CNN-based diagnosis of COVID-19 Pneumonia: A comparative study on different image preprocessing methods

Yi Cui[1, *, †]
[1]School of Information Science and Technology
North China University of Technology
Beijing, China
[*]Corresponding author's e-mail:
17151010406@mail.ncut.edu.cn

Jimin Ding[2, *, †]
[2]Department of Computer Science and Information Engineering
National Central University, Taiwan
Hangzhou, China
[*]Corresponding author's e-mail:
dingjimin123@gmail.com

Mingrui Liu[3, *, †]
[3]College of Electronic and Optical Engineering & College of Microelectronics
Nanjing University of Posts and Telecommunications
Nanjing, China
[*]Corresponding author's e-mail:
b18021618@njupt.edu.cn

Xinyuan Liu[4, *, †]
[4]School of Computing Science
Newcastle University
Newcastle, United Kingdom
[*]Corresponding author's e-mail:
liuxinyuan1998@gmail.com
[†]These authors contributed equally.

***Abstract*—CT image diagnosis of COVID-19, an infectious disease that causes respiratory problems, proved efficient with CNN-based methods. The accuracy of these machine learning methods relies on the quality and dispersion of the training set, which has often been ensured by utilizing the preprocessing strategies. However, few studies investigated the impact of different preprocessing methods on accuracy rates in diagnosing COVID-19. As a result, a comparative study on different image preprocessing methods was done in this work. Two popular preprocessing methods contrast limited adaptive histogram equalization (CLAHE) and Discrete Cosine Transform (DCT), which were processed and compared in a CNN-based diagnosis framework. With a mixed and open-source dataset, the experimental results showed that DCT based preprocessing method had a higher accuracy on the test set, which was 92.71%.**

Keywords- COVID-19; Convolutional Neural Network; Preprocess; Contrast Limited Equalization Histogram; Discrete Cosine Transform

I. INTRODUCTION

It has been more than one year since the first outbreak of COVID-19. However, the epidemic continues to spread around the world. According to Xinhua News Agency, nearly 80000 new crown cases have been confirmed in Catalonia, Spain, in two weeks [1].

To suppress the epidemic, timely diagnosis and effective isolation of the sick patients play a significant role. Currently, the main diagnosis is a throat swab or CT image of the lung. The former is neither accurate nor efficient, while the latter is more accurate [2]. Studies have shown that some special symptoms of early COVID-19 will be shown in the lungs of patients [3]. These signs can be clearly reflected in the chest radiographs that the common CT manifestations of both lungs have multiple patchy ground-glass shadows or consolidation shadows. Both are mainly distributed along with the bronchial vascular bundle and subpleural, shown as fine mesh shadows [4]. As long as these symptoms can be recognized, the diagnosis can be completed quickly.

However, the recognition accuracy of the imaging doctor not only fluctuates greatly but also the process of observing the image takes lots of time. Such efficiencies are unrealistic when the epidemic is rampant, and thousands of cases are being confirmed daily. The automated identification of chest radiographs with AI technology can determine whether the patient has COVID-19 within 10 seconds. The accuracy rate can be maintained at more than 97%, which greatly increases the work efficiency [5].

The mainstream AI technology used to diagnose the COVID-19 is the convolutional neural network-based (CNN-based) strategy. The basic idea is to train a specific supervised network using a dataset of chest radiographs from preprocessed lung CT images of both healthy individuals and COVID-19 patients [6]. M. Rahimzadeh utilized resnet50v2 network combined Xception to improve the classification accuracy [7]. H. Mukherjee proposed Deep Neutral Network (DNN) to improve the accuracy rate [8]. Most of these studies paid attention to the architecture of neural networks with less discussion about preprocessing. The performance difference between different preprocessing methods is worth examining since they would lead to different results [9].

In this work, a convolutional neural network (CNN) with different preprocessing methods, contrast limited adaptive histogram equalization (CLAHE), and Discrete Cosine Transform (DCT) was implemented to achieve the diagnosis of COVID-19. Furthermore, the influence of the two data preprocessing methods on the determine accuracy was compared through the result accuracy. CLAHE is a classic histogram equalization algorithm mainly used in medical images [10]. The main function of the CLAHE algorithm is to enhance image contrast and suppress noise. DCT is mainly used for data or image compression, and it can transform the signal in the airspace to the frequency domain [11]. This research can increase people's understanding of two image pretreatment methods by comparing the accuracy of the results produced by the two preprocessing methods, which can help people choose how to conduct the metadata preprocess of convolutional neural network analysis.

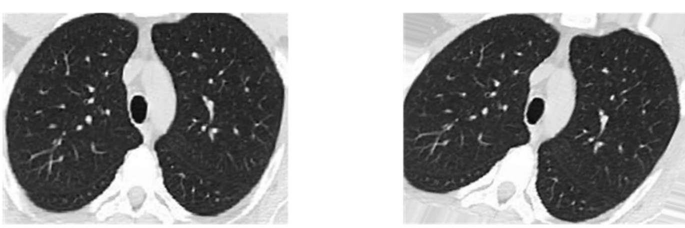
II. DATASETS AND METHODS

A. Datasets

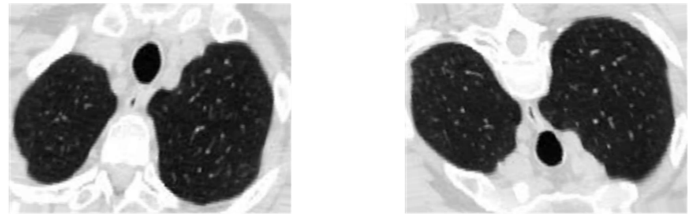
Due to the limit of collections of COVID-19 CT scans, two datasets are combined and used, including UCSD-AI4H-COVID-CT [12] and SARS-Cov-2 [13]. The utility of all of these built datasets were confirmed by some senior radiologists who have intensively practiced diagnosis and treatment of COVID-19 patients [12]. After some random rotation and flipping, we get 2473 images in total. Some examples of images are shown in Fig.1. These images are separated into three sets: train set, validation set, and test set. The specific divination is shown in TABLE I.

TABLE I. THE SPECIFIC DIVINATION OF THE DATASET

	COVID	NON-COVID
Train set	1017	976
Validation set	114	119
Test set	129	118



(a) Originally (b) rotate 15



(c) Originally (d) flip vertical

Figure 1. Examples of images in our dataset. Some random rotation and flipping were used to enlarge the dataset of this work. (b) shows a CT image with a random rotation of 15 degrees, and (d) shows one with a vertical flipping. All the CT images in the original dataset were rotated and flipped in this random way.

B. Method

A diagnosis structure that is based on CNN is used in the present work. First original datasets are enhanced to increase the resolution and contrast of images, and then the enhanced images are processed with the help of the Wiener filter to reduce noise. After two different preprocessing methods, images are input into CNN with inception V1 to get the accuracy of diagnosis for the three datasets. Our algorithm process is shown in Fig.2.

1) Preprocess

a) CLAHE

First, the CLAHE algorithm is used to enhance images. CLAHE is proved to be efficient in medical image enhancement [14]. It mainly uses contrast limit cropping and bilinear interpolation to avoid oversaturate and local over-enhancement. After image enhancement, the Wiener filter [15] is applied to remove the noise. The Wiener filter is a good way to extract the signal from noise. Finally, the bicubic interpolation is used to resize images.

For our experiment, we set the size of the sub-block to 8x8 and the cutting coefficient to 0.01 and use the bottom right quadrant 10×10 to estimate the noise and multiply a factor of 7 to reduce the noise.

b) DCT

First, the DCT transform is done to extract the low-frequency part and keep it unchanged. Then a factor is multiplied by all the other magnitudes to enhance images [16]. At the same time, the same procedure is used to reduce the noise in images by applying a Wiener filter to the bottom right quadrant magnitude. Finally, the DCT inverse transform is applied to resize and output final images. The process is shown in Fig.3. For our experiment, we set it to 1.4.

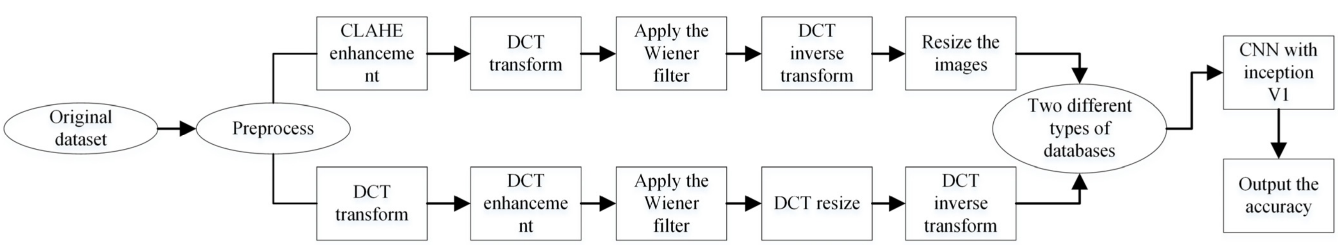


Figure 2. Algorithm process of our method. Before being input into the CNN with inception V1, two different preprocessing methods were applied to the images. Both methods contained five steps in specific, which includes image enhancement, noise reduction and resizing. For the neural network part, the modified inception V1 was used in this work.

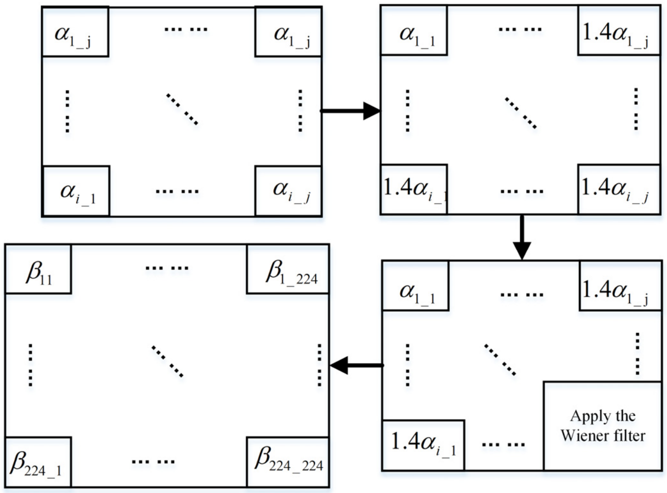


Figure 3. Algorithm process of DCT. In the frequency domain, there were three steps to implement this method. The first step was to enhance the high frequency part, the second step was to reduce the noise with the Wiener filter, and the third step was to resize the images with DCT inverse transform.

2) *CNN*

CNN with the inception V1 was used as our model to classify the CT images. Inception V1 is designed by Google, which can improve the performance and accuracy of CNN [17]. The struct of inception V1 is shown in Fig.4.

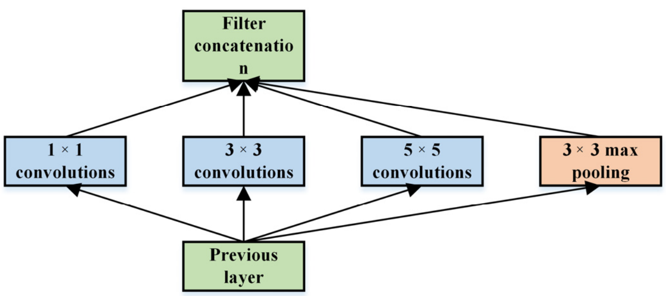


Figure 4. Inception V1 [17]

We change the struct of the inception V1, from 1×1 convolutions & 3×3 convolutions & 5×5 convolutions to 3×3 convolutions & 5×5 convolution & 7×7 convolutions. The struct of the modified inception V1 is shown in Fig.5.

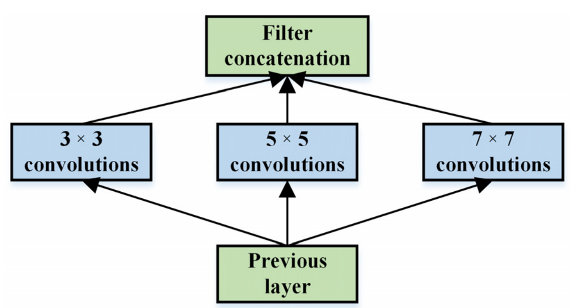


Figure 5. The modified Inception V1 in this work. The 3×3 max pooling was removed, and the size of the convolution kernel was changed.

ReLU was set as the activation function of the network, and the cost function was cross entropy with L2 regularization [18]. The parameters of the whole network were optimized via generalized adam with default hyper parameters in Tensorflow.

III. RESULTS

As is shown in Fig.6, there were fifty epochs in this work, and the accuracy of training, validation and test set was calculated to evaluate the effectiveness of the neural network. It can be seen that the accuracy of the training and validation set increases as the epoch increases from 1 to 50 for both preprocessed methods, and the training loss decreases to 0 and gets converged. The training accuracy of CLAHE starts from 0.7, and DCT starts from 0.53. It can be seen that both methods get converged at around the twentieth epoch, but CLAHE based method gets converged faster than DCT based method. Meanwhile, the validation loss oscillates as the epoch increases, but the amplitude of oscillation of DCT is less than CLAHE, and the accuracy of DCT is higher than CLAHE for most epochs; the validation loss of DCT is less than CLAHE. What's more, the accuracy of the test set of the CLAHE method is 0.9150, and the accuracy of the DCT method is 0.9271.

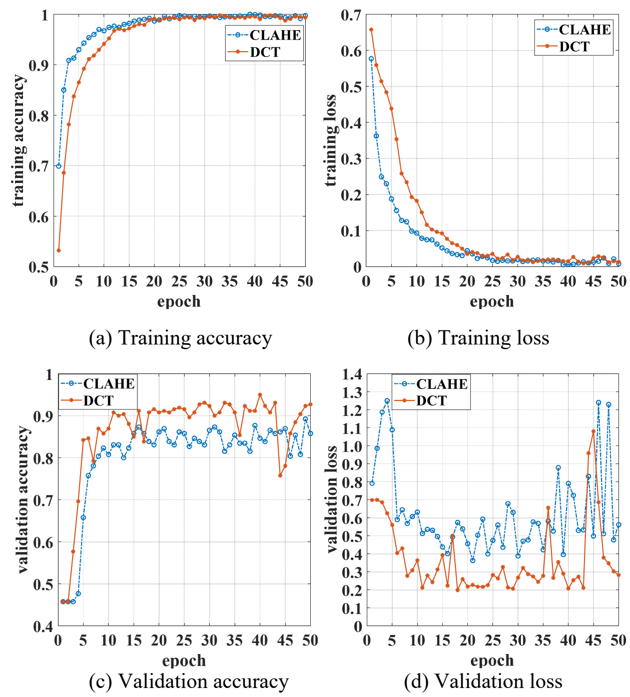


Figure 6. Loss and accuracy of the training set and validation set. Fifty epochs were used to evaluate the results and compare the differences between two preprocessing methods

IV. DISCUSSION

In this work, two preprocessing methods for CNN-based diagnosis of COVID-19 were processed and compared. We can see from Fig.6 (a) & (b) that preprocessing method CLAHE finishes the training process faster than method DCT, and they achieve the same training result as the epoch increases. As a result, these two methods achieve the comparably same result in the training process. However, method DCT has a better performance in the validation set. Besides, method DCT has a higher accuracy on the test set. In general, it can be seen that DCT is a better preprocessing method. Compared with CLAHE, it enhances the high-frequency part of medical images to extract the details and features. As a result, the contrast of CT images increased, and these extracted details and features of images serve as some important input features for the neural network to classify the images. By contrast, method CLAHE aims to change the histogram of images, and these images would have a “balanced” histogram. As a result, some unimportant details would be enhanced and bring some trouble for the neural network to classify the images. As a result, method DCT makes it easier for CNN to diagnose the nidus.

There are some limitations of this work. Due to the limit of our dataset, both two methods have an over-fitting problem, but we can see from Fig.6 (c) & (d) that the DCT method weakens this problem. What’s more, the CNN with inception V1 was used to classify images in this work, but there are some advanced models to use. Despite these limitations, we believe this work serves a purpose when it comes to deciding which preprocessing method to be used in diagnosing COVID-19 pneumonia with the neural network.

V. Conclusion

Image preprocessing is a critical step for subsequent diagnosis in medical image processing. In this paper, a comparative study of two preprocessing methods was done. Both the CLAHE-based method and the DCT-based method were implemented in the CNN-based diagnosis of COVID-19. With a combined and open-source dataset, the accuracy of the test set of our modified CNN was calculated. The results showed that the DCT-based method had a higher accuracy which was 92.71%, in the test set, and its validation loss was lower than the CLAHE-based method. As a result, the DCT-based method was a better preprocessing method compared with the CLAHE-based method in this work. It illustrates that the DCT-based preprocessing method is better to be used in the CNN-based diagnosis of COVID-19.

Acknowledgment

The authors would like to thank Munib Wober for his guidance and essential feedback throughout this work, Fei Shen’s help in revising the draft. Appreciation also goes to Zhenshan He at North China University of Technology for his advice in improving the performance of this model.

References

[1] “emergency COVID-19, Spain to Tighten Quarantine Measures”, Xinhua News Agency, 15th.July. 2021

[2] X. Xu et al., “A Deep Learning System to Screen Novel Coronavirus Disease 2019 Pneumonia,” Engineering, p. 8, pp. 1122-1129, 2020, doi: 10.1016/j.eng.2020.04.010.

[3] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, and J. Liu, “Chest CT for Typical Coronavirus Disease 2019 (COVID-19) Pneumonia: Relationship to Negative RT-PCR Testing,” Radiology, vol. 296, no. 2, pp. E41–E45, Aug. 2020, doi: 10.1148/radiol.2020200343.

[4] A. Smargiassi et al., “Lung ultrasonography for early management of patients with respiratory symptoms during COVID-19 pandemic,” J Ultrasound, vol. 23, no. 4, pp. 449–456, Dec. 2020, doi: 10.1007/s40477-020-00501-7.

[5] R. Lokwani, A. Gaikwad, V. Kulkarni, A. Pant, and A. Kharat, “Automated Detection of COVID-19 from CT Scans using Convolutional Neural Networks:,” in Proceedings of the 10th International Conference on Pattern Recognition Applications and Methods, Online Streaming, --- Select a Country ---, 2021, pp. 565–570. doi: 10.5220/0010293605650570.

[6] S. Kugunavar and C. J. Prabhakar, “Convolutional neural networks for the diagnosis and prognosis of the coronavirus disease pandemic,” Vis. Comput. Ind. Biomed. Art, vol. 4, no. 1, p. 12, Dec. 2021, doi: 10.1186/s42492-021-00078-w.

[7] M. Rahimzadeh and A. Attar, “A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2,” Informatics in Medicine Unlocked, vol. 19, p. 100360, 2020, doi: 10.1016/j.imu.2020.100360.

[8] H. Mukherjee, S. Ghosh, A. Dhar, S. M. Obaidullah, K. C. Santosh, and K. Roy, “Deep neural network to detect COVID-19: one architecture for both CT Scans and Chest X-rays,” Appl Intell, vol. 51, no. 5, pp. 2777–2789, May 2021, doi: 10.1007/s10489-020-01943-6.

[9] S. Kido, Y. Hirano, and N. Hashimoto, “Detection and classification of lung abnormalities by use of convolutional neural network (CNN) and regions with CNN features (R-CNN),” in 2018 International Workshop on Advanced Image Technology (IWAIT), Chiang Mai, Jan. 2018, pp. 1–4. doi: 10.1109/IWAIT.2018.8369798.

[10] A. M. Reza, “Realization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) for Real-Time Image Enhancement,” The Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology, vol. 38, no. 1, pp. 35–44, Aug. 2004, doi: 10.1023/B:VLSI.0000028532.53893.82.

[11] Khayam, Syed Ali. "The discrete cosine transform (DCT): theory and application." Michigan State University 114 (2003): 1-31.

[12] X. Yang, X. He, J. Zhao, Y. Zhang, S. Zhang, and P. Xie, “COVID-CT-Dataset: A CT Image Dataset about COVID-19,” p. 15. arXiv: 2003.13865v3 [cs.LG] 17 Jun 2020.

[13] J. P. Cohen, P. Morrison, and L. Dao, “COVID-19 Image Data Collection,” p. 5. arXiv: 2003.11597v1 [eess.IV] 25 Mar 2020.

[14] P. Singh, R. Mukundan, and R. De Ryke, “Feature Enhancement in Medical Ultrasound Videos Using Contrast-Limited Adaptive Histogram Equalization,” J Digit Imaging, vol. 33, no. 1, pp. 273–285, Feb. 2020, doi: 10.1007/s10278-019-00211-5.

[15] K. Zhong, X. Lei, and S. Li, “Wiener Filter Based Channel Estimation for High-Speed Communication Environments,” Wireless Pers Commun, vol. 69, no. 4, pp. 1819–1845, Apr. 2013, doi: 10.1007/s11277-012-0665-8.

[16] I. Hajj-ahmad and M. Wober, “IQA: Processing, Image. The Role of DCT Algorithms in Automatic.,” Image Processing Image Quality Image Capture Systems Conference, PORTLAND, OR, pp. 148–149, May 17, 1998.

[17] C. Szegedy et al., “Going deeper with convolutions,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, Jun. 2015, pp. 1–9. doi: 10.1109/CVPR.2015.7298594.

[18] G. Litjens et al., “A survey on deep learning in medical image analysis,” Medical Image Analysis, vol. 42, pp. 60–88, 2017, doi: 10.1016/j.media.2017.07.005.