Research on a New Convolutional Neural Network Model Combined with Random Edges Adding

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Abstract. It is always a hot and difficult point to improve the accuracy of convolutional neural network model and speed up its convergence. Based on the idea of small world network, a random edge adding algorithm is proposed to improve the performance of convolutional neural network model. This algorithm takes the convolutional neural network model as a benchmark, and randomizes backwards and cross-layer connections with probability p to form a new convolutional neural network model. The proposed idea can optimize the cross layer connectivity by changing the topological structure of convolutional neural network, and provide a new idea for the improvement of the model. The simulation results based on Fashion-MINST and cifar10 data set show that the model recognition accuracy and training convergence speed are greatly improved by random edge adding reconstructed models with a probability p = 0.1.

Key Words: CNN, random edge addition, small world model

1 Introduction

Convolutional neural networks (CNN) are becoming more and more popular in various learning tasks, especially in visual computing applications. The biggest advantage of it is that it has the ability to represent learning, thus, it can learn the characteristics of the data itself, avoiding the trouble of traditional manual feature extraction. Therefore, the application of convolutional neural networks and the study of model structure have been hot spots for scholars to explore. In the era of big data, the amount and variety of data in the visual field is increasing. To ensure that the model can better learn the characteristics of the data, the scale of the model has also evolved toward complex aspects and the training overhead has accordingly increased. With the increase of the depth and complexity of the model, a series of problems are caused, which make it difficult to train the model, e.g. the gradient disappears [1,2]. In order to solve the gradient problem of the model, the researchers proposed the Highway network [3], adding a bypass connection in the CNN architecture to enhance the information flow between layers, but this method is controlled by a gating function, which depends on data, so it is more difficult to train. ResNet [4] uses identity connection or skip connection to solve the gating parameter problem of Highway network. However, the connection mode used in this network excessively follows the modular structure, and there is a lot of redundancy in deep ResNet. Subsequent researchers have improved their structure based on ResNet [5,6] to further improve the accuracy of image classification. Szegedy.C et al. Introduced the inception structure into short connections[7], which improved the model's convergence speed. Therefore, the introduction of short connections in the model will greatly benefit the performance of the model.

Convolutional neural networks have a more significant effect in simulating the structural
characteristics of biological neural networks in terms of network depth, but their performance is far from the advanced features of real biological neural networks. Biological neurological research shows that the neural network of the brain has inherent random characteristics to a certain extent [8]. The connection of the brain's network structure [9] belongs to a new type of network proposed by Watts [10], namely the small world network, which between the regular network and the random network. The small-world network will improve the propagation efficiency of its network structure. However, Convolutional neural network is a kind of feedforward neural network with deep structure, and its connection architecture is approximately regular. Therefore, how to make the network structure with random features and improved network efficiency in a convolutional neural network is a key issue.

Therefore, in this paper, a method combining the small-world idea of randomly adding edges [11] is proposed to change the topology of the traditional CNN to achieve optimal cross-layer connectivity. The added edge is to introduce new short connection or long-range connection, which avoids the modularization and regularization of ResNet. In order to better analyze the performance of the model, experiments were performed on the Cifar10 and Fashion-minist datasets. The experimental results show that the method improves the model's convergence speed and recognition performance. The main contributions of this paper are as follows: Firstly, the application of the idea of complex networks to artificial neural networks to guide the improvement of models to provide a new theoretical basis; Secondly, randomness introduces short connections to avoid the disappearance of gradients and improve the model performance; Thirdly, The method of random edge adding enhances the randomness of the model to ensure the model has certain small-world characteristics, making the model more bionic and smarter.

The remaining organizations of this paper are as follows: In the second part of this paper, the model used in the experiment and the steps of combining the random edge adding method with convolution neural network are introduced in detail; In the third part, the model combining the random edge adding idea is applied to the Cifar10 and Fashion-MINST datasets and the performance of the model is analyzed comprehensively; In the fourth part, we summarizes the whole paper and puts forward new thoughts and prospects.

2 Improved model of convolutional neural network based on random edge

2.1 Random edge adding theory

With the study of complex network theory, researchers have applied the analysis methods of complex network to various fields of life, such as neural system, social network, protein network, etc., while the common complex network models are regular network, random network, small world network, scale-free network. Small-world networks are the most typical of complex networks. Networks with small-world characteristics have a certain degree of resistance to attacks and speed up the network's propagation efficiency. Common methods for constructing small-world networks include Randomized reconnection, namely the WS algorithm [10] and the random edge adding method, namely the NW algorithm [11], but the method of random reconnection can easily cause the network to generate outliers and block the network's information flow. Therefore, the method of random edge-addition can avoid the possibility of outliers.

The core idea of NW algorithm is to random adding edges to form sparse long range connections and dense short range connections with probability p. The steps of the NW algorithm are as follows:
1) Initially a ring-shaped regular network of N nodes, each vertex is connected to its K neighbors and satisfies $N >> K >> \ln(N) >> 1$ (K / 2 connections on each side);

2) Randomly select new nodes to reconnect with regular network nodes with probability $p$, but exclude situations where they are connected to themselves and repeatedly connected;

3) Repeat 2) until all nodes are traversed.

The changing process of the NW algorithm is shown in Fig.1. Changing the $p$ value can realize the transition from the nearest coupling network ($p = 0$) to the global coupling network ($p = 1$). When $p$ is small enough and $N$ is large enough, the NW small world model is essentially equivalent to the WS small world model.

![Fig.1. Random edges adding.](image)

### 2.2 Improved model of convolutional neural network

The inspiration of convolutional neural networks is derived from the mammalian visual system [12]. Compared with ordinary feed forward neural networks, the biggest difference in structure is mainly the depth of the model. The deep neural network makes the model have a strong learning ability to learn the underlying characteristics of the data deeper, so convolutional neural networks have excellent performance in various fields, such as medical diagnosis[13], speech recognition [14], video recognition [15], image recognition [16], Natural language processing [17], etc.

In order to avoid the influence of the unique advantages of other convolutional neural network structures on the experiment. The model adopted in this paper will be based on the general convolutional neural network as shown in Fig.2. The model has 11 convolutions, 2 pooling layers, and a full connection layer for classification, with a total of 14 layers of plain network structure. The parameters of each layer are shown in Table 1. If the Cifar10 data set is input into the model, the size of the output feature map is shown in Table 1. In order to reduce the complexity of the experiment, the size of the feature map in this structure is the same.

![Fig.2. CNN model structure.](image)

| Data Input | CONV1 | Maxpooling | CONV2 | CONV3 | CONV4 | CONV5 | CONV6 | CONV7 | CONV8 | CONV9 | Avgpooling | Classification |
|------------|-------|------------|-------|-------|-------|-------|-------|-------|-------|-------|------------|----------------|

**Table 1.** CNN model structure parameter table.
| Layer name | Output size | Kernel size |
|------------|-------------|-------------|
| Conv-1     | 32*32*64    | (3*3,64), stride=1 |
| Maxpool    | 15*15*64    | (3*3), stride=2 |
| Conv-2     | 15*15*256   | [1*1,64, stride=1] |
|            |             | [3*3,64, stride=1] |
|            |             | [1*1,256, stride=1] |
| Conv-3     | 15*15*256   | (3*3*256), stride=1 |
| Average pool | 7*7*256    | (2*2), stride=2 |

In the table, the output size is 15 *15 * 64, which means that the size of the feature map is 15 * 15...64 represents a total of 64 feature maps whose size is 15 * 15, and the kernel size is (3 * 3,64). which means that the size of the convolution kernel is 3 * 3, 64 is the number of filters, and stride = 1 means the convolution step size is 1.

We combine the convolutional neural network with the idea of randomized edge addition and propose a convolutional neural network based on random edge added, which is NWCNet. According to the graph theory, we consider the feature map of each layer of the convolutional neural network as a node, and the connection of the edges in the network is defined as the operation module, which includes operations such as Conv, BN, Relu, etc., which are expressed as Convolution, Batch Normalization, non-linear activation function. In order to generate the NWCNet network model, the initial graph randomly adds short or long-range connections with probability p. In order to ensure that the information flow of the convolutional neural network is consistent with the change of the topological structure graph, it is necessary to determine whether the dimension of the feature map of each layer is consistent. If they are consistent, they can be connected together identically in the manner of the ResNet network. If they are not consistent, a convolution operation must be performed to ensure that the dimensions of the feature map are consistent. The specific operation is shown in Fig.3. When all nodes are traversed, the NWCNet model is obtained. The detailed generation process is shown in Table 2.

![Fig.3. Connection operation form.](image-url)
The left picture is the connection operation performed when the feature map dimensions are the same when connected; the right picture is the connection operation performed when the feature maps are not consistent. The gray arrows are the directions of the information flow, X_l and X_{l+1} means the feature maps of the start and end layers when the connection operation is performed, respectively.

Table 2. NWCNet model generation process.

| Input: CNN and probability p |
|-------------------------------|
| Output: NWCNet model          |
| Initial network structure and probability p |
| Select nodes with probability p and reconnect randomly |
| Determine whether the feature maps are consistent and select the corresponding connection operation mode |
| Repeat operation 2 to traverse all nodes |
| End, model generation         |

3 Performance Evaluation

With the Use of image classification, we did some experiments to verify the network architecture generated by different p probabilities. All experiments were performed on a Windows 10 system with a processor AMD Ryzen 5 2600X. The implementation of the code was based on the Keras platform.

3.1 Dataset

In order to illustrate the validity of the experimental results, we use two data sets to evaluate the performance of the model in this paper, which are the Cifar10 dataset and the Fashion-MNIST dataset.

The Cifar10 dataset was collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. The Cifar10 dataset consists of 10 classes with a total of 60,000 color images, which size is 32 * 32. There are 50,000 training images and 10,000 test images. We also use the standard data enhancement method, which is horizontal flipping to process the cifar10 dataset.

The Fashion-MNIST dataset contains 10 categories of images with a total of 70,000 grayscale images, which size is 28 * 28. Each category of the training dataset contains 6000 samples and each category of the test dataset contains 1000 samples. Therefore, there are 60000 samples in the training dataset and 10000 samples in the test dataset.

3.2 Experimental analysis

In the experiment, we use the optimizer of MomentumOptimizer, where the momentum is 0.9 and the weight decay is 0.01. In addition, the learning rate is set to 2e-2 and it decays exponentially with a decay rate of 0.96. The loss function of the model uses cross-entropy function. Models are trained 25 epochs and the training sample of each batch is 128. To avoid other random effects, this experiment does not use dropout.

Both of the experiments use the same parameter settings and we take the average value under the 5 times of repeated experiment with different probability p. The performance of the model is measured by the loss of the training and the accuracy of the test. The experimental results are shown in Fig.4 and Fig.5. The left picture shows the loss of the training and the right picture shows the accuracy of the test. With the use of random edges adding, we found that it has the highest accuracy and the fastest loss reduction in the Fashion-Mnist dataset when we reconstructed the model at probability p=0.1. Then, the performance of probability p=0.3 is better. Both of which are better than the original model with p = 0. When the
probability changed into $p = 0.5$ and $p = 1$, the results were slightly worse than the original network structure. In a short, it is most beneficial to reconstruct the model with a random edge adding with probability $p = 0.1$, which also conforms to the law of small world reconstruction model[18]. Under the Cifar10 dataset, whose advantages are not as obvious compare with the fashion-mnist dataset, but the result of it has also confirmed that the model reconstruction is the most beneficial at probability $p=0.1$ and better than the original structure model. Therefore, it is most beneficial to reconstruct the model by the way of random edge adding with probability $p = 0.1$ combined with convolutional neural network, which can improve the accuracy of the model and accelerate the convergence speed of the model.

![Figure 4](image_url)

**Fig.4.** Experimental results of the Fashion-Mnist dataset under different probability $p$.

![Figure 5](image_url)

**Fig.5.** Cifar10 dataset experimental results under different probability $p$.

### 4 Conclusion

In this paper, we propose a NWCNet model, which is combine convolutional neural network with small-world idea, that is random edge adding algorithm. The idea of random edge adding is incorporated into the model and the interesting characteristics of the small world network are used to change the topology of the traditional CNN. It can enhances the randomness of the model and avoids the information redundancy by the excessive with modular connection in ResNet. To show the network properties of NWCNet, this experiment will be performed on the Fashion-mnist and Cifar10 datasets. To avoid the effect of randomness, each experiment is repeated multiple times to take the average value. From the experiment, it can be found that Probabilistic randomization and edge reconstruction model greatly improve the recognition accuracy of the model and the convergence speed of training. When the probability $p$ increases, the performance of the model will decreases. Anyway, the convolutional neural
network combined with the random edge adding idea can improve the performance of the model and provide new ideas for the improvement of the model. In the future, the idea of small world can be further introduced into the inter-layer structure of the model to explore the performance of the model.

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References

1. Glorot,Y.Bengio.:Understanding the difficulty of training deep feedforward neural networks[C].In Proceedings of the thirteenth international conference on artificial intelligence and statistics(2010), 249–256.
2. Bengio,Simard,P.Frasconi,: Learning long-term dependencies with gradient descent is difficult[J] . IEEE transactions on neural networks,1994,5(2), 157–166.
3. Srivastava,R.K., K.Greff., J.Schmidhuber,: Training very deep networks[C]. In Proceedings of the 28th International Conference on Neural Information Processing Systems,2015,2377-2385.
4. He,K.M.,X.Zhang.,S.Ren,: Deep residual learn ing for image recognition[C]. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2016,770–778.
5. Targ,S.D.Almeida, K.Lyman,: Resnet inresnet: generalizing residual architectu--res. arXiv preprint arXiv:1603.08029,2016.
6. Xie,S., R.Girshick & P. Dollar,et al.: Aggregated residual transformations for deep neural networks[C]. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition ,2017:1492-1500.
7. Szegedy,C. S.Ioffe & V. Vanhoucke, et al.Inception-v4, inception-resnet and the impact of residual connections on learning[C]. In Proceedings of the Thirty first AAAI Conference on Artificial Intelligence, 2017.
8. Hu,S.G., X.X.Liao & X.R.Mao.:Stochastic Hopfield neural network[J].Journal of Physics A: Mathematical and General,2003,36(9):2235-2249.
9. Achard,S.: A resilient,low-frequency,small-world human brain functional network with highly connected association cortical hubs[J]. J. Neurosci,2006, 26(1):63.
10. Watts,D.J. & S.H.Strogatz.: Collective dynamics of small-world Network [J]. Nature,1998,393(4):440-442.
11. Newman,M.E.J & D.J.: Watts. Renormalization Group Analysis of the Small-World Network Model[J]. Working Papers, 1999, 263(4–6):341-346.
12. Hubel,D.H. & T.N.: Wiesel. Receptive fields, binocular interaction and functional architecture in the cat\'s visual cortex[J]. The Journal of Physiology, 1962, 160(1):106-154.
13. Demir,F., A. Sengur & V. Bajaj.:Convolutional neural networks based efficient approach for classification of lung diseases[J]. Health Information Science and Systems,2019,8(1):1-8.
14. Londhe,N.D., G.B. Khirsagar & H. Tekchandani.: Deep convolution neural network based speech recognition for Chhattisgarhi[C]. In Proceedings of the 5th international conference on signal processing and integrated networks (SPIN),2018:667–671.
15. Mazumdar,M., V. Sarasvathi & A. Kumar.: Object recognition in videos by sequential frame extraction using convolutional neural networks and fully connected neural networks[C]. In Proceedings of the 2017
16. Cheng, F.C., H. Zhang & W.J. Fan, et al.: Image recognition technology based on deep learning[J]. Wirel Pers Commun, 2018, 102: 1917–1933.

17. Lin, Y.O, H. Lei & X.Y. Li, et al.: Deep learning in NLP: methods and applications[J]. J Univ Electron Sci Technol China 2017, 46(6): 9-19.

18. Li, X.H., X.L.Li & J.H.Zhang, et al.: A New Multilayer Feedforward Small-world Neural Network with Its Performances on Function Approximation[C]. In Proceedings of the IEEE International Conference on Computer Science & Automation Engineering. 2011: 353-357.