2020 IEEE Bombay Section Signature Conference (IBSSC) | 978-1-7281-8993-2/20/$31.00 ©2020 IEEE | DOI: 10.1109/IBSSC51096.2020.9332210

Covid Detection from CXR Scans using Deep Multi-layered CNN

1st Rajarshi Bhadra
Department of Electrical Engineering
Future Institute of Engineering and Management
Kolkata, India
rajarshi.bhadra.fiem.ee17@teamfuture.in

2nd Subhajit Kar, *Member, IEEE*
Department of Electrical Engineering
Future Institute of Engineering and Management
Kolkata, India
subhajit.kar@teamfuture.in

***Abstract*—Severe Acute Respiratory Syndrome Corona virus 2 (SARS-COV-2) also known as COVID-19 has been emerged as a pandemic throughout the globe recently. Therefore, accurate diagnosis of COVID-19 is necessary to fight against this pandemic situation. In this context, chest X-ray (CXR) scans play an important role in the diagnosis of the corona virus. In this paper, an intelligent detection and classification technique of COVID-19 has been proposed to assist doctors in their diagnostic prediction. A deep multi-layered convolution neural network (CNN) has been proposed to detect COVID-19 accurately from CXR scans. The proposed methodology has experimented on a combination of multiple open source publicly available datasets. Experimental results demonstrate the efficacy of the proposed methodology in COVID-19 detection from CXR images.**

***Index Terms*—COVID-19 Detection, CXR scans, Deep Learning, Multi-layered CNN**

I. Introduction

The outbreak of SARS-COV-2 at Wuhan in China spread rapidly across the world by early 2020. The World Health Organization (WHO) has termed it as COVID 19 and declared it as a pandemic in January, 2020 [1].Till Sep 12, 2020 around 28.3 million people have been affected by this virus and the numbers are increasing day by day.

Real time PCR test has been used now a days as a standard diagnostic tool for pathogenic test [2]. In this test, RNA from nasal or throat swab has been extracted. If the genetic sequence of this RNA is same with COVID-19, the result would be positive. However, in many cases, the patients are asymptotic but the outcome of their PCR test becomes covid positive [3]. Excessive testing would lead early detection of COVID-19 and thereby reduce the spread in the community [4].

Recently reported literature elaborates that different medical imaging modalities such as CT scans, X-rays plays important role in accurate detection of COVID-19 [5]–[10]. Rahimzadeh et al. proposed a concatenated CNN architecture using Xception and ResNet 50 V2 models for classifying COVID-19 cases using CXR images [5]. 180 images of COVID-19 patients, 6054 images of pneumonia patients and 8851 images of normal people have been used by the authors and 99.56% accuracy has been reported. An Artificial Intelligence-based system has been used by Alqudah et al. to classify COVID-19 cases from chest X-ray images [6]. The images have been classified by support vector machine, random forest and CNN technique and 95.2% accuracy have been reported. A Generative Adversarial Network (GAN) has been proposed by Loey et al. for the same purpose [7]. Three pre-trained models such as Alexnet, GoogleNet and ResNet18 have been used by them in the proposed meyhodology. Their system has been evaluated on 69 cases of COVID-19, 79 cases of pneumonia bacteria, 79 images of pneumonia virus and 79 cases of normal people. GoogleNet has been selected as main deep learning technique with 80.6% test accuracy for four classes, 99.9% test accuracy for two classes and Alexnet with 85.2% test accuracy for three classes. A transfer learning technique using Inception V3, ResNet50, MobileNet and Xception models has been proposed by Sethi et al. with 329 COVID-19 cases and 5298 normal cases [8]. More than 95% accuracy has been reported by them except using ResNet architecture. Islam et al. have proposed a CNN combined with Long Short Term Memory (LSTM) Network on 1525 COVID-19, 1525 pneumonia and 1525 normal chest X-ray images and 99% test accuracy has been reported [9]. DeTrac deep CNN has been proposed by Abbas et al. with 95% accuracy in COVID-19 detection [10].

The methodologies reported in the literature [5]–[10] performs the detection and classification on CXR scans using different complex neural network architectures like MobileNet, ResNet etc. These pre-trained neural network architectures may result good classification accuray but they are complex and takes more time to get trained. In contrast, a light weight less complex deep multi-layered CNN architecture has been proposed in this paper which not only gets trained significantly faster but also helps detecting COVID-19 cases more accurately. The proposed methodology has been implemented on 1330 images of COVID-19 cases, 1330 images of pneumonia cases and 1330 images of normal cases. The dataset has been split into training, validation and blind test sets in the ratio of 80 : 10 : 10. In this paper, 10-fold cross validation has been performed on training and validation sets. The blind testing has been performed on 10% data and this 10% data has never been used for training and validation purpose. This blind testing concept makes the proposed methodology robust. Experimental results demonstrate that the proposed light weight deep multi-layered CNN structure performs satisfactorily in COVID-19 detection in terms of blind test accuracy.

The rest of the paper has been organized as follows.

© IEEE 2021. This article is free to access and download, along with rights for full text and data mining, re-use and analysis.

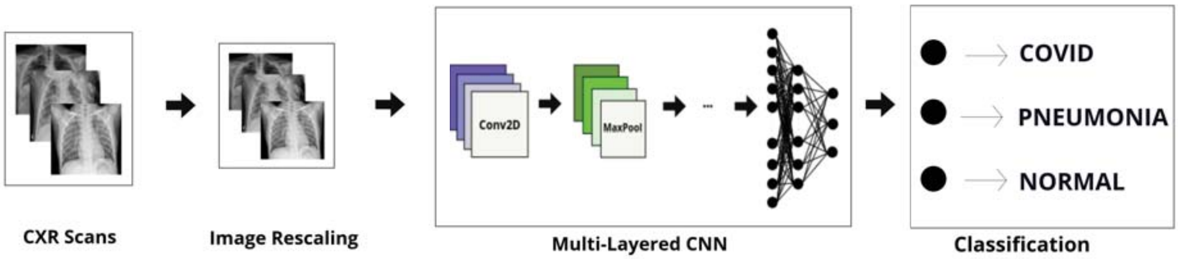

Fig. 1. Block Diagram of Proposed Methodology.

The proposed methodology has been described in section II. Section III describes the dataset used. The experimental results have been demonstrated in section IV. Section V shows novelty of our research and finally section VI concludes the paper.

II. Proposed Methodology

The block diagram of the proposed methodology has been shown in Fig. 1. First the non-uniform images have been scaled to maintain uniformity. Then the scaled images have been used as input to the proposed deep multi-layered CNN structure. Finally, the output layer performs the classification task.

The proposed deep multi-layered CNN having 5 layers has been elaborated in Fig. 2. Convolution operations of 3 x 3 kernels have been performed in each layer with unit stride sliding window and single padding. Rectified linear unit (ReLU) [11] has been used as the activation function. A 2 x 2 max pooling operation has also been performed to utilize the results of convolution operation from each layer into a more compact tensor. In the proposed technique, the three dimensional tensors have been converted to one dimensional feature vectors consisting 4096 neurons after the multi-layered structure. Thereafter, a dense layer of 128 neurons, a dropout layer consisting 50% dropout rate and an output layer consisting 3 neurons have been used. ReLU and Softmax has been used as activation functions in dense layer and output layer respectively. ReLU is defined as:

$$y = max(0, x) \tag{1}$$

where, x is the input to ReLU activation function and y is it's output. The SoftMax activation function is defined as,

$$\hat{y}_i = \frac{e^{y_i}}{\sum_{j=1}^{k} e^{y_j}} \tag{2}$$

where, y_i is i^{th} logit value, k is total number of logits, $\hat{y}_i$ denotes predicted probability of a particular sample. The probabilities of each class have been evaluated in the output layer of the proposed multi-layered CNN structure. A specific output node (Logit) having the highest probability value represents the classification of the corresponding class. A first order gradient-based optimization process known as Adam optimizer [12] has been used in the training phase of the proposed methodology to optimize the training process. The Adam optimizer is defined as:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{3}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{4}$$

where, m_t and v_t are estimates of the first moment (the mean) and the second moment (the uncentered variance) of the gradients respectively, g_t is gradient at time t, β_1 and β_2 are exponentially decay rates for moment estimates. The $\beta 1$ and $\beta 2$ values have been selected experimentally as 0.9 and 0.999 respectively. The categorical cross entropy loss has been used as cost function in the proposed algorithm. The cost function $J(\theta)$ can be defined as:

$$J(\theta) = -\sum_{c=1}^{M} y_{i,c} log(p_{i,c}) \tag{5}$$

where, M denotes number of classes, $y_{i,c}$ is a binary indicator (0 or 1) that indicates whether c is the correct class, $p_{i,c}$ denotes predicted probability between 0 and 1.

III. Dataset used

In this paper, CXR images of COVID-19 positive patients, pneumonia patients and non-covid patients have been used for detection and classification purpose. The images of covid positive CXR images have been collected from [13], [14] and from [15] and the CXR scans for pneumonia and non-covid patients have been collected from [16]. The dataset of [13] contains 886 CXR images of COVID-19 positive patients. As all the CXR scans in other datasets have Posterior-Anterior (PA) projections, only PA projected 180 images have been used from [13]. The dataset of [14] contains 238 CXR images of COVID-19 positive cases and [15] contains 912 augmented CXR images. The dataset of [16] contains 1583 CXR images of Normal Patients and 4273 CXR images of Pneumonia patients. To make the dataset balanced, 1330 CXR images of COVID-19, 1330 CXR images of Pneumonia and 1330 CXR images of Normal cases has been used from all the data sources. The CXR scans from the datasets are shown in Fig. 3.

IV. Experimental Result Analysis

A. Experimental setup

The dataset has been splitted in 80%, 10% and 10% for training, validation and testing. The results were obtained using 10-fold cross-validation (10-fold CV) technique. The initial learning rate has been selected as 0.0001 experimentally.

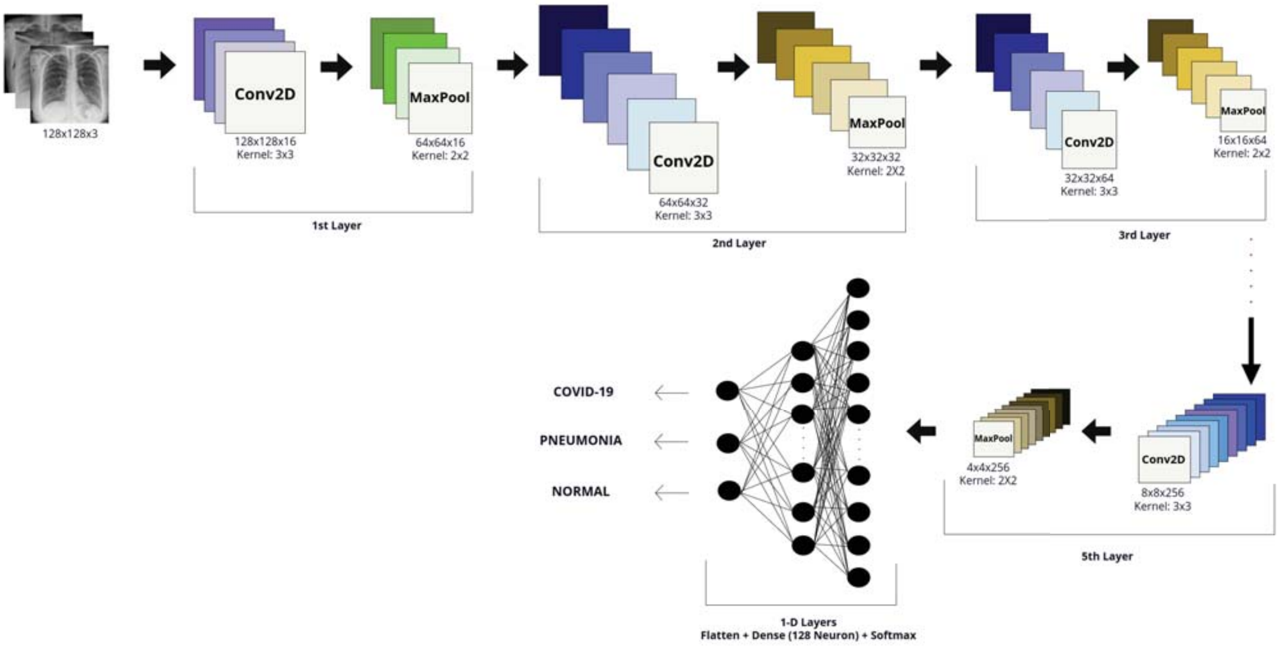

Fig. 2. Proposed Multi-layered CNN Architecture.

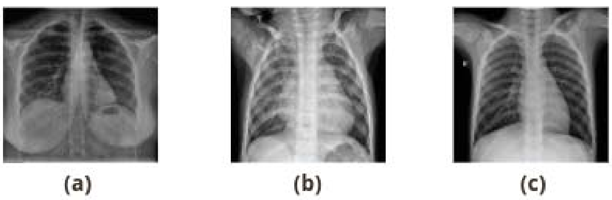

Fig. 3. CXR Scans. (a) Covid (b) Pneumonia (c) Normal

However, the learning rate is further decreased by a factor of 10 after every 10 epochs. The proposed training algorithm has been shown in Algorithm 1. The batch size of the proposed algorithm has been selected as 10 for 30 epochs experimentally. The CNN model has been implemented using Python3 and the Keras packages using Tensorflow2 on an AMD Ryzen 5 2400G (4 Cores, 8 Threads) CPU, NVIDIA RTX 2060 graphics card (6GB DDR6 VRAM, 192 bits), 16GB DDR4 RAM clocked at 3000mHz, 480 GB SSD (SATA Interface).

Algorithm 1: Proposed Training Algorithm

- Create a Multi-layered CNN with 1 Convolution layer & 1 MaxPool layer in each layer for 5 layers.
- Train using Adam Optimizer for 30 epochs.
- Reduce the learning rate by a factor of 10 after 10 epochs.

B. *Results Analysis*

In this paper the training, validation and testing have been performed on 3192, 399 and 399 images respectively. The test set has been evaluated as blind testing i.e. the test images have never been used for training and validation purpose. This blind testing formulation makes the proposed system more robust. The 10 fold training and validation performance has been shown in Fig. 4. A 10-fold CV training accuracy of 99.5 ($\pm$0.001)%, 10-fold cross validation accuracy of 97.6 ($\pm$0.011)% and blind test accuracy of 99.1% have been achieved by the proposed technique. The classification results have further been reconfirmed by precision, recall and f1 score in Table I. Furthermore, the classification result has been analyzed by calculating the confusing matrix shown in Fig. 5. The confusion matrix shows the number of blind test samples classified correctly and the recall values for each class. It represents that the proposed methodology performs satisfactorily on blind test dataset.

V. Discussion

The dataset has also been trained using different neural network architecture like VGG16, VGG19, Mobilenet, InceptionV3 and Resnet50. The comparative result has been shown in Table II. The proposed model takes less time to be trained and performed satisfactorily in terms of blind test accuracy. The hyper-parameters have been chosen experimentally in the proposed methodology. A dropout rate less than 50% results

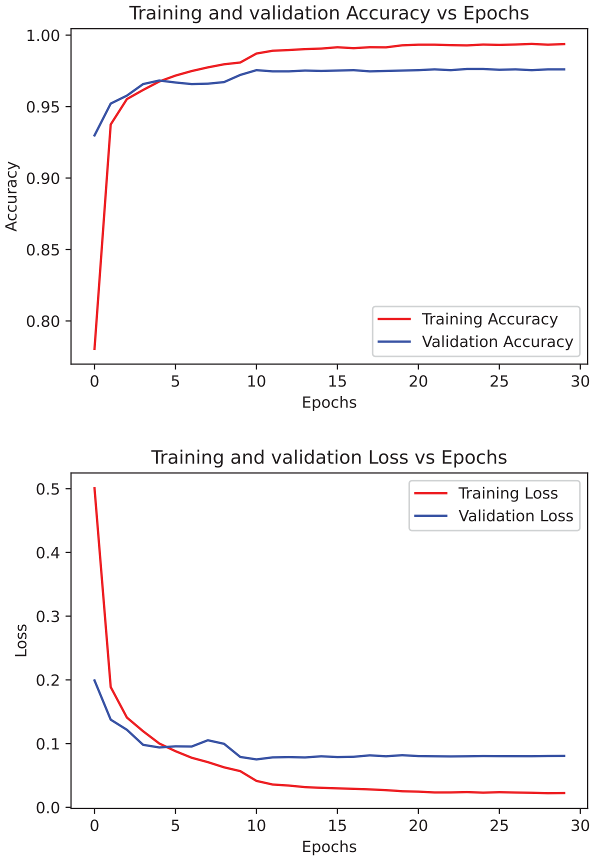

Fig. 4. Training & Validation Characteristics (10-fold CV).

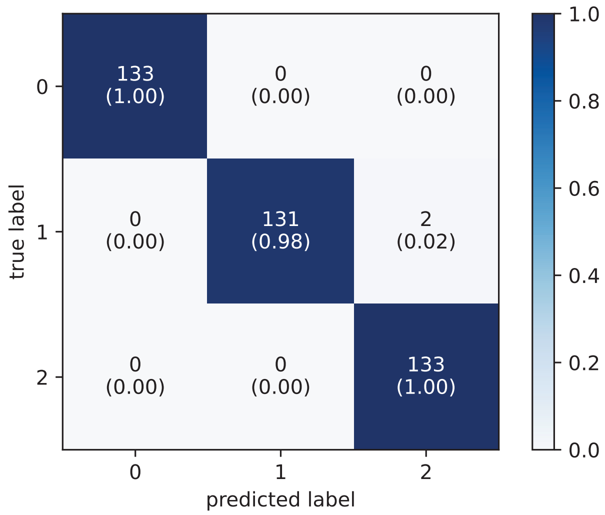

Fig. 5. Confusion Matrix. (0) Covid (1) Pneumonia (2) Normal

TABLE II
MODEL COMPARISON WITHOUT TRANSFER LEARNING

Model	Blind Test Accuracy	Training Time
VGG16 [17]	93.9%	549 seconds
VGG19 [18]	92.2%	668 seconds
Mobilenet [19]	98.8%	224 seconds
InceptionV3 [20]	99.5%	457 seconds
Resnet50 [21]	98.3%	537 seconds
Proposed	**99.1%**	**114 seconds**

over-fitting in the training process. Batch size of 10 has been selected as sweetest spot for getting good accuracy. A higher batch size results less training time with less classification accuracy.

VI. Conclusion

In this paper, a light weight multi-layered CNN architecture has been proposed to detect and classify CXR images of COVID-19 patients. 10-fold cross validation technique and blind testing have been performed in the proposed methodology to make the system more robust. A blind test accuracy of 99.1% has been obtained by the proposed technique. Therefore, the proposed methodology can be used as a second opinion for medical professionals with their diagnostic prediction of COVID-19. The data augmentation using Generative Adversarial Network can be used in future to increase the number of training images for better classification performance.

TABLE I
CLASSIFICATION PERFORMANCE

Training Accuracy (10-fold CV)	Validation Accuracy (10-fold CV)	Testing Accuracy (Blind)
99.5 ($\pm$0.001)%	97.6 ($\pm$0.011)%	99.1%

Class	Precision	Recall	F1-Score
Covid	1.00	1.00	1.00
Normal	0.99	0.98	0.99
Pneumonia	0.99	1.00	0.99

Sensitivity	Specificity
98.8 %	99.4%

References

[1] P. Chatterjee, N. Nagi, A. Agarwal, B. Das, S. Banerjee, S. Sarkar, N. Gupta, R. R. Gangakhedkar *et al.*, "The 2019 novel coronavirus disease (covid-19) pandemic: A review of the current evidence," *Indian Journal of Medical Research*, vol. 151, no. 2, p. 147, 2020.

[2] G. Pascarella, A. Strumia, C. Piliego, F. Bruno, R. Del Buono, F. Costa, S. Scarlata, and F. E. Agrò, "Covid-19 diagnosis and management: a comprehensive review," *Journal of Internal Medicine*, 2020.

[3] J. He, Y. Guo, R. Mao, and J. Zhang, "Proportion of asymptomatic coronavirus disease 2019: A systematic review and meta-analysis," *Journal of medical virology*, 2020.

[4] C. P. West, V. M. Montori, and P. Sampathkumar, "Covid-19 testing: the threat of false-negative results," in *Mayo Clinic Proceedings*, vol. 95, no. 6. Elsevier, 2020, pp. 1127–1129.

[5] M. Rahimzadeh and A. Attar, "A new modified deep convolutional neural network for detecting covid-19 from x-ray images," *arXiv preprint arXiv:2004.08052*, 2020.

[6] A. Alqudah, S. Qazan, H. Alquran, I. Abuqasmieh, and A. Alqudah, "Covid-2019 detection using x-ray images and artificial intelligence hybrid systems," 03 2020.

[7] M. Loey, F. Smarandache, and N. E. M Khalifa, "Within the lack of chest covid-19 x-ray dataset: A novel detection model based on gan and deep transfer learning," *Symmetry*, vol. 12, no. 4, p. 651, 2020.

[8] R. Sethi, M. Mehrotra, and D. Sethi, "Deep learning based diagnosis recommendation for covid-19 using chest x-rays images," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*. IEEE, 2020, pp. 1–4.

[9] M. Z. Islam, M. M. Islam, and A. Asraf, "A combined deep cnn-lstm network for the detection of novel coronavirus (covid-19) using x-ray images," *Informatics in Medicine Unlocked*, p. 100412, 2020.

[10] A. Abbas, M. M. Abdelsamea, and M. M. Gaber, "Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network," *arXiv preprint arXiv:2003.13815*, 2020.

[11] R. Arora, A. Basu, P. Mianjy, and A. Mukherjee, "Understanding deep neural networks with rectified linear units," *arXiv preprint arXiv:1611.01491*, 2016.

[12] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[13] J. P. Cohen, P. Morrison, and L. Dao, "Covid-19 image data collection," *arXiv 2003.11597*, 2020. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset

[14] https://github.com/agchung/Actualmed-COVID-chestxray-dataset.

[15] S. Alqudah, Ali Mohammad; Qazan, "Augmented covid-19 x-ray images dataset," *Mendeley Data, V4*, 2020.

[16] P. Mooney, "Chest x-ray images (pneumonia)," https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

[17] S. Tammina, "Transfer learning using vgg-16 with deep convolutional neural network for classifying images," *International Journal of Scientific and Research Publications (IJSRP)*, vol. 9, p. p9420, 10 2019.

[18] M. Shaha and M. Pawar, "Transfer learning for image classification," in *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2018, pp. 656–660.

[19] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," *CoRR*, vol. abs/1704.04861, 2017. [Online]. Available: http://arxiv.org/abs/1704.04861

[20] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," 2015.

[21] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *CoRR*, vol. abs/1512.03385, 2015. [Online]. Available: http://arxiv.org/abs/1512.03385