Deep Learning Based on High-Dimensional Tensor for COVID-19 Diagnosis

1st Qiaoping Wang
College of Mathematics and Computer Science/College of SoftWare
Fuzhou University
Fuzhou, China
w_pingzi1998@163.com

2nd Wenye Wang
College of Mathematics and Computer Science/College of SoftWare
Fuzhou University
Fuzhou, China
yyr6661@sina.com

3rd Xiaoyun Chen
College of Mathematics and Computer Science/College of SoftWare
Fuzhou University
Fuzhou, China
c_xiaoyun@fzu.edu.cn

4th Li Chen
The School of Basic Medical Sciences
Fujian Medical University
Fuzhou, China
chenli118@fjmu.edu.cn

5th Wenjian Chen
College of Mathematics and Computer Science/College of SoftWare
Fuzhou University
Fuzhou, China
xiangshuo1996@sina.com

***Abstract*—The breakout and rapid spread of coronavirus disease 2019 (COVID-19) has become a global health concern. The disease has infected more than 18.7 million people and caused more than 707,000 deaths all over the world, as of August 6 in 2020. Computed tomography (CT) is promising to provide screening and testing for COVID-19. This paper proposes cross-layer connection neural network based on high-dimensional tensor to classify the CT scans. Cross-layer connected network DenseNet and ResNet have sophisticated network structure residual block and dense block which perform well in extracting deep features. Specifically, we choose 1, 4, 8, 16 and 32 as input tensor dimensions to respectively conduct experiments on the two neural networks. Extensive experimental results show that when DenseNet-121 is the backbone network and the tensor dimension is 16, the experimental results are the best, and the accuracy and AUC are both 0.92, precision is 0.90, F1 is 0.95 and recall is 0.99.**

Keywords—COVID-19, CT, deep learning, tensor, dataset

I. Introduction

Coronavirus disease 2019 is an individual-to-individual transmissible pneumonia caused by severe respiratory disease coronavirus (SARS-COV-2, also known as COVID-19 or 2019-nCov). The current tests are mostly based on reverse transcription polymerase chain reaction (RT-PCR) [1]. The computed tomography (CT) scans usually show abnormalities, such as small areas of ground glass opacity (GGO, the most common feature in COVID-19) [2]. During the peak time of COVID-19 outbreak, to mitigate the shortage of RT-PCR test kits, hospitals also adopt other auxiliary methods such as CT scans for screening and diagnosing COVID-19. COVID-19 diagnosis relies on clinical symptoms, such as positive CT images or positive pathogenic testing, and epidemiological history. Many efforts have been devoted to developing deep learning methods of testing based on CT scans [3]-[8]. Fig.1 shows CT scans of patients that are positive for COVID-19.

To mitigate the burdens of medical professionals in interpreting CT or X-ray images, some researchers focus on developing deep learning methods that can help to predict whether the CTs are positive. Shi Z et al. [3] propose the integration of a region growing strategy and random walk strategy. The region-based methods work well with more subtle pneumonia features, so this method lacks accuracy in dealing with complex pathological regions and needs a lot of

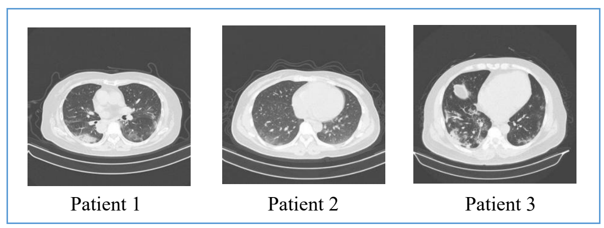

Fig. 1. CT scans of patients that are positive for COVID-19.

CT scans. He et al. [4] build a publicly available dataset containing hundreds of COVID-19 and non-COVID-19 CTs. According to the dataset, they propose a self-trans approach which integrates contrastive self-supervised learning with transfer learning to learn powerful feature representations for reducing the risk of overfitting. Chen et al. [5] construct an identification system of COVID-19 based on UNet++ using CT scans. I. Razzak et al. [6] use pre-trained knowledge to improve the diagnostic performance using transfer learning techniques. In [7], they study and investigate COVID-19 pneumonia from 51 patients of Wuhan, China. This method based on computer-aided detection will provide doctors and medical practitioners with real-time help. In addition to CT scans, X-ray is also an imaging method for detecting COVID-19 pneumonia. E. Luz et al. [8] exploit an EfficientNet neural network architecture for detecting any abnormality caused by COVID- 19 through chest radiography images.

A. Contributions

In this paper, a COVID19-CT dataset is created on the basis of 17,544 CT scans from 32 patients. Considering that the CT

DOI 10.1109/ISPDS51347.2020.00045

scans of each patient are continuous and similar, the CT images are divided into sets with a fixed size, and the images contained in each set are spliced into a high-dimensional tensor in the channel dimension. This method makes the training process more stable for COVID-19 diagnosis and achieves high testing accuracy and precision based on CTs.

In order to select the appropriate basic backbone networks, several neural networks are tested on our dataset. The results confirmed that the two cross-layer connection neural networks ResNet and DenseNet outperform as the baseline networks. ResNet relies on the residual block to realizing cross layer connection [11], and DenseNet is based on the dense block to achieve feature reuse and cross layer connection [12]. The experiments are divided into several parts, the first part of which is based on the two cross-layer connected network with tensors of different dimensions as inputs. Further, experiments with different network depths are performed based on the tensors of the same dimension. Although this method takes more time in the training phase, the performance of the model is satisfactory. With DenseNet-121 being backbone network and the input channels being 16, our approach achieves an F1 of 0.95, a precision of 0.90, and an AUC of 0.92 in diagnosing COVID-19 from CT scans.

This paper consists of five sections. Section II reviews the related works. The methodology and the dataset are described in Section III. Section IV presents the experiments and conclusions are pointed out in Section V.

II. Related Work

A. Application of deep learning in medical imaging

Deep learning based on X-ray images and CT scans has already been explored for the detection and classification tasks in the medical field. For example, Jiang et al. [13] propose a DenseNet-based tumor recognition and classification model which inherits the fully-connected architecture of DenseNet. They introduce the group normalization concept and replace batch normalization with it. In [14], Liu et al. use improved ResNet for brain tumor classification which can achieve an accuracy of 0.95. Moreover, deep learning performs well in medical image segmentation. V. Alex et al. [15] utilize ResNet-18 as a pre-trained network to process a multi-modality dataset that contains 23 classes and 4 modalities. W. Ausawalaithong et al. [16] use Densenet-121 combined with transfer learning scheme to predict lung cancer according to chest X-ray images.

B. Convolutional neural network based on cross-layer connection

The residual neural network ResNet first proposed shortcut connection, which made the hidden layer fitting identity mapping solve the degradation problem well and greatly expand the depth of the network. $F(X) = H(X) - X$ is recorded as residual between input and output. Where X is the input and $H(X)$ is the desired underlying mapping. The formulation of $F(X) + X$ can be realized by feedforward neural networks with "shortcut connections" as Fig.2.

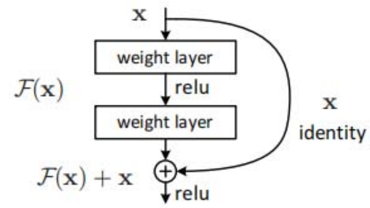

Fig. 2. Shortcut connection illustration of the ResNet architecture.

To improve the information flow between different layers, DenseNet proposes dense connection which introduces cross – layer connections from any layer to all their precedent layers. X_A can be computed as (1):

$$X_A = H_A([X_0, X_1, \cdots, X_{A-1}]) \quad (1)$$

where $[X_0, X_1, \cdots, X_{A-1}]$ refers to the combination of the feature-maps produced in layers $0, \ldots, A-1$, and $[\cdot]$ denotes the concatenation operation which is shown in Fig.3. $H_A(\cdot)$

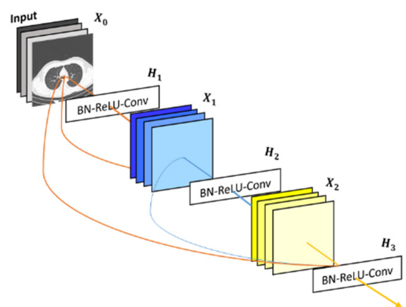

Fig. 3. Dense connection illustration of the DenseNet architecture.

represents a composite of some operations [17], which is a joint action between features of each layer including: batch normalization, ReLU activation function, and convolution operation (3×3 and 1×1 convolution).

C. Transfer learning

Transfer learning can take advantage of pre-trained weights on large-scale datasets such as ImageNet [18] to accelerate or enhance the learning process, then fine-tune the weights on the target task. This technique has generally applied to several computer vision tasks because most real-world problems typically do not have millions of labeled data points to train such complex models [19]. DL needs lots of data to train a neural network from scratch but tend to have insufficient data. In medical domain, transfer learning is widely used for medical image classification and detection.

The main steps for transfer learning applied to a new task are: 1) Copy the weights from the pre-trained model preparing for a new task and adjust the network structure of the new model adapting to the new problems; 2) Initialize the layer that we added and define the appropriate optimization algorithm and settings for training.

III. Methods

A. Dataset about COVID-19

The dataset contains 13,998 CT scans labeled as being positive for COVID-19 from 20 confirmed cases. 3,546 CT scans that are Non-COVID-19 from 12 patient cases are also added to the dataset. Some patients took CT images several times on different dates, so the number of images will increase a lot. Fig.4 shows CT images taken by a confirmed case on different dates. The pathological features are not obvious in the early stage, but show the characteristics of COVID-19 over time. Some CTs do not have clear and complete lungs because parts of them are blocked or from different perspective as shown in Fig.5. In order to improve the generalization of the model, we do not remove these CT images and keep all CTs taken by all dates .

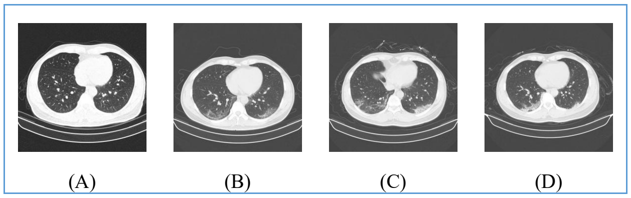

Fig. 4. The CT images above are from a confirmed patient taken on different date; (A) Taken by the patient on January 29; (B) Taken by the patient on February 2; (C) Taken on the 5th of February; (D) Taken on the 12th of February.

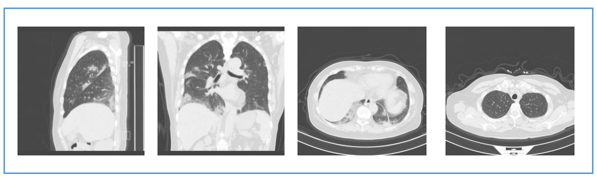

Fig. 5. CT images from a confirmed patient's other perspectives or do not contain clear and complete lung.

B. *Cross-layer connected neural network based on high-dimensional tensor for COVID-19 diagnosis*

In the CT dataset, each patient has continuous and many CT images, so we take fixed number of CT images which are called a set to splice in the channel dimension as shown in Fig.6. The spliced results is high-dimensional tensor sample that is composed of a continuous slice of CT images. The label of the tensor sample is the label of the corresponding patient and dimension is the set size. Labeled high dimensional tensor samples are used as training set. We use DenseNet as the backbone network as an example to introduce the detection of COVID-19 based on the high-dimensional tensor method.

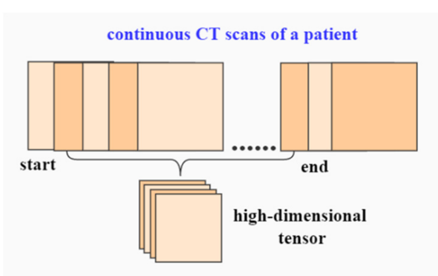

Fig. 6. Constructing high-dimensional tensor based on continuous CTs.

Densely connected neural network implement cross-layer connections in dense blocks. The densely connected blocks based on the high dimensional tensor method can extract deep level information, which is helpful for the final prediction as shown in Fig.7. The dense block of DenseNet includes two convolutional projection layers for dimension reduction and two layers for extracting features [21]. Convolutional layers use batch regularization (BN) to regularize the distribution of feature data in hidden layers and use the ReLU activation function to extract non-linear features. The hidden layer output of can be calculated as follows:

$$x_l = f_l(Cat(x_{l-1}, conv(x_{l-1}) + b_l)) \qquad (2)$$

where x_l is the output of layer l, $Cat(\cdot)$ is channel connection, activation function is $f_l(\cdot)$, b_l is bias, conv$(\cdot)$ is convolution.

IV. Experimens and Dissusion

To demonstrate the effectiveness of the approach proposed in this paper, we extensively evaluate the different neural networks as baseline backbones. Furthermore, based on the feature extraction with high-dimensional tensor method, we train models on different tensor dimensions. The following subsections introduce the datasets, experimental settings, and experimental results for these different approaches.

A. *Datasets split*

The dataset was split into a training set, and a test set by patient IDs, then a validation set was chose from training set containing 2 COVID-19 and 2 Non-COVID-19 patients. To balance the positive and negative samples in training set as much as possible, we randomly select 11 positive patients and 9 negative patients and save the IDs of patients as the training set. Table I shows the specific division of dataset.

TABLE I. Statistics of Data Split

	Classes	Train set	Test set	Val set
Patients	COVID-19	11	9	2
	Non-COVID-19	9	3	2
CT images	COVID-19	6963	7035	-
	Non-COVID-19	2759	787	-

During the training phase, we adopt two strategies to select the train set and test set: 1) When training with single CT images as training samples, we will randomly select similar number of COVID-19 and Non-COVID-19 CT images to balance the train set; 2) When training based on high-dimensional tensors as training samples, we use all of the COVID-19 CT images as training set. In addition, tensor sample is made up of a continuous slice of CT images, so each time the slice starts at a different position, the tensor sample will be different. In order to avoid randomness, we took 100 different tensor samples for each patient in the test set, and finally 1200 high-dimensional tensors were used as the test set.

B. *Experimental Settings*

The experiments are based on PyTorch and networks are trained with two GTX 2080Ti GPUs. Binary cross-entropy serves as the loss function. Batch normalization is applied through all models. Contrast enhancement is implemented to each image in COVID19-CT dataset. Hyperparameters are fine-tuned on training stage.

1) Implementation details: the Adam (adaptive motion estimation) [22] optimizer is used with an initial learning rate of

0.001. Adam uses the first-order and second-order moment estimation of gradient to dynamically adjust the learning rate of each parameter. The cosine learning rate are applied to the optimizer. Kaiming initialization [23] is used to initialize parameters and the dimension of tensor is selected from set $\{1,4,8,16,32\}$.

2) Evaluate metric: we evaluate the experimental results using the five metrics [24]:

(1) Accuracy (ACC) measures the proportion of correct prediction match with the ground-truth.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP is the number of CT images that are positive and prediction result is also positive, while FP is the number of CT images that are negative but prediction result is positive. The meaning of TN and FN are similar to the above.

(2) Precision can describe how many of the predicted positive examples are true.

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

(3) Recall indicates how many positive cases in the sample are predicted correctly.

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

(4) F1-score is the harmonic mean value of precision rate and recall rate.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

(5) AUC is the area under receiver operating characteristic curve which shows the changing relationship of true positive rate and false positive rate.

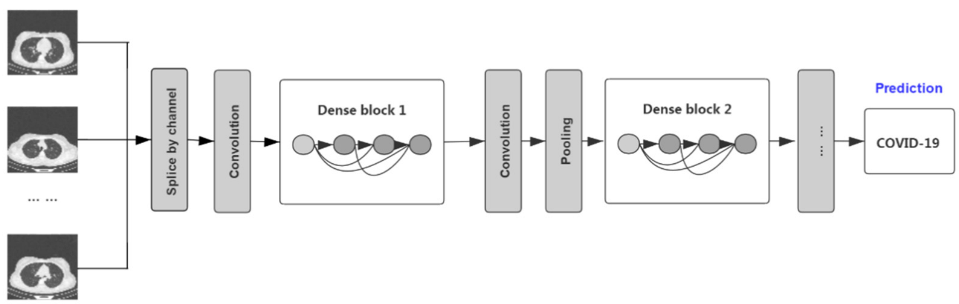

Fig. 7. DenseNet neural network based on high-dimensional Tensor for COVID-19 diagnosis.

C. Experiment on basic neural backbone networks

We first experiment on several different backbone networks including ResNet-18, ResNet-50, DenseNet-121, DenseNet-169, EffificientNet-b0 [25] and ShuffleNetv2 [26]. EfficientNet systematically studies model scaling and determines that carefully balancing of network depth, width and resolution can bring better performance. Shufflenetv2 is a lightweight network of CNN, it has a good balance between speed and accuracy.

Specially, the baseline neural networks are pre-trained on the ImageNet. The domain is obviously much broader than the COVID-19 CT dataset that is implemented in this paper. The structures of the pre-training networks are modified to adapt to binary classification for single channel CT images task. Adam is used as optimizer with a minibatch size of 16, and the learning rate is adjusted by the cosine learning rate scheduler.

TABLE II. PERFORMANCE COMPARISON ON DIFFERENT BACKBONE NEURAL NETWORKS FOR COVID-19 DIAGNOSIS

Network	Accuracy	Precision	Recall	F1	AUC
ResNet-18	**0.84**	**0.93**	**0.90**	**0.91**	**0.70**
ResNet-50	0.83	0.93	0.88	0.90	0.73
EfficientNetb0	0.78	0.89	0.85	0.87	0.65
DenseNet-121	**0.87**	**0.94**	**0.91**	**0.93**	**0.78**
DenseNet-169	0.89	0.92	0.96	0.96	0.61
ShuffleNetv2	0.81	0.92	0.86	0.89	0.64

Table II shows the following points: First, the overall performance of the two cross-layer connection networks ResNet and DenseNet is better than that of EfficientNet and shufflenetv2, with higher accuracy and AUC. Second, the overall performance of ResNet-18 is better than that of ResNet-50. The accuracy and recall are higher, although the AUC is 3% lower. ResNet-18 has fewer parameters, and we can see from the training process that the loss reduction is more stable. Third, the performance of DenseNet-121 and DenseNet-169 have no significant difference (the former has slightly worse accuracy but much better AUC). Considering the number of parameters and training time costs, DenseNet-121 and ResNet-18 are used as the baseline neural networks.

B. Experiment on the two cross-layer connection neural network based on high-dimensional tensor

In the previous part, ResNet-18 and DenseNet-121 have been selected as the backbone networks. In this part, tensor dimensions are selected from$\{1,4,8,16,32\}$. Specially, we use the Adam optimizer with a batch size of 5 with the initial learning rate 0.001. Fine-tuning the parameters during the training process is essential to improve performance.

TABLE III. COMPARISON OF RESNET-18 BANSED ON DIFFERENT TENSOR SIZE FOR COVID-19 DIAGNOSIS

Tensor size	Accuracy	Precision	Recall	F1	AUC
1	0.83	0.93	0.90	0.91	0.70

4	0.78	0.88	0.82	0.85	0.70
8	0.82	0.89	0.86	0.88	0.77
16	0.90	0.90	0.97	0.93	0.80
32	**0.91**	**0.90**	**0.99**	**0.94**	**0.85**

Table III shows the experimental results of ResNet-18 based on different tensor dimensions. It can be seen that with the increase of tensor dimension, the accuracy of the model is improved. When the tensor dimension is 16, the diagnostic accuracy of the model is about 6% higher than that of the 1-dimensional tensor. Further, the prediction accuracy is 0.91 and recall and AUC are highest 0.99, 0.85 respectively when the input tensor dimension is 32. The experimental results not only illustrate the effectiveness of ResNet-18 based on the high-dimensional tensor, but also show that this method has strong feature extraction capabilities. The method of using high-dimensional tensor as model input makes the model can extract more rich features, which helps to predict COVID-19. Fig.8 on the right shows that although the loss fluctuates between 0-2000 iterations, it can quickly achieve stability.

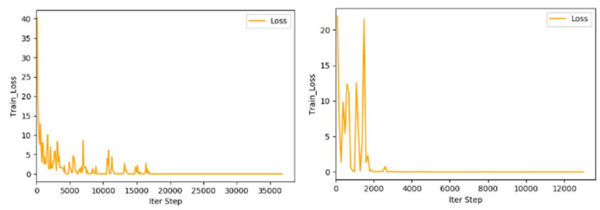

Fig. 8. The loss of ResNet-18 as backbone network. Left: loss of the traditional training method; Right: loss of the training method based on 32-dimensional tensor.

TABLE IV. COMPARISON OF DENSENET-121 BANSED ON DIFFERENT TENSOR SIZE FOR COVID-19 DIAGNOSIS

Tensor size	Accuracy	Precision	Recall	F1	AUC
1	0.87	0.94	0.91	0.93	0.78
4	0.91	0.89	0.99	0.94	0.72
8	0.91	0.90	0.98	0.94	0.73
16	**0.92**	**0.90**	**0.99**	**0.95**	**0.92**
32	0.91	0.90	1.00	0.95	0.75

Table IV shows the performance on different tensor dimensions conducted on DenseNet-121. The accuracy and precision are increased by about 10% and F1 by about 6%. When the dimensions of the input tensor are 4, 8 and32, the performance of the model is almost the same. However, each evaluation metric is significantly improved compared to 1-dimensional tensor. Meanwhile, compared with the 16 dimension tensor, The AUCs of the network using other tensor dimensions as inputs are significantly lower than 0.92, concentrated around 0.73, and improved by 19% (absolute improvement).

To sum up, on the basis of taking high-dimensional tensor being a training sample, the two cross layer connected neural networks have better performance than traditionally using an image as a training sample. The performance of DenseNet-121 network is better than ResNet-18. Fig.9 on the right shows that loss tends to stabilize after 10,000 iterations, and loss on the left figure occasionally has some shocks.

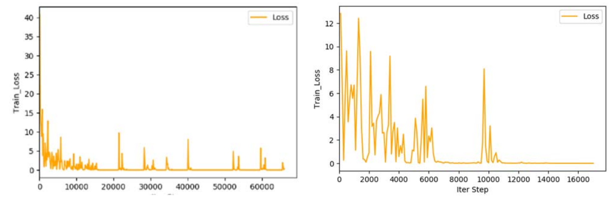

Fig. 9. The loss of DenseNet-121 as backbone network. Left: loss of the traditional training method; Right: loss of the training method based on 16-dimensional tensor.

E. Experiment on the different neural networks as baselines based on 16-dimensional tensor for COVID-19 diagnosis

Through the previous experiments, the results outperform when the input tensor is 16 based on DenseNet-121. So we do some extension experiments.

TABLE V. PERFORMANCE COMPARISON ON DIFFERENT NEURAL NETWORKS BASED ON THE INPUT TENSOR SIZE IS 16

Network	Accuracy	Precision	Recall	F1	AUC
ResNet-18	**0.90**	**0.90**	**0.97**	**0.93**	**0.80**
ResNet-50	0.81	0.89	0.86	0.87	0.71
ResNeSt-50	**0.92**	**0.89**	**1.0**	**0.94**	**0.88**
DenseNet-169	0.90	0.88	0.99	0.93	0.77
DenseNet-121	**0.92**	**0.90**	**0.99**	**0.95**	**0.92**

Another thing that we are interested in investigating is: the training effect of the recently proposed ResNeSt neural network based on the method proposed in this paper. It presents a modular split-attention block that enables attention across feature-map groups. Specially, ResNeSt preserves the overall ResNet structure to be used in downstream tasks without introducing additional computational costs [27]. The accuracy rate of ResNeSt-50 is about 11% higher than that of ResNet-50, and the AUC is higher about 17%.The structure of ResNeSt yields much better performance that can make the extracted features more discriminative and that is helpful in distinguishing COVID-19 CTs from Non-COVID-19 CTs.

Table V shows the results based on backbone ResNet-18 are better than that on ResNet-50. Recall and F1 are higher and AUC increased by about 9%. When DenseNet has 121 network layers, the AUC is about 15% higher than has 169 layers. The performance benefits from more sophisticated network structure like residual connection [28] and dense connection [29]. Such experimental results not only illustrate the effectiveness of high-dimensional tensor training method, but also provide concrete evidence that cross layer connection neural networks have strong feature representation learning capabilities.

V. CONCLUSIONS

In this paper, we build COVID19-CT, a dataset containing 13998 CT scans positive for COVID-19. Taking into account the characteristics of the dataset, we develop deep learning methods based on high-dimensional tensor to accurately diagnose COVID-19 based on CT scans. We respectively choose ResNet, ShufflenNetv2, EfficentNet and DenseNet to do pre experiments, and the results of cross-layer connection neural networks are better. In the present study, we analyzed the experimental results, and verified its effectiveness in diagnosis COVID-19. After data preprocessing and image contrast enhancement, we experimented on different tensor dimension based on ResNet and DenseNet. As a result, when the dimension is 16 based on DenseNet-121, the values of the five evaluation metrics are the best.

At the same time, the results of the 16-dimensional tensor based on different backbone networks verify that based on DenseNet-121 has the best effect. The training method using high-dimensional tensor composed of fixed set size CT images as the model inputs can effectively spread the shallow feature information to the deep network, which make the diagnosis results more accurate. The effectiveness of this method is demonstrated through extensive experiments. However, because the number of patient samples is small, the model is likely to be over-fitted. In the future, we will establish a more complete COVID-19 dataset to make CT scans more reliable and effective in diagnosis of COVID-19.

Acknowledgement

This work was supported by the National Nature Science Foundation of Fujian Province, China (2018J016666) and the Fujian Medical Emergency Project (2020JY003).

References

[1] C. Sivakorn, V. Luvira, S. Muangnoicharoen, P. Piroonamornpun, and T. Ouppapong, "Case Report : Walking Pneumonia in Novel Coronavirus Disease (COVID-19): Mild Symptoms with Marked Abnormalities on Chest Imaging," pp. 2–4, 2020, doi: 10.4269/ajtmh. 20-0203.

[2] T. Ai et al., "Correlation of Chest CT and RT-PCR Testing in Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases". Radiology 2020, in press.

[3] Z. Shi et al., "Many Is Better Than One : An Integration of Multiple Simple Strategies for Accurate Lung Segmentation in CT Images," vol. 2016, 2016, DOI: 10.1155/2016/1480423.

[4] X. He et al., "Sample-Efficient Deep Learning for COVID-19 Diagnosis Based on CT Scans," medRxiv, vol. XX, no. Xx, p. 2020.04.13.20063941, 2020, doi: 10.1101/2020.04.13.20063941.

[5] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, S. Hu, Y. Wang, X. Hu, B. Zheng, et al., "Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study," medRxiv, 2020.

[6] I. Razzak, S. Naz, A. Rehman, A. Khan, and A. Zaib, "Improving Coronavirus (COVID-19) Diagnosis using Deep Transfer Learning," medRxiv, no. 1, p. 2020.04.11.20054643, 2020, doi: 10.1101/2020.04.11.20054643.

[7] Song, F., Shi, N., Shan, F., Zhang, Z., Shen, J., Lu, H., Ling, Y., Jiang, Y., Shi, Y.: Emerging 2019 novel coronavirus (2019-ncov) pneumonia. Radiology p. 200274 (2020).

[8] E. Luz, P. L. Silva, R. Silva, L. Silva, G. Moreira, and D. Menotti, "Towards an Effective and Efficient Deep Learning Model for COVID-19 Patterns Detection in X-ray Images," pp. 1–10, 2020.

[9] Jiang, Di & Liu, Hui & Guo, Qiang & Zhang, Caiming. (2020). Cyclic DenseNet for Tumor Detection and Identification. 10.1007/978-3-030-37352-8_42.

[10] Liu, Dunsheng & Liu, Yuanning & Dong, Liyan. (2019). G-ResNet: Improved ResNet for Brain Tumor Classification. 10.1007/978-3-030-36708-4_44.

[11] V. Alex, M. Khened, S. Ayyachamy, and G. Krishnamurthi, "Medical image retrieval using Resnet-18 for clinical diagnosis," vol. 1095410, no. March 2019, p. 35, 2019, doi: 10.1117/12.2515588.

[12] W. Ausawalaithong, A. Thirach, S. Marukatat, and T. Wilaiprasitporn, "Automatic Lung Cancer Prediction from Chest X-ray Images Using the Deep Learning Approach," BMEiCON 2018 - 11th Biomed. Eng. Int. Conf., 2019, doi: 10.1109/BMEiCON.2018.8609997.

[13] Jiang, Di & Liu, Hui & Guo, Qiang & Zhang, Caiming. (2020). Cyclic DenseNet for Tumor Detection and Identification. 10.1007/978-3-030-37352-8_42.

[14] Liu, Dunsheng & Liu, Yuanning & Dong, Liyan. (2019). G-ResNet: Improved ResNet for Brain Tumor Classification. 10.1007/978-3-030-36708-4_44.

[15] V. Alex, M. Khened, S. Ayyachamy, and G. Krishnamurthi, "Medical image retrieval using Resnet-18 for clinical diagnosis," vol. 1095410, no. March 2019, p. 35, 2019, doi: 10.1117/12.2515588.

[16] W. Ausawalaithong, A. Thirach, S. Marukatat, and T. Wilaiprasitporn, "Automatic Lung Cancer Prediction from Chest X-ray Images Using the Deep Learning Approach," BMEiCON 2018 - 11th Biomed. Eng. Int. Conf., 2019, doi: 10.1109/BMEiCON.2018.8609997.

[17] G. Pleiss, D. Chen, G. Huang, T. Li, L. van der Maaten, and K. Q. Weinberger, "Memory-Efficient Implementation of DenseNets," 2017.

[18] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in CVPR, 2009.

[19] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," 32nd Int. Conf. Mach. Learn. ICML 2015, vol. 1, pp. 448–456, 2015.

[20] F. Nüske, P. Gelß, S. Klus, and C. Clementi, "Tensor-based EDMD for the Koopman analysis of high-dimensional systems," 2019.

[21] M. Wang, J. Zhou, W. Mao, and M. Gong, "Multi-scale convolution aggregation and stochastic feature reuse for densenets," Proc. - 2019 IEEE Winter Conf. Appl. Comput. Vision, WACV 2019, pp. 321–330, 2019, doi: 10.1109/WACV.2019.00040.

[22] J. Dodge, G. Ilharco, R. Schwartz, A. Farhadi, H. Hajishirzi, and N. Smith, "Fine-Tuning Pretrained Language Models: Weight Initializations, Data Orders, and Early Stopping," 2020.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," in Proceedings of the IEEE international conference on computer vision, pp. 1026–1034, 2015.

[24] J. Zhao, Y. Zhang, X. He, and P. Xie, "COVID-CT-Dataset: A CT Scan Dataset about COVID-19," pp. 1–5, 2020.

[25] M. Tan and Q. V. Le, "Effificientnet: Rethinking model scaling for convolutional neural networks," arXiv preprint arXiv: 1905.11946, 2019.

[26] N. Ma, X. Zhang, H. T. Zheng, and J. Sun, "Shufflenet V2: Practical guidelines for efficient cnn architecture design," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 11218 LNCS, pp. 122–138, 2018, doi: 10.1007/978-3-030-01264-9_8.

[27] R. S. Networks et al., "ResNeSt: Split-Attention Networks." https://arxiv.org/abs/2004.08955.

[28] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778, 2016.

[29] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700–4708, 2017.