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Detecting COVID-19 from Chest X-ray Images using Modified Inception Deep Learning Model

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ABSTRACT
The novel Coronavirus (COVID-19) had outbroken in the entire world and caused a pandemic situation. This disease affects the human respiratory system and force to death. The Chest X-ray is one of the essential tools that will suggest detecting infected COVID-19 patients at any stage. The death ratio can be reduced if COVID-19 can be estimated at early stage. Artificial Intelligence (AI) and Deep learning (DL) can be used for this purpose. Hence, this paper applies the modified Inception-Net DL model for detecting coronavirus using the publicly available Chest X-rays datasets. The proposed model performs augmentation, feature extraction, and disease classification. In this study, two public Chest X-ray datasets were utilized, gathered from different patients with COVID-19 and common Pneumonia. The proposed model has been tested on these datasets and found overall accuracy as 99.36% and 98.0% for CoVira-Loc dataset and CovNorm-Loc dataset respectively.

KEYWORDS
COVID-19, Chest X-ray, Artificial Intelligence, Deep Learning, CNN, Inception Module, Classification.

1. INTRODUCTION

The origin of the coronavirus name is taken from Greek and its meaning is crown or halo, which alludes to the virus look, indicates viral infection. It looks like a royal crown under an electron microscope. Thus, it is also known as the Crowned Virus [1]. Early instances of animal to human transmission of this disease have been traced to wild animals sold at Huanan seafood market in Wuhan, China. This indicates that the pandemic had a zoonotic origin. Some studies considered bats as the origin.

The Coronavirus is a member of the single-stranded RNA virus (+ssRNA) family, which is usually found in animals [2]. It primarily spreads among humans by droplets produced by infected person at the time of speaking, coughing and sneezing. Because the droplets are heavy in weight to travel long distance, they transfer from one human to another when they came in contact. As of now, there are around 40 distinct species of coronavirus family, out of which seven have been proven to be transmitted to people via most common infection like common cold [3]. This virus produces mild symptoms, such as common cold, fever, muscles pain, dry cough, and breath shortness, in around 99% of patients. The remaining patients can have serious or critical situations such as Heart attack, Kidney failure, Pulmonary edema, and Septic shock [2].

Human-to-human transmission has fueled its fast expansion, approximately 47Cr confirmed cases, including 61L deaths in different countries as of March 21, 2022.

The spike in number of COVID-19 infected patients has kept medical diagnosis systems under severe strain. How- ever, this spread might be considerably halted if an early effective screening tool for detecting COVID-19 is developed. Researchers and doctors faced a formidable task in finding techniques to promptly diagnose these conditions [4]. Detection of the virus at early stage and isolation of the infected patients is crucial in controlling and dealing with the COVID-19 plague. The following are the most often utilized COVID-19 testing tools:

- **Reverse Transcription Polymerase Chain Reaction (RT-PCR)** - The conventional and accepted screening method for detection of coronavirus is RT-PCR, although it suffers from lot of limitations. The recall range of this method is 70% to 90%. Along with the low sensitivity, it has an issue of delayed result as it may take around 2 days to generate the report after the lab test [5]. Due to the large number of tests that must be evaluated, it may take approximately five days or more in some countries. The tradeoff for this diagnosis method comes with high requirement of manpower and also with the risk of trans- mission of infections to the testing medical staff. We have seen that the existing medical system was overwhelmed by high demand of such kits during the pandemic. Hence, least dependency on medical diagnosis infrastructure will be preferred for initial screening process.

- **CT - Scan** - It is a complementary tool for the detection of COVID-19. Ground Glass Opacities (GGO) located at peripheral lungs and consolidation, interlobular septal thickening, and indications of air bronchogram were identified as popular indications on CT-Scan of COVID-19

- **Chest X-ray images (CXR images)** - Despite the avail- ability of a wide range of imaging techniques, it is believed that chest radiography has limited sensitivity for crucial clinical findings [7]. The simple availability of X-ray equipment, during the shortage of testing work- benches and kits, mandates its use to detect COVID-19 occurrences. CXR images suggest that early indication of COVID-19 infection is detected in the posterior portions and lower lobes of the lungs, with a subpleural and peripheral distribution as shown in Fig. 1. Among other available imaging techniques, X-ray is cheap and plays significant role in identifying COVID-19 at the time of pandemic. This study considered online available CXR images for training the model.

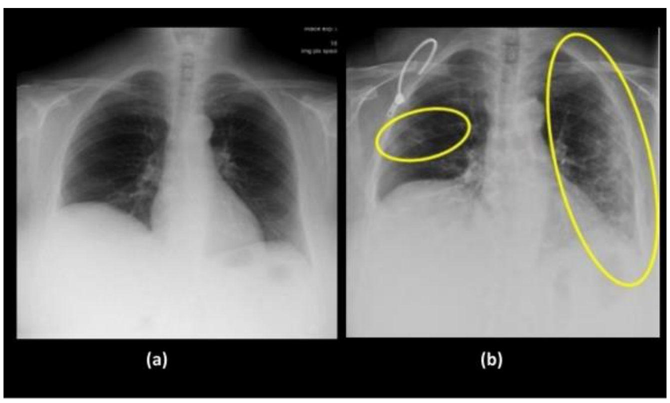


Fig. 1 CXR images of Normal and COVID-19 patients. (a) The CXR image of a normal patient (b) The CXR image of patient typical subpleural peripheral opacity [8].

The remaining portion of the paper is organized as follows: Section 2 addresses review of comparable works. Section 3 presents detailed explanation of the model proposed in this paper. Section 4 describes the datasets in detail, along with the results of implementation and a comparison of the proposed model to previous works. Finally, section 5 brings the paper to conclusion.

2. LITERATURE REVIEW

It is found that various applied literature is present to automate the process of diagnosing spread of infection caused by Coronavirus using Chest X-rays. The employment of Convolutional Neural Network (CNN) architectures in the classification domain is very common. Many DL architectures are either basic CNN or a variant of the basic

infected patients [6]. This method is not only expensive but is also hazardous to health. One can either acquire infection from the equipment itself or fall prey to the radiations which are of high magnitude.

patients [6]. This method is not only expensive but is also hazardous to health. One can either acquire infection from the equipment itself or fall prey to the radiations which are of high magnitude.

CNN architecture. Khan et al. [9] implemented a Deep Convolutional Neural Network (DCNN) model named as CoroNet for multi class classification. The dataset used for this experiment consist of CXR images of healthy people, CXR images of people infected with Coronavirus, Viral Pneumonia and Bacterial Pneumonia. They performed multi-class classification among these 4 classes. They considered approximately 1251 CXR images for this work. Their model had achieved accuracy of95% for multi-class classification and 99% for binary class classification. This study hampered by low sample sizes of dataset. Wang et al. [10] has also performed experiments with DCNN and proposed a model named as COVID-Net. They considered around 12,990 CXR images for their study. They had achieved 93.3% accuracy. The accuracy of this method is comparatively less and also has imbalanced dataset size such as - 8000 CXR images of normal cases, 5538 of non-COVID- 19 pneumonia cases and only 266 of Coronavirus infected cases.

Transfer Learning (TL) model is also considered as one of the promising techniques used in detection of diseases on the normal and medical images. Farooq et al. [11] proposed a fine-tuned ResNet-50 model for classification of CXR images. They followed three steps process by resizing the input image size to 128x128x3, 224x224x3, and 229x229x3 pixels respectively. They have also changed the values of hyper-parameters of the network at each stage. This helps them in getting accuracy of 96.33% in 41 number of epochs. Minaee et al. [12] also used TL for training four variants of CNN models. They considered around 2000 CXR images for training purpose and 3000 CXR images to evaluate the model. This study obtained recall of 98% and specificity of 90%. Eswara et al. [13] also proposed a fine-tuned ResNet-50 model for detecting Coronavirus using CXR images. They considered around 3500 CXR images for ternary classification. Their proposed model achieved accuracy of 98%. Bhattacharyya et al. [14] detected COVID-19 from CXR pictures using a mix of SVM and CNNs. Bargshady et al. [15] implemented a model using Generative Adversarial Network (GAN) along with semi-supervised Cycle-GAN for data augmentation and Inception-Net V3 for classification. Their proposed model achieved accuracy of 94.2%. The limitation of this study is that it considered only one public repository for their dataset. Chakraborty et al. [16] implemented a model by using segmentation as a preprocessing technique and ResNet18 model for classification. Segmentation technique removes the unwanted regions form the X-ray image and keeps the desired lung tissues. They considered around 10,000 samples for this study. Their proposed model achieved accuracy of 96.43% with recall of 93.68%. Most of the above-mentioned studies had used transfer learning for classification using pre-trained weights. This technique has a disadvantage that DL models is not processing original dataset, specifically the COVID-19 dataset. Thus, these weights may result with bias prediction.

3. METHODOLOGY

During the early stage of COVID-19 infection, the posterior portions and lower lobes of the lungs get contaminated. This results in the formation of GGO and consolidation on the Chest X-ray images [17]. The observations from GGO indicate the formation of hazy shade of grey at lower lobes with visible white lung outlines that represent blood veins. In case of critical COVID-19 patients, the diffuse or multifocal consolidation are detected in chest x-ray images, resulting in 'white lung'. To investigate these findings from the medical images, optimized deep learning approach is needed that can extract hierarchical image features. The Inception block, which is the foundation component of the famous Inception Net [18], has the capability of evaluating spatial data at numerous resolutions.

A. Inception-Net V3

The Inception network marked a turning point in the evolu- tion of CNN classifiers. Prior to its development, most popular CNNs merely built convolutional layers deeper and deeper in the hopes of boosting performance. The Inception network, on the other hand, is complex. It used a variety of strategies to boost performance in terms of speed and precision. The following are some of the technologies: -

• **Factorized Convolutions** - General Deep Neural Net- works have a high computational cost. For reducing this cost, inception module includes an additional convolu- tional layer of kernel size 1x1 before the layers with kernel size 3x3 and 5x5. Though it may appear that adding an extra operation is paradoxical, 1x1 convolu- tional layers are significantly less expensive than 5x5 convolutional layers, and it also helps in reducing the number of input channels. To boost computing speed, it factorises a 5x5 convolution into two 3x3 convolution operations. Although it may appear to be paradoxical, a convolution layer with kernel size 5x5 costs 2.78 times more than a layer with kernel size 3x3. So, stacking two 3x3 convolutions actually improves performance.

• **Asymmetric Convolutions** - This Inception model also include asymmetric convolutions instead of symmetric convolutions. A 3x3 convolution, for example, is identical to first conducting a 1x3 convolution and then doing a 3x1 convolution on its result. It is proved that this approach is 33% less expensive than a single 3x3 convolution.

The proposed architecture is based on convolutional layers and inception blocks. The Inception module's inherent architecture allows it to do multi-resolution analysis. Kernels of different sizes are employed in certain layers of standard CNN models to collect information via convolution. In an inception module, on the other hand, kernels with variable receptive field widths such as 1x1, 3x3, and 5x5 are employed in parallel fashion among different layers. The major advantage of this technique is that it enables the model to detect features of different sizes. The retrieved feature maps are then layered depth-wise to gen- erate the inception module's output. Along with the preceding feature maps, a pooling layer of size 3x3 is also stacked. The feature maps obtained from the concatenated layers of the inception module are high in quality and deliver important features to the next convolution layer. The architecture of Inception-V3 block, refer for this work, is shown in Fig. 2.

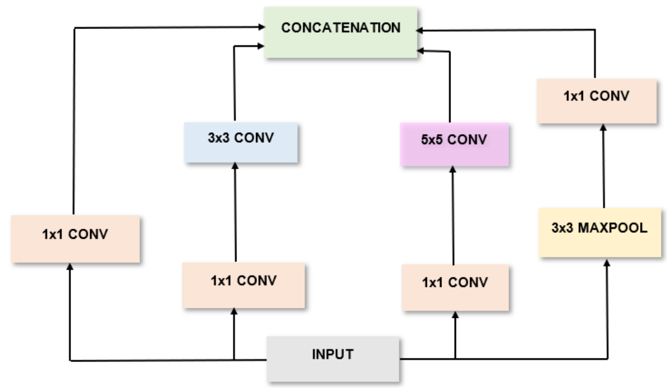


Fig. 2 Architecture of Inception-V3 block A as defined in [19]

The proposed model modifies the original Inception-Net with stack of 3 inception blocks as stated in Figure 3 and named this modified model as Inception-LeNet. Following that, a Global Average Pooling layer are cascaded to lower the output dimension. Then a dense layer is added with an activation function as softmax classifier to predict the final output. The input is routed through convolutional blocks of filter size 3x3 and 1x1 with max-pooling layer in order to reduce the dimensionality. 2 dropout layers are also included in the model to reduce the problem of overfitting. The archi- tecture of the Inception-LeNet is shown in Fig. 3.

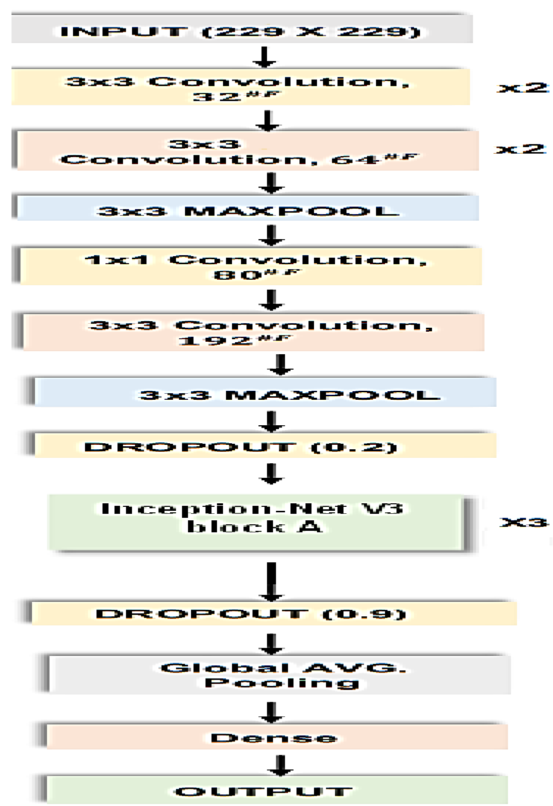


Fig. 3 Architecture of Proposed Model, Inception-LeNet

4. EXPERIMENTAL DETAILS AND RESULTS

A. *Data acquisition and preparation*

For any effective DL classification model, dataset plays an important role. These learning models are driven by data. Although, COVID-19 is a fairly new disease but still, multitude of datasets have been made available due to ongoing research. This easy accessibility of data guided our study and we have gathered CXR images from two pubic data sources. The public datasets taken into consideration are: Covid-ChestXray- Dataset [20] and COVID-19 Radiography Database [4]. Covid-ChestXray-Dataset is a public github repository of dataset available for Chest X-ray images of COVID-19, cre- ated by Joseph et al. For analytical reasons, the authors acquired radiological images from several legitimate records of COVID-19 events. This is the mostly used COVID-19 research dataset employed by many researchers. As of now, it contains 930 COVID-19 Chest radiography images. COVID-19 Radiography Database consists of around 3599 CXR images of COVID-19, approximately 10,000 CXR images of normal person and 1345 CXR images of Viral Pneumonia. For this study, the images from these two sources are merged to form the two datasets used in this study to analyze the performance of the Inception-LeNet. This merging is performed to make the dataset sample size balanced so that the performance can be measured efficiently. The obtained subsets are:

- **CovNorm-Loc Datset (D1)-** It contains CXR images of people infected with Coronavirus and CXR images of healthy people. This dataset has divided into two subsets i.e., Training and Testing set. Training set consist of 4160 CXR images and testing set consist of 3010 CXR images respectively.
- **CoVira-Loc Dataset (D2)** - It contains CXR images of people infected with Coronavirus and CXR images of people infected with Viral Pneumonia. Training set of this dataset consist of 2360 CXR images and testing set consist of 517 CXR images respectively**.**

For the experiment, data is splitted in training and validation sets in ratio of 80:20. Detailed knowledge of both the dataset is shown in Table I.

Table 1 statistics of datasets D1 and D2

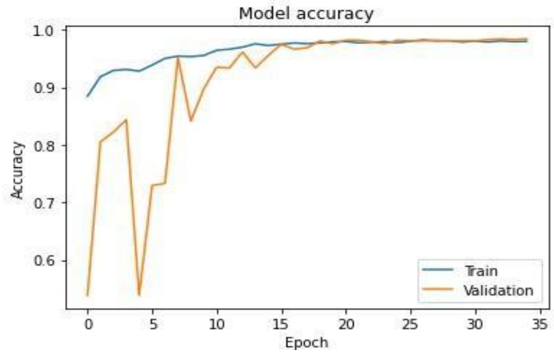
	CovNorm-Loc (D1)	
	Training Data	Testing Data
Covid-19	2150	1507
Normal	2010	1503
	CoVira-Loc (D2)	
	Training Data	Testing Data
Covid-19	1125	264
Viral-Pneumonia	1235	253

B. *Fine-tuning the parameters of the proposed architecture*

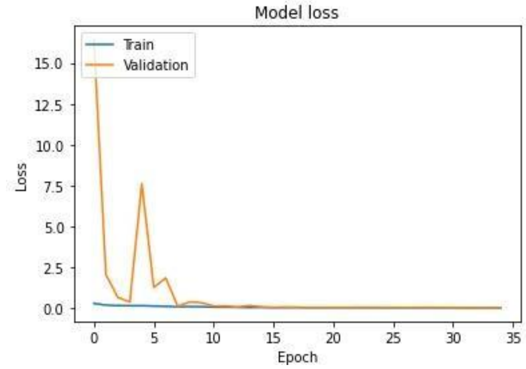
To construct an optimum DL model in the area of medical research, it is necessary to guarantee that the quality of the publicly available dataset size is enough for training and testing the models. To ensure this, data augmentation techniques can be employed. For this study, input size of image is 229 x 229 x 3 and various data augmentation techniques are used to avoid overfitting. During training, images are randomly rotated by 15 degrees, shear range and zoom range are set to 10% and 20% respectively. Furthermore, both the width shift (horizontal translation of the picture) and the height shift (vertical translation of the imagery) are considered as 10%. Horizontal flipping is also enabled.

The hyperparameters selected in this study are following: Learning rate = 1e-2, Epochs = 35 for D1 and 20 for D2, and Batch size = 64. A dynamic technique was chosen to update the Learning Rate (LR) of the model automatically. Initially, LR is set to 1e-2. The used technique lowered the LR with a factor of two whenever the validation loss stayed constant or cannot reduce for more than three epochs. To avoid overshooting, this technique alters the behavior of lowering the velocity when the obtained weight vectors reached close to the global minima. The beginning value of LR is 0.001, reduction factor is 0.5, minimum learning rate is e−4 and patience factor are 3 epochs respectively. These values are selected by analyzing classification results multiple times.

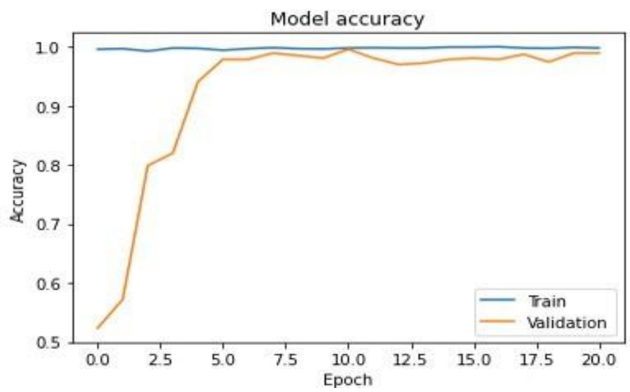
The study of detecting Coronavirus form CXR images has been divided into two parts. First part performs the classification among CXR images of non-infected people (Normal) and COVID-19 infected people. Second part performs the classification among CXR images of people infected with Coronavirus and CXR images of people infected with Viral Pneumonia. Precision, Accuracy, Recall and Area Under a Receiver Operating Characteristic Curve (AUC) are four metrices considered for evaluating the efficiency of the proposed model. Figure 4 depicts the plots for accuracy and model loss on both the datasets D1 and D2 respectively. In case of D1 dataset, minimum validation loss achieved is 0.0471 with accuracy of 98.44% at 27th epoch. Model's overall accuracy is 98.00%. The AUC value achieved is 0.938. It is observed that for D2 dataset, minimum validation loss is achieved as 0.01 with an accuracy of 99.58% at 11th epoch. Overall accuracy achieved for this dataset is 99.36%. The AUC value achieved is 0.953. Other performance metrices of the proposed work are shown in Table II. Confusion matrices of the proposed model on CovNorm-Loc dataset and CoVira-Loc dataset are shown in Table III and Table IV respectively.



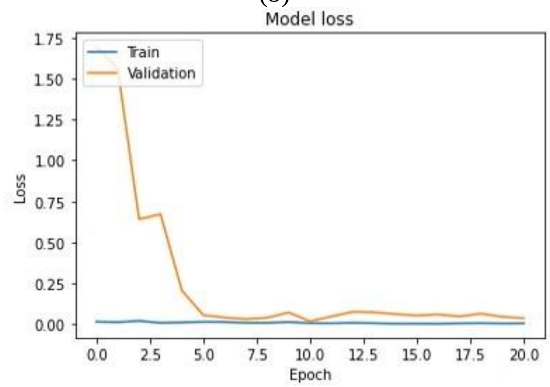
(a)



(b)



(c)



(d)

Fig. 4. The accuracy and validation loss plots : (a) & (b) represent the plots for CovNorm-Loc dataset and (c) & (d) represent the plots for CoVira-Loc dataset

Table 2 Precision and recall metric on D1 and D2 datasets on the proposed model

	D1	
	Precision	Recall
Covid-19	0.94	0.95
Normal	0.95	0.93
	D2	
	Precison	Recall
Covid-19	1.00	0.91
Viral-Pneumonia	0.91	1.00

C. Comparative analysis of the proposed model

Various researchers have done work in the field of detecting Coronavirus by using Chest X-ray. A comparative analysis is performed to compare the performance of the proposed model. Table V summarizes comparisons of the most recent and popular relevant studies using accuracy as the metric. It is observed that Inception-LeNet has performed better in comparison to the literature model with an average accuracy as 98% and 99.36% for D1 and D2 respectively. Table V demonstrates that the sample size of dataset used for this study is larger than the sample sizes used by authors of [21], [22], [23], [24]. The proposed model also showed lower validation loss such as 0.0471 for D1 and 0.01 for D2 datasets respectively.

Table 3 Confusion matrix of inception-lenet on covnorm-loc Dataset (D1)

Ground truth	**Predicted class**		**Total**
	Pneumonia	COVID-19	
Pneumonia	252.00	1.00	253.00
COVID-19	34.00	230.00	264.00

Table 4 Confusion matrix of inception-lenet on covira-loc dataset (D2)

Ground truth	**Predicted class**		**Total**
	COVID-19	Normal	
COVID-19	1404.00	99.00	1503.00
Normal	77.00	1430.00	1507.00

Table 5 Comparison between proposed method and existing methods

Authors	Number of samples	Model Used	Accuracy
Shadin et al. [21]	1553 CXR images	Inception V3	85.94%
Sethy and Behra [22]	25 COVID-19(+ve) 25 COVID-19 (−ve)	ResNet50 + SVM	95.38%
Aslan et al. [23]	219 Covid-19(+ve) 1341 Healthy people 1345 Viral-Pneumonia	DenseNet201 + SVM	96.29%
Ines Chouat et al. [24]	500 Covid-19(+ve) 500 Normal CXR images	Xception	98.00%
Proposed Work	3657 Covid-19(+ve) 3513 Normal	Inception-LeNet	98.00%
	1389 Covid-19(+ve) 1488 Viral-Pneumonia		99.36%

5. CONCLUSION

In this paper, a model "Inception-LeNet" inspired by Inception-Net V3 architecture is proposed to automate the process of detecting Coronavirus by using Chest X-ray images. To test the performance of Inception-LeNet, two datasets are taken into consideration. The proposed model obtains an accuracy of 98% for D1 and 99.36% for D2 with AUC values as 0.938 and 0.953 for D1 and D2 respectively. It is observed that Inception-LeNet surpassed the existing result of various literature works in the field of detecting COVID-19 CXR images from the non-COVID-19 CXR images in terms of great accuracy and AUC value. Furthermore, Inception- LeNet consumes fewer computing resources than the original Inception-V3 architecture due to its smaller number of parameters. As a result, researchers and doctors can detect and classify COVID-19 in less time and with better efficiency. This work can be expanded in the future to deal with datasets having image noise, fine and negligible differences between CXR image of healthy person and CXR image of Coronavirus infected person, ensuring the robustness of the model. The novelty is here extracted high dimension feature map by applying custom convolution layers.

Future scope: In future, different deep learning and vision transformer models can be improved by collecting large dataset, and then applies many pre-processing techniques, new features, and finding the severity of individual respiratory diseases. The same would be applicable for various types of medical tools, such as CT, CXR, thermal imaging.

REFERENCES

1. Roosa K, Lee Y, Luo R, Kirpich A, Rothenberg R, Hyman JM, Yan P, Chowell G. (2020). Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. *Infectious Disease Modelling*, 5, 256-63. https://www.sciencedirect.com/science/article/pii/S2468042720300051
2. Zhang W. (2020). Imaging changes of severe COVID-19 pneumonia in advanced stage. *Intensive care medicine*, 46(5), 841-3. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7080018/
3. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, 395(10223), 497-506. https://pubmed.ncbi.nlm.nih.gov/31986264/
4. Chowdhury, M.E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M.A., Mahbub, Z.B., Islam, K.R., Khan, M.S., Iqbal, A., Al Emadi, N. and Reaz, M.B.I. (2020). Can AI help in screening viral and COVID-19 pneumonia? *IEEE Access*, 8, 132665-132676. https://arxiv.org/abs/2003.13145
5. Kanne JP, Little BP, Chung JH, Elicker BM, Ketai LH. (2020). Essentials for radiologists on COVID-19: an update—radiology scientific expert panel. *Radiology*, 296(2), E113-4. https://pubmed.ncbi.nlm.nih.gov/32105562/
6. Li Y, Xia L. (2020). Coronavirus disease 2019 (COVID-19): role of chest CT in diagnosis and management. *AJR Am J Roentgenol*, 214(6), 1280-6. https://pubmed.ncbi.nlm.nih.gov/32130038/
7. Annarumma M, Withey SJ, Bakewell RJ, Pesce E, Goh V, Montana G. (2019). Automated triaging of adult chest radiographs with deep artificial neural networks. *Radiology*, 291(1), 196-202. https://pubs.rsna.org/radiology/doi/10.1148/radiol.2018180921
8. Jain G, Mittal D, Thakur D, Mittal MK. (2020). A deep learning approach to detect Covid-19 coronavirus with X-Ray images. *Biocybernetics and Biomedical Engineering*, 40(4), 1391-405. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7476608/
9. Khan AI, Shah JL, Bhat MM. (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*, 196, 105581. https://www.sciencedirect.com/science/article/pii/S0169260720314140
10. Wang L, Lin ZQ, Wong A. (2020). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Scientific Reports*, 10(1), 1-2. https://www.nature.com/articles/s41598-020-76550-z
11. Farooq M, Hafeez A. (2020). Covid-resnet: A deep learning framework for screening of covid19 from radiographs. *arXiv preprint arXiv:2003.14395*, Mar 31. https://arxiv.org/abs/2003.14395
12. Minaee S, Kafieh R, Sonka M, Yazdani S, Soufi GJ. (2020). Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. *Medical Image Analysis*, 65, 101794. https://pubmed.ncbi.nlm.nih.gov/32781377/
13. Rao GE, Rajitha B. TRNetCoV: Transferred Learning-based ResNet Model for COVID-19 Detection Using Chest X-ray Images. In *Machine Learning and Deep Learning in Medical Data Analytics and Healthcare Applications* (pp. 219-234). CRC Press.
14. Bhattacharyya A, Bhaik D, Kumar S, Thakur P, Sharma R, Pachori RB. (2022). A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8457928/
15. Bargshady G, Zhou X, Barua PD, Gururajan R, Li Y, Acharya UR. (2022). Application of CycleGAN and transfer learning techniques for automated detection of COVID-19 using X-ray images. *Pattern Recognition Letters*, 153, 67-74. https://researchprofiles.canberra.edu.au/en/publications/application-of-cyclegan-and-transfer-learning-techniques-for-auto
16. Chakraborty, S., Murali, B. and Mitra, A.K. (2022). An Efficient Deep Learning Model to Detect COVID-19 Using Chest X-ray Images. *International Journal of Environmental Research and Public Health*, 19(4), 2013. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8871610/
17. Kong W, Agarwal PP. (2020). Chest imaging appearance of COVID-19 infection. *Radiology: Cardiothoracic Imaging*, 2(1), e200028 .https://pubmed.ncbi.nlm.nih.gov/33778544/
18. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. (2016). Rethinking the inception architecture for computer vision.

https://arxiv.org/abs/1512.00567

19. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. (2015). Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition 2015* (pp. 1-9). https://arxiv.org/abs/1409.4842

20. Cohen JP, Morrison P, Dao L, Roth K, Duong TQ, Ghassemi M. (2020). Covid-19 image data collection: Prospective predictions are the future. *arXiv preprint arXiv:2006.11988*. Jun 22. https://arxiv.org/abs/2006.11988

21. Shadin NS, Sanjana S, Lisa NJ. (2021). COVID-19 Diagnosis from Chest X-ray Images Using Convolutional Neural Network (CNN) and InceptionV3. In *2021 International Conference on Information Technology (ICIT)*, Jul 14 (pp. 799-804). IEEE .https://www.researchgate.net/publication/353555817_COVID-19_Diagnosis_from_Chest_X-ray_Images_Using_Convolutional_Neural_Network_CNN_and_InceptionV3

22. Sethy, P.K. and Behera, S.K. (2020). Detection of coronavirus disease (covid-19) based on deep features. https://www.preprints.org/manuscript/202003.0300/v1

23. Aslan, M.F., Sabanci, K., Durdu, A. and Unlersen, M.F. (2022). COVID-19 diagnosis using state-of-the-art CNN architecture features and Bayesian Optimization. *Computers in Biology and Medicine*, 105244. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8770389/

24. Chouat I, Echtioui A, Khemakhem R, Zouch W, Ghorbel M, Hamida AB. (2022). COVID-19 detection in CT and CXR images using deep learning models. *Biogerontology*, Jan 22:1-20. https://pubmed.ncbi.nlm.nih.gov/35064446/

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