of correctly classified instances. The sensitivity, which represents the true positive rate, reached 97.0%, highlighting the model's ability to accurately detect positive cases. Furthermore, the specificity, which measures the true negative rate, was recorded at 97.32%, demonstrating the model's capability to correctly identifynegative cases.

These high accuracy, sensitivity, and specificity values indicate the effective- ness and reliability of our proposed CNN model for ECG signal classification.

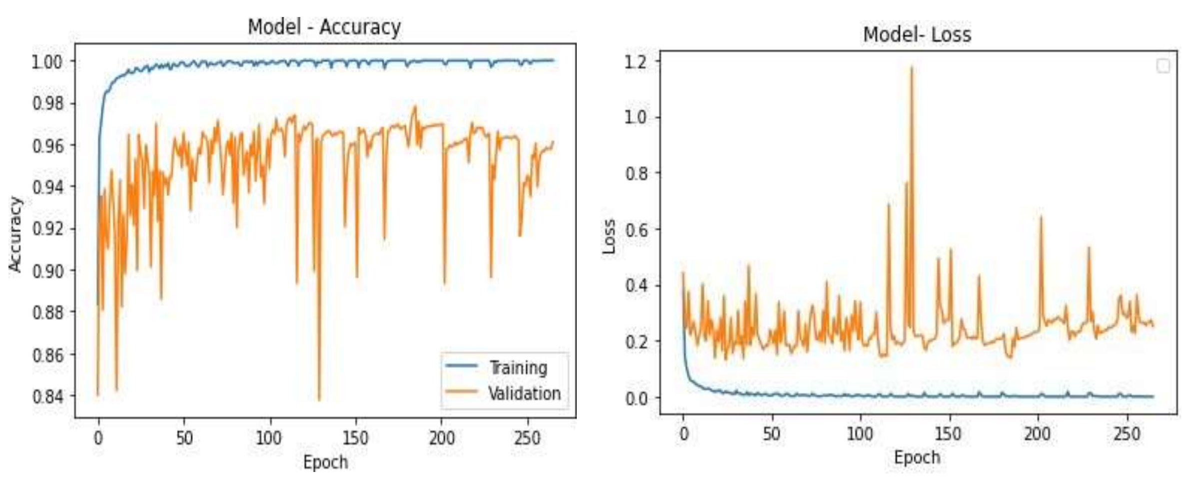

Fig. 5. Accuracy and Loss of the trained model

This study have obtained the confusion matrix for our model, which serves as a solid confirmation of its performance. The confusion matrix allows us to assess how this studyll the model is classifying instances by providing a breakdown of predictedand actual class labels.

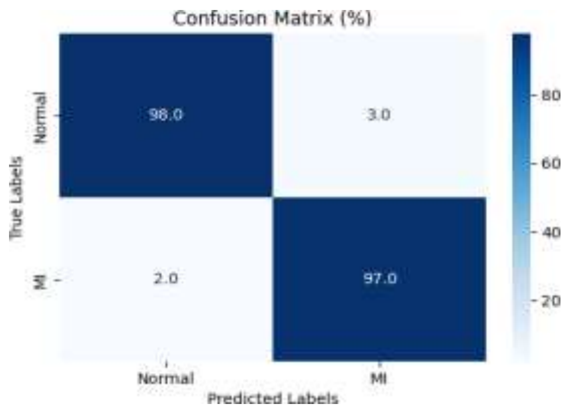

Fig. 6. Confusion Matrix

Table 2. Compilation of Chosen Research on MI Detection and Diagnosis Utilizing ECG Signals from PTBDB

Author, year	Number of leads	Notable Features	Number ECG beats	Classifier	Performance
Lahiri etal [13]	12	Detection of R peaks The fract dimension of ECG phase space	64 680 R-peaks	RNN	Acc = 96.00%
Sharma et al.,2015 [14]	12	Wavelet transform Multiscale energeyanalysis	549 records	SVM	Acc = 96.00% Sen = 93.00% Spec = 99.00%
Arif et al. ,2012 [15]	12	QRS detection Discrete wavelettransform	N : 3 200 MI : 16 960	KNN	Sen = 99.97% Spec=99.00%
Acharya etal.2017	II	R-peaks detection(Tompkins) 11-layer deep neural Network	N: 10546 MI : 40 182	CNN	Acc = 95.22% Sen = 95.49% Spec = 94.19%
ProposedMethod	**II**	**R-peaks detection:Wavelet transfromPreprocessing: Wavelet transform No feature selection**	**N: 10 546 MI : 40 182**	**CNN**	**Acc = 97.8% Sen = 97% Spec = 97.32%**

5 Conclusion

In conclusion, our methodology has demonstrated remarkable performance in the classification of electrocardiogram (ECG) signals into two categories: normal and myocardial infarction (MI). Through the integration of convolutional neural networks (CNN) and the Daubechies wavelet transform, we successfully extracted crucial features and achieved accurate differentiation between normal and MI ECG patterns.

The obtained accuracy of 97.8% signifies the model's ability to make highly precise classifications. This high accuracy rate has significant implications for improving the efficiency and accuracy of cardiovascular diagnostics, ultimately leading to enhanced patient care and treatment outcomes.

For future work, we have identified potential avenues for further improvement. Firstly, by incorporating a residual architecture such as ResNet or DenseNet, we can explore the benefits of deeper networks and residual connections to potentially enhance the model's performance. Additionally, increasing the size of the training data can contribute to even better accuracy by providing a more diverse and comprehensive representation of ECG patterns.

By continuing to refine our methodology through these future directions, we anticipate further advancements in ECG signal classification, ultimately leading to more accurate and efficient cardiovascular diagnostics in clinical practice.

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