Cardiac and Cardiovascular Research (2020) Volume 1 Issue 1, *7 pages*.
doi: 10.54517/ccr.v1i1.1893

ORIGINAL RESEARCH ARTICLE

Research on the identification of myocardial infarction location based on multiresolution residual network

***Ji Qi*[1,2] *Hua Jiang*[3], *Ruiqing Zhang*[1], *Yang Shen*[1], *Yanni Tong*[1], *Xianzheng Sha*[1 *], *Shijie Chang*[1,*]**

[1].Biomedical Engineering Department of China Medical University, Shenyang 110122, Liaoning, China. E-mail: xzsha@ cmu. edu. cn; shjchang@mail. cmu. edu. cn

[2].Department of Medical Equipment, The Fourth Affiliated Hospital of China Medical University, Shenyang 110032, Liaoning, China.

[3].Department of Cardiovascular Medicine, The First Affiliated Hospital of China Medical University, Shenyang 110054, Liaoning, China.

ABSTRACT

In order to realize the classification and recognition of anterior myocardial infarction, inferior myocardial infarction, anterior septal myocardial infarction and normal ECG signals, this study takes the clinical database as the experimental data source, extracts the training set and test set data for training and testing the network model, optimizes the traditional neural network, and designs a new network algorithm: multi-resolution residual network. The multi-resolution residual network is visually compared with the traditional network to evaluate the recognition effect of the model. The test set accuracy of multi-resolution residual network is 91.8%, which is higher than that of classical neural network. The algorithm in this study can assist doctors in the diagnosis of myocardial infarction diseases, and has certain clinical significance.

Keywords: myocardial infarction; electrocardiogram; deep learning; convolutional neural network; residual network

1. Introduction

Myocardial infarction can be divided into seven locations: inferior wall, anterior wall, anterior septal wall, extensive anterior wall, anterior wall, high lateral wall and posterior wall. Generally, compared with myocardial infarction in other simple locations, the lesion area of anterior wall myocardial infarction is larger [1]. The location diagnosis of myocardial infarction can accurately judge the location of coronary artery lesions, help doctors to carry out targeted interventional therapy, and also provide an important basis for clinical observation of the condition and prognosis[2]. Twelve lead ECG can clearly show a variety of pathological sites of myocardial infarction. It is a non-invasive detection method with accurate diagnosis and low cost.

The principle of 12 lead ECG is to detect the change of action potential of cardiac conduction system in each cardiac cycle through electrodes connected to chest leads and limb leads, so as to form an ECG waveform with potential changing with time[2].

ARTICLE INFO
Received: June 9, 2020 | Accepted: July 20, 2020 | Available online: August 5, 2020

CITATION
Qi L, Jiang H, Zhang, R, et al. Research on the identification of myocardial infarction location based on multi–Resolution residual network. Cardiac and Cardiovascular Research 2020; 1(1): 7 pages.

Accurate interpretation of ECG requires doctors to have a solid professional foundation and rich experience, but manual interpretation of ECG is prone to misjudgment and omission, and the workload is heavy. In order to solve the above problems, this study designed an ECG aided diagnosis algorithm, which can accurately analyze the ECG automatically and get the results, so as to reduce the burden of doctors and improve work efficiency.

In recent years, researches on ECG aided recognition have emerged one after another, such as digital filtering, wavelet transform and other technologies, followed by feature extraction technology and in-depth learning methods in recent years [3]. Deep learning is a kind of machine learning. Traditional machine learning has input layer, hidden layer and output layer. Deep learning has multiple hidden layers. The main frameworks of deep learning include convolutional neural network (CNN) [4], recurrent neural networks (RNN) [5], long short term memory network (LSTM) [6]. Residual network (RESNET) is a variant of CNN. Its unique short connection structure has better classification effect for complex data [7]. RESNET won the first place in ilsvrc 2015 image recognition competition. RESNET also has certain applications in semantic segmentation [8], voice interference detection [9], traffic vehicle recognition [10] and other research fields. In addition, the researchers proposed to apply the multi-resolution network to the neural network to increase the network width and improve the recognition accuracy. The multi-resolution network can be applied to large-scale scene classification [11], action recognition [12], biometrics [13], etc.

In the field of medical ECG recognition, deep learning also has some successful practices. For example, kiranyaz et al. [14] studied ventricular ectopic beat (veb) and supraventricular ectopic beat (sveb) based on CNN model and multi-layer perceptron (MLP) model, and obtained a recognition accuracy of more than 95%; isin et al. [15] used CNN to classify MIT BIH data and obtained an accuracy of 92.4%; rajpurkar et al. [16] used RESNET model to study arrhythmia data and obtained an average recognition accuracy of 80.9%.

At present, according to the published literature, there is no research on the location of myocardial infarction using deep learning technology. Based on RESNET, this study proposes an improved multi-resolution residual network. This network can be applied to the automatic identification of myocardial infarction location, and can assist doctors in diagnosis, which has certain clinical significance.

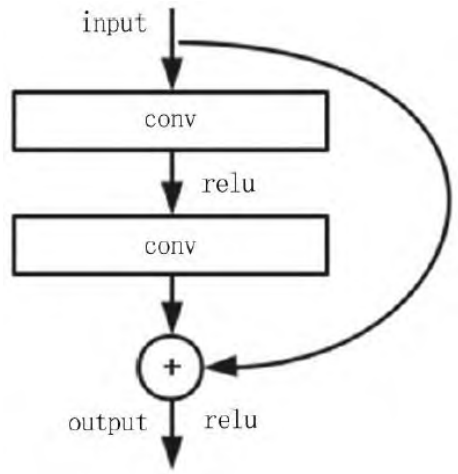

Figure 1. Residual njianetworks.

2. Algorithm design

2.1. Residual network

Residual network (RESNET) is an optimization based on CNN in terms of structure. A RESNET block is composed of two convolution layers and a cross layer connection, as shown in Figure 1. The algorithm is as follows:

$$y_l = f_{\text{relu}}[\text{conv}(i)] \tag{1}$$

$$y_{l+1} = \text{conv}\left(y_l\right) \tag{2}$$

$$o = f_{\text{relu}}\left(i + y_{l+1}\right) \tag{3}$$

Where, y is the output of a specific layer, f_{relu} is the activation function, i is the input of RESNET block, conv is the convolution algorithm, and o is the output of RESNET block.

The main feature of RESNET is the short connection technology, which introduces the input into the output after the convolution layer, so as to realize cross layer connection. RESNET's unique cross layer connection structure can solve the training degradation and over fitting problems when the network is very deep. RESNET can enable the network to be fully trained. With the deepening of the network, the accuracy rate increases significantly. However, when the network depth is greater than 152 layers, it will enter the platform stage, and the accuracy rate will not be significantly improved[7].

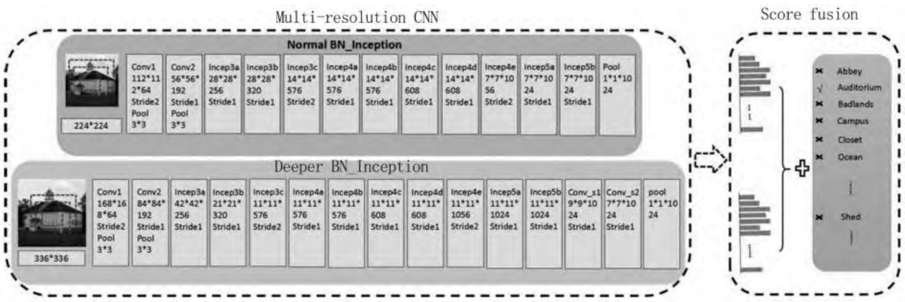

Figure 2. Multi resolution CNN.

2.2. Multi resolution network

The multi-resolution network is proposed for complex image recognition tasks. The image information in different scale spaces is different, and the common network structure is prone to misjudgment. The multi-resolution network can train the coarse resolution and fine resolution networks at the same time, as shown in Figure 2.

The coarse resolution network uses the larger receiving domain to obtain the image information, and the fine resolution network uses the smaller receiving domain to obtain the image information. The data feature information obtained from the training of the two networks is integrated to obtain the predicted value of the output layer. The network structure of coarse resolution and fine resolution is usually composed of CNN. The two networks correspond to perceptual domains of different sizes in the image area, and the effect of image recognition is complementary, thus improving the accuracy of image recognition [13].

2.3. Network algorithm designed in this study

After layer normalization, the output end is transmitted downward along the main body of the frame. When classic CNN networks such as RESNET are used to train myocardial infarction data, the trained network model has poor convergence effect and low recognition accuracy. To solve these problems, the network designed in this study further optimizes the RESNET network, as shown in Figure 3 and Figure 4. The optimized network is a 31 layer network with 9 convolution layers as the main body. Each convolution layer is followed by a batch normalization (BN) layer. BN layer is an optimization algorithm for solving covariant displacement, that is, limiting the input value of neurons in each layer of the network to a normal distribution with a mean value of 0 and a variance of 1, which makes the gradient larger, the training process converges faster, and the training speed faster, thus reducing the gradient disappearance problem [17].The training steps of the network are as follows:

(1) As shown in Figure 3, the training set data enters the first convolution layer and is activated by the corrected linear units (relu) function after passing through the BN layer. Relu can effectively alleviate the gradient disappearance problem with the deepening of the network structure and improve the training efficiency [18].

(2) The convoluted local characteristic data enters the RESNET network structure after the down sampling operation in the max pool layer of the third

layer. The remaining eight convolution layers form four RESNET modules with short connections, and each RESNET module has two convolution layers. The algorithm of max pool layer is shown in formula (4):

$$y_j^l = f(\beta_j^l \mathrm{down}(y_j^{l-1}) + b_j^l) \qquad (4)$$

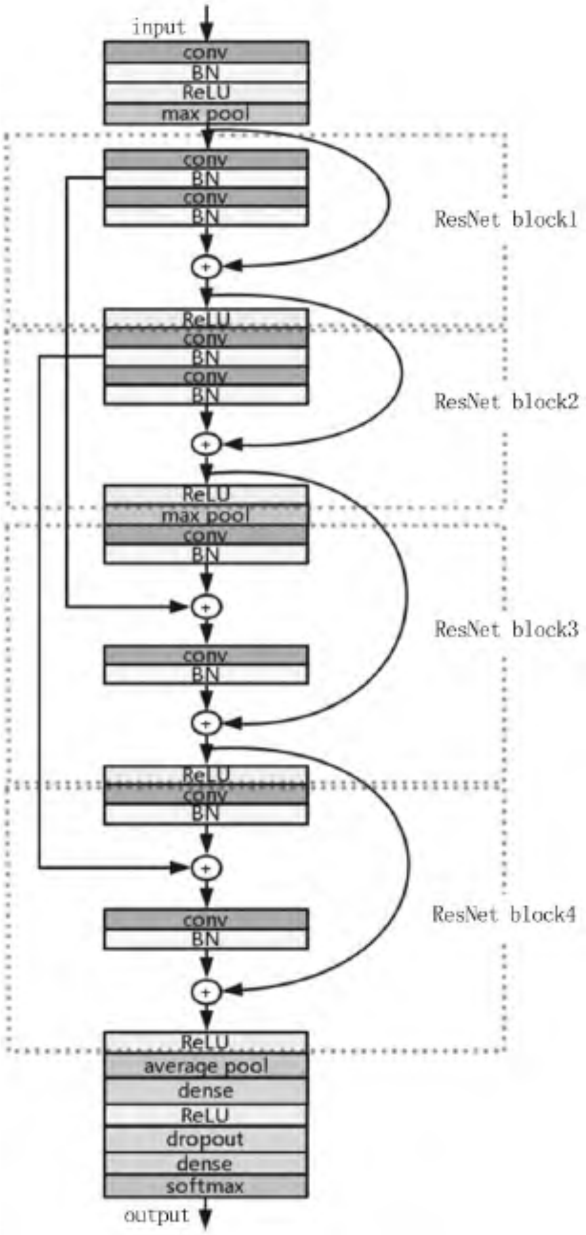

Figure 3. Modifiedresnet.

Where, y_j^l is the jth output of layer L, f is the activation function, *b* is the addition offset, *β* Offset for multiplication.

(3) After the first convolution layer in group 1 RESNET module is normalized by BN layer, its output is transmitted downward along the frame body and connected to the output end of the first convolution layer in group 3 RESNET module.

(4) After the first convolution layer in group 2 RESNET modules is normalized by BN layer, the output end is transmitted downward along the frame body and connected to the output end of the first convolution layer in group 4 RESNET modules. The output of group 2 RESNET module is processed by max pool layer.

(5) The RESNET module in group 4 is activated by the relu function after passing through the average pool layer and the full connection layer, and then uses the dropout layer. Its function is that during each training, the network will randomly make the corresponding number of neurons not participate in the training according to the coefficient set by the user, so as to reduce the over fitting phenomenon [19], and finally get the output through the full connection layer and softmax classifier.

In this study, the RESNET network is improved and the multi-resolution network is introduced. See Figure 4. The convolution kernel in the coarse resolution network and the fine resolution channel is 1 respectively × 81 and 1 × 9. Input the network shown in Fig. 2 above into the two resolution channels respectively, and add the output trained by the two channels to obtain the final recognition result.

In this study, the network structure is called multi resolutionresnet.

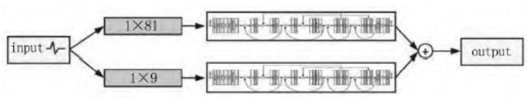

Figure 4. Multi resolutionresnet.

3. Data

The data of this study was supported by the First Affiliated Hospital of China Medical University. All cases used in the study were collected from the existing ECG records archived in the ECG workstation, which is a digital electrocardiograph (Nihon Kohden). The electrocardiograph outputs a standard 12 lead ECG with a sampling rate of 12 bits /1000 Hz (12 lead synchronous acquisition), a common mode rejection ratio of 120 db and a frequency response of 0.05–160 Hz (3 db). All patients were examined in the examination room, separated from the doctor's office, and ECG data were transmitted through the network. ECG examination was performed according to standard procedures: the patient was in supine position, the limb leads were bonded with conductive clips, and the chest leads were bonded with disposable conductive paste. The duration of each ECG data was 2.5 s.

In this study, a total of 3549 data including anterior myocardial infarction (AMI), inferior myocardial infarction (IWMI) and anterior septal myocardial infarction (ASMI) and 6250 normal ECG data were selected from the above ECG data original records. Among them, the gender, age and race of patients in each record were randomly selected. See Table 1 for the training set and test set data designed in this study.

Table 1 The distribution of training set and test set.

Data set	**AMI**	**IWMI**	**ASMI**	**NORMAL**	**Total**
Training set	682	1 088	1 079	5 000	7 849
Test set	160	270	270	1 250	1 950
Category label	0 0 0 1	0010	0100	1000	

4. Results

4.1. Training methods

The classical convolutional neural networks lenet, vgg16 and resnet34 are compared with the multi-resolution residual network proposed in this study. The training set data are used to train the four network algorithms respectively, and the test set data are input into the trained model to obtain the recognition results.

The development platform used in this study is windows 10 operating system, cntk 2.0, and the programming language is Python 3.5.2. Computer configuration: The CPU is Intel Core i7 8700 3.3 ghz, the graphics card is NVIDIA geforce gtx1080, and the memory size is 16 G.

The multi-resolution residual network parameters designed in this study are set as follows:

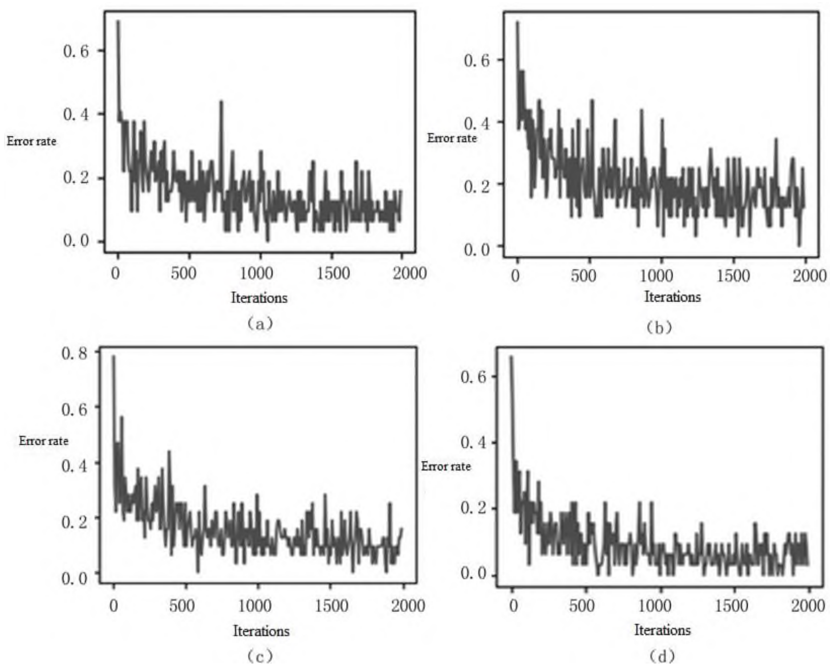

Figure 5. Comparison of Multi resolutionresnet and classic CNN's convergent curve on train data(a). Lenet; (b). VGG; (c). Resnet34; (d). Multi resolutionresnet.

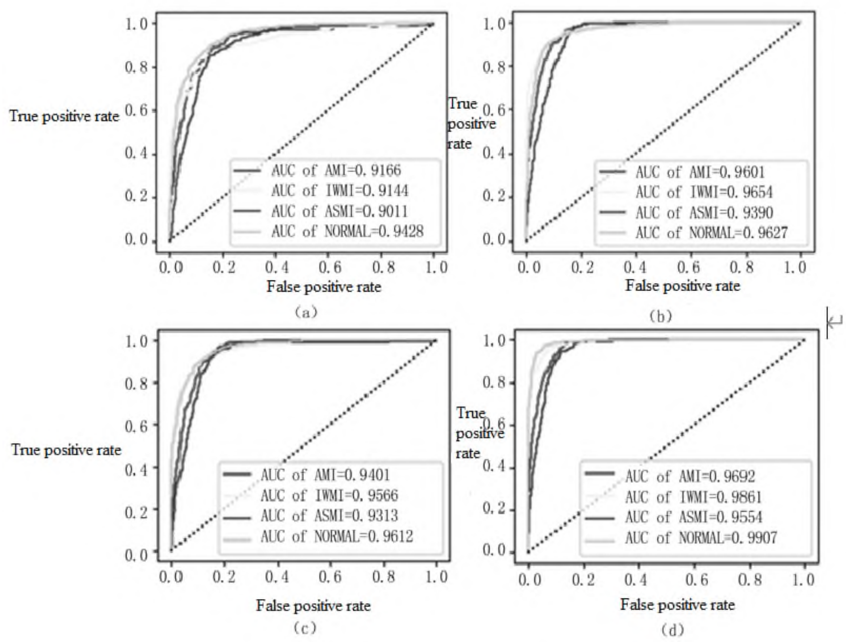

Figure 6. Comparison of Multi resolutionresnet and classic CNN'sROC curve on train data(a). Lenet; (b). VGG; (c). Resnet34; (d). Multi resolutionresnet.

The learning rate is 0.000025–0.0001, and the input data size is 12 × one × 1400, the number of nodes in the input layer is 16800, and the number of nodes in the hidden layer is 32–256, with 2000 iterations.

4.2. Result analysis

The training set and test set data shown in Table 1 are selected from the clinical database and trained based on lenet34, vgg16, resnet34 and the multi-resolution residual network designed in this study. The recognition results are shown in **Table 2**. The recognition accuracy of the multi-resolution residual network is 91.8%, which is higher than the other four networks.

Table 2. Comparison of Multi resolutionresnet and classic

Network model	Accuracy (%)
Lenet	81.2
Vgg16	85.2
Resnet34	854
Multi - resolution resnet	91.8

In order to analyze the convergence of data in the iteration process, the convergence curves of the above four networks are shown in **Figure 5**. Compared with the classical CNN network, the convergence curve of the multi-resolution residual network drops faster, the convergence process is more stable, and the convergence effect is better.

The receiver operating characteristic (ROC) curve of the test set is shown in **Figure 6**. The horizontal axis represents 1 specificity, the vertical axis represents sensitivity, and the AUC is the area under the curve. The closer the curve is to the upper left corner, the higher the accuracy of the model and the stronger the ability to identify diseases.

5. Discussion

In this study, a multi-resolution residual network is designed based on the classical neural network and applied to the location and recognition of myocardial infarction. The recognition accuracy of multi-resolution residual network is higher than that of classical neural network; compared with the classical neural network, the multi-resolution residual network has better convergence effect, and its diagnostic ability is stronger according to the analysis of ROC curve.

The experiment shows that the multi-resolution residual network can be applied to the clinical ECG auxiliary diagnosis task in the field of myocardial infarction localization and recognition. In the future research, more data will be collected and deep neural network training will be carried out on ECG data other than myocardial infarction, in order to identify more cardiovascular diseases by using deep learning technology, to achieve a wider application in clinical ECG data automatic diagnosis.

Conflict of interest

The authors declare no conflict of interest.

References:

1. Guojihong New concept electrocardiogram [m] Beijing: Peking University Medical Press, 2014
2. Liu Wenxia, Wang Sheng, Ma Yi Progress in the study of electrocardiographic localization of blood vessels causing acute inferior myocardial infarction. Armed police medicine 2018; 29 (6): 635–638
3. Lvcongmin, Tang Jianmin Clinical practical electrocardiography. Beijing: Science Press, 2016
4. Lecun Y, Bengio Y, Hinton G. Deep learning. Nature 2015; 521(7553): 436–444.
5. Lecun Y, Bottou L, Bengio Y, et al. Gradient based learning applied to document recognition. P IEEE, 1998; 86(11): 2278–2324.
6. Robinson A J. An application of recurrent nets to phone probability estimation. IEEE Transactions on Neural Networks 1994; 5 (2): 298–305.
7. Simonyan K, Zisserman A. Very deep convolutional networks for large- scale image recognition. Computer Science, 2014.
8. He K, Zhang X, Ren S, et al. Deep residual learning for image recognition. Computer Vision and patternrecognition. IEEE 2015; 770–778.
9. Wu Z, Shen C, Hengel AVD. Wider or deeper: revisiting the resnet model for visual recognition. Patternrecognition 2019; 90: 119–133.
10. Chen ZX, Xie ZF, Zhang WB, et al. resnet and model fusion for automatic spoofing detection. Proc. Interspeech 2017; 102–106.
11. Wang L, Guo S, Huang W, et al. Knowledge guided disambiguation for large scale scene classification with multi resolution cnns. IEEE Transactions on Image Processing, 2017, 26 (4): 2055–2068.
12. Xue WC, Zhao HH, Zhang LQ. Encoding multi resolution two- stream cnns for action recognition. International Conference on Neural Information Processing, 2016: 564–571.
13. Zhang Q, Zhou D, Zeng X. Heartid: a multiresolution convolutional neural network for ECG based biometric human identification in smart health applications. IEEE Access 2017: 1–1.
14. Kiranyaz S, Ince T, Gabbouj M. Real time patient specific ecgclassification by 1D convolutional neural networks. IEEE Transactions on Bio medical Engineering 2016; 63(3): 664.
15. Isin A, Ozdalili S. Cardiac arrhythmia detection using deep learning. Procedia Computer Science 2017; 120: 268–275.
16. Rajpurkar P, Hannun AY, Haghpanahi M, et al.Cardiologist level arrhythmia detection with convolutional neural networks. [2017–07–06]. http//cn. Arxiv. Org/ abs/1707.01836.
17. Ioffe S, Szegedy C. Batch normalization: accelerating deep network training by reducing internal covariate shift. Arxiv preprint arxiv: 1502.03167, 2015.
18. Nair V, Hinton GE. Rectified linear units improve restricted boltzmann machines. Proceedings of the 27th International Conference on Machine Learning (ICML 10). Haifa 2010; 807–814.
19. Simonyan K, Zisserman A. Very deep convolutional networks for large scale image recognition. Arxiv preprint arxiv 1409.1556, 2014.