Int. J. Nonlinear Anal. Appl. 13 (2022) 1, 2245-2251
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.5923

Deep convolutional neural network classified the PNEUMONIA and Coronavirus diseases (COVID-19) by softmax nonlinearity function

Mali H. Hakem Alameady[a], Maryim Omran Mosa[a], Amir Ali Aljarrah[a,*], Huda Saleem Razzaq[a]

[a] *Department of Computer Science, Faculty of Computer Science and Maths, University of Kufa, Najaf, Iraq*

(Communicated by Madjid Eshaghi Gordji)

Abstract

A deep learning powerful models of machine learning indicated better performance as precision and speed for images classification. The purpose of this paper is the detection of patients suspected of pneumonia and a novel coronavirus. Convolutional Neural Network (CNN) is utilized for features extract and it classifies, where CNN classify features into three classes are COVID-19, NORMAL, and PNEUMONIA. In CNN updating weights by CNN backpropagation and SGDM optimization algorithms in the training stage. The performance of CNN on the dataset is a combination between Chest X-Ray dataset (1583-NORMAL images and 4272-PNEUMONIA images) and COVID-19 dataset (126-images) for automatically anticipate whether a patient has COVID-19 or PNEUMONIA, where accuracy 94.31% and F1-Score 88.48% in case 60% training, 20% testing, and 20% validation.

Keywords: Deep learning, convolutional neural network, and Coronavirus Disease (COVID-19).
2010 MSC: Primary 90C33; Secondary 26B25.

1. Introduction

This section will coronavirus describe and deep learning convolution neural network describe. In 2019 detect novel COVID-19, where not found vaccine or any known effective treatment when the epidemic spread. Human Coronaviruses spread all over the world [2, 13]. At the end of 2019, the novel coronavirus disease occurred in the city of Wuhan, China [7]-[17]. On January 24, 2020, Huang et

*Corresponding author

Email addresses: maali.alameedi@uokufa.edu.iq (Mali H. Hakem Alameady), maryimo.alkuzaay@student.uokufa.edu.iq (Maryim Omran Mosa), amir.aljarrah@student.uokufa.edu.iq (Amir Ali Aljarrah), hudasaleem.hs93@gmail.com (Huda Saleem Razzaq)

Received: September 2021 *Accepted:* November 2021

al. [20] summarized characteristics of 41 patients with COVID-19, were symptoms of this illness are fever, cough, fatigue, myalgia, acute respiratory distress, and acute heart injury. Human-to-human transmission of COVID-19 for the first time [21]. With the rapid development of computer technology, digital image processing technology and widely applied in the medical field, content segmentation, enhancement, and etc [9, 14]. Deep learning technologies, such as convolutional neural network (CNN) with the strong ability of nonlinear modeling in medical image processing [10-22]. Chest X-ray dataset have set chest X-ray images (infected PNEUMONIA or uninfected NORMAL). There are disadvantage is X- ray examination demand a radiology expert and need huge time when individuals are ill the world over. Therefore building automated system is required to provides medical experts significant time.

Deep Convolutional Neural Network (DCNN) or symbolize (CNN) used in many domain such as computer vision, image processing, network, recognition, classification, and etc. DCNN is simulates brain in signals identifying and have many hidden layers with input and output layers, where it ability on automatic features extract instead of manually extraction based on set of layers [11]. DCNN have many layers: Convolutional (Con), pooling, Rectified Linear Unit (ReLU), and Fully Connected (FC) layers [15]. Convolutional layer have many filters which include trained weights by backpropagation model. The main role of Con layer is to find traits of image by convolved between filters and whole image [8]. Pooling layer is compute maximum value of a local part (n*n) of convolutional feature, it reduces size of feature [16]. ReLU is a non-linear operation, it select maximum value between zeros and traits values. Fully Connected layer input of this layer are result of the pooling or Con layers. Final, Softmax layer used to classify traits into N-Classes. The problem of this paper, there are many people infected with (COVID-19, and PNEUMONIA) and need experienced doctors to detect and diagnose their infection, it require time if large numbers of infected. So technology used to provide support for the medical aspects that help in diagnosis. The aim of this paper determine patient if he is normal or has the infected, where applied deep convolutional neural network. The remaining parts of paper will organized as follows, section (2) explain methodology, section (3) explain performance experiment, and section (4) show conclusion.

2. Methodology

This section introduces proposed model and flowchart for COVID-19, PNEUMONIA, and NORMAL classification by using deep convolutional neural network.

2.1. Proposed CNN-COVID-19 model

It model automatically predict if patient has COVID-19 or PNEUMONIA, used X-ray dataset to exam COVID-19, NORMAL and PNEUMONIA. The CNN training for automatically detect of coronavirus samples and evaluate the results by run some measures. Input of CNN-COVID-19 model is images of dataset, output is patient classification into COVID-19, PNEUMONIA, and NORMAL, and structure of CNN-COVID-19 model have 26 layers as explain in Tab. 1 to classify and extracted features from images automatically. There are many methods used to updating the weight used backpropagation model [8] and SGDM models [12], where weight update with mini batch.

Table 1: CNN-COVID-19 Model.

Layers indexes	Layers Name	Layers Type	Stride	Learnable
1	Image input	200x300x3	-	-
2	'conv1'	Convolution 201x301x8	1	2x2x3x8
3	'batchnorm1'	Batch normalization 201x301x8	-	1x1x8
4	'relu1'	ReLU 201x301x8	-	-
5	'poo1'	Max Pooling 100x150x8	2	-
6	' conv2'	Convolution 100x150x16	1	3x3x8x16
7	'batchnorm2'	Batch normalization 100x150x16	-	1x1x16
8	' relu2'	ReLU. 100x150x16	-	-
9	'conv3'	Convolution 101x151x32	1	2x2x16x32
10	' batchnorm3'	Batch normalization 101x151x32	-	1x1x32
11	'relu3'	ReLU 101x151x32	-	-
12	'pool2'	Max Pooling 50x75x32	2	-
13	'conv4'	Convolution 50x75x64	1	3x3x32x64
14	' batchnorm4'	Batch normalization 50x75x64	-	1x1x64
15	'relu4'	ReLU 50x75x64	-	-
16	'pool3'	Max Pooling 25x37x64	2	-
17	'conv5'	Convolution 26x38x128	1	2x2x64x128
18	' batchnorm5'	Batch normalization 26x38x128	-	1x1x128
19	'relu5'	ReLU 26x38x128	-	-
20	'pool4'	Max Pooling 13x19x128	2	-
21	'conv6'	Convolution 13x19x256	1	3x3x128x256
22	' batchnorm6'	Batch normalization 13x19x256	-	1x1x256
23	'relu6'	ReLU 13x19x256	-	-
24	'fc1'	Fully-Connected 1x1x3	-	3x63232
25	'softmax'	Softmax 1x1x3	-	-
26	'classoutput'	Classification output	-	-

2.2. Flowchart of proposed model

This section show flowchart of proposed model as follows:

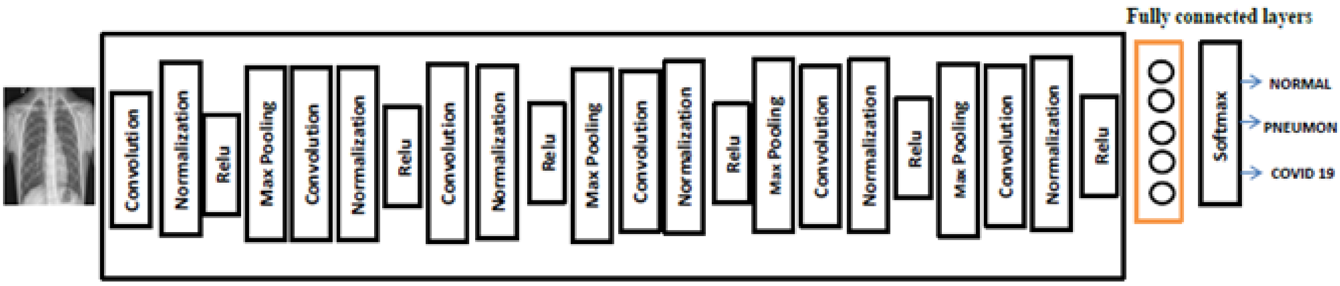

Figure 1: CNN-COVID-19 Model.

3. Performance experiment

In this section explain dataset used and evaluation metrics as follows:

3.1. DATASET

It is combination between two dataset. First chest-X-ray images dataset which contains images of NORMAL people and infected with PNEUMONIA. Second Chest X-Ray COVID-19 images. Format images in the dataset are JPEG with different resolution pixels and different sizes. Used dataset to classify the persons into three labels COVID-19, NORMAL and PNEUMONIA. The total number for each label not equal due to the images of coronavirus not available enough so the number of COVID-19, NORMAL, and PNEUMONIA are 126, 1583, and 4272 respectively. Fig. 2 shown COVID-19. Dataset publishing in the GitHub repo or Kaggle's. Fig. 3 presents some COVID-19 and NORMAL images dataset.

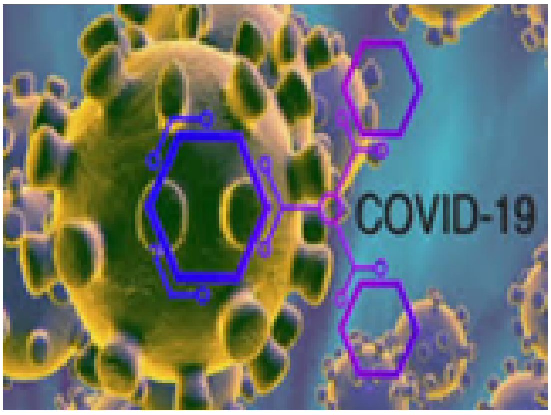

Figure 2: COVID-19 Coronavirus.

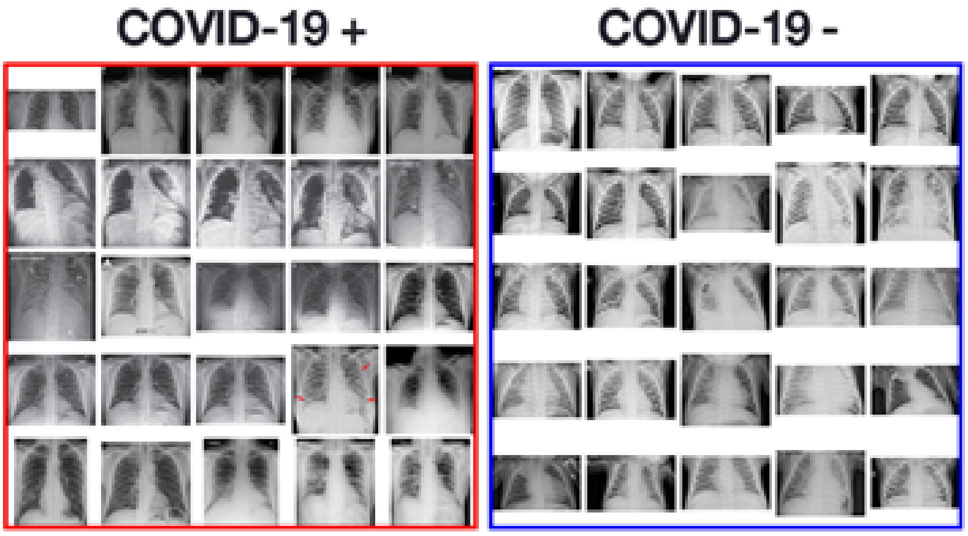

Figure 3: X-ray images on the left have COVID-19 samples (infected), whereas X-ray images on the right normal samples (uninfected).

3.2. Evaluation metrics

The accuracy of a technique decides how correct values predicted. Precision decides what number predictions correct. Recall is number of the correct outcomes found. F1-Score combination precision and recall to compute balanced average result. Tab. 2 show evaluation metrics. The following equations explain TP, TN, FP and FN are "True Positive", "True Negative", "False Positive", and "False Negative" respectively relies on a confusion Matrix [18, 3].

$$\text{Accuracy} = \frac{\sum_{j=1}^{n} TP_j + TN_j}{\text{Total}} \times 100\% \tag{3.1}$$

$$\text{Recall} = 1/n \times \sum_{j=1}^{n} \frac{TP_j}{TP_j + FN_j} \times 100\% \tag{3.2}$$

$$\text{precision} = 1/n \times \sum_{j=1}^{n} \frac{TP_j}{TP_j + FP_j} \times 100\% \tag{3.3}$$

$$\text{F1\_score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Precision+Recall}} \times 100\% \tag{3.4}$$

Dataset will split images to 60% training, 20% validation, and 20% testing that mean 3590 of training, 1195 of validation and 1196 images of testing. Backpropagation and SGDM algorithms used to update weight in training stage of CNN, where Mini-Batch 50 and learning rate 10^{-5}. The errors of Softmax function calculate for all MiniBatch and update weight of backpropagation. Fig. 4 shows that CNN-COVID-19 model accuracy rate and loss rate.

Table 2: Evaluation Metrics of CNN-COVID-19

Performance Matrix	CNN-COVID-19
Accuracy	0.9431
Precision	0.8979
Recall	0.8720
F-Measure	0.8848

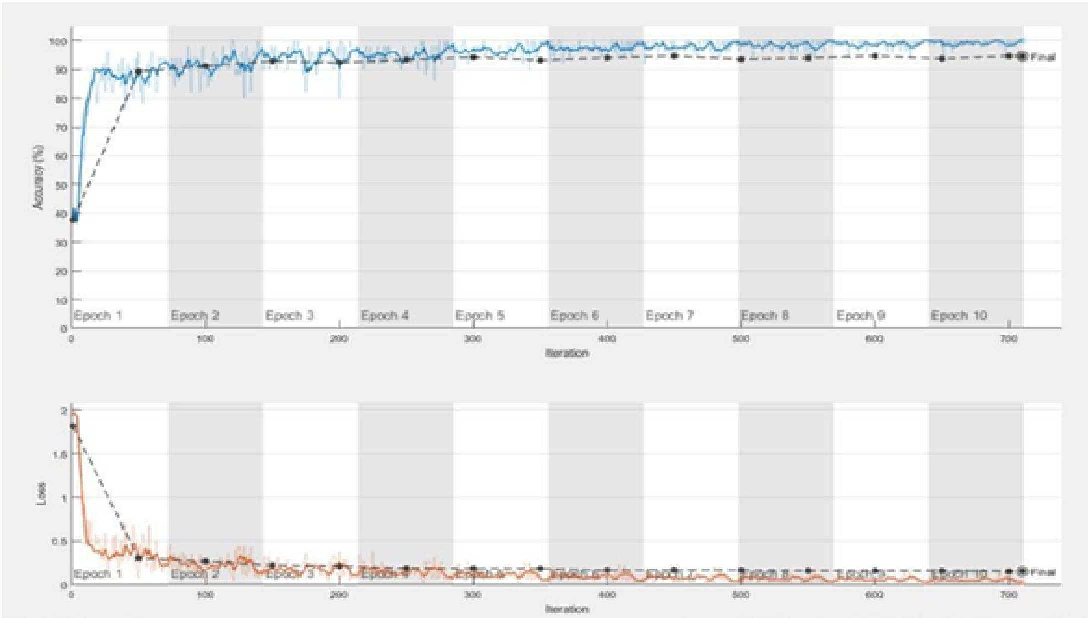

Figure 4: CNN-COVID-19 model of 60% training and 40% testing.

4. Conclusion

The deep learning models is effective for classification of patients. In this case study, presented method to detect COVID-19, PNEUMONIA, and NORMAL automatically by deep learning technologies. Models mechanism can be classify with accuracy rate of 94.31 % in case 60% of tanning, 20% validation, and 20% testing. CNN-COVID-19 model evaluated with ten number epochs, where learning process will stable in constant range. Result of this model could be a promising diagnostic method for doctors.

References

[1] M. Akagi, Y. Nakamura, T. Higaki, K. Narita, Y. Honda, J. Zhou, Z. Yu, N. Akino and K. Awai, *Deep learning reconstruction improves image quality of abdominal ultra-high-resolution CT*, European Radiology 29(11) (2019) 6163–6171.

[2] V. Aladinskiy, A. Zhebrak, B. Zagribelnyy and V. Terentiev, *Potential COVID-2019 3C-like protease inhibitors designed using generative deep learning approaches*, Insilico Medicine Hong Kong Ltd A 307 (2020).

[3] A.A. Aljarrah and A. H. Ali, *Human activity recognition using PCA and BiLSTM recurrent neural networks*, 2nd Int. Conf. Engin. Technol. Appl. IEEE (2019).

[4] Y. Bai, L. Yao and T. Wei, *Presumed asymptomatic carrier transmission of COVID-19*, Jama 323(14) (2020) 1406–1407.

[5] D.J. Carretero, D. B. Pelaez, G.R. Washko and F.N. Rahaghi, *Pulmonary artery–vein classification in CT images using deep learning*, IEEE Trans. Medical Imag. 37(11) (2018) 2428–2440.

[6] J. Cohen and D. Normile, *New SARS-like virus in China triggers alarm*, Sci. 367(6475) (2020) 234–235.

[7] V.M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer, D.K. Chu, T. Bleicker and S. Brünink, et al, *Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR*, Euro Surveill. 25(3) (2020) 2000045.

[8] A.F. Gad, *Practical Computer Vision Applications Using Deep Learning with CNNs*, Apress, 2018.

[9] M. Gharbi, J. Chen, J.T. Barron, S.W. Hasinoff and F. Durand, *Deep bilateral learning for real-time image enhancement*, ACM Trans. Graphics 36(4) (2017) 1–12.

[10] M.H. Hesamian, W. Jia, X. He and P. Kennedy, *Deep learning techniques for medical image segmentation: achievements and challenges*, J. Digital Imag. 32(4) (2019) 582–596.

[11] P. Kim, *MATLAB Deep Learning: With Machine Learning, Neural Networks and Artificial Intelligence*, Apress, 2017.

[12] D.P. Kingma and J. Ba, *Adam: A method for Stochastic Optimization*, arXiv preprint arXiv:1412.6980, (2014) 1–15.

[13] P. Liu, L. Shi, W. Zhang, J. He, C. Liu, C. Zhao, S.K. Kong, J.F. Chuen Loo, D. Gu and L. Hu, *Prevalence and genetic diversity analysis of human coronaviruses among cross-border children*, Virology J. 14(1)(2017) 1–8.

[14] X. Liu, S. Guo, B. Yang, S. Ma, H. Zhang, J. Li, C. Sun, L. Jin and X. Li, *Automatic organ segmentation for CT scans based on super-pixel and convolutional neural networks*, J. Digital Imag. 31(5) (2018) 748–760.

[15] B. Moons, D. Bankman and M. Verhelst, *Embedded Deep Learning*, Springer, 2018.

[16] J. Nagi, F. Ducatelle, G.A.D. Caro, D. Cireşan, U. Meier, A. Giusti, F. Nagi and J. Schmidhube, *Max-pooling convolutional neural networks for vision-based hand gesture recognition*, IEEE Int Conf Signal Image Proces Appl (2011) pp. 342–347.

[17] Y. Qu, E. Kang and H. Cong, *Positive result of Sars-Cov-2 in sputum from a cured patient with COVID-19*, Travel Medic. Infect. Disease 34 (2020) 101619.

[18] M. Sokolova and G. Lapalme, *A systematic analysis of performance measures for classification tasks*, Inf. Process. Manag. 45(4) (2009) 427–437.

[19] X. Xu, X. Jiang, C. Ma, P. Du and X. Li, *A deep learning system to screen novel coronavirus disease 2019 pneumonia*, Engin. 6(10) (2020) 1122–1129.

[20] X. Yang, Y. Yu, J. Xu, H. Shu, J. Xia and H. Liu, *Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study*, Lancet Respiratory Medicine 8(5) (2020) 475–481.

[21] P. Yu, J. Zhu, Z. Zhang and Y. Han, *A familial cluster of infection associated with the 2019 novel coronavirus indicating possible person-to-person transmission during the incubation period*, J. Infect. Diseases 221(11) (2020) 1757–1761.

[22] W. Zhu, Y. Huang, L. Zeng, X. Chen, Y. Liu, Z. Qian, W. Fan and X. Xie, *AnatomyNet: Deep learning for fast and fully automated whole-volume segmentation of head and neck anatomy*, Medical Phys. 46(2) (2019) 576–589.