Transfer learning based Covid-19 detection using Radiography Dataset

Primanshu
Department of Computer Engineering
Delhi Technological University
Delhi, India
primanshu.dtu@gmail.com

Garima Chhikara
Department of Computer Engineering
Delhi Technological University
Delhi, India
garimachhikara@dtu.ac.in

Prashant Rana
Department of Computer Engineering
Delhi Technological University
Delhi, India
ranapraveen02@gmail.com

Nitin
Department of Computer Engineering Delhi Technological University
Delhi, India
nitinkr8991@gmail.com

2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) | 978-1-6654-3789-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICACITE53722.2022.9823611

Abstract—COVID-19 is a worldwide pandemic that affected health care and lifestyle all over the world and early discovery is critical for controlling virus spread and mortality. The principal diagnostic test is the RT-PCR test, while test results are pending, spotting probable COVID19 infections on a chest X-ray may aid in restricting high-risk individuals if the diagnosis is done early. Most medical systems have X-Ray equipment, and since most modern X-Ray systems are automated, there is no need to transfer samples. Therefore, we recommend building a Deep Convolutional Neural Network-based technique that works on Radiography images for identifying COVID-19 positive patients. Here we have applied transfer-learning over some widely used deep CNN models like NasNet, DenseNet121, VGG19, ResNet50, and Xception. We have compared the performance of each model by running them over the COVID19 Radiography Dataset. Around 40K chest X-ray photos of COVID patients were used to build training, test, and validation sets. Since earlier research, there has been significant improvement in the number of data points to better train the CNN models. This study aims to identify the best of the available solutions that can be used by medical staff to swiftly discover COVID positive persons by just using the patient's Chest X-Ray diagnosis.

Index Terms*—*NasNet, DenseNet121, VGG19, ResNet50, Xcep-tion, Transfer Learning

I. Introduction

The worldwide coronavirus disease pandemic remains a major cause of concern, with the potential of affecting global health. One of the first steps is to detect infections early in limiting the spread of disease in this pandemic. The current standard for sickness diagnosis is RT-PCR test. However, because of the rapid spread of COVID-19, laboratory kits are in short supply, providing a hurdle. As a result, during the COVID-19 outbreak, radiological tests have become more desirable for identifying illnesses.

Despite the fact that CT scans have been shown to be more successful, the related rise in radiological tests and the increasing patients number make it difficult for each individual patient to rely on chest CT scans from diagnosis through discharge. Furthermore, radiology departments are under strain because of the large reliance on CT scans, making chest X-rays a more plausible option for COVID19 detection. Chest X-rays are beneficial in tracing the course of lung abnormalities, despite the fact that in COVID-19 they are less sensitive in detecting early-stage pulmonary involvement. Previous research has identified and described many radio-graphic symptoms of COVID-19, including reticular interstitial thickening, consolidation, pleural effusion, lung nodules and ground-glass opacities.

Researchers have begun utilising cutting-edge deep learningapproaches to detect COVID19 in patients due to the rapid spread of COVID19 over the world. Recent advancements in transfer learning have also proved its mantle in the field of computer vision, NLP, etc. [1], [2]. Moreover, the boom in theinternet and technology has opened paths for using computer- aided disease diagnosis, among other use cases. [3].

II. Related Work

The authors of [4] suggested a framework model based on Capsule Networks for using X-ray images to diagnose Covid-19 sickness. Multiple convolution layers and capsules are employed in this suggested study to address the problem of class imbalance. They demonstrated COVID-satisfactory CAPS performance on a reduced set of trainable parameters in an experimental study. The authors cited the examined trained model, which is publicly available and open-source [5]. As a consequence, they determined that the model which is suggested has a 95.7 per cent accuracy, a 90 per cent sensitivity, and a 95.80 per cent specificity while utilising a smaller set of trainable parameters. The authors of [5] looked at the first three Covid-19-suffered patients in France. Two of them were diagnosed in Paris, while the third was diagnosed in Bordeaux. Before getting into touch with Covid-19 infections they were in Wuhan, China.

The author of [7] presented a hybrid artificial intelligence system that utilised machine learning and deep learning tech-niques. Using chest X-ray pictures, the suggested approach

is specifically designed to detect Covid-19 instances. The authors of [8] performed a Middle East Respiratory Syndrome radiologic investigation on a new coronavirus. They looked at the case of a 30 years old man who was experiencing diarrhoea, stomach and fever. The authors looked at how infected people were treated using chest X-rays [9].

They also used this model to enhance the findings ofa dataset of CT images and chest X-rays that they had gathered. They also addressed in [10] what types of measures hospital personnel must follow to reduce the danger to healthy individuals and what precautions must be taken when caring for patients infected with covid-19. The authors described the etiologic epidemic in Wuhan, China, in [11]. Also, they highlighted the issue of the epidemic's actual aetiology. In this study, they assess the influence of travelling on covid-19.

The authors of [12] used the Support Vector Machine approach to detect pneumothorax. The scientists employed multi-scale texture segmentation to distinguish the areas of damaged lungs in the recommended detection model after eliminating contaminants from chest pictures. This modification was also utilised to change the texture so that numerous overlapping blocks could be discovered. Finally, the researchers used rid boundary to pinpoint a complete sickness zone that had the aberrant component. The authors of [13] looked at examined chest CT images from 21 corona virus patients in China. The consequences of the covid-19 disease on human lungs are of attention to the writers. For extracting features, the authors then suggested a COVID-RENet model and using CNN for classification in [14]. The authors of this paper employed CNNto extract features and then applied Support Vector Machine to enhance the performance of classification. On a gathered dataset of Covid-19, they employed 5-fold cross-validation. This suggested method is primarily intended for use by amedical practitioner in the early detection of Corona virus infected individuals. The scientists used a deep learning(DL) algorithm on a chest CT imaging dataset in order to determinethe Covid-19 effects on those who had pneumonia or lung illness in [15].

Furthermore, one of the authors in [16] published research on covid-19's effects on the kidney and acute renal failure. [17] looked at a dataset of 50 individuals with Covid-19 illness and divided them into two groups which are good and poor. The dynamics of viral and serological shedding were studied. The authors then discovered a link between lung infections and poor recovery as a risk factor. As a consequence, they came to the conclusion that 58 per cent of the patients recovery was precarious.

The authors of [18] published research that looked at the overall Covid-19 infected people number and fatality cases throughout the world. The authors of [20] described how a new coronavirus was found in Wuhan, China, as a new pneumonia disease. The main purpose of this research was to demonstrate COVIDX-Net, a novel deep learning network that may assist clinical practitioners in autonomously diagnosing Covid-19 illness using X-ray pictures.

III. Preliminaries

CNN has been effectively employed in a variety of domains,including skin cancer diagnosis, facial recognition, and object identification. Deep CNN models sometimes take weeks to train if the dataset is very large. To speed up this process, weights from pre-trained models created on common computervision benchmark datasets can be reused.

Transfer learning (Fig. 1) [24] strategy, which comes under deep learning, involves training the model on a problem thatis similar to the one we need to solve. The pre-trained model'sone or more layers are then used in a new model that is trainedon the job at hand.

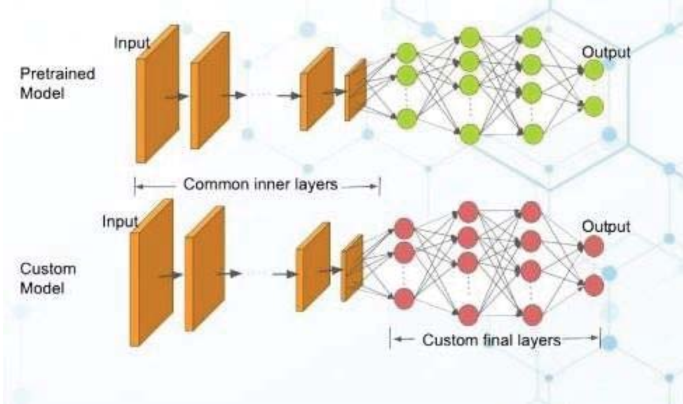

Fig. 1. Transfer Learning Architecture [24]

For picture categorization, a number of high-performing models have been created, like:

A. NasNet

NAS stands for Neural Search Architecture Network. The concepts of this model are somewhat different from classic models like GoogleNet, and it may have a breakthrough inAI. NasNet has been used to build networks that outperform hand-built topologies.

Based on the search space, search methodology, and perfor- mance measurement mechanism employed, NAS approaches are classified as follows:

- The search space determines the type(s) of ANN thatcould be built and optimised.
- The search strategy determines the method used to ex-plore the search space.
- To evaluate the performance of a hypothetical ANN basedon its design, a performance estimation approach is used.

B. VGG19

VGG19 is a CNN model that has already been trained to extract features that identify items and it is being used to classify things that aren't visible. The aim of VGG was to increase the depth of the CNNs in order to improve classification accuracy. The number after the model stands for the number of weight layers it contains, VGG19 has 19 weight layers.

C. ResNet

ResNet stands for Residual Network, it is a new form of neural network. Residual neural networks use skip connections, also known as shortcuts, to go around some layers. Skip connections were used by ResNet to transmit data across layers, which helps researchers and data scientists in building more complicated networks. If the connection is skipped, the network will be able to understand global characteristics. Due to max-pooling, information in CNN can be lost. It improves the image's ability to detect little things. ResNet50 is a common ResNet variant that consists of 48 Convolution layers along with one MaxPool layer and one Average Pool layer.

D. DenseNet

DenseNet was created to address the effect of the vanishing gradient on the accuracy of high-level neural networks. On the one hand, ResNet uses an additive technique to mergethe previous layer with the future layer, whereas DenseNet concatenates the previous layer's output with the future layer'soutput. A DenseNet is a convolutional neural network that connects all layers directly using Dense blocks, resulting in dense connections. To keep the feed-forward nature, each layergets new inputs from all previous levels and transmits its own feature maps to all subsequent layers.

E. Xception

Xception developed by the Google team is a depth-wise sep- arable convolutions-based deep convolutional neural network architecture. A 299x299 RGB image is the Xception's input format. It comprises 126 layers in total, 36 of which are convo- lutional layers for feature extraction. To decrease the number of parameters, a global average pooling layer substitutes the fully-connected layer, and the softmax function is employedto produce the prediction. There are 36 convolutional layers which are organised into 14 modules, with the exception beingthe first and last, all of which have are having linear skip connections around them. The Xception model uses depth- wise separable convolution, which reduces convolution costs significantly. There are only a few successful cases because Xception is a new paradigm.

IV. Data Set

Our chosen models have been trained and evaluated on a well-known dataset which is COVID-19 Radiography Dataset [21] [22].

The COVID-19 Radiography Dataset repository is publicly present on Kaggle. The collection includes 11,956 COVID-19 positive cases, as well as 10,701 Normal, 11,263 Lung Opacity, and Viral Pneumonia images. All of the images are in the .png file type and have a resolution of 299X299 pixels. Thisdataset was created in conjunction with medical practitioners by Qatar University, the University of Dhaka, and a research team from Pakistan and Malaysia.

V. Proposed Methodology

This research uses deep learning (DL) approaches to de- velop diagnostic algorithms that divide X-Ray pictures into four categories: covid, normal, lung opacity, and viral pneu- monia. To classify COVID-19 from CXR pictures, the four-classifier diagnostic system employs an end-to-end DL ar- chitecture. Our four-classifier DL system predicts COVID-19 from raw images and divides X-ray images into the categories listed above without requiring feature extraction, unlike tradi- tional medical image classification techniques, which require a two-step process (manual feature extraction and image recognition).

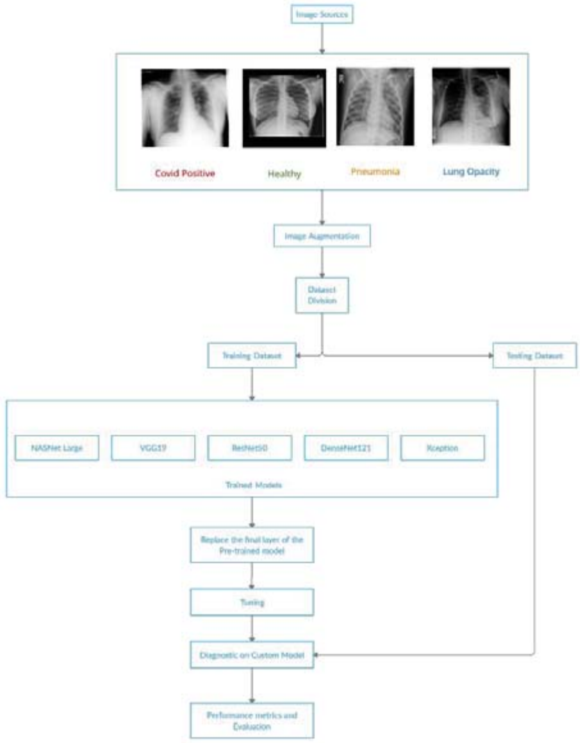

Fig. 2. Proposed Methodology flow chart[24]

ImageNet weights were utilised as the foundation for allof the five models: NasNet, ResNet, VGG19, DenseNet and Xception. The Keras applications class lets us import a CNN with no parameters and a 2D Global Average Pooling. Then a Dense layer receives all of the previous layer's outputs and feeds them to all of its neurons, with each neuron delivering one output to the next layer. Following that, a Dropout layer is introduced as a regularisation strategy to decrease overfitting and enhance generalisation error. This is based on the ideathat big neural networks on short datasets tend to overfit the training data, lowering validation accuracy. When a model overfits, it learns the statistical noise in the training data, which leads to poor performance when the model is tested on new data, such as our validation dataset.

Then, as the output layer, a 4 unit dense layer was added using the softmax function as the activation function. In a neural network model that predicts a multinomial probability distribution, softmax is typically utilised in the output layer. In other words, it may be used to classify many classes.

Finally, the model was built using an Adam optimizer and a categorical cross-entropy loss function (because the model's output is categorical). The cross-entropy loss enables the CNN to be trained so that it outputs the probability over the classes for each picture, allowing for probabilistic image differentiation.

All of our trials and approaches were done on Google Collab. On the Radiography Dataset, all transfer learning models were trained for 30 epochs with a batch size of 32.

The overall proposed approach as shown in Fig. 2 includes:

- Consolidate CXR pictures from many sources for Covid- Negative participants, patients with pneumonia, other bacterial infections, or those who are healthy, and COVIDpatients.

- sort the photos into mentioned four groups (covid, normal, lung opacity, viral pneumonia)
- Only keeps frontal CXR pictures.
- Resize images to a standard scale that the model will accept.
- Make three independent datasets out of the images: training, testing, and validation. One small portion is preserved as a validation set for evaluating the trained model's efficacy, while the rest is folded into five folds. One fold is chosen as test data each time, while theremaining folds are chosen as training data.
- Use the training set photos to train the models NASNet Large, VGG19, ResNet50, DenseNet121, and Xception and then use the test set images to conduct the loss reduction. Calculate the 5-fold cross-validation weights depending on the test set.
- Run the trained models on the test dataset separately and analyse the loss and accuracy of each model.

VI. Result Discussion

TABLE I. Model Accuracy And Loss

Model	Accuracy	Loss
NasNet Large	95.30	0.351
ResNet50	98.09	0.199
VGG19	97.16	0.217
DenseNet121	96.48	0.258
Xception	95.41	0.327

During the experiment, The 80:20 split of the dataset was done and the model was trained on 80 per cent of the dataset and the remaining 20 per cent was kept for evaluation. We did the comparison of each model on various parameters like loss function and accuracy to evaluate which model performed the best on this dataset.

Table I represents the accuracy achieved with each model. After testing our models, we received the following results

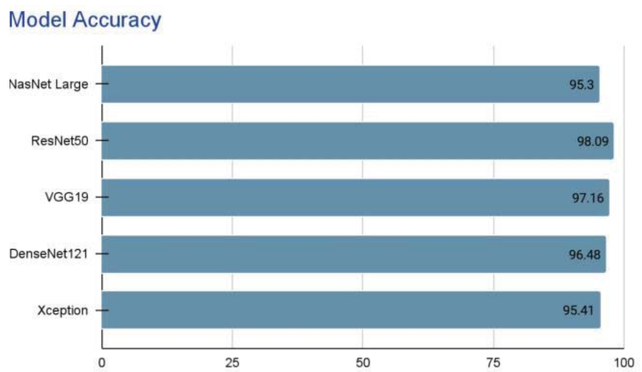

Fig. 3. Comparison of Model Accuracy

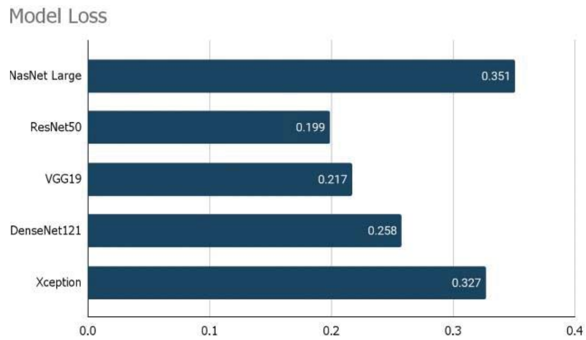

Fig. 4. Comparison of Model Loss

TABLE II. Performance Metrics Of Different Models

Model	Sensitivity	Specificity	Precision	F1 Score
ResNet50 Large	0.9418	0.9889	0.9458	0.9438
VGG19	0.9141	0.9835	0.9192	0.9167
DenseNet121	0.9010	0.9779	0.8935	0.8972
NasNet Large	0.8712	0.9698	0.8558	0.8634
Xception	0.8476	0.9777	0.8934	0.8699

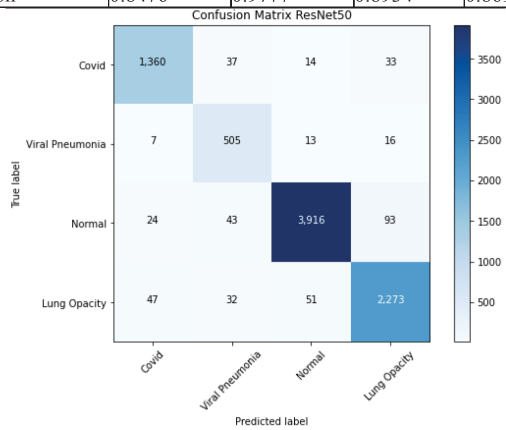

Fig. 5. Confusion Matrix for ResNet50 Model

- ResNet50 model was 98.09 per cent accurate, while the NasNet Large Model was 95.30 per cent accurate, the VGG19 model was 97.16 percent accurate, the DenseNet121 model was 96.48 percent accurate, and the Xception model was 95.41 per cent accurate.

Table II represents performance metrics of the models. Based on TN (True Negatives), TP (True Positives), FN (False Negatives) and FP (False Positives) we calculate the performance metrics like sensitivity, specificity, precision, andF1 score.

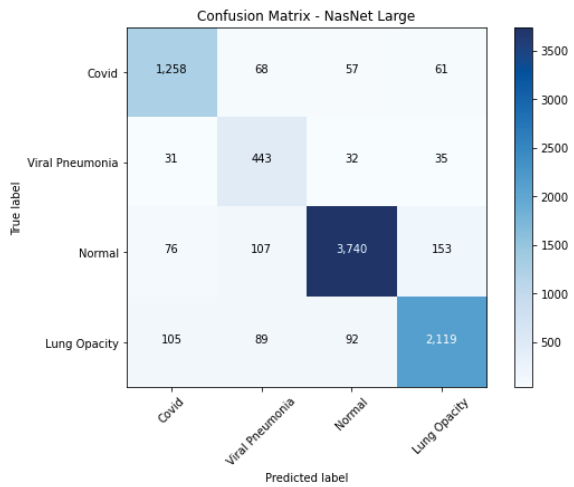

Fig. 6. Confusion Matrix for NasNet Large Model

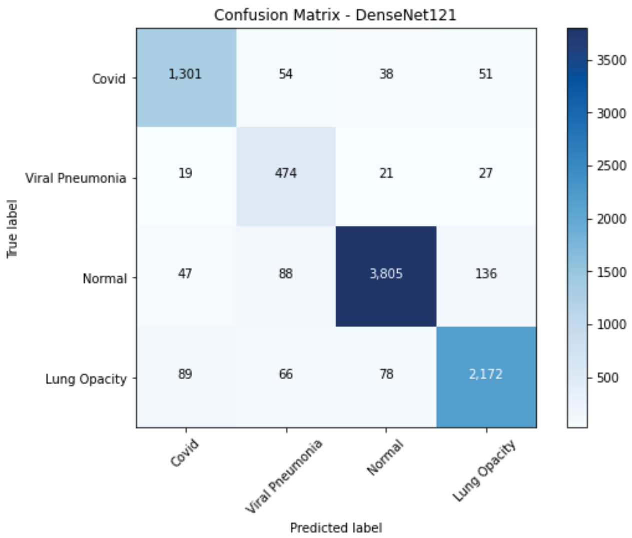

Fig. 7. Confusion Matrix for DenseNet121 Model

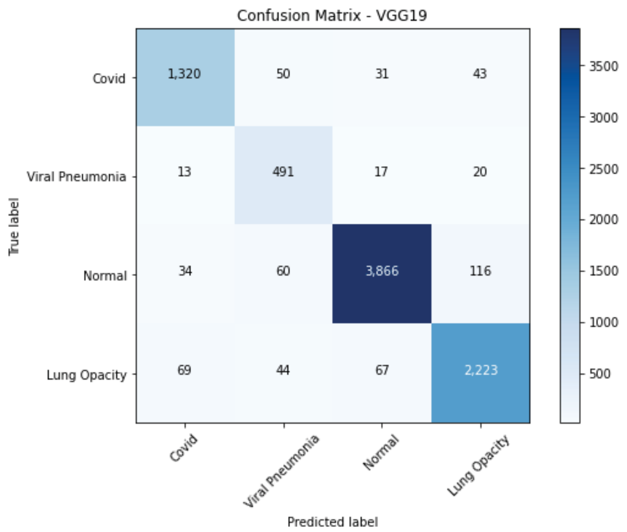

Fig. 8. Confusion Matrix for VGG19 Model

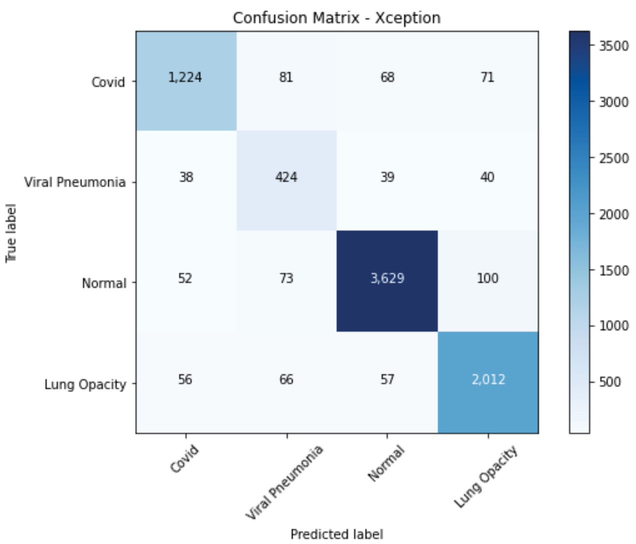

Fig. 9. Confusion Matrix for Xception Model

By observing the accuracy of each model from Fig. 3 we can say that the ResNet50 model was able to achieve the highest accuracy of 98.09% on the Covid-19 radiography dataset.

Fig. 4 represents the model loss, which is the penalty for bad prediction. Looking at the results we can conclude that ResNet50 had the lowest loss standing at 0.199 followed by VGG19, DenseNet121, Xception, and NasNet Large standing at a loss of 0.217, 0.258, 0.327, and 0.351 respectively.

Fig. 5, Fig. 6, Fig. 7, Fig. 8, Fig. 9 show the confusion matrices for each of the 5 models. A confusion matrix(also called an error matrix) allows the performance visualization ofan algorithm. Looking at the figures, it can be stated that the false positives and false negatives for the Covid-19 cases are significantly less. Furthermore, the model accuracy (Fig. 3) and model loss (Fig. 4) plot show the performance of each model relative to each other, where ResNet50 outperforms each model followed by VGG19, DenseNet121, Xception and NasNet Large.

VII. Conclusion And Future Work

By retraining five CNN models (NASNet Large, ResNet50,VGG19, DenseNet121, Xception) using a publicly accessible dataset, we suggested DL-based methods for the automated de-tection of COVID-19 using CXR pictures. The four-classifier approach divided X-ray pictures into four categories: covid, lung opacity, normal, and viral pneumonia. We carried outa thorough analysis to establish the efficacy of each of thefive CNN models and discovered that the ResNet50 model surpasses the others. Furthermore, we conducted a thorough comparison study by comparing the results of this study to those of other studies, and we observed that the proposedclassifier systems outperform the comparable current systems.ResNet50 model was 98.09 per cent accurate, while the NasNet Large Model was 95.30 per cent accurate, the VGG19model was 97.16 per cent accurate, the DenseNet121 model was 96.48 per cent accurate, and the Xception model was 95.41 per cent accurate.

In future, We want to use other datasets to test our model. We also intend to test our method with bigger COVID-19 X-ray imaging datasets and clinical trials. We expect that our research, together with the GUI interface, will allow doctors to quickly identify afflicted people using computer-assisted analysis.

References

[1] Mallik A, Khetarpal A, Kumar S. ConRec: malware classification using convolutional recurrence. Journal of Computer Virology and Hacking Techniques. 2022 Feb 9:1-7.

[2] Khetarpal A, Mallik A. Visual Malware Classification Using Transfer Learning. In2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT) 2021 Sep 15 (pp. 1-5). IEEE.

[3] Kumar S, Mallik A, Panda BS. Link prediction in complex networks using node centrality and light gradient boosting machine. World Wide Web. 2022 Feb 12:1-27.

[4] Afshar P, Heidarian S, Naderkhani F, Oikonomou A, Plataniotis KN, Mohammadi A (2020) Covid-caps: a capsule network-based framework for identification of covid-19 cases from x-ray images. arXiv preprint arXiv:2004.02696

[5] Chowdhury ME, Rahman T, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, ..., Reaz MBI (2020) Can AI help in screening viral and COVID-19 pneumonia?. arXiv preprint arXiv:2003.13145

[6] Stoecklin SB, Rolland P, Silue Y, Mailles A, Campese C, Simondon A, Mechain M, Meurice L, Nguyen M, Bassi C, Yamani E (2020) First

cases of coronavirus disease 2019 (COVID-19) in France: surveillance, investigations and control measures. Eurosurveillance 25(6):2000094

[7] Alqudah AM, Qazan S, Alqudah A (2020) Automated Systems for Detection of COVID-19 using chest X-ray images and lightweight convolutional neural networks

[8] Choi WJ, Lee KN, Kang EJ, Lee H (2016) Middle East respiratory syndrome-coronavirus infection: a case report of serial computed tomo- graphic findings in a young male patient. Korean J Radiol 17(1):166–170

[9] Ayan E, Ünver HM (2019) Diagnosis of pneumonia from chest X-ray images using deep learning. In 2019 Scientific Meeting on Electrical- Electronics & Biomedical Engineering and Computer Science (EBBT) (pp. 1-5). IEEE.

[10] Basile C, Combe C, Pizzarelli F, Covic A, Davenport A, Kanbay M, Kirmizis D, Schneditz D, van der Sande F, Mitra S (2020) Recommen-dations for the prevention, mitigation and containment of the emerging SARS-CoV-2 (COVID-19) pandemic in haemodialysis centres. NephrolDialysis Transplantation 35:737–741

[11] Bogoch II, Watts A, Thomas-Bachli A, Huber C, Kraemer MU Khan K (2020) Pneumonia of unknown etiology in Wuhan, China: Potential for International Spread Via Commercial Air Travel. J Travel Med

[12] Chan YH, Zeng YZ, Wu HC, Wu MC, Sun HM (2018) Effective pneumothorax detection for chest X-ray images using local binary pattern and support vector machine. J Healthcare Eng 2018:1–11

[13] Chung M, Bernheim A, Mei X, Zhang N, Huang M, Zeng X, Cui J, Xu W, Yang Y, Fayad ZA, Jacobi A (2020) CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology 295(1):202–207

[14] Cohen JP, Morrison P, Dao L (2020) COVID-19 image data collection. arXiv preprint arXiv:2003.11597

[15] Dadário AMV, Paiva JPQ, Chate RC, Machado BS, Szarf G (2020) Re- garding artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology:201178

[16] Diao B, Feng Z, Wang C, Wang H, Liu L, Wang C, Wang R, LiuY, Liu Y, Wang G, Yuan Z (2020) Human kidney is a target for novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection. medRxiv

[17] Fu S, Fu X, Song Y, Li M, Pan PH, Tang T, Zhang C, Jiang T, Tan D, Fan X, Sha X (2020) Virologic and clinical characteristics for prognosis of severe COVID-19: a retrospective observational study in Wuhan, China.medRxiv

[18] Hassani RTJ, Sandali O (2020) Le nouveau coronavirus Covid-19: quelsrisques ophtalmiques? J Francais D'Ophtalmologie 43(4):291

[19] Hassanien AE, Mahdy LN, Ezzat KA, Elmousalami HH, Ella HA (2020)Automatic X-ray COVID-19 lung image classification system based on multi-level Thresholding and support vector machine. medRxiv

[20] Hemdan EED, Shouman MA, Karar ME (2020) Covidx-net: a frame-work of deep learning classifiers to diagnose covid-19 in x-ray images. arXiv preprint arXiv:2003.11055

[21] M.E.H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M.A. Kadir,

[22] Z.B. Mahbub, K.R. Islam, M.S. Khan, A. Iqbal, N. Al-Emadi, M.B.I. Reaz, M. T. Islam, "Can AI help in screening Viral and COVID-19 pneumonia?" IEEE Access, Vol. 8, 2020, pp. 132665 - 132676.

[23] Rahman, T., Khandakar, A., Qiblawey, Y., Tahir, A., Kiranyaz, S., Kashem, S.B.A., Islam, M.T., Maadeed, S.A., Zughaier, S.M., Khan,

[24] M.S. and Chowdhury, M.E., 2020. Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-ray Images.

[25] M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," in IEEE Access, vol. 8, pp. 132665-132676, 2020, doi: 10.1109/ACCESS.2020.3010287.

[26] Image available at https://www.analyticssteps.com/blogs/how-transfer- learning-done-neural-networks-and-convolutional-neural-networks.