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A deep learning-based myocardial infarction classification based on single-lead electrocardiogram signal

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ABSTRACT

Acute myocardial infarction (AMI) carries a significant risk, emphasizing the critical need for precise diagnosis and prompt treatment of the responsible lesion. Consequently, we devised a neural network algorithm in this investigation to identify myocardial infarction (MI) from electrocardiograms (ECGs) autonomously. An ECG is a standard diagnostic tool for identifying acute MI due to its affordability, safety, and rapid reporting. Manual analysis of ECG results by cardiologists is both time-consuming and prone to errors. This paper proposes a deep learning algorithm that can capture and automatically classify multiple features of an ECG signal. We propose a hybrid convolutional neural network (CNN) and long short-term memory (LSTM) for automatically diagnosing MI. To generate the hybrid CNN-LSTM model, we proposed 39 models with hyperparameter tuning. As a result, the best model is model 35, with 86.86% accuracy, 75.28% sensitivity and specificity, and 83.56% precision. The algorithm based on a hybrid CNN-LSTM demonstrates notable efficacy in autonomously diagnosing AMI and determining the location of MI from ECGs.

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1. INTRODUCTION

Myocardial infarction (MI), commonly known as a heart attack, happens when the flow of oxygen-rich blood to a section of the heart is reduced, causing damage or death to that part of the heart [1]–[3]. This condition is predominantly caused by coronary artery disease, also referred to as coronary heart disease. The primary risk factors for this disease include an unhealthy diet, lack of physical activity, tobacco use, and excessive alcohol consumption. To detect MI tests such as the electrocardiogram (ECG) and cardiac enzyme tests are used. However, cardiac enzymes can only be detected several hours after the attack and may provide inaccurate results if tested too soon. Conversely, ECG offers quicker results, facilitating early intervention before further tests are conducted [4]–[6].

An ECG is a device that measures the heart's electrical activity. Cardiologists can identify abnormalities in certain areas of the heart by analyzing the electrical activity through the heart muscle [3]. The P wave is generated by the sinoatrial node, the heart's pacemaker, and indicates atrial depolarization or contraction. The QRS complex represents the atrioventricular node and shows ventricular depolarization or contraction, while the T wave indicates ventricular relaxation or repolarization [7], [8]. During an MI, the

ECG may show a prolonged ST interval, ST-segment elevation or depression, and changes in the T wave shapes. The ST segment begins at the J point, which follows the S wave, and ends at the onset of the T wave [9], [10].

Manual analysis of ECG results by cardiologists is both time-consuming and prone to errors. Many attempts have recently been made to use machine learning models to automatically detect MI from ECG signals [11]. Despite their strong performance in MI prediction, these machine learning techniques necessitate handcrafted feature extraction, which is extremely engineering-intensive and significantly relies on human knowledge for manual parameter tweaking. An ECG signal's numerous characteristics can be automatically classified by a deep learning algorithm. Classifying multilead or single-lead ECG data to automatically diagnose problems like atrial fibrillation, hypertrophic cardiomyopathy, anemia, and other ailments is one use of deep learning in the medical domain [12], [13]. In order to automatically diagnose MI, the goal of this study was to create a hybrid convolutional neural network (CNN), long short-term memory (LSTM), and assess the model's performance. In order to find regional patterns within the convolution window, CNNs can extract local features from the ECG signal series. Through weight-sharing, the CNN convolution layer makes it possible to extract and learn low-level hierarchical and invariant characteristics from unprocessed data [14], [15]. We also suggest the LSTM architecture as a classifier. By using multiplicative gates to keep a steady error flow through the internal states of memory cells, LSTM, a kind of recurrent network, solves the gradient issue that arises in recurrent neural networks (RNNs). Long-term dependencies in ECG sequences have been successfully captured by LSTM [16], [17].

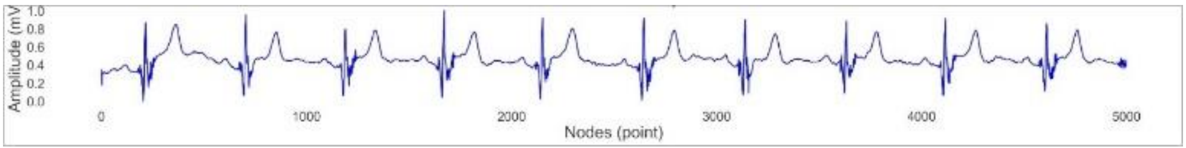
2. RESEARCH METHOD

2.1. Data preparation

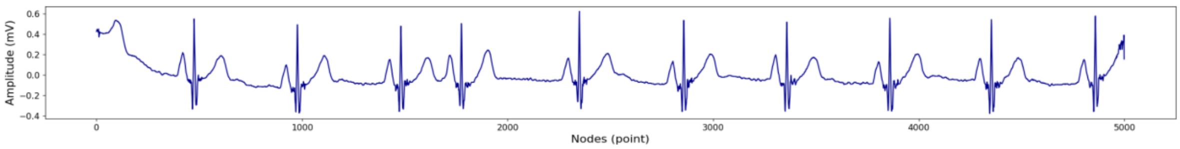
The PTB-XL database, the biggest publicly available electrocardiography dataset to date, was just made available for use in this investigation [18]. With a total of 18,885 different patients' 10-second, 12-lead ECGs are included in the database, for a total of 21,837 entries. Of these records, 5,486 belong to MI patients and 9,528 belong to healthy controls (HC). MI records contained eight sub-MI, i.e., acute left MI (ALMI), acute MI (AMI), anteroseptal MI (ASMI), impending left MI (ILMI), impending MI/inferior MI (IMI), isolated posterior left MI (IPLMI), isolated posterior MI (IPMI), and left MI (LMI). The records are offered in two formats with varying sampling frequencies: 500 and 100 Hz. The 500 Hz files are downsampled, and the records are kept in waveform database (WFDB) format with a resolution of 1 µV/LSB. Table 1 contains a list of all the records that were experimented with. Figure 1 presents the sample records of HC (Figure 1(a)) and MI (Figure 1(b)).

Table 1. The experimented records of the PTB-XL database

Class		Records
HC		9,528
MI	ALMI	163
	AMI	290
	ASMI	1,883
	ILMI	393
	IMI	2,329
	IPLMI	50
	IPMI	30
	LMI	132
Total		14,798



(a)



(b)

Figure 1. The sample records of (a) HC and (b) MI

2.2. Electrocardiogram pre-processing

ECG signals can become corrupted during acquisition due to various artifacts and interferences such as muscle contraction, baseline drift, electrode contact noise, and power line interference [19]–[21]. Because it can split an ECG signal into several frequency bands and effectively represent non-stationary signals, the discrete wavelet transform (DWT) is frequently used for preprocessing ECG signals (noise removal) [19]–[21]. The discrete input signal is passed through a number of low-pass and high-pass filters in order for the DWT to function. With wavelet coefficients dictating the number of decomposition levels for a series of signal processing procedures, it analyzes signals at various resolution levels. The signal-to-noise ratio (SNR), which offers details on signal quality, is used to gauge how effective denoising is. The SNR results are displayed in Table 2. According to the results, bior1.3 has the greatest SNR rating, measuring 12.962 dB.

This study has balanced the amplitude range for computational efficiency after removing ECG noise. Using one of the processing subpackages that includes WFDB signal-processing tools for reading, writing, and processing WFDB signals and annotations, we applied a normalization bound. By setting the lower limit to zero and the upper limit to one, the values of the signal data were modified to fall inside a predetermined range. The signal length of an ECG signal is 1,000 nodes. The ECG signals have been divided into 400 nodes in order to determine fix length as shown in Figure 2.

Table 2. The results of averaged SNR

Wavelet function	SNR value (averaged)
sym5	11.312
sym6	11.185
sym7	12.710
sym8	11.552
db2	10.560
db4	11.635
db5	12.911
db6	11.786
db7	11.662
bior1.3	12.962
bior6.8	11.644
haar	11.662

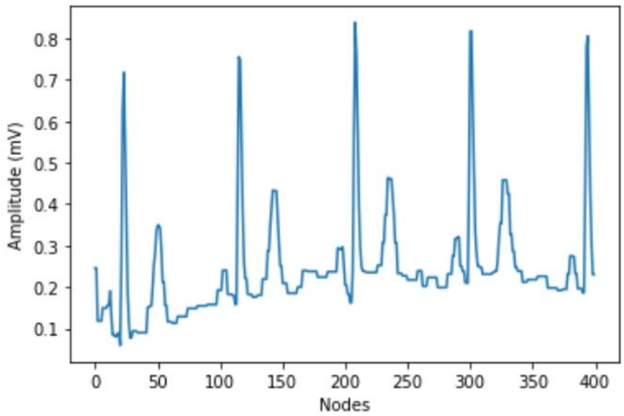


Figure 2. The segmented ECG signals into 400 nodes

2.3. A hybrid convolutional neural network and long short-term memory

A one-dimensional (1D)-CNN is a type of CNN specifically designed to process one-dimensional data, such as time series or sequences [22]–[24]. Unlike the more common two-dimensional (2D)-CNNs used for images, 1D-CNNs are particularly effective for tasks involving sequential data. In 1D-CNNs, filters slide over the input data in one dimension, typically along the time axis. These filters detect patterns such as trends or periodicity in the data. Similar to 2D-CNNs, pooling layers in 1D-CNNs reduces the dimensionality of the feature maps, retaining the most important features while reducing computational complexity. Max pooling and average pooling are common pooling techniques. Convolutional layers are followed by non-linear activation functions, such as rectified linear units (ReLU), which add non-linearity and allow the network to recognize intricate patterns [25], [26]. 1D-CNNs are strong instruments for identifying significant patterns in sequential data, allowing for precise and effective analysis and forecasting. The completely connected layers have been swapped out for LSTM in this investigation. One kind of RNN architecture called LSTM is especially well-suited for processing and forecasting data that is sequential, like ECG signals. LSTMs are extremely successful for time-series analysis because, in contrast to conventional RNNs, they are made to capture long-term dependencies and solve the vanishing gradient problem [2], [27]. To generate the hybrid CNN-LSTM model, we proposed 39 models with hyperparameter tuning. We are concerned with batch size (8, 16, and 32), learning rate (0.001-0.00001), and epochs (50, 100, 200, 300, and 400). Table 3 lists the hyperparameter tuning model of MI classification with hybrid CNN-LSTM.

Table 3. The hyperparameter tuning of MI classification with hybrid CNN-LSTM

Model	Batch size	Learning rate	Epoch
1	8	0.001	50
2	8	0.001	100
3	8	0.001	200
4	8	0.001	300
5	8	0.001	400
6	16	0.001	100
7	16	0.001	200
8	16	0.001	300
9	16	0.001	400
10	32	0.001	100
11	32	0.001	200
12	32	0.001	300
13	32	0.001	400
14	8	0.0001	50
15	8	0.0001	100
16	8	0.0001	200
17	8	0.0001	300
18	8	0.0001	400
19	16	0.0001	100
20	16	0.0001	200
21	16	0.0001	300
22	16	0.0001	400
23	32	0.0001	100
24	32	0.0001	200
25	32	0.0001	300
26	32	0.0001	400
27	8	0.00001	50
28	8	0.00001	100
29	8	0.00001	200
30	8	0.00001	300
31	8	0.00001	400
32	16	0.00001	100
33	16	0.00001	200
34	16	0.00001	300
35	16	0.00001	400
36	32	0.00001	100
37	32	0.00001	200
38	32	0.00001	300
39	32	0.00001	400

2.4. Performance evaluation

Performance evaluation quantitatively measures how effectively a trained model meets specific evaluation metrics in machine learning. This data helps decide whether the model is ready for further testing, wider deployment, or requires additional training. Model performance evaluation involves monitoring to gauge the model's effectiveness at its designated task. There are various methods to conduct model evaluation during this monitoring process. Classification metrics are typically applied to the discrete values produced by a model after it has classified all the given data. To clearly present the raw data required for calculating these metrics, a confusion matrix can be created for the model. This matrix not only shows how often the model's predictions were correct but also specifies the ways in which they were correct or incorrect. These variables are typically denoted as true negative (TN), false positive (FP), true positive (TP), and false negative (FN) (refer to (1)-(4)). From the data in a confusion matrix, several commonly useful classification metrics can be calculated,

$$Accuracy = \frac{\sum_{i=1}^{l} TP_i + \sum_{i=1}^{l} TN_i}{\sum_{i=1}^{l} TP_i + \sum_{i=1}^{l} TN_i + \sum_{i=1}^{l} FP_i + \sum_{i=1}^{l} FN_i} \quad (1)$$

$$Sensitivity = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + \sum_{i=1}^{l} FN_i} \quad (2)$$

$$Specificity = \frac{\sum_{i=1}^{l} TN_i}{\sum_{i=1}^{l} TN_i + \sum_{i=1}^{l} FP_i} \quad (3)$$

$$Precision = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + \sum_{i=1}^{l} FP_i} \quad (4)$$

where l is the total number of class-i.

3. RESULTS AND DISCUSSION

In this study, the model was generated by splitting 80% of the data for training and the remaining set for validation. There were 11,838 segmented-rhythm used for the training set and 2,959 segmented-rhythm for the validation set. The experiments are conducted with Intel(R) Core(TM) I7-10700K CPU @ 3.80 GHz (16 CPUs) ~3.8 GHz and two NVIDIA GeForce RTX 2070 SUPER 24 GB GPU (8 GB Dedicated, 16 GB Shared). We have used Python language programming with Visual Studio Code version 1.86.1 on Windows 10 Pro 64 Bit. The libraries are NumPy, Pandas, Matplotlib, Seaborn, WFDB, PyWavelets, SciPy, and TensorFlow. The performance results of 39 CNN-LSTM models can be presented in Table 4. Table 4 shows the varying results in accuracy, sensitivity, specificity, and precision. Among 39 CNN-LSTM models, the best model is model 35, with 86.86% accuracy, 75.28% sensitivity and specificity, and 83.56% precision. There are extremely imbalanced records in HC and sub-MI classification.

Table 4. The performance results of 39 CNN-LSTM models

Model	Results (%)			
	Accuracy (ACC)	Sensitivity (SEN)	Specificity (SPE)	Precision (PRE)
1	78.11	50.00	50.00	78.11
2	78.11	50.00	50.00	78.11
3	78.11	50.00	50.00	78.11
4	78.11	50.00	50.00	78.11
5	78.11	50.00	50.00	78.11
6	78.11	50.00	50.00	78.11
7	78.11	50.00	50.00	78.11
8	78.11	50.00	50.00	78.11
9	78.11	50.00	50.00	78.11
10	78.11	50.00	50.00	78.11
11	78.11	50.00	50.00	78.11
12	78.11	50.00	50.00	78.11
13	78.11	50.00	50.00	78.11
14	81.00	98.92	57.98	81.29
15	50.00	80.90	82.33	80.90
16	84.41	76.37	76.37	77.29
17	84.36	76.71	76.71	77.18
18	84.02	76.15	76.15	76.66
19	86.78	77.52	77.52	81.80
20	85.39	76.53	76.53	79.09
21	86.54	76.62	76.62	81.67
22	84.75	76.83	76.83	77.82
23	86.35	77.01	77.01	81.02
24	85.10	76.85	76.85	78.45
25	85.14	75.73	75.73	78.83
26	83.95	75.27	75.27	76.66
27	78.69	53.74	53.74	68.79
28	80.78	59.12	59.12	76.21
29	86.00	72.98	72.98	82.80
30	86.52	76.34	76.34	81.78
31	86.37	74.97	74.97	82.29
32	78.77	52.58	52.58	72.84
33	79.49	55.46	55.46	73.20
34	84.92	72.45	72.45	79.77
35	86.86	75.28	75.28	83.56
36	78.69	52.19	52.19	73.19
37	78.81	52.91	52.91	72.16
38	79.94	57.23	57.23	73.58
39	79.14	54.97	54.97	71.01

A confusion matrix (CM) is a tool used in machine learning and statistics to evaluate the performance of a classification algorithm [28], [29]. It provides a summary of the prediction results on a classification problem, showing the number of correct and incorrect predictions broken down by each class. This allows for a detailed analysis of how well the classifier is performing. A CM for a binary classification problem is typically a 2×2 table, but it can be extended to an N×N table for multi-class classification problems. As presented in Figure 3, there are 205 and 531 misclassified as HC and MI. This is because there are sub-MI as represented as MI. The heart receives nourishment from several arteries, making it possible for MI to happen in various regions. If the blood supply to any of these areas is interrupted, the electrical activity of the muscle fibers in that region begins to alter. The specific alterations observed in ECG recordings vary based on the electrodes utilized.

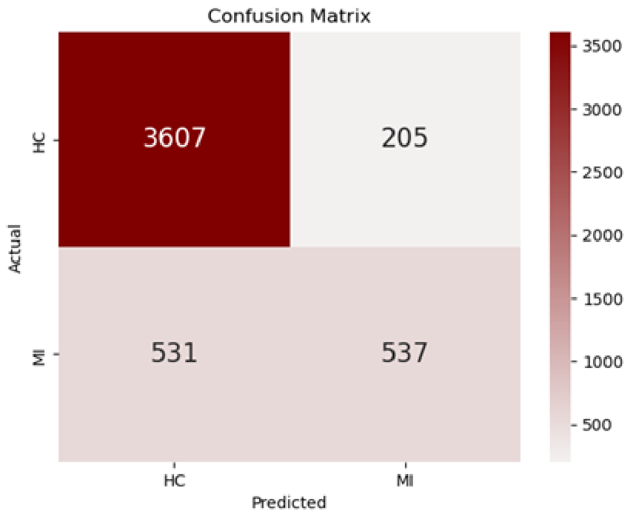


Figure 3. The heatmap CM of HC and MI classification

4. CONCLUSION

MI is an injury to the heart muscle brought on by a thrombus obstructing the coronary arteries, which stops blood flow. If this condition is not treated quickly to reopen the coronary artery via percutaneous or surgical procedures, it may result in irreversible damage, including myocardial tissue death. Therefore, in order to avoid complications like cardiac failure, arrhythmia, and death, early detection and diagnosis are essential. ECG is commonly used to diagnose acute MI, although it is sensitive to inter-observer variability and requires expert interpretation. Manually analyzing ECG data by a cardiologist takes a lot of time and is error-prone. A deep learning method that can automatically recognize and categorize a variety of ECG signal properties is proposed in this study. A hybrid CNN-LSTM based on a deep learning algorithm was proposed in this paper. To generate the hybrid CNN-LSTM model, we proposed 39 models with hyperparameter tuning. As a result, the best model is model 35 has 86.86% accuracy, 75.28% sensitivity and specificity, and 83.56% precision. The algorithm based on a hybrid CNN-LSTM demonstrates notable efficacy in autonomously diagnosing AMI and determining the location of MI from ECGs.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available in the PTB-XL, a large publicly available electrocardiography dataset (https://physionet.org/content/ptb-xl/1.0.3/).

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