Predicting COVID-19 from Chest X-ray Images using a New Deep Learning Architecture

Zakariya A. Oraibi[†], Safaa Albasri[‡]
[†]Dept. of Computer Science, College of Education for Pure Sciences, University of Basrah, Basrah, Iraq
[‡]Dept. of Electrical Engineering, College of Engineering, Mustansiriyah University, Baghdad, Iraq

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Abstract

The spread of coronavirus disease in late 2019 caused huge damage to human lives and forced a chaos in health care systems around the globe. Early diagnosis of this disease can help separate patients from healthy people. Therefore, precise COVID-19 detection is necessary to prevent the spread of this virus. Many artificial intelligent technologies for example deep learning have been used for this task employing chest X-ray images. In this paper, we propose to classify chest X-ray images using a new end-to-end convolutional neural network architecture. The new model consists of six convolutional blocks, each block consists of one convolutional layer, one ReLU layer, and one max-pooling layer. The new model was applied on a challenging imbalanced COVID-19 dataset of 5000 images, divided into two classes: COVID and Non-COVID. In experiments, the input image is first resized to $256 \times 256 \times 3$ *before being fed to the model. Two metrics were used to test our new model: sensitivity and specificity. A sensitivity rate of 97% was achieved along with a specificity rate of 99.32%. Results show that our proposed model outperforms state-of-the-art deep learning methods in terms of specificity and produces comparable results in terms of sensitivity.*

I. Introduction

Biomedical image analysis and classification successfully thrived due to the use of artificial intelligence techniques and Covolutional Neural Networks (CNNs) [1][2][3]. These techniques are used to help doctors in diagnosing diseases. The coronavirus disease was first discovered in Wuhan, China in late 2019 and caused a global pandemic [4]. Millions of people died and hundreds of millions were infected by this virus which forced World Health Organization (WHO) to declare it a pandemic. The virus changed the life of people around the world and caused a global lockdown to maintain the spread of the disease [5]. In 2021, the effect of the virus was curbed by the introduction of COVID-19 vaccines which helped to reduce the number of deaths and infections among individuals.

Techniques that use machine learning algorithms and deep learning are powerful to classify patient chest X-ray images into COVID and Non-COVID. Since X-ray images are available in many clinics and diagnostic centers and acquiring them has been made easy, it has become easy for researchers to employ them for the task of detecting COVID-19 patients [6]. Methods that use deep learning architectures showed huge potential in the fields of image classification, detection, and segmentation. Furthermore, using deep learning technique helped to analyze huge amount of COVID-19 images in a short period of time without the need to consult a radiologist to perform this task [7].

Deep learning models in the literature that were applied for this task can be divided into two types: models that created a new deep learning architectures and trained them from scratch and models that used transfer learning on pretrained networks. For the first type, new architectures were proposed including DeTraC by Abbast et al. [8], PDCOVIDNet by Chowdhury et al. [9], 38 layers CNN model proposed by Reshi et al. [10], and an optimized deep learning model proposed by Pathan et al. [11] by employing a technique called Grey Wolf Optimizer (GWO) to optimize network parameters. All these methods showed

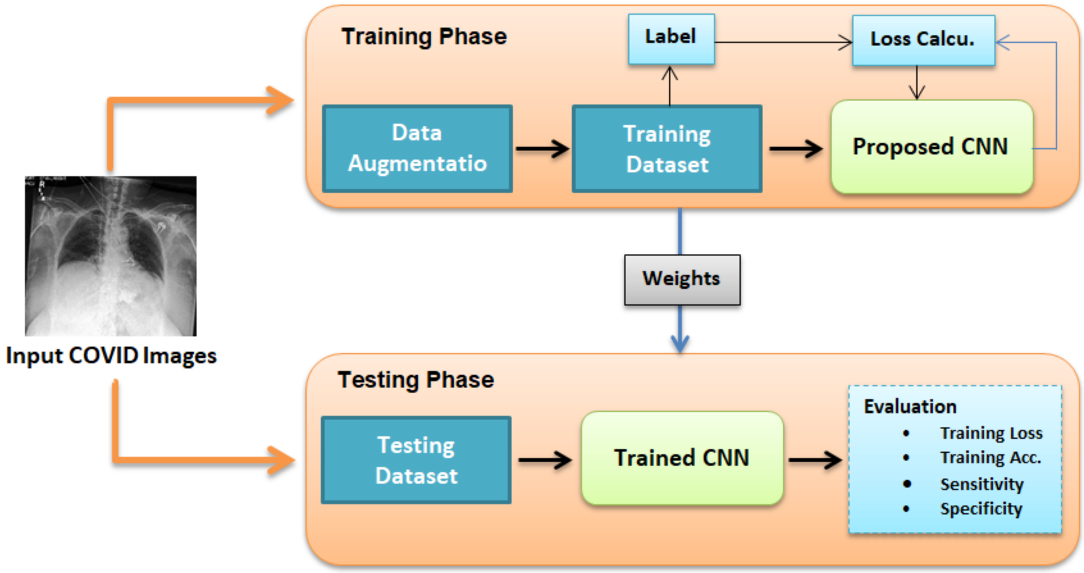

Fig. 1. COVID Classification Pipeline.

a higher COVID-19 classification accuracy.

The second type of models include the work of Ahuja et al. [12] that used pretrained models: ResNet18, ResNet50, ResNet101, and SqueezeNet. Khan et al. [13] also proposed to use four deep learning models with transfer learning, ResNet121, ResNet50, VGG16, and VGG19. In addition, Wang et al. [14] used Xception model with transfer learning to achieve a higher classification accuracy.

In this paper a new deep learning architecture is proposed to classify chest X-ray images into two classes: COVID and Non-COVID. Six convolutioanl blocks were used with each block consists of a one convolutional layer, one ReLU layer, and one max-pooling layer. In addition, regularization techniques were used to improve the performance of the new model by adding batch normalization and dropout. The new model requires input images to be resized to $256 \times 256 \times 3$. The performance of the new model was evaluated on a COVID-19 dataset that has 5000 images collected by Minaee et al. [15]. The model showed high sensitivity and specificity rates in comparison with other deep learning models applied on the same dataset.

The remaining sections of the paper are organized as follows: Section 2 describes the new architecture. Section 3 details the dataset used in our work and the experimental results. Finally, section 4 concludes the paper and highlights the future work.

II. Methodology

The new CNN architecture is presented in this section. Figure(1) shows the pipeline for the COVID-19 classification process. Data augmentation was also used on the original dataset in order to balance the number of training images in both classes. Figure (2) presents the proposed CNN architecture. This architecture was trained from scratched using X-ray images to predict COVID-19 patients.

The proposed architecture uses six convolutional blocks as illustrated in Figure (2). Each block consists of one convolutional layer followed by a ReLU as an activation function and a max-pooling layer. Fully connected layer is added at the end to perform the classification task. The model performance was further improved by adding batch normalization layer in each block and dropout. These regularization techniques prevent our model from overfitting during training stage. The advantage of going deep with CNN is to allow our model to efficiently learn complex features from the input COVID image. As a result, our model generates more convolutioanl maps. Convolutioanl operations and max-pooling are described in the following equations below:

$$f_{m,n} = \sum_{a=1}^{L} \sum_{b=1}^{D} f_{m+a,n+b} K_{a,b} \tag{1}$$

Eq. 1 shows the convolutional operation used in our experiments. M and N represent the dimensions of

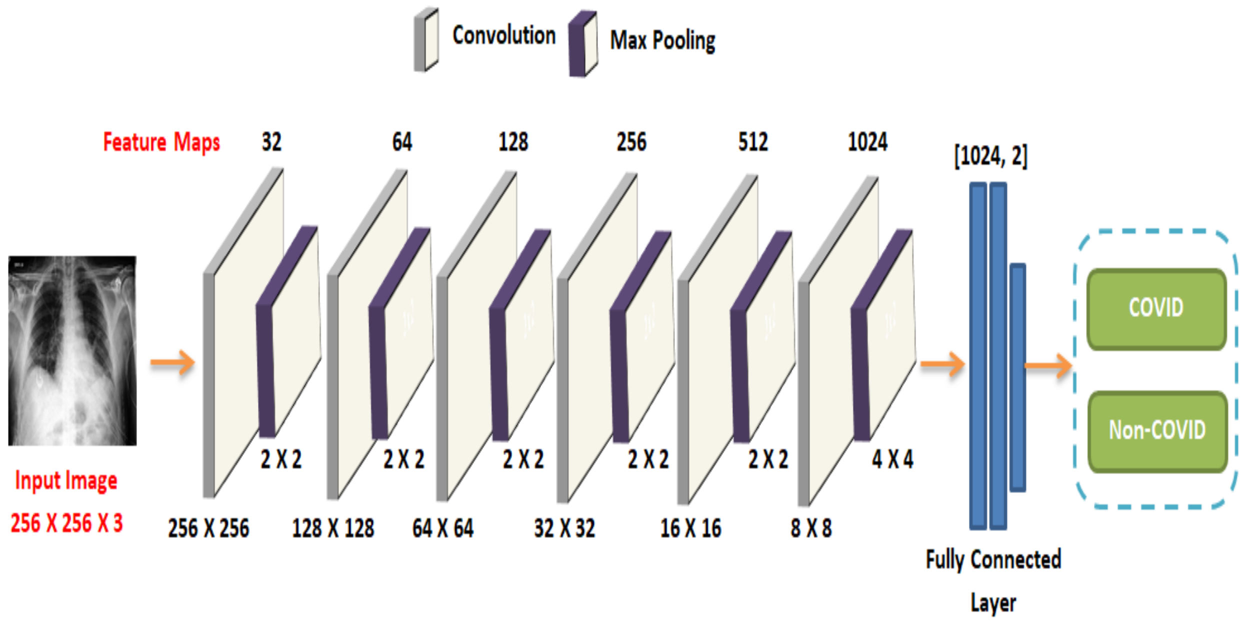

Fig. 2. The Proposed CNN Architecture. Six Convolutional Blocks are Used.

the input feature map f. A kernel of size $(L \times D)$ is employed and represented as K.

$$f_{m,n}^{max} = max_{a=1,..,wz,b=1,..,wz} f_{m+a,n+b} \quad (2)$$

Eq. 2 represents the max-pooling operations with wz represents the window size of max-pooling operation.

III. Experimental Results

A. Materials

A challenging COVID-19 dataset was used to evaluate our new CNN model. This dataset is called COVID-Xray-5k [15] and it was collected by Minaee et al. for research purposes. To collect the full dataset, authors used images from two different datasets. COVID-19 sample images were derived from another dataset called Covid-Chest-dataset [16]. On the other hand, Non-Covid samples were derived from a dataset called Chex-Pert dataset [17]. In total, we are provided with 2000 images for training and 3000 images for testing. Image samples of both classes are shown in Figure (3).

Because the number of training images are insufficient to train our model properly, augmentation was used to increase the number of images for both classes. Augmentation was performed using rotation, shifting, shearing, and zooming techniques. Finally, we increased the COVID class from 84 to 2134 images and the Non-Covid was increased from 2000 to 3480.

Metrics used to evaluate our new model includes both sensitivity and specificity. These metrics are commonly used in the field of biomedical image analysis and they are suitable to report classification results especially when we are provided with an imbalanced dataset. he equations to calculate both metrics are as written below:

$$Sensitivity = \frac{TCC}{TC} \quad (3)$$

where TTC is the number of images correctly predicted as COVID-19. TC is the total number of COVID-19 images.

$$Specificity = \frac{NCC}{NC} \quad (4)$$

where NCC is the number of images correctly predicted as Non-COVID. NC is the total number of Non-COVID images.

B. Results

In the implementation, PyTorch 1.11.0 machine learning framework was used. During the training stage, both Adam and SGD optimizers were used to check which one performs better. We have also used a batch size of $128 \times 128 \times 3$. The maximum number of

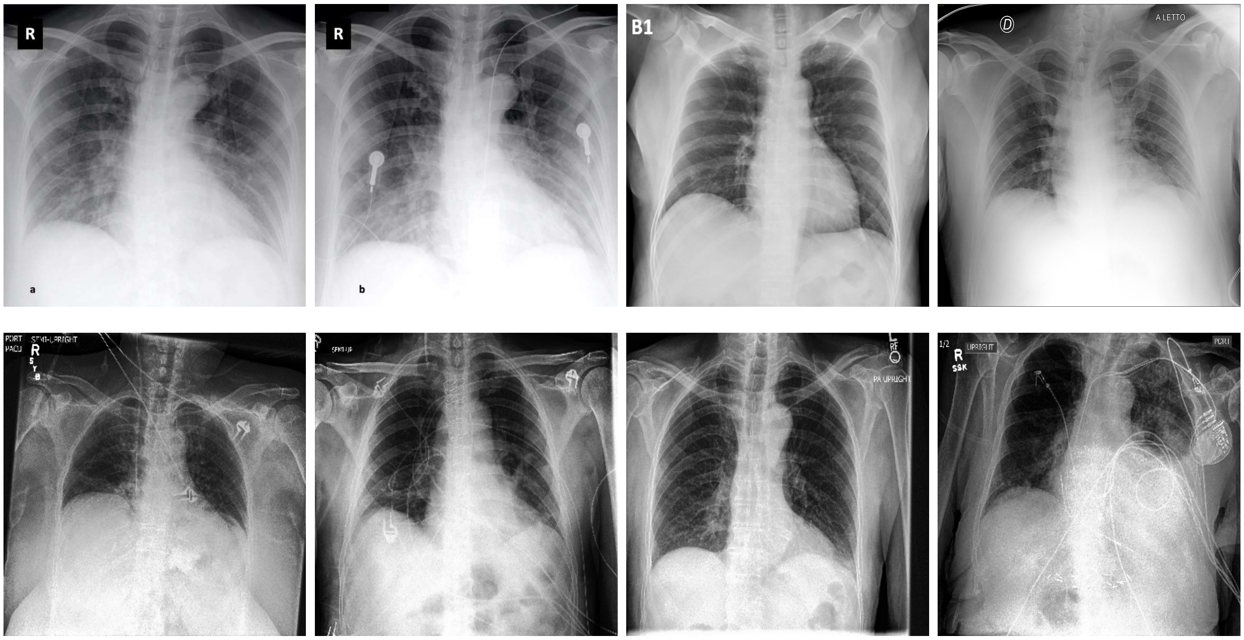

Fig. 3. Sample images from the COVID dataset. Samples of the first row are COVID-19 images. Samples of the second row are Non COVID-19 images.

epochs used were 15. In addition, we used two learning rate values, 0.001 and 0.0001 to evaluate the training performance. For the loss function, we used cross-entropy to evaluate the performance of the classification task. Finally, all experiments and analysis related to our model are done on the Google Colaboratory platform with a Tesla GPU.

Table I shows results using different optimizers and different learning rates. Moreover, batch normalization was used along with a dropout value of 0.1. From this table we can observe that the new model achieves best specificity rate (99.32%) with Adam optimizer and a learning rate of 0.001. On the other hand, the best sensitivity rate (97.0%) was achieved using SGD optimizer with a learning rate of 0.001. Figure (3) shows the training loss vs the validation loss during the training stage after 15 epochs.

TABLE I. Model Performance using Adam and SGD Optimizers.

Optimizer	Learning Rate	Sensitivity	Specificity
Adam	0.001	95.0%	**99.32%**
Adam	0.0001	95.0%	99.13%
SGD	0.001	**97.0%**	95.67%
SGD	0.0001	97.0%	87.34%

Table II shows a comparison between our new CNN model and the deep learning architectures performed on the same dataset. We can observe that our model achieves comparable results in terms of sensitivity with 97%. In addition, our model outperforms all the deep learning models in terms of specificity with 99.3%.

TABLE II. Comparison with State-of-the-Art Models.

Model	Sensitivity	Specificity
ResNet18 [18]	98.0%	90.7%
ResNet50 [18]	98.0%	89.6%
SqueezeNet [19]	**98.0%**	92.9%
Densenet-121 [20]	98.0%	75.1%
Proposed [Adam, 0.001]	95.0%	**99.32%**
Proposed [SGD, 0.001]	97.0%	95.67%

The advantage of using end-to-end deep learning model to perform COVID-19 classification task is that we perform training on the provided images only once. On the other hand, if we use deep features [1] we need to use another classifier to perform the classification task, hence we need to train two models (the CNN model and the traditional classifier). Furthermore, texture features [21][22] can be used in biomedical image analysis but the performance can not be guaranteed to outperform deep learning techniques.

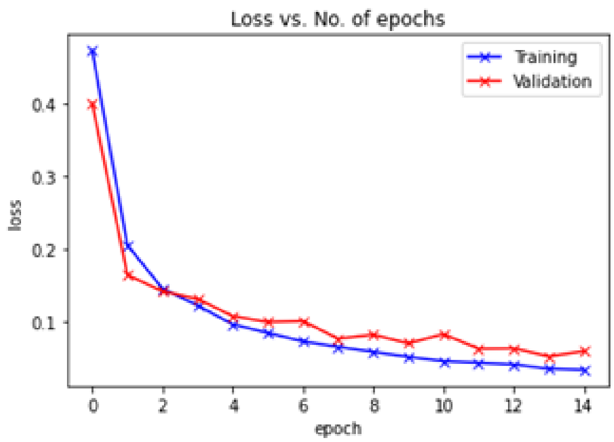

Fig. 4. Training Loss vs Validation Loss.

IV. Conclusions

A new deep learning architecture is introduced in this paper that uses few convlutional blocks to produce high COVID-19 classification accuracy. Only six convolutional blocks are employed with one convolutional layer per block. Furthermore, the performance of the new model was improved by adding batch normalization and dropout. Results conducted on a standard COVID-19 dataset of 5000 images showed high specificity and sensitivity rates compared to state-of-the-art deep learning models. The sensitivity rate achieved in our work is 97% and the specificity rate is 99.32%. For the future work, we intend to expand our model by adding residual layers in the convolutional blocks to further improve the performance. For the imbalanced data provided by the dataset, we plan to explore the possibility of generating new images using generative advarsarial neural networks and use them in the training stage.

References

[1] Z. A. Oraibi, H. Yousif, A. Hafiane, G. Seetharaman, and K. Palaniappan, "Learning local and deep features for efficient cell image classification using random forests," in *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 2446–2450, IEEE, 2018.

[2] V. S. Prasath, Y. M. Kassim, Z. A. Oraibi, J.-B. Guiriec, A. Hafiane, G. Seetharaman, and K. Palaniappan, "Hep-2 cell classification and segmentation using motif texture patterns and spatial features with random forests," in *Pattern Recognition (ICPR), 2016 23rd International Conference on*, pp. 90–95, IEEE, 2016.

[3] Z. A. Oraibi and S. Albasri, "Prediction of covid-19 from chest x-ray images using multiresolution texture classification with robust local features," in *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, pp. 663–668, IEEE, 2021.

[4] L. Pang, S. Liu, X. Zhang, T. Tian, and Z. Zhao, "Transmission dynamics and control strategies of covid-19 in wuhan, china," *Journal of Biological Systems*, vol. 28, no. 03, pp. 543–560, 2020.

[5] Z. A. A. Alyasseri, M. A. Al-Betar, I. A. Doush, M. A. Awadallah, A. K. Abasi, S. N. Makhadmeh, O. A. Alomari, K. H. Abdulkareem, A. Adam, R. Damasevicius, *et al.*, "Review on covid-19 diagnosis models based on machine learning and deep learning approaches," *Expert systems*, vol. 39, no. 3, p. e12759, 2022.

[6] M. E. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. Al Emadi, *et al.*, "Can ai help in screening viral and covid-19 pneumonia?," *IEEE Access*, vol. 8, pp. 132665–132676, 2020.

[7] A. Kumar, A. R. Tripathi, S. C. Satapathy, and Y.-D. Zhang, "Sars-net: Covid-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network," *Pattern Recognition*, vol. 122, p. 108255, 2022.

[8] A. Abbas, M. M. Abdelsamea, and M. M. Gaber, "Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network," *Applied Intelligence*, vol. 51, no. 2, pp. 854–864, 2021.

[9] N. K. Chowdhury, M. Rahman, M. A. Kabir, *et al.*, "Pdcovidnet: a parallel-dilated convolutional neural network architecture for detecting covid-19 from chest x-ray images," *Health information science and systems*, vol. 8, no. 1, pp. 1–14, 2020.

[10] A. A. Reshi, F. Rustam, A. Mehmood, A. Alhossan, Z. Alrabiah, A. Ahmad, H. Alsuwailem, and G. S. Choi, "An efficient cnn model for covid-19 disease detection based on x-ray image classification," *Complexity*, 2021.

[11] S. Pathan, P. Siddalingaswamy, and T. Ali, "Automated detection of covid-19 from chest x-ray scans using an optimized cnn architecture," *Applied Soft Computing*, vol. 104, p. 107238, 2021.

[12] S. Ahuja, B. K. Panigrahi, N. Dey, V. Rajinikanth, and T. K. Gandhi, "Deep transfer learning-based automated detection of covid-19 from lung ct scan slices," *Applied Intelligence*, vol. 51, no. 1, pp. 571–585, 2021.

[13] I. U. Khan and N. Aslam, "A deep-learning-based framework for automated diagnosis of covid-19 using x-ray images," *Information*, vol. 11, no. 9, p. 419, 2020.

[14] D. Wang, J. Mo, G. Zhou, L. Xu, and Y. Liu, "An efficient mixture of deep and machine learning models for covid-19 diagnosis in chest x-ray images," *PloS one*, vol. 15, no. 11, p. e0242535, 2020.

[15] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. J. Soufi, "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning," *arXiv preprint arXiv:2004.09363*, 2020.

[16] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, "Covid-19 image data collection: Prospective predictions are the future," *arXiv preprint arXiv:2006.11988*, 2020.

[17] J. Irvin, P. Rajpurkar, M. Ko, Y. Yu, S. Ciurea-Ilcus, C. Chute, H. Marklund, B. Haghgoo, R. Ball, K. Shpanskaya, *et al.*, "Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 590–597, 2019.

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

[19] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and ¡ 0.5 mb model size," *arXiv preprint arXiv:1602.07360*, 2016.

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

[21] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[22] Z. A. Oraibi, M. Irio, A. Hafiane, and K. Palaniappan, "Texture classification using multiple local descriptors," in *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, pp. 1–7, IEEE, 2017.