MODIFIED VGG DEEP LEARNING ARCHITECTURE FOR COVID-19 CLASSIFICATION USING BIO-MEDICAL IMAGES

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Abstract. The world encountered a deadly disease by the beginning of 2020, known as the coronavirus disease (COVID-19). Among the different screening techniques available for COVID-19, chest radiography is an efficient method for disease detection. Whereas other disease detection techniques are time consuming, radiography requires less time to identify abnormalities caused by the disease in the lungs. In this study, one of the standard deep learning architectures, VGGNet, is modified for classifying chest X-ray images under four categories. The planned model uses images of four classes, namely COVID, bacterial, normal, and viral images. The performance matrices of the planned model are compared with five deep learning architectures, namely VGGNet, AlexNET, GoogLeNET, Inception-v4, and DenseNet-201.

Keywords: X-Ray, Deep Learning, VGGNet, Image Classification, COVID-19

1. INTRODUCTION

By the termination of 2019, a coronavirus disease (COVID19) had happened in the capital of Wuhan, China. summarized the clinical features of 41 patients infected by COVID-19. All of them indicated symptoms such as fever, cough, fatigue, or myalgia [1]. Furthermore, COVID pneumonia was confirmed in all the 41 patients based on chest radiography, which recorded some irregularities in the chest [2]. The increasing number of COVID-19 patients with serious breathing problems has caused the full occupancy of intensive care units, causing severe burden to the health care system of many developed countries. Hence, the early detection of COVID cases is necessary to manage the situation. The present clinical practice to diagnose the disease at its initial stage is by contrary transcript polymerase chain reaction, which identifies traces of virus-related RNA from mucus or nasopharyngeal scrub. This technique identifies a minimal number of positive cases. The proposed system outperforms this technique using X-ray chest images of COVID-19 patients, which differ from images of new bacterial and viral pneumonia radiography, as demonstrated in Figure 1.

In medical image analysis, several deep learning algorithms continue to demonstrate excellent performances for pulmonic nodes [3], classification of benign or malignant tumors in MRI images [4], pulmonary tuberculosis investigation, and virus estimations [5]. Chest radiography remains an effective screening method to identify COVID patients at an early stage [8]. This has motivated several researchers to adopt artificial-intelligence-based systems to identify COVID-19 with better accuracy [9]. Many automatic prediction methods developed based on pretrained deep learning models have been used for identifying COVID-19 using X-ray images [10]. Narin et al. [11] achieved a 100% accuracy for an X-ray dataset containing 10 COVID-19 samples by adopting Inception-ResNetV2 pretrained models. Handcrafted features and feature selection steps were eliminated in the proposed models. ResNet50
proved to be an effective pretrained model among the other two pretrained models, i.e., AlexNet and DenseNet-201. Chest X-ray images are the finest device for COVID-19 classification, and pretrained models yield high accuracy with a small dataset [6, 7]. The proposed model was developed to classify four different classes, i.e., COVID, bacteria, viral, and normal. The performance of the proposed modified VGG architecture for COVID-19 disease classification was compared with five standard CNN architectures, i.e., VGGNet, AlexNet, GoogLeNET, Inception-v4, and DenseNet-201. The database collected from the Kaggle Competition, GitHub [16] was used in the present study. An SVM classifier was fed with features extracted from the ResNet50 [9], [14] CNN model. The X-ray image dataset from GitHub, Kaggle, repository were used to test the performance of the system. The system achieved an 85.38% accuracy. According to Fei et al. [13], [14], [16] COVID-19 is still new, and the number of associated experiments reported in the literature for comparison is few.

2 PROPOSED METHODOLOGY

Visual data such as images are processed well by CNNs; hence they are preferred by most researchers owing to their promising results. A CNN network is constructed with alternate convolutional layers [13, 16] with a completely connected layer as the final layer. The pooling layer and activation functions are inserted between the convolutional layer with varying weights [19]. Additionally, a max-pooling layer [18] is used in the existing convolutional architecture [17].

Here, we propose a modified VGGNet to categorise chest X-ray images into four separate labels: COVID-19, bacteri pneumonia, viral pneumonia, and normal X-ray. The overall schematic of the planned model is shown in Figure 1. The standard VGG architecture uses an input image measuring 224 × 224, and it demonstrates good accuracy compared with other standard architectures used for biomedical applications [16]. Hence, our goal in this study is to fine-tune VGGNet, which has an input size of 200 × 200. Three different pooling layers were used in our experiment to obtain a high classification accuracy [20]. A max-pooling layer [17] [18] is often used in existing convolutional architecture.

![Figure 1. Typical chest radiography images: (a) Bacterial pneumonia; (b) COVID-19 pneumonia; (c) No pneumonia; (d) Viral pneumonia [12].](image)

Here, we propose a modified VGGNet to classify four classes: COVID, bacteria, viral, and normal. The overall proposed flow model is shown in Figure 2. The standard VGG architecture comprises an input image measuring 224 × 224, and it demonstrates good accuracy compared with other standard architectures used for biomedical applications [17]. Therefore, our goal in this study is to fine-tune VGGNet, which has an input size of 200 × 200, and test it with three different pooling layers to obtain a high classification accuracy.
Figure 2. Schematic representation of convolution neural network models for prediction of bacteria, COVID-19, normal, and viral cases

2.1. Dataset Description

In this paper, we describe the exposed-source data from GitHub, accessed from https://github.com/lindawangg/COVID-Net. Figure 4 shows the dataset description for four different classes (bacteria, COVID-19, normal, and viral), including the number of training and testing images. The database contains 231 radiography images collected from 45 COVID-19 patients, including 2503 images for bacteria, 1341 images for normal, and 1345 for viral. The proposed modified VGG architecture for COVID chest radiography image which is shown in Figure 3. The following layers are the Conv → Conv → Pooling-layer → Conv →Conv → Pooling layers.

Before the flattened layer with $6 \times 6 \times 128$ feature maps, a flattened dense layer comprising $1 \times 4608$ feature vectors exists, followed by two dense layers containing 512 and 256 neurons, separately. The final SoftMax layer has four neurons to classify COVID, bacteria, viral, or normal. Table 1 shows a summary of the proposed architecture.
Table 1. Summary of proposed VGGNet architecture for COVID chest radiography image classification

| Layer | Size | Feature Map Size | Filter Size | Activation |
|-------|------|----------------|-------------|------------|
| Input Image | 1 | 200x200x1 | - | - |
| 1. Conv2D 1 | 32 | 200x200x32 | 3x3 | ReLU |
| 2. Conv2D 2 | 32 | 200x200x32 | 3x3 | ReLU |
| 3. Max or Avg | 32 | 100x100x32 | 2x2 | ReLU |
| 4. Conv2D 3 | 64 | 100x100x64 | 3x3 | ReLU |
| 5. Conv2D 4 | 64 | 100x100x64 | 3x3 | ReLU |
| 6. Max or Avg | 64 | 50x50x64 | 2x2 | ReLU |
| 7. Conv2D 5 | 128 | 50x50x128 | 3x3 | ReLU |
| 8. Conv2D 6 | 128 | 50x20x128 | 3x3 | ReLU |
| 9. Max or Avg | 128 | 50x50x128 | 2x2 | ReLU |
| 10. FC1 | - | 4608 | - | ReLU |
| 11. FC2 | - | 512 | - | ReLU |
| 12. FC3 | - | 256 | - | ReLU |
| 13. Output | - | 4 | - | SoftMax |

Figure 3. Proposed modified VGGNet architecture for COVID chest radiography image classification.

Figure 4. Dataset description of four different classes.
2.2 Experimental Results and Discussion

2.2.1 Performance Measurement

In this section, we analyze some important performance measurements such as accuracy, precision, sensitivity, and specificity [24] to estimate the results of our projected method and compare it with five other existing architectures [17]. The training and validation accuracy obtained for the maximum pooling and average pooling used in the proposed architecture are shown in Figure 5. As shown, the maximum pooling yielded a better accuracy compared with the architecture with average pooling layers. This may be due to the higher variations in intensity values in the disease-affected regions. The training and validation accuracy saturated within 20 epochs, as shown in Figure 5. The number of epochs for the training iterations was fixed at 20 because the validation functions and accuracy function saturated.

In this study, a comparison [12] was performed based on the training loss and accuracy, as shown in Figure 6. The proposed modified VGG architecture indicated less validation loss and a greater accuracy contrasted with the other pretrained models. Additionally, when compared with the other models, the Modified VGGNet required a shorter duration to be trained. The training accuracy values of Inception-v4, AlexNet, VGGNet, GoogLeNet, DenseNet-201, and modified VGGNet are shown in Figure 7.

As shown by the loss graph in Figure 7, the loss value decreased at the training stage for the six different trained models. Furthermore, the proposed modified VGGNet model resulted in a rapid loss decrease of 0.0008. The confusion matrices of the six different CNN architectures are shown in Figure 8[23]. The modified VGGNet trained model classified 66 images as COVID-19, as well as 391, 744, and 386 images as normal, bacterial, and viral, respectively which is provided in Table 2. The performance metric comparisons of six models using the same test data are shown in 3 based on the metrics. The performance metrics obtained using the proposed model were 98% for accuracy, 89% precision, 100% specificity value, and 91% sensitivity. The modified VGGNet model delivered the best results compared with the other five models. Furthermore, compared with the results presented in [24, 25], the proposed model obtained an accuracy of 0.98, precision 0.882, specificity 0.994, and sensitivity 0.96. Hence, the modified VGGNet model performed better than all other existing architectures, as shown in Figure 8.
Table 2. Comparison of implementation of proposed model with active architecture based on standard metrics (a. Accuracy of covid19, b. precision of COVID-19, c. Sensitivity of COVID-19, d. Specificity of COVID-19)

| Parameters          | Comparison of Different Convolutional Neural Networks |
|---------------------|-------------------------------------------------------|
|                     | Modified VGGNet | VGGNet | GoogleNet | Inception-v4 | AlexNet | DenseNet-201 |
| Overall Accuracy    | 0.977          | 0.954  | 0.947     | 0.939        | 0.939   | 0.936         |

(b)

| Parameters          | Comparison of Different Convolutional Neural Networks |
|---------------------|-------------------------------------------------------|
|                     | Modified VGGNet | VGGNet | GoogleNet | Inception-v4 | AlexNet | DenseNet-201 |
| Precision of COVID-19 | 0.892       | 0.743  | 0.736     | 0.658        | 0.632   | 0.600         |

(c)

| Parameters          | Comparison of Different Convolutional Neural Networks |
|---------------------|-------------------------------------------------------|
|                     | Modified VGGNet | VGGNet | GoogleNet | Inception-v4 | AlexNet | DenseNet-201 |
| Sensitivity of COVID-19 | 0.957       | 0.833  | 0.768     | 0.754        | 0.725   | 0.696         |

(d)

| Parameters          | Comparison of Different Convolutional Neural Networks |
|---------------------|-------------------------------------------------------|
|                     | Modified VGGNet | VGGNet | GoogleNet | Inception-v4 | AlexNet | DenseNet-201 |
| Specificity of COVID-19 | 0.994859     | 0.987781| 0.987967  | 0.98267     | 0.981517| 0.979592     |

Figure 6. Performance comparison of proposed modified VGGNet with standard deep learning architectures based on accuracy.

Figure 7. Performance comparison of proposed modified VGGNet with standard deep learning architectures based on loss.
CONCLUSIONS

Among the numerous screening techniques, chest radiography is preferred as it is an efficient technique for the rapid identification of abnormalities. In this dataset, we used approximately 2503 images with bacterial pneumonia, 1345 with COVID-19, and 1341 normal computed radiography images. These images were used for training the model. A modified VGGNet, which had an input size of 200 × 200 and three different pooling layers, was used to obtain a good prediction rate. Subsequently, its performance was compared with those of VGGNet, GoogLeNet, Inception-v4, AlexNet, and DenseNet-201. The results of the performance metrics indicated that the modified VGGNet yielded better results compared with the other techniques.

References

[1] O. Gozes, M. Frid-Adar, H. Greenspan, P. D. Browning, H. Zhang, W. Ji, and E. Siegel, “Rapid AI development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using deep learning CT image analysis,” arXiv preprint arXiv:2003.05037, 2020.
[2] S. Tian, N. Hu, J. Lou, K. Chen, X. Kang, Z. Xiang, H. Chen, D. Wang, N. Liu, D. Liu, G. Chen, Y. Zhang, D. Li, J. Li, H. Lian, S. Niu, L. Zhang, and J. Zhang, “Characteristics of COVID-19 infection in Beijing,” Journal of Infection, 2020.
[3] S. Wang, B. Kang, J. Ma, X Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, and B. Xu “A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19),” MedRxiv. 2020.
[4] Y. Zhang, X. Dong, L Wu, and S. Wang, “A hybrid method for MRI brain image classification,” Expert Systems with Applications, vol. 38, no. 8, pp. 10049-10053, 2011.
[5] S. W. Chung, S. S. Han, J. W. Lee, K. S. Oh, N. R. Kim, J. P. Yoon, and Y. M. Noh, “Automated detection and classification of the proximal humerus fracture by using deep learning algorithm,” Acta Orthopaedica, vol. 89, no. 4, pp. 468-473. 2018.
[6] H. Lu, C. W. Stratton, and Y. W. Tang, “Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle,” Journal of Medical Virology, vol. 92, no. 4, pp. 401-402, 2020.
[7] J. Li, H. Yang, W. A. Peer, G. Richter, J. Blakeslee, A. Bandopadhyay, and B. Krizek, “Arabidopsis H+-PPase AVP1 regulates auxinmediated organ development,” Science, vol. 310, no. 5745, pp. 121-125, 2005.

[8] W. Alhazzani, M. H. Møller, Y. M. Arabi, M. Loeb, M. N. Gong et al., “Surviving Sepsis Campaign: guidelines on the management of critically ill adults with Coronavirus Disease 2019 (COVID-19),” Intensive care medicine, pp. 1-34, 2020.

[9] L. Wang, and A. Wong, “COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images,” arXiv preprint arXiv:2003.09871, 2020.

[10] Updated, I. P. A. C. recommendations for use of personal protective equipment for care of individuals with suspect or confirmed COVID19. 2020.

[11] A. Narin, C. Kaya, and Z. Pamuk, “Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks,” arXiv preprint arXiv:2003.10849, 2020.

[12] J. P. Cohen, M. Paul, and D. Lan, “COVID-19 image data collection,” arXiv preprint arXiv:2003.11597, 2020.

[13] L. Sun, Z. Mo, F. Yan, L. Xia, L., F. Shan, X. Ding, W. Shao, F. Shi, H. Yuan, H. Jiang, D. Wu, Y. Wei, Y. Gao, W. Gao, H. Sui, D. Zhang, and D. Shen, “Adaptive feature selection guided deep forest for COVID-19 classification with chest CT,” IEEE Journal of Biomedical and Health Informatics, 2020.

[14] R. S Sabeenian, M. E. Paramasivam, R. Anand, and P. M Dinesh, “Palm-leaf manuscript character recognition and classification using convolutional neural networks,” In Computing and Network Sustainability, pp. 397-404, Springer, Singapore, 2019.

[15] A. Raju, T. Shanthi, R. S. Sabeenian, and S. Veni, “Real time noisy dataset implementation of optical character identification using CNN,” International Journal of Intelligent Enterprise, vol. 7, no. 13, pp. 67-80, 2020.

[16] R. Gentleman and V. J. Carey, “Unsupervised machine learning,” In Bioconductor case studies, Springer, New York, NY, pp. 137-157, 2008.

[17] L. Wang, S. Guo, W. Huang, and Y. Qiao, “Places205-vggnet models for scene recognition,” arXiv preprint arXiv:1508.01667, 2015.

[18] T. Shanthi, R. S. Sabeenian, and R. Anand, “Automatic diagnosis of skin diseases using convolution neural network,” Microprocessors and Microsystems, 103074, 2020.

[19] P. Ballester, and R. M. Araujo, “On the performance of GoogLeNet and AlexNet applied to sketches,” In Thirtieth AAAI Conference on Artificial Intelligence, 2016.

[20] M. Z Alom, M. Hasan, C. Yakopcic, T. M. Taha, V. K. Asari, and V. K. Asari, “Improved inception-residual convolutional neural network for object recognition,” arXiv 2017. arXiv preprint arXiv:1712.09888, 2020.

[21] F. Iandola, M Moskewicz, S. Karayev, R. Girshick, T. Darrell, and K. Keutzer, “Densenet: implementing efficient convnet descriptor pyramids,” arXiv preprint arXiv:1404.1869, 2014.

[22] R. Sachin, V. Sowmya, D. Govind, and K. P. Soman, “Dependency of various color and intensity planes on CNN based image classification,” In International Symposium on Signal Processing and Intelligent Recognition Systems, Springer, Cham, pp. 167-177, 2017.

[23] S. Srinivasan, V. Ravi, S. V, M. Krichen, D. B. Noureddine, S. Anivilla, and S. K. P, “Deep convolutional neural networks for image spam classification,” 2020 6th Conference on Data Science and Machine Learning Applications (CDMA), 2020.

[24] S. Visa, B. Ramsay, A. Ralescu, and E. V. D. Knaap, “Confusion matrix-based feature selection,” MAICS, 710, pp. 120-127, 2011.

[25] W. Zhu, N. Zeng, and N. Wang, “Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS implementations,” NESUG Proceedings: Health Care and Life Sciences, Baltimore, Maryland, 19, 67, 2010.
[26] P. Hu, F. Wu, J. Peng, Y. Bao, F. Chen, and D. Kong, “Automatic abdominal multi-organ segmentation using deep convolutional neural network and time-implicit level sets,” International Journal of Computer Assisted Radiology and Surgery, vol. 12, no. 3, pp. 399411, 2017