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Myocardial infarction detection based on deep neural network on imbalanced data

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Abstract
Myocardial infarction (MI) is an acute interruption of blood flow to the heart, which causes the heart to suffer from a deficiency of blood and ischemia, so the heart muscle is damaged, and cells can die and lose their function. Despite the low incidence of MI in the world, it is still a common disease-causing death. Therefore, detecting the MI signals early can reduce mortality. This paper presented a method based on a deep convolutional neural network (CNN) for the detection of MI automatically. The proposed CNN is an end-to-end model without requiring any stages of machine learning and requires only one stage to detect MI from the input signals. In the case of imbalanced data, we optimize our deep model with a new loss function named the focal loss to deal with this case by constituting the loss indirectly the focus in those difficult classes. The Physikalisch-Technische Bundesanstalt (PTB) dataset was employed in the validation to classify the signals to normal and MI. The performance of our technique alongside state-of-the-art in the area shows an increase in terms of average accuracy and F1 score. Results show that focal loss improves the detection accuracy by 9% for detecting MI signals. In summary, the proposed method achieved an overall accuracy, precision, F1 score, and recall of 98.84%, 98.31%, 97.92%, and 97.63, respectively using focal loss and overall accuracy of 89.72%, a precision of 88.52%, a recall of 81.11% and F1 score of 83.02% without using focal loss. Our method using focal loss is an effective tool to perform a fast and reliable MI diagnosis to assist the cardiologists in detecting MI early.

Keywords CNN · Myocardial infarction · End-to-end · PTB · Focal loss · Imbalanced data

1 Introduction

Myocardial infarction (MI), also identified as heart attack [1], is severe heart disease a life threat caused by blood retention as a result of the blockage of one of the coronary arteries, resulting in damage or complete death to part of muscle heart. The seizure is often a medical emergency that threatens the patient's life and requires immediate medical attention [2]. MI is still one of the most serious diseases that may cause death. The latest statistics indicate that the death rate from MI is 30% within 30 days if it is not treated [3]. MI characteristics include abnormal Q wave appearance, ST-segment elevation, and T-wave inversion [4]. The presence of abnormal Q waves on the 12-lead ECG signifies a prior transmural MI. The ST-segment changes on the standard ECG that are associated with acute ischemia or infarction are due to the flow of current across the boundary between the ischemic and non-ischemic zones referred to as injury current. Some of the T-wave changes are associated with the post reperfusion phase. Figure 1 shows an example of ECG signal in case ST elevation.

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The condition is diagnosed by the electrocardiogram (ECG), which is an electric signal produced by the heart. Therefore, early detecting the MI using ECG signals is a vital task to reduce mortality. Manual detection of large amounts of the MI signals is time-consuming and can be tedious. As a result, some researchers have proposed different approaches to analyze the ECG data automatically for MI detection [6–22].

Numerous studies have been implemented to detect MI automatically by investigating ECG signals using machine learning and data mining techniques [6–12]. However, there are main disadvantages associated with the prior studies that our study endeavors to fill the gap. These drawbacks are as follows:

- Majority of previous studies are utilizing very complex frameworks to build a predictive model for MI detection.
- Implement the model into big datasets are usually costly in terms of time.
- Developing a hardware that can coordinate with the model becomes hard due to memory constraints.
- High imbalance data between different classes, which lead to detect MI incorrectly.

To address the above-mentioned issues, an end-to-end deep learning approach based on convolutional neural network (CNN) and focal loss for automatically detection of MI is proposed. In comparison to most of the previous techniques, our proposed solutions are computationally efficient, robust, and can be employed in the future studies for real-time detection of MI.

1.1 Goals

Our main goals are as follows:

Goal 1: Design novel method based on CNN for automatically detection of MI.

Goal 2: Design an end-to-end approach, which perform feature extraction and classification automatically.

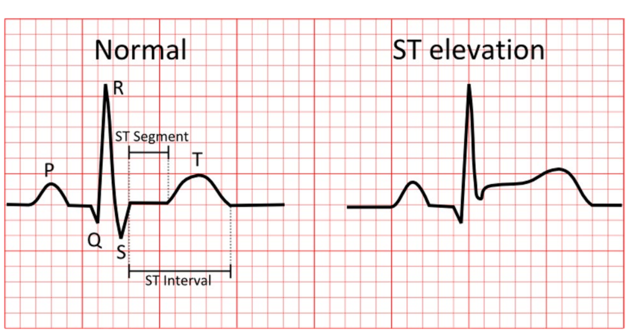

Fig. 1 Illustration of one of the MI characteristics [5]

Goal 3: Design an optimization technique as a solution to the imbalanced data problem.

Goal 4: Verify our solution based on MI detection.

1.2 Novelty

The main novel contributions of this work are:

Contribution 1: Deep CNN model—Designed three blocks of convolutional composed of several one-dimensional (1D) convolutional layers in each one with kernel size 2 and the stride is set to 1, which are activated by ReLU [25] activation function + batch normalization [26] and dropout [27] operations + two dense layers and a SoftMax layer.

Contribution 2: End-to-end method—Designed a novel and efficient end-to-end deep method without requiring any stages of machine learning and require only one stage to detect MI from the input signals, which achieve high accuracy on the big data and reduce the cost of implementation.

Contribution 3: Optimization technique—Applied new optimization technique based on focal loss to achieve with imbalance data a high training accuracy by constituting the loss indirectly the focus in those difficult classes. Table 1 summarized all parameters used in this study.

1.3 Structure of the paper

The structure of the rest of this paper as follows. The related works are introduced in Sect. 2. The dataset used to evaluate our method, and the architecture of our end-to-end CNN method with approaches employed to solve the problem of data imbalanced are described in Sect. 3. Experimental results and discussion are given in Sects. 4 and 5, respectively. Conclusions and future works are given in Sect. 6.

2 Related work

Most works reviewed earlier present a solution based on deep CNN. The use of CNN is spread in many fields [28–32], especially in the medical fields due to its high performance in disease detection [33–38]. Basically, the CNN is a multilayer perceptron network (MLP) [39] in which each neuron has an activation function that links the weighted inputs to the output. CNN has an input layer, several hidden layers (e.g., Max-pooling, convolutional, and fully connected layers), and an output layer, and each of these layers accomplishes different tasks on the input data (as discuss in Sect. 3.3). The following are the state-of-the-art approaches that used CNN for MI detection:

- Baloglu et al. [13] established a model for diagnosis the MI automatically on standard 12 leads ECG data. They

Table 1 Parameters definition

Parameter	Meaning
P	The predictable probability of the model
y	The ground-truth class
Ce	Cross entropy
α	The reverse of the class frequency
Fl	Focal loss
γ	Adjustable parameter
Pre	Precision
Reca	Recall
F1	F1-score

used CNN model for feature extraction. They achieved an accuracy of 99.78% for MI detection using PTB database.

- Jafarian et al. [14] presented a method for MI localization and detection using CNN on 12 leads ECG data. First, the authors performed preprocessing phase on the input signals and fed it to the CNN model. They obtained an accuracy of 98.21%, a specificity of 98.01%, and a sensitivity of 97.5% for MI detection on PTB database.
- Liu et al. [15] developed a method for MI detection based on multiple feature branch CNN (MFB-CNN) on 12 leads ECG data. They learned each feature using feature branch and summarized these features using global fully connected SoftMax layer. They achieved an average accuracy of 99.95% using PTB database.
- Liu et al. [16] presented an ECG healthcare system for MI detection using Multilead-CNN (ML-CNN). They introduced beat segmentation algorithm with fuzzy information granulation (FIG) for preprocessing and fed it to the 2D-CNN for final decision. They achieved an accuracy, a specificity, and a sensitivity of 96%, 97.37%, and 95.40%, respectively, for MI detection on PTB database.
- Alghamdi et al. [17] presented a method for MI detection based on transfer deep learning method. They transform the input 1D ECG signals to 2D ECG image and then fed these images to the 2D-CNN for feature extraction. Finally, they used Q-Gaussian multiclass support vector machine (QG-MSVM) [52] as a separated classifier for classification. They achieved the best accuracy, sensitivity, and specificity of 99.22%, 99.15%, and 99.49%, respectively, using PTB database for MI detection.
- Feng et al. [18] introduced a deep learning method for MI detection based on combination of CNN and recurrent neural network (RNN). They segmented the input ECG signals in the preprocessing stage and fed it to the deep model for feature extraction and classification. They obtained an accuracy of 95.4%, a sensitivity of 98.2%, a specificity of 86.5%, and an F1 score of 96.8% using PTB database for MI classification.

From the previous discussion, we can show that the majority of the previous works obtained low performance and these results are not enough to push these techniques in clinical testing and usage. Unlike the previous methods, the proposed method can empower MI detection and contribute to the improvement of clinical software tools.

3 Assumptions, materials, and methods

In this research, to fully detect MI, a novel end-to-end deep CNN method is proposed. The main assumptions of our novel method are as follows:

3.1 Assumptions

Assumption 1: No preprocessing stages or signal filtering.

Assumption 2: No segmentation or QRS detection.

Assumption 3: Use of an end-to-end CNN method reduce both the complexity and the cost.

Assumption 4: Use of cross-validation technique to overcome the overfitting.

Assumption 5: Use of focal loss to address imbalanced data.

Assumption 6: Use SoftMax activation function for classification ECG signals to MI and normal.

One of the advantages of our method is that it reduces the impact of imbalanced ECG classes using Focal loss, since it focuses on the loss of the minority classes. Also, using end-to-end deep CNN method reduces the computational complexity, which can be used in the future for Internet of medical things (IoMT) applications and use it in cloud or mobile for making real-time diagnosis.

3.2 Materials

The Physikalisch-Technische Bundesanstalt (PTB) dataset [40] from the PhysioNet [41] was employed in this study to fairly compare the performance of our approach with the results obtained from state-of-the-art methods. The descriptions of this dataset are as follows:

- There are 549 realizations of standard 12-lead ECG signals for 290 subjects aged from 17 to 85 years.
- The characteristics of the signals: 1000 Hz sampling rate and 16 bit resolution.
- 368 out of 549 records and 147 out of 290 subjects are categorized as MI cases.
- The ECG signals were consequent from one lead (Lead II).
- Each segment is composed of 20s data samples.

Table 2 The distribution of the data in each class

MI Class	Segments number
Infero-postero-lateral (IPLMI)	305
Antero-lateral (ALMI)	308
Anterior (AMI)	311
Infero-lateral (ILMI)	318
Antero-septal (ASMI)	389
Inferior (IMI)	455
Normal	427

Table 2 describes the PTB database. It presents distribution of the data between each class, the MI locations, and the number of segments. In this study, the balance of the data is not important aspect as we use focal loss method to overcome this problem. Figure 2 shows samples of three recordings from the PTB database.

3.3 Methods

Figure 3 shows the general block diagram of the proposed end-to-end method. The ECG raw data collected from the input device are fed directly to the proposed CNN and classify into two classes (normal and MI).

- The imbalanced data problem

In any datasets there is some degree of imbalance [42] and it does not affect the performance of the method if this degree is low. However, in medical diagnosis and especially in our case MI detection, data are highly imbalanced, where the number of normal records (181 records) are limited in number compare to MI records (368 records) and thus cause the following problems:

1. Problem in learning as most observations are easy samples.
2. Degeneration of the classifier model because of these easy samples.

In this study, we used focal loss to solve the imbalanced data problem for MI detection.

- Focal loss

Recently, researchers proposed many solutions for imbalanced data in many fields [43–46]; for instance, Chen et al. [43] used ensemble learning techniques to address the class

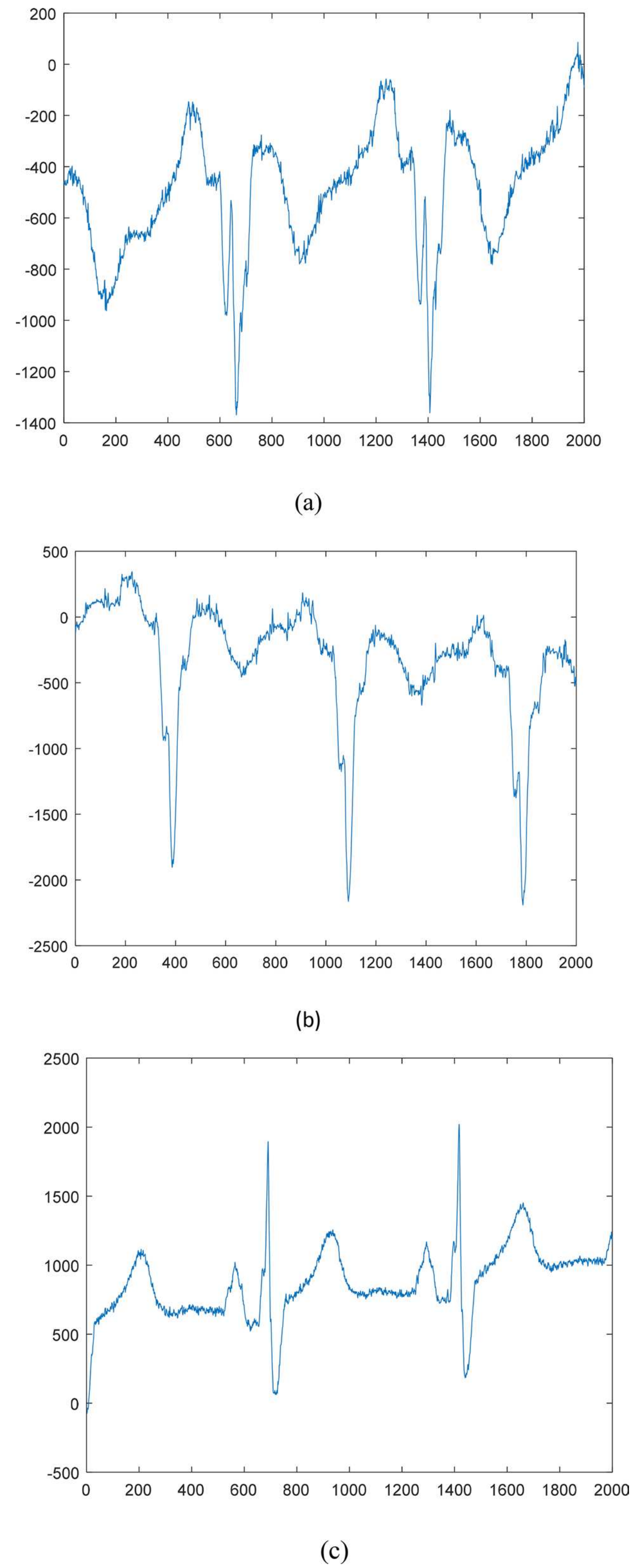

Fig. 2 Examples of three recordings from the PTB database

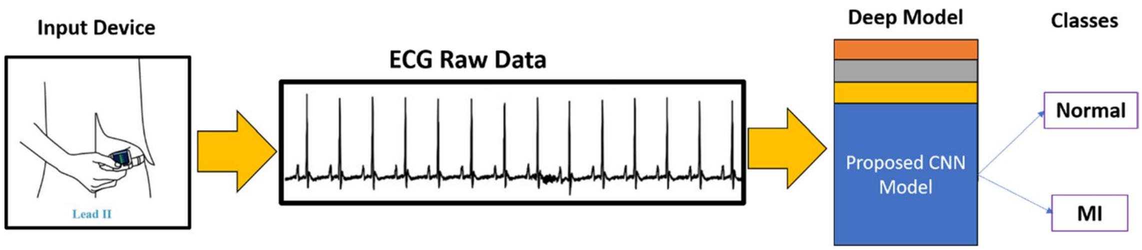

Fig. 3 General Block Diagram of our end-to-end Method

imbalance problem. Another study to deal with noisy imbalanced data based on Radial-Based Oversampling (RBO) is presented by Koziarski et al. [44]. One of the common solutions is the focal loss, which is first introduced as a solution for object detection [47]. The focal loss function is introduced based on cross-entropy (Ce) [48] for binary classification:

$$\mathrm{Ce}(p,y)=\begin{cases}-\log(p) & \text{if } y=1\\ -\log(1-p) & \text{otherwise,}\end{cases} \tag{1}$$

where $p\in[1,0]$ is the predictable probability of the model and $y\in\{\pm 1\}$ is the ground-truth class. Moreover, authors in [47] added a weighting term α to deal with class imbalance for positive class and $(1-\alpha)$ for negative class as the following:

$$\alpha_t=\begin{cases}\alpha & \textit{if } y=1\\ 1 & \text{otherwise } -\alpha,\end{cases} \tag{2}$$

$$\mathrm{Ce}(p_t)=-\alpha_t\log(p_t), \tag{3}$$

where α is the reverse of the class frequency or improved as an adjustable parameter to be established by the cross-validation and p_t define as:

$$p_t=\begin{cases}p, & y=1\\ 1-p, & \text{otherwise.}\end{cases} \tag{4}$$

Focal loss (Fl), is an expansion of cross-entropy loss formed by adding a weighted term in obverse, in which α and γ are two adjustable parameters, and formally, its form is as follows:

$$\mathrm{Fl}=-\alpha_t(1-P_t)^{\gamma}\log(P_t). \tag{5}$$

- The focusing γ (gamma) parameter is a positive value which adjusts the rate at which easy samples are downweighted. When $\gamma=0$, the function of focal loss is equivalent to categorical cross-entropy Ce, and as γ is amplified, the consequence of the modulating factor is increased, as well ($\gamma=2$ is the best in the experiments).
- The second parameter α (alpha) is employed to balance the focal loss, which improved the accuracy over the non-α-balanced.

The architecture of our model is presented in Fig. 4. It is composed of the following:

- The proposed model
  - Three blocks of convolutional composed of four 1D convolution layers in each one. Each layer has 512 filters for feature extraction. The kernel size is 2 and the stride is 1.
  - The batch normalization after every block to normalize the data and improve the classification performance.
  - Dropout technique is used after the batch normalization to prevent the network from overfitting. It is important in complex network and a few labeled samples.
  - ReLU [25] is used as an activation function with all layers. We used ReLU, because it does not saturate comparing with other common activation function such as sigmoid or tanh, which are saturate. In addition, it does not activate all the neurons at the same time.
  - Three dense layers headed by a global average pooling [49].
  - A SoftMax layer for classifying the signals to MI and normal.
  - Adam optimization algorithm [50] is used for optimization and applied the focal loss to solve the data imbalanced problem. Table 3 shows the details of all layers and parameters of the proposed model.

- Cross-validation

  A cross-validation is an essential tool in the data world toolbox, as it helps for better use of the data. It is used to assessment the proficiency of machine learning models. In this paper, we employed the stratified *five*fold

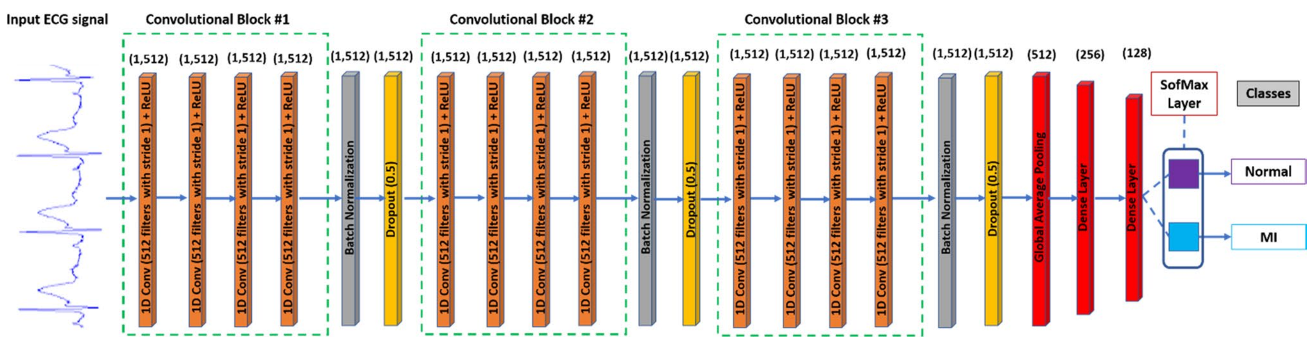

Fig. 4 The architecture of our deep model

cross-validation technique [51] in the learning processing, where the results are verified on the test data. This technique is worked as follows:

- Shuffle the MI data randomly.
- Divide the data into five equally sized subsets.
- For each of these subsets, 1/3 of the instances should be from the one class, and the remaining points should be in the other class.
- Run five experiments where 80% of the data for training and the remaining partition (20% of the data) for testing.
- Calculate the detection accuracy.
- Repeat the process four more times, rotating the test data, so that each group serves as a test set exactly once.
- Compute the average performance on the five experiments and reported the detection result.

4 Experimental results

In our study, we used the following tools for implementation:

–MATLAB 2019a software with deep learning toolbox.
–PC workstation with 3.30-GHz CPU.

Table 3 The details of all layers of the proposed model

Layers	Name	Kernel size	# of filters	Stride	Input shape
1	1D Conv + ReLU	1×2	512	1	1024×1
2	1D Conv + ReLU	1×2	512	1	1024×512
3	1D Conv + ReLU	1×2	512	1	1024×512
4	1D Conv + ReLU	1×2	512	1	1024×512
5	Batch Normalization	1×2	512	1	1024×512
6	Dropout	1×2	512 (rate = 0.5)	1	512×512
7	1D Conv + ReLU	1×2	512	1	512×512
8	1D Conv + ReLU	1×2	512	1	512×512
9	1D Conv + ReLU	1×2	512	1	512×512
10	1D Conv + ReLU	1×2	512	1	512×512
11	Batch normalization	1×2	512	1	512×512
12	Dropout	1×2	512 (rate = 0.5)	1	256×512
13	1D Conv + ReLU	1×2	512	1	256×512
14	1D Conv + ReLU	1×2	512	1	256×512
15	1D Conv + ReLU	1×2	512	1	256×512
16	1D Conv + ReLU	1×2	512	1	256×512
17	Batch normalization	1×2	512	1	256×512
18	Dropout	1×2	512 (rate = 0.5)	1	128×512
19	Global pooling	1×2	256	2	512
20	Dense		128		256
21	Dense		128		128
22	SoftMax		2		128

–32 GB RAM.
–NVIDIA GeForce GTX 1080 (GPU).

We propose to illustrate the efficiency of the proposed approach by comparing the performances of our deep model using and without using focal loss. In addition, the performance is compared with the results from recent works in the literature.

4.1 Performance metrics

The following metrics are employed to assess the performance of our method:

1. **Accuracy**, which is the proportion of the number of signals that predicted correctly to the total of the input samples:

$$\text{Accuracy} = \frac{(\text{True positive} + \text{true negative})}{(\text{True positive} + \text{true negative} + \text{false positive} + \text{false negative})}. \tag{6}$$

2. **Precision (pre)**, which is the proportion of the true positive samples and the overall predicted positive observations and is given by:

$$\text{Pre} = \frac{(\text{True positive})}{(\text{True positive} + \text{false positive})}. \tag{7}$$

3. **Recall** (**Reca**), which is the portion of the true positive samples and the overall predicted negative observations and is given by:

$$Reca = \frac{(\text{True Positive})}{(\text{True Positive } + \text{ False Negative})}. \tag{8}$$

4. **F1 score (F1)**, which is a vital metric that used to evaluate the classification and is given by:

$$\text{F1} = \frac{2 \times (\text{Reca} \times \text{Pre})}{\text{Reca} + \text{Pre}}. \tag{9}$$

4.2 Results

The training of the proposed model was done with 400 batch size value and 0.0001 learning rate for the Adams optimizer. In addition, the dropout rate is 0.5 and the focal parameters are $\alpha = 0.5$ and $\gamma = 2$. We selected these values as these values give highest performance with our model for MI detection. In this paper, the following experiments were done:

1. **The first experiment**: Train the model + observe the convergence rate of the model with and without using focal function.
2. **The second experiment**: Compared the proposed model using focal loss with the state-of-the-art approaches.

1. **First experiment**

   Figures 5 and 6 show the plot of accuracy and loss values of our method for each epoch using focal loss and without focal loss, respectively. From the figures, we can observe the following:

   – The method using loss function starts with a much lower loss value than the method without focal loss.
   – Also, the method using focal loss converges much earlier than the method without using focal loss.
   – The two models practically converge after training with 100 epochs, so the number of epochs is set to 100 for all experiments.

   Figure 7 shows two confusion matrices of the proposed method using focal loss and without using focal loss, in which we observe clearly how the correct classifications for the normal and MI classes.

   Table 4 shows the results of our method using focal loss and without using focal loss in terms of Accuracy, Pre, Reca, and F1 (computed using Eqs. 6, 7, 8, and 9).

   From the table, we can show that the proposed method using focal loss performs better than the one without using focal loss.
2. **Second experiment**

   Table 5 presents the comparison of our model using focal loss with the state-of-the-art approaches for MI detection.

5 Discussion

From the results in Fig. 7, we can show that the number of correctly detected as MI signals is increased from 1817 to 2087, and normal signals are increased from 338 to 416, which are equal to 6% and 3.1%, respectively. The increase in the correct detection is because of using focal loss with our method. However, the proposed method misclassified some ECG signals from MI signals as belonging to the normal signals, which the misclassified increased from 11 to 89. In addition, from normal signals as belonging to the MI signals, which the misclassified increased from 19 to 169.

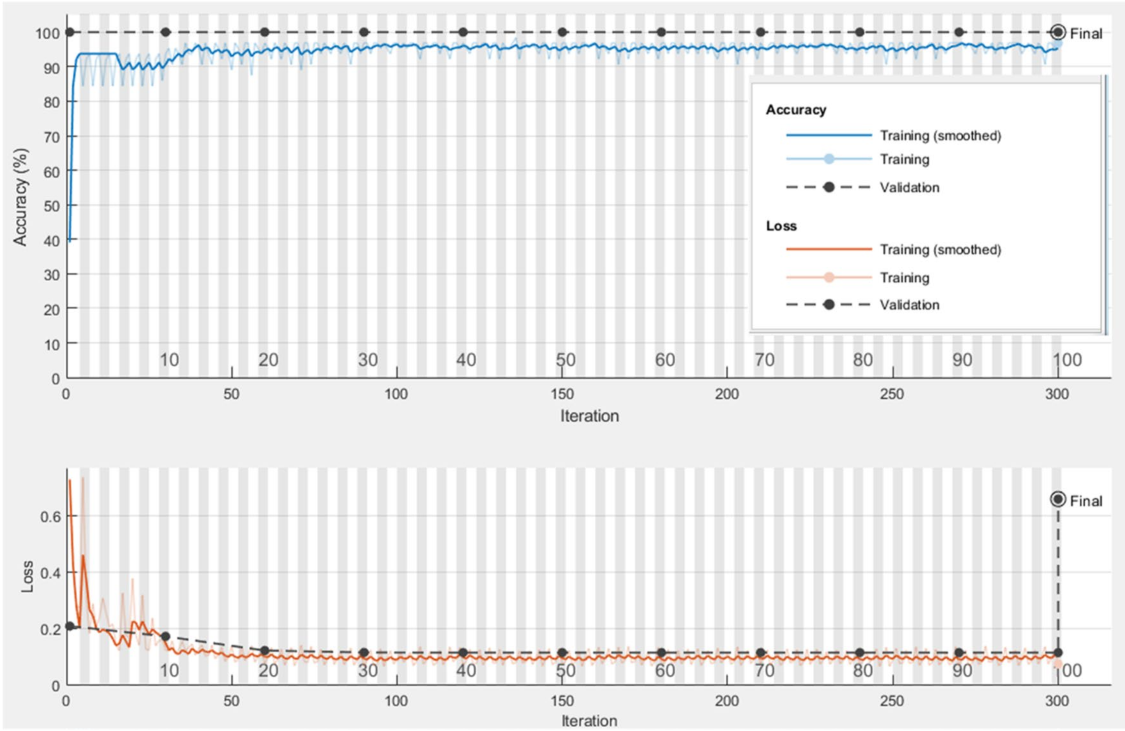

Fig. 5 Accuracy and Loss curves using Focal loss

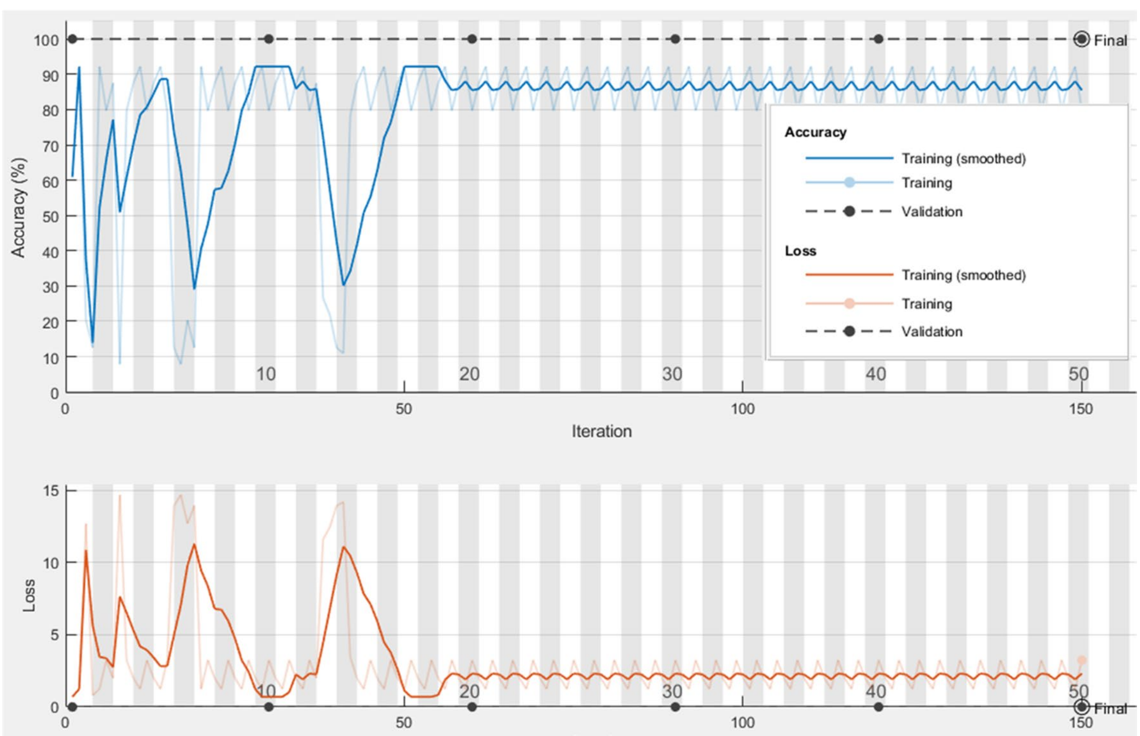

Fig. 6 Accuracy and loss curves without using Focal loss

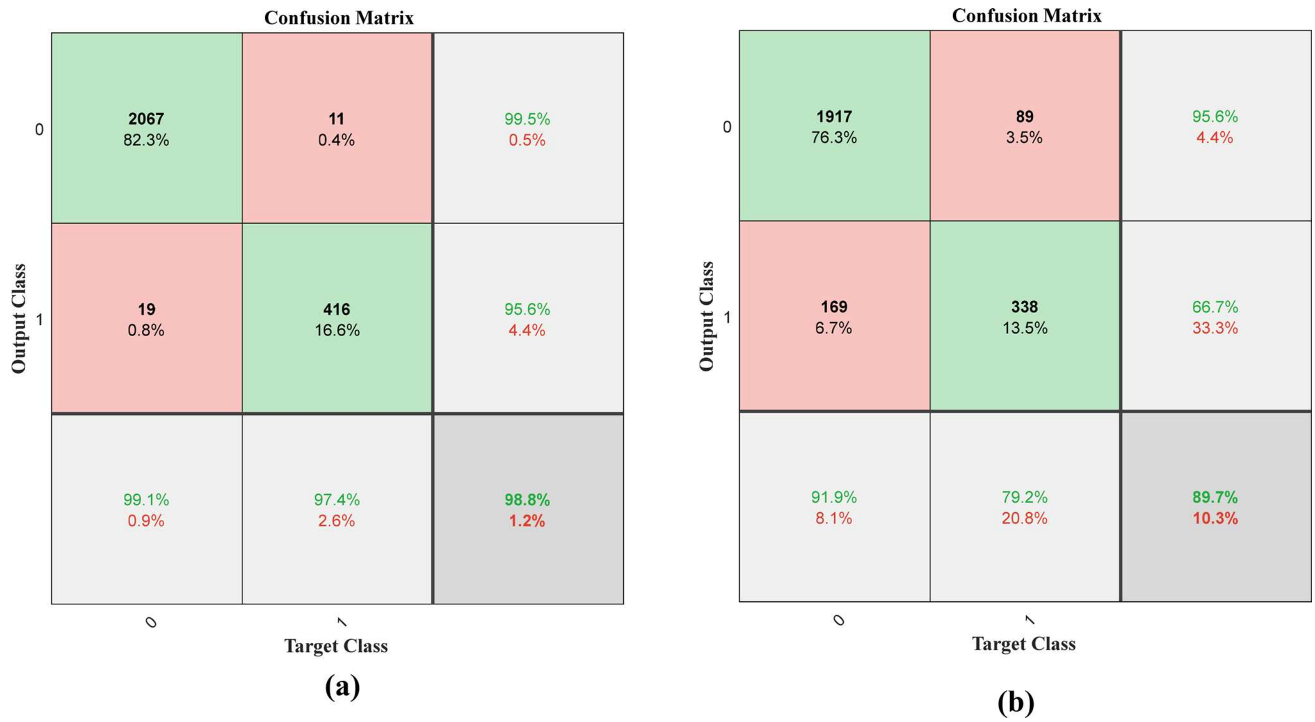

Fig. 7 The confusion matrices of the proposed model **a** using focal loss and **b** without focal loss

Table 4 Results of the proposed deep method with and without using focal loss

Class	With focal loss			Without focal loss		
	Prec	Reca	F1	Prec	Reca	F1
Normal (%)	97.42	95.63	96.51	79.15	66.66	72.37
MI (%)	99.08	99.47	99.27	91.89	95.56	93.68
Overall accuracy (%)	98.84			89.72		
Training time (s)	512.24			533.45		

Table 5 Comparison of performance results of the proposed model to other models from literature For MI detection

Authors/year	Method	Accuracy (%)	Prec (%)	Reca (%)	F1 (%)
Baloglu et al. [13] (2019)	CNN	99.7	–	–	–
Jafarian et al. [14] (2020)	Preprocessing + CNN	98.2	98.1	97.5	97.7
Liu et al. [15] (2018)	MFB-CNN	98.7	–	–	–
Liu et al. [16] (2018)	ML-CNN	96	97.4	95.4	96.4
Alghamdi et al. [17] (2020)	Transfer deep learning	99.2	99.5	99.2	–
Feng et al. [18] (2019)	CNN + RNN	95.4	98.2	86.5	96.8
Fu et al. [21] (2020)	MLA-CNN-BiGRU	96.50	–	–	–
Prabhakararao and Dandapat [22] (2020)	MLDA-RNN	97.79	–	–	–
Proposed (2020)	CNN + focal loss	98.8	98.3	97.6	97.9

CNN convolutional neural network, *MFB* multiple feature branch, *ML* multi-lead, *RNN* recurrent neural network, *BIGRU* bidirectional gated recurrent unit, *MLDA-RNN* multi-lead diagnostic attention-based recurrent neural network

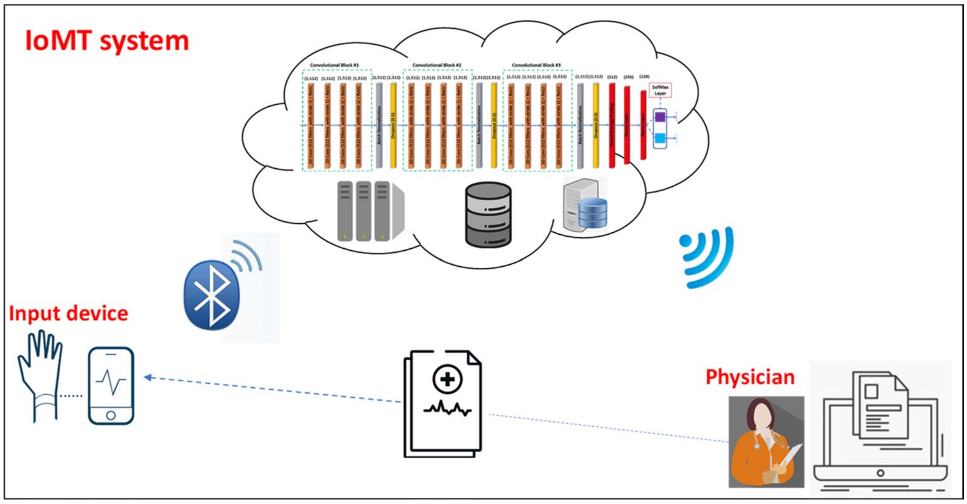

Fig. 8 IoMT system for MI detection

In addition to the results in Fig. 7, from the results of Table 4, we can observe the following:

–Using focal loss increase the correct detection of MI signals, hence, increase the overall performance of the system from 89.72 to 98.84% in terms of accuracy.
–There is a significant increase for F1 score measure when using focal loss especially in case normal class, where it increased from 72.37 to 96.51% when using focal loss.
–All performance metrics (Pre, Reca, and F1) for the MI and normal classes have slightly increased.
–The training time is decreased when using focal loss. The proposed system using focal loss spends approximately 8.5 min for the training of all data, while the system without using focal loss spends approximately 9 min training time.

Comparing to other previous works, as shown in Table 5, we can observe that our model is more robust than other methods, especially in terms of F1-scores, which being a significant performance metric specifically for imbalanced data.

The majority of previous works [13–17] were used 12 ECG leads, which increase the time of training. Also, many works [14,17,18] needed high-level equipment during the training. Moreover, some previous works [17,18] used separated classifiers and preprocessing stages, which make the method more complex. In addition, most of these methods [14–17] used 2D-CNN, which increase the cost of computation and the time of the detection. Finally, all works [13–18] need big data to obtain high accuracy. Our method overcomes most of these problems.

5.1 Advantages of our work

–The proposed method is totally automatic (end-to-end) and we do not need to do preprocessing or used separate classifiers.
–Achieved higher accuracy on small data compared to other previous works [13–18].
–Can deal with imbalanced data.
–Our method is robust as it achieved high detection accuracy with stratified fivefold cross-validation method.
–The proposed approach is simple and easy to operate.

5.2 Disadvantages of our work

–Working on limited number of data, and we need to test our method on more data.
–We focused only on MI detection, and we need also to test our method for MI localization.
–We also used CNN as a deep learning approach for MI detection.

5.3 Differences with previous works

–Using focal loss with deep learning to achieve a high training accuracy with imbalance data.
–Structure of the model, three convolutional blocks composed of several 1D convolution layers and the use of global average pooling in the dense layers.
–Using only one lead ECG signals for the detection.

In summary, according to the advantages of the proposed method, we can use it in the future for IoM applications, where we can use it for health care in smart cities (see Fig. 8) as follows:

- The ECG signals acquired from the sensors or the input devices.

- The signals are sent to the cloud through Bluetooth of the Mobile (the input device) for processing using the proposed model.
- Our model makes the decision if the signal is MI or normal and send the decision to check by the physician.
- The system can notify the final results immediately to the patients after the decision is made.
- This IoMT system will reduce the workload in hospitals as it is a fully automated system.

6 Conclusion and future works

The main objectives of this study were to develop a new model for MI detection and to deal with imbalanced data. The main contributions of this paper are the design of a novel end-to-end model based on CNN to classify the ECG signals to normal and MI, and propose a new method for imbalanced data based on focal loss. Our method achieved an accuracy, a precision, F1 score, and a recall of 89.72%, 85.52%, 82.99%, and 81.11%, respectively, without using focal loss and 98.8%, 98.3%, 97.6%, and 97.9%, respectively, using focal loss. Experimental results show that applying the loss function to the proposed method leads to increase the overall performance by 9%. Comparing to other previous works, the proposed method is more robust and more efficient especially in case of imbalanced data.

In the future, we can include the following:

- Testing our method on other types of ECG data such as arrhythmia signals [53–55].
- Improve the accuracy of the proposed system through working on big data, and it can be done using augmentation techniques [56] or working on other data [57].
- Testing the efficiency of our method on other signals such as EEG [58–61].
- Testing our method when applying optimization techniques such as genetic algorithm (GA) [62–64].
- As this work and all previous works develop the deep learning-based CNN, we decide to use other deep learning approaches to detect the MI signals such as ResNet [65].

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