Automatic COVID-19 Detection from X-Ray images using Ensemble Learning with Convolutional Neural Network

AMIT KUMAR DAS[1,2], SAYANTANI GHOSH[1], SAMIRUDDIN THUNDER [2], ROHIT DUTTA [2], SACHIN AGARWAL [2] and AMLAN CHAKRABARTI [1]

[1] A. K. Choudhury School of Information Technology, University of Calcutta, Kolkata, India
[2] Institute of Engineering & Management, Kolkata, India
email: amitkrdas.kol@gmail.com; sayantani31g@gmail.com; samirtd2000@gmail.com; rohitdutta2510@gmail.com; agarwalsachin518@gmail.com; acakcs@caluniv.ac.in

Abstract. Covid-19 continues to have catastrophic effects on the lives of human beings throughout the world. To combat this disease it is necessary to screen the affected patients in a fast and inexpensive way. One of the most viable steps towards achieving this goal is through radiological examination, Chest X-Ray being the most easily available and least expensive option. In this paper we have proposed a Deep Convolutional Neural Network based solution which can detect the Covid-19 +ve patients using chest X-Ray images. To test the efficacy of the solution we have used publicly available chest X-ray images of Covid +ve and -ve cases. 538 images of Covid +ve patients and 468 images of Covid -ve patients have been divided into 771 trainable images and 235 testing images. Our solution gave a classification accuracy of 95.7% and sensitivity of 98% in the test set-up. We have developed a GUI application for public use. This application can be used on any computer by any medical personnel to detect Covid +ve patients using Chest X-Ray images within a very few seconds.

Keywords. Coronavirus; Covid-19; Ensemble Learning; Deep Learning; Convolutional Neural Network

1 Introduction

Coronavirus, as confirmed by WHO [1], records the first official case in Wuhan, the largest metropolitan area of the Hubei province in China. It has already taken several thousands of lives till date and has millions of confirmed cases across the world. An epidemic which took the shape of a pandemic, has a catastrophic effect on health and welfare of the global population. This has caused Severe Acute Respiratory Syndrome coronavirus (SARS-CoV) and the infirmity is known as coronavirus disease 2019 (acronym Covid-19) [3]. This coronavirus belongs to the same family as that of SARS and MERS, but with a more virulent and aggressive nature (2019-nCoV). This contagious infection spreads much faster (through respiratory droplet infection) than other normal flu.

Right now, the majority of tests being used to diagnose Covid-19 are genetic tests known as Reverse Transcription Polymerase Chain Reaction (RT-PCR). These tests are very accurate. Even if there is only a tiny amount of virus in the patient sample, it can be detected and measured. However, it is worth noting that PCR test is very complicated, time consuming and costly. So not all healthcare facilities have the ability to perform it. Perceiving these limitations, a stand-in approach to detect the disease can be radiography scanning, where chest radiography images can be analyzed to detect the presence of, or the symptoms of the novel coronavirus. Studies show that viruses belonging to this family demonstrate significant manifestation in radiographic images [2], [5], [6], [7], [10], [12], [14], [18]. Therefore, it can be said that classification with the help of radiographic images, such as chest X-ray (CXR), can be accurate but at the same time much faster and less expensive than the PCR test. Furthermore, chest X-rays are economical than other radiological tests like CT scans and available in almost every clinic.

The only perceived challenge in CXR-based detection of Covid-19 patients is that trained doctors may not be available all the time, especially in remote areas. Also, the radiological manifestations related to Covid-19 are new and unfamiliar with many experts not having past experience with Covid-19 positive patient CXRs. So, we have proposed a simple and inexpensive deep learning based technique to classify Covid-19 +ve and -ve cases using CXR images. Using this technique a near-accurate detection of Covid-19 positive patients can be done in a few seconds. As a part of this research, we have also contributed a tool which can be used to detect Covid-19 positive patients. Even in the absence of a radiologist or if there any difference in opinions of the doctors, this deep learning based tool will always give an opinion without the need of human intervention. In this article, with the data available from open sources we have shown the efficacy of the proposed tool in terms of the classification accuracy and the sensitivity. It has also been compared with some existing benchmark works by other researchers.

There are few works which have used only the individual deep learning techniques with CXR images [2], [31], [32] to make Covid-19 +ve and -ve prediction. One work has attemted to develop a custom network [5]. But our work is focused on using multiple state-of-the-art deep learning models and then ensembling them to achieve a better accuracy. It is based on the simple philosophy that an ensemble of multiple models provide better performance compared to individual models [4].

The remaining part of the paper is organized as follows:

- Section 2 lays down the related research, their approaches and their methodology.
- Section 3 contains details about our proposed technique along with some context around the state-of-the-art models that we have used.
- In Section 4 we have discussed about experimental set-up used in our research.
- Section 5 presents the experimental results including classification accuracy, sensitivity and F1-score obtained from the proposed work.
- Finally in section 6, the paper has been concluded with a summary of outcome of our research.

2 Related works

Studies show that Chest X-Ray (CXR) images, Computed tomography (CT) scans, Magnetic Resonance Imaging (MRI) scans are considered in improving the analysis of presence of viruses in the lungs. In multiple works, deep learning based techniques have been developed to identify pneumonia, different classes of thoracic diseases [10], [11], [12], [12], skin cancer [22], haemorrhage classification [23], etc. from medical images. Some of these works have given promising results with relatively simple architecture [10].

In a work [9], a convolutional neural network (CNN) model has been used to identify Covid-19 patients with the help of CT scan images. There are several more research works to detect the presence of Covid-19 virus in the human lungs with the help of CT scan [9], [18], [19], [20]. In [18], a multi-task, self supervised AI model have been developed for the diagnosing of the Covid-19 virus in human lungs with the help of CT scan images, with an accuracy of 89%. An automatic segmentation and quantification of the lungs is done in [19]. [20] describes a fully automatic framework to detect coronavirus affected lungs from chest CT scan images and differentiated it from other lung diseases. However, [16] and [17] have concluded that CXR images are better than any other means in the detection of Covid-19 because of their promising results along with the availability of CXR machines and their low maintenance cost.

There have been multiple works done by researchers in the area of Covid-19 patient detection using CXR images. In one such work [2], transfer learning have been used with Inception-v3 network to classify normal, pneumonia and Covid-19 patients using CXR images. Another work [6] has used the DenseNet with ChexNet architecture to seggregate normal subjects, bacterial and viral pneumonia patients and Covid-19 patients. [7] has used a concatenated Xception and ResNet50 v2. Another work [8] has used ResNet to detect viral pneumonia and Covid-19 patients. Unavailability of large number of image data of Covid-19 +ve patients is a challenge faced by most researchers working in this area. Development of CovidGAN for the generation of data artificially has been done in a work [21] - which in turn will help in improved Covid-19 detection.

Apart from using individual state-of-the-art deep learning models, there has been one work [5] which has developed a custom architecture termed as CovidNet architecture for the classification of Covid-19 patients, healthy subjects and pneumonia patients. This custom network, designed using a lightweight projection-expansion-projection-extension (PEPX) design pattern, has demonstrated a classification accuracy of 94% - a result that outperforms laboratory testing.

As can be observed, most of the works related to Covid-19 detection from CXR images have utilized individual deep learning models e.g. DenseNet, ResNet, Xception, etc. None of the works have tried to combine the models to multiply their capability of classification. Various works done on Ensemble Learning with Deep Neural Networks show that ensembling learning methods are superior in prediction than an individual model and also helps in preventing overfitting[36]. In [37], a weighted average of the output probabilities have been introduced as a method for ensembling. It is found to be better than unweighted average. In another work [38], relative performance of the different ensemble methods with Convolutional Neural Networks like unweighted average, majority voting, Bayes Optimal Classifier and Super Learner have been compared. In this research we have proposed a new method to ensemble three state-of-the-art CNN models - DenseNet201, Resnet50V2 and Inceptionv3 to classify Covid-19 +ve patients from CXR images.

3 Proposed Approach

In real life, we always prefer to come up with medical diagnosis based on multiple medical expert views. Combined opinion of the medical experts help in reaching to a more reliable conclusion. Following the same philosophy, multiple benchmark CNN models have been adopted in our proposed work. They have been trained individually to make independent predictions. Then the models are combined, using a new method of weighted average ensembling technique, to predict a class value. This new proposed ensembling method is expected to make the prediction more robust. Our proposed work comprises of three pre-trained CNN models - DenseNet201 [33], Resnet50V2 [34] and Inceptionv3 [35]. The biggest advantage of Dense Convolution Network or DenseNet, shown in Fig. 1, is that it requires comparatively fewer parameters than similar types of traditional CNN. An additional reason to choose DenseNet is that each layer takes the feature maps of all preceding layers as inputs. This helps to strengthen feature propagation and encourages feature reuse. ResNet50v2, shown in Fig. 3, is a contemporary convolutional network which is easier to train than any

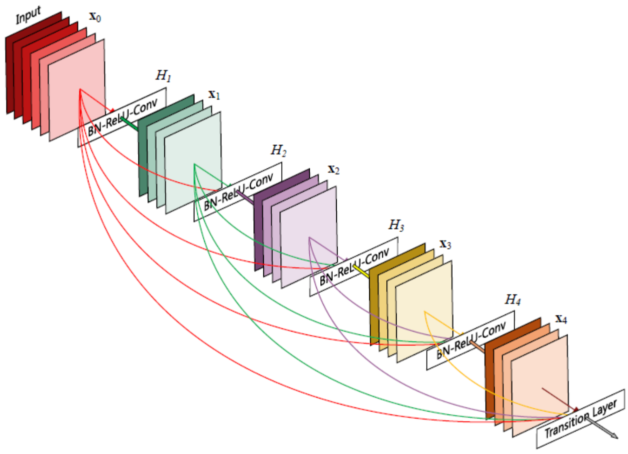

Figure 1. DenseNet architecture [33]

other deep convolutional neural networks, yields greater accuracy and converges faster. It also addresses the vanishing or exploding gradient problems by the use of "residual blocks" in the architecture. In a residual network, multiple residual blocks stacked up one after another. Each residual block, shown in Fig. 2, is formed of short-cut connections skipping one or more layers. In ResNet50, 3-layer residual blocks are used. The Inception model, shown in Fig. 5,

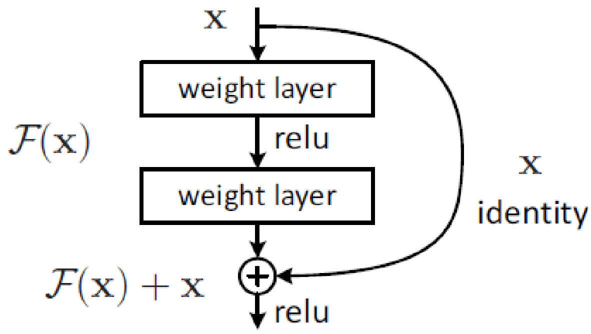

Figure 2. Residual block [34]

is the most prominent model that can accomplish very high accuracy to extract the features and classify images based on those features. Inception v3 has a 48-layer deep architecture consisting of 11 inception modules. Each inception module, shown in Fig. 4, consists of convolution filters, pooling layers and ReLU (Rectified Linear Unit) activation function. As a means of regularization, before a fully connected layer, a dropout of 0.6 is added.

One salient point in our proposed approach is that we have used a new weighted average based ensembling method to combine individual CNN models. In this method, if one

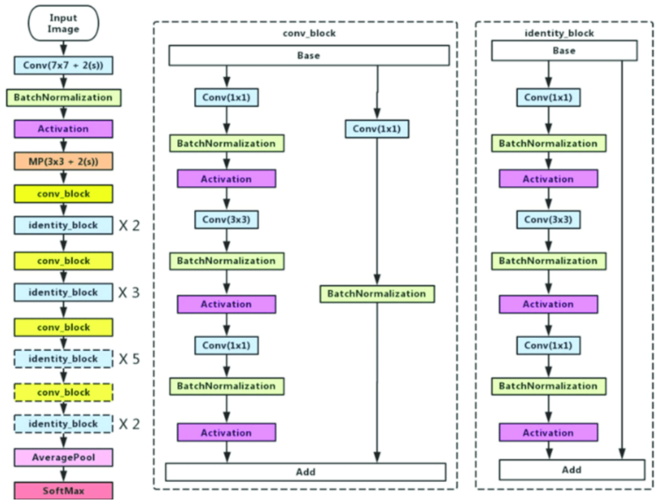

Figure 3. ResNet architecture [34]

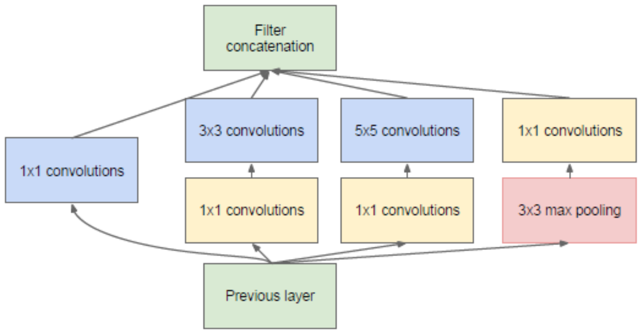

Figure 4. Inception module [35]

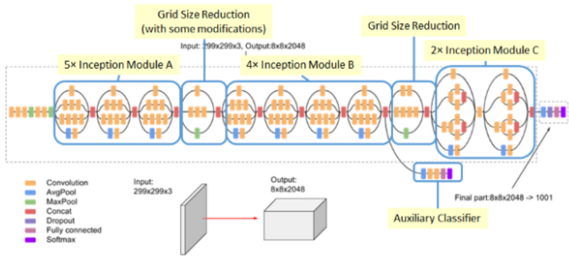

Figure 5. Inceptionv3 architecture [35]

model, say ResNet50v2, is performing better than the other two models i.e. having lower validation error, it is assigned a higher weight so that its contribution in deciding the class value is higher. Assuming the accuracy percentage of the i-th model as a_i, the validation error is (100 - a_i). We define a factor k_i as below:

$$d_i = 100 - a_i \quad (1)$$

$$D = \sum {d_i}^2 \quad (2)$$

$$k_i = \frac{{d_i}^2}{D} \quad (3)$$

Weight of the i-th network is defined as:

$$w_i = \frac{\frac{1}{{k_i}^2}}{\sum \frac{1}{{k_i}^2}} \quad (4)$$

Let us assume that the output from the neural networks are of the form $[y_0, y_1]$, where y_0 denotes the probability of Class 0 and y_1 denotes the probability of Class 1. Let the predictions from the three different models be of the form $[y_{01}, y_{11}]$, $[y_{02}, y_{12}]$, $[y_{03}, y_{13}]$ for models 1, 2 and 3 respectively. Let the weights calculated using the proposed method mentioned in equation 4 be $[w_1, w_2, w_3]$ for the models respectively. Then the weighted probability is calculated as:

$$Average = [\frac{w_1 \times y_{01} + w_2 \times y_{02} + w_3 \times y_{03}}{w_1 + w_2 + w_3}, \frac{w_1 \times y_{11} + w_2 \times y_{12} + w_3 \times y_{13}}{w_1 + w_2 + w_3}]$$

The overall proposed approach, as summarized in Fig. 6, includes:

- Consolidation of CXR images for healthy subjects, patients having pneumonia or other bacterial infection and Covid patients from different sources
- Retaining only frontal CXR images
- Resizing images to a uniform size
- Divide the images into two portions - one major portion to train the models and another portion for testing the efficacy of the trained model
- While dividing the images into training and testing, ensure that there is no patient overlap i.e. different images of the same patient is not present in both training and testing datasets
- Train the models - DenseNet201, ResNet50v2 and Inceptionv3
- Run the trained models on the test images and select class label value 0 or 1 based on weighted average ensembling of the 3 models

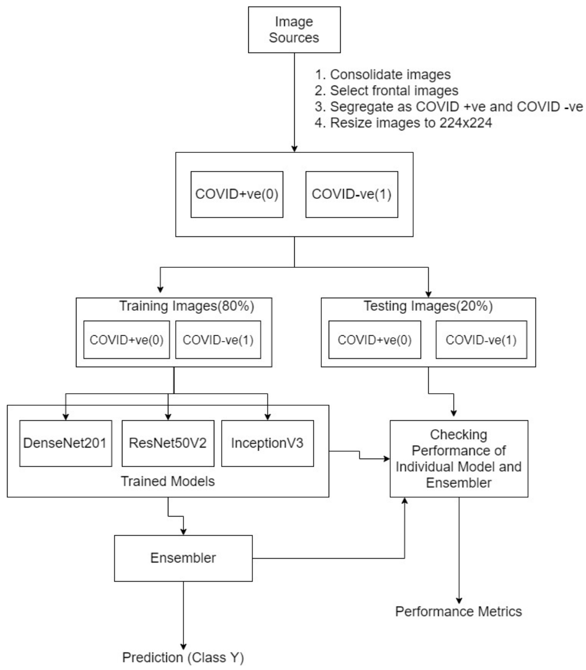

Figure 6. Proposed approach

4 Methods and Materials

4.1 *Dataset Generation*

For this research work, we have collected the images from different open sources [24], [25], [26], [27], [28], [29], [30]. These open source public datasets contain CXR images of Covid-19 positive patients, patients having pneumonia and other infections, primarily collected from European countries. This data contains CXR images of different patients from which only the frontal images are considered and lateral images are discarded. This is because our region of interest is lungs and lungs can be better examined with a frontal view than a lateral one. The original set of CXR images are labelled as COVID-19, Pneumonia and Normal. However, for this work we have segregated the images into two broad categories - COVID-19 POSITIVE (referred as class 0) and COVID-19 NEGATIVE (referred as class 1). For Class 0 there are 538 images similar to images shown in Fig. 7 whereas for Class 1 there are 468 images of Covid negative patients similar to images in Fig. 8.

4.2 *Pre-processing*

The consolidated images are first normalized and resized into 224×224 shaped images. Then the images are shuffled and splitted into training and testing data, where the test size is 20% and the rest are for training purposes. Thus the training data has 771 images where 438 images are for class 0 and 333 images are for class 1. The testing data has 235 images where 100 images are for class 0 and 135 images for class 1. However, if there are 2 or more images of the same patient, it is ensured that those images are either marked as training data or as test data - but not in both. In case the same patient's images are kept both in training and test data, there is a possibility that the results will be overly promising because of patient overlap. With this, the image folders are ready for training the model followed by testing the efficacy of the trained model.

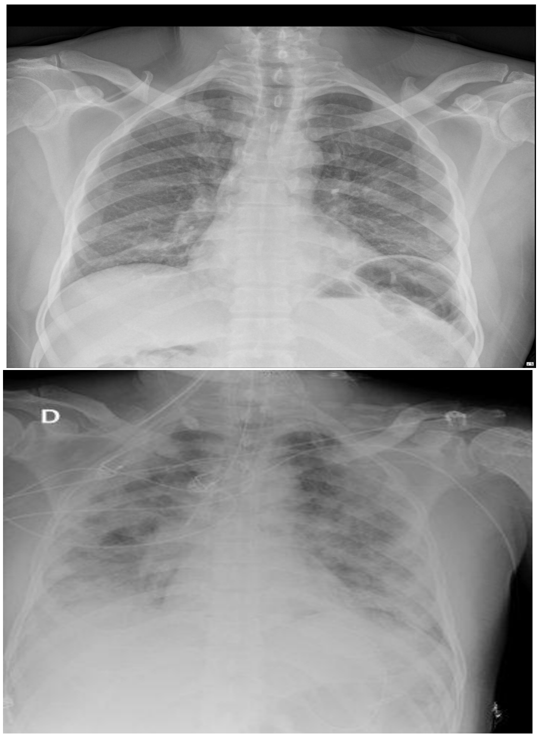

Figure 7. CXR images of Covid-19 positive subjects [29]

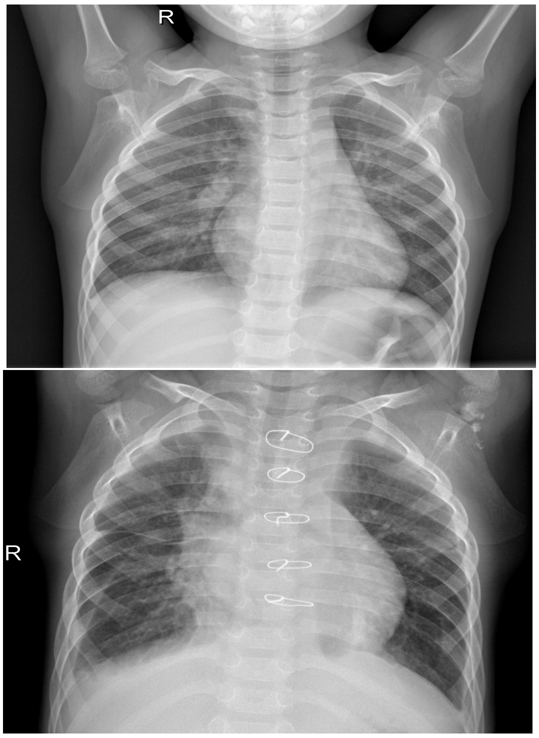

Figure 8. CXR images of Covid-19 negative subjects [27]

4.3 *Tools Used*

We have used Google Colab GPU (Tesla K80 12GB GDDR5 VRAM), Python 3.7 and TensorFlow 2.2.0. For the implementation of CNN, the deep learning library of TensorFlow 2.2.0 is used and the training and the testing procedures are done in Google Colab platform.

4.4 *Performance Metrics*

To evaluate the performance of the proposed approach, the metrics adopted are classification accuracy, sensitivity and F1-score, measured as follows:

Classification accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

Sensitivity = $\frac{TP}{TP+FN}$

F1 Score = $\frac{2 \times sensitivity \times precision}{sensitivity+precision}$

where TP stands for True Positive, FP for False Positive, FN for False Negative and TN for True Negative. In a confusion matrix, the Covid-19 +ve cases that are correctly classified by the model are termed as True Positive and incorrectly classified as Covid -ve are termed as False Positive. Similarly, Covid -ve subjects classified correctly are termed as True Negative and incorrectly classified as Covid +ve are termed as False Negative.

4.5 *Compared ensemble techniques*

In this paper we have proposed a new weighted average based ensemble technique. However, alongside the results from the individual networks used in the ensemble, we have also compared the results from the from proposed algorithm with the other ensemble algorithms. There are three commonly used ensemble techniques with which we have compared our proposed work.

- Unweighted average approach [38] which takes unweighted average of the output score / probability for all the base learners to generate the predicted score / probability.
- Weighted average approach (by accuracy) [37] which calculates the weights based on the accuracy as shown below:
$$w_i = \frac{A_i}{\sum A_i} \tag{5}$$
- Weighted average approach (by ranked accuracy) [37] which calculates the weights based on ranked accuracy as shown below:
$$w_i = \frac{R(A_i)}{\sum R(A_i)} \tag{6}$$

5 Experiments and Results

All the models have been trained for 60 epochs with Early Stopping callbacks (patience = 10 epochs). Adam optimizer, a combination of SGD with momentum and RMSProp, is used for faster convergence with the parameters as learning rate $\alpha = 0.0001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 1 \times 10^{-7}$.

The same optimiser is used for all the three models and then the models are saved as .h5 files. The time taken for model training are - 31 seconds / epoch for DenseNet201 and 17 seconds / epoch for the each of the models ResNet50v2 and Inceptionv3.

In Fig. 9, 10 and 11 the gradual change in loss (both training as well as validation / testing) through the epochs have been depicted for all the three models DenseNet201, ResNet50 and Inceptionv3 respectively. This illustrates that Inceptionv3 has the lowest loss while training the models.

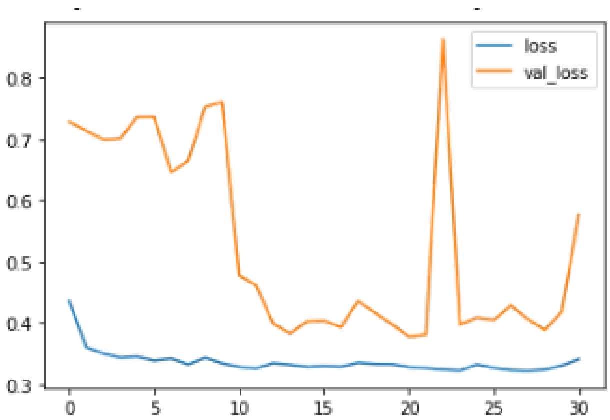

Figure 9. Training and validation loss of DenseNet201

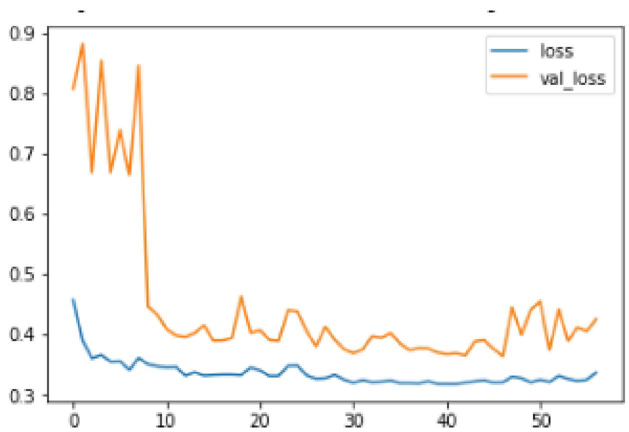

Figure 10. Training and validation loss of ResNet50v2

The confusion matrix, presented in Fig. 12 shows that out of 100 Covid +ve patients, 98 have been correctly diagnosed by our proposed model from the CXR images. Only 2 out of 100 Covid +ve patients have been wrongly classified as Covid -ve. Similarly, out of 135 Covid -ve patients, 127 patients have been correctly diagnosed from the CXR images. Only 8 patients have been wrongly identified as Covid +ve.

The table 1 shows the summarization of parameters, validation accuracy, sensitivity and F1-score of the state-of-the-art CNN model and our proposed model. It is evident from the summary that the performance of our proposed solution, is better than the individual models. The closest performance is that of ResNet50v2.

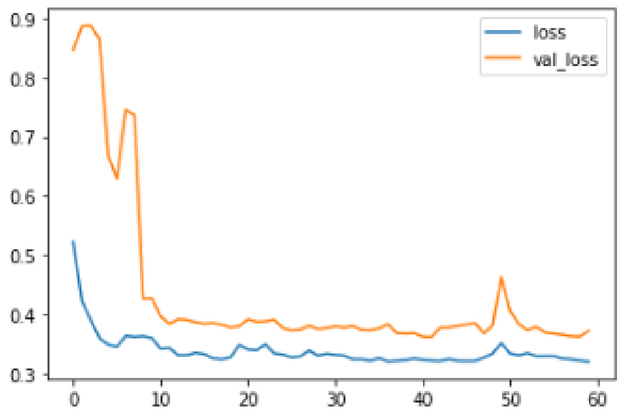

Figure 11. Training and validation loss of Inceptionv3

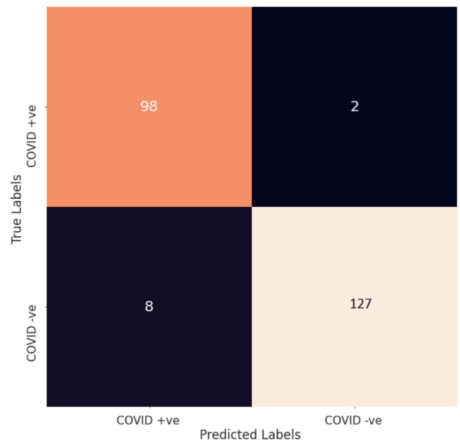

Figure 12. Confusion matrix for the ensembling

Table 1. Summary of performance

Models	**Parameters**	**Validation Accuracy**	**Sensitivity**	**F1-Score**
Individual networks				
DenseNet201	18,325,826	93.6%	92%	94.4%
ResNet50_v2	23,568,898	95.3%	**98%**	95.8%
Inception_v3	21,806,882	94%	93%	94.8%
Ensembled networks				
Unweighted average		94.5%	95%	95.1%
Weighted average (accuracy)[37]		94.5%	95%	95.1%
Weighted average (rank)[37]		95.3%	97%	95.8%
Proposed Approach		**95.7%**	**98%**	**96.2%**

5.1 *The Prototype Tool*

Based on the proposed solution, a simple desktop tool for the detection of Covid-19 positive and negative cases has been developed. This allows any medical personnel to browse a chest X-ray image and feeding it to the application. The application in turn will execute the model proposed in this work and provide the label for the given Chest X-Ray image. As a result, this will detect the Covid +ve and Covid -ve cases along with their probabilities as shown in Fig. 13. This can be used on platforms like Windows, Mac and Linux. This interface can be used in any Covid-19 testing centres or other health facility for fast detection of the disease. This ready to use tool along with the underlying code for data preparation and model training is available publicly at `https://github.com/CUIEMCovidProject/COVID-19-Detection-Using-Ensemble-Learning`.

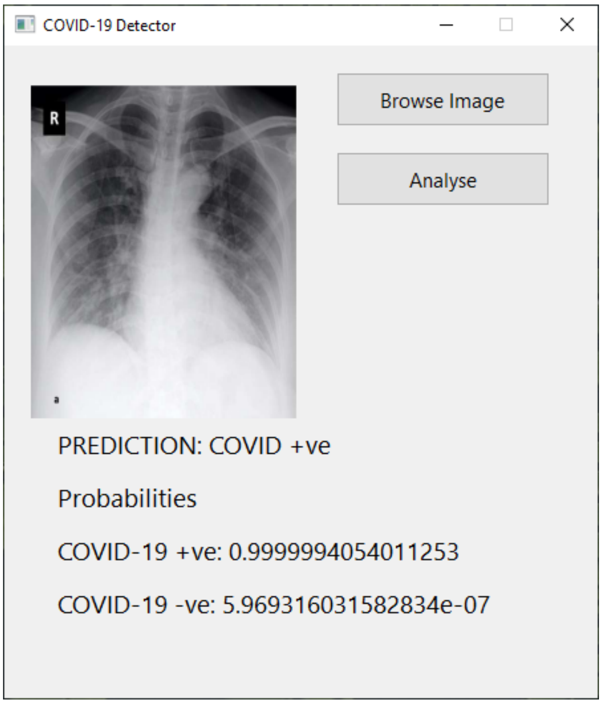

Figure 13. GUI-based tool for Covid-19 detection

6 Conclusion

Fast and timely detection of Covid +ve patients are necessary to avoid spreading of the disease and keeping it in control. This research work has been done to detect the Covid +ve patients from Chest X-Ray images in a simple and inexpensive way. In the work proposed in this paper, three state-of-the-art deep learning models have been adopted and ensembled. The proposed model has achieved a classification accuracy of 95.7%. Even more important fact is it has given a sensitivity of 98% i.e. out of 100 Covid +ve patients, 98 can correctly diagnosed by our proposed model. It is believed that this research work along with the GUI interface will help the doctors to detect the affected patients with the help of computer aided analysis, that too within a few seconds. We do believe that this will significantly add a value in the medical field.

7 Acknowledgements

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References

[1] WHO - Emergencies preparedness, response. World Health Organization. (2019, December 31). Pneumonia of unknown cause China. https://www.who.int/csr/don/05-january-2020-pneumonia-of-unkown-cause-china/en/?mod=article_inline

[2] Makris, A., Kontopoulos, I., & Tserpes, K.. COVID-19 detection from chest X-Ray images using Deep Learning and Convolutional Neural Networks. medRxiv.2020.

[3] The SARS-CoV-2 outbreak: What we know

[4] Ensemble Learning to Improve Machine Learning Results. https://blog.statsbot.co/ensemble-learning-d1dcd548e936

[5] Wang, L., & Wong, A.. COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. 2020.

[6] Mangal, A., Kalia, S., Rajgopal, H., Rangarajan, K., Namboodiri, V., Banerjee, S., & Arora, C.. CovidAID: COVID-19 Detection Using Chest X-Ray. ArXiv, abs/2004.09803. 2020.

[7] Rahimzadeh, M., & Attar, A.. 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, 19, 100360 - 100360. 2020

[8] Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., Y, L., Chen, Y., Su, J., Lang, G., Li, Y., Zhao, H., Xu, K., Ruan, L., & Wu, W.. Deep Learning System to Screen Coronavirus Disease 2019 Pneumonia. ArXiv, abs/2002.09334.2020.

[9] Singh, D., Kumar, V., Vaishali, & Kaur, M.. Classification of COVID-19 patients from chest CT images using multi-objective differential evolutionbased convolutional neural networks. European Journal of Clinical Microbiology & Infectious Diseases, 1 - 11. 2020.

[10] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., et al.: Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225 2017.

[11] Ranjan, E., Paul, S., Kapoor, S., Kar, A., Sethuraman, R., Sheet, D.:Jointly learning convolutional representations to compress radiological images and classify thoracic diseases in the compressed domain (12 2018)

[12] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R.M.: Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classication and localization of common thorax diseases. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 20972106 (2017).

[13] Yao, L., Poblenz, E., Dagunts, D., Covington, B., Bernard, D., Lyman, K.: Learning to diagnose from scratch by exploiting dependencies among labels. arXiv preprint arXiv:1710.10501 (2017).

[14] Wang, L., Wong, A.: Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest radiography images. 2020.

[15] Y. Wang, C. Dong, Y. Hu, C. Li, Q. Ren, X. Zhang, H. Shi, and M.Zhou,Temporal changes of CT ndings in 90 patients with COVID-19 pneumonia:A Longitudinal Study,Radiology,Mar.2020,Art.no.200843. [Online].

[16] M.-Y. Ng, E. Y. Lee, J. Yang, F. Yang, X. Li, H. Wang, M.-M.-S. Lui, C. S.-Y. Lo, B. Leung, P.-L. Khong, C. K.-M. Hui, K.-Y. Yuen, and M. D. Kuo,Imaging prole of the COVID-19 infection:Radiologic ndings and literature review, Radiol., Cardiothoracic Image, vol. 2, no. 1, 2020, Art. no. e200034.

[17] C. Huang et al., Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China, Lancet, vol. 395, pp. 497506, Feb. 2020.

[18] Yan, Q., Wang, B., Gong, D., Luo, C., Zhao, W., Shen, J., Shi, Q., Jin, S., Zhang, L., & You, Z. (2020). COVID-19 Chest CT Image Segmentation - A Deep Convolutional Neural Network Solution. ArXiv, abs/2004.10987.

[19] Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M., Xue, Z., Shen, D., & Shi, Y. (2020). Lung Infection Quantification of COVID-19 in CT Images with Deep Learning. ArXiv, abs/2003.04655.

[20] Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q., Cao, K., Liu, D., Wang, G., Xu, Q., Fang, X., Zhang, S., Xia, J., & Xia, J. (2020). Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT. Radiology.

[21] Waheed, A., Goyal, M., Gupta, D., Khanna, A., Al-Turjman, F., & Pinheiro, P.R. (2020). CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection. IEEE Access, 8, 91916-91923.

[22] E. Andre, K. Brett, A Roberto et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature, vol. 542, no. 7639, pp. 115118, 2017.

[23] M. Grewal, M. M. Srivastava, P. Kumar, and S. Varadarajan, Radiologist level accuracy using deep learning for hemorrhage detection in CT scans, 2017, http://arxiv.org/abs/1710. 04934.

[24] https://twitter.com/ChestImaging/status/1243928581983670272

[25] https://www.sirm.org/category/senza-categoria/covid-19/

[26] Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilcus, S., Chute, C., Marklund, H., Haghgoo, B., Ball, R.L., Shpanskaya, K.S., Seekins, J., Mong, D.A., Halabi, S.S., Sandberg, J.K., Jones, R., Larson, D.B., Langlotz, C.P., Patel, B.N., Lungren, M.P., & Ng, A.Y. (2019). CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison. AAAI.

[27] https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[28] Cohen, J.P., Morrison, P., & Dao, L. (2020). COVID-19 Image Data Collection. ArXiv, abs/2003.11597.

[29] Linda Wang, Alexander Wong, Zhong Qiu Lin, James Lee, Paul McInnis, Audrey Chung, Matt Ross, Blake Van-Berlo, Ashkan Ebadi, FIgure 1 COVID-19 Chest X-ray Dataset Initiative, https://github.com/agchung/Figure1-COVID-chestxray-dataset

[30] Kong, Weifang, and Prachi P. Agarwal. "Chest imaging appearance of COVID-19 infection." Radiology: Cardiothoracic Imaging 2, no. 1 (2020): e200028. https://pubs.rsna.org/doi/full/10.1148/ryct.2020200028

[31] Apostolopoulos, I.D., & Bessiana, T. (2020). Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. Physical and Engineering Sciences in Medicine, 1 - 6.

[32] Ilyas, M., Rehman, H., & Nat-Ali, A. (2020). Detection of Covid-19 From Chest X-ray Images Using Artificial Intelligence: An Early Review. ArXiv, abs/2004.05436.

[33] Huang, Gao, Zhuang Liu and Kilian Q. Weinberger. "Densely Connected Convolutional Networks." 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017): 2261-2269.

[34] He, Kaiming, Xiangyu Zhang, Shaoqing Ren and Jian Sun. "Deep Residual Learning for Image Recognition." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR): 770-778, 2016.

[35] Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke and Andrew Rabinovich. "Going deeper with convolutions." 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR): 1-9, 2015.

[36] Tao, Sean. “Deep Neural Network Ensembles.” ArXiv abs/1904.05488, 2019.

[37] Frazao, Xavier, and Luis A. Alexandre. ”Weighted convolutional neural network ensemble.” Iberoamerican Congress on Pattern Recognition. Springer, Cham, 2014.

[38] Ju, Cheng, Aurlien Bibaut, and Mark van der Laan. ”The relative performance of ensemble methods with deep convolutional neural networks for image classification.” Journal of Applied Statistics 45.15 : 2800-2818, 2018.