Chest X-Ray Image-based COVID-19 Recognition using Modified Artificial Neural Network

Urooba Zaki[1]
Institute of Information and Communication Technology, University of Sindh, Jamshoro, Pakistan
zurooba6@yahoo.com

Muhammad Ahmed Zaki[2*]
Department of Computer Systems Engineering, Mehran University of Engineering and Technology, Jamshoro, Pakistan
ahmed_zaki64532@yahoo.com

Sanam Narejo[3]
Department of Computer Systems Engineering, Mehran University of Engineering and Technology, Jamshoro, Pakistan
sanam.narejo@faculty.muet.edu.pk

***Abstract*—Coronavirus commonly identified as novel Covid19 first appeared in Wuhan, China. It has now become the largest issue of the contemporary period spreading throughout the globe with unparalleled force. Covid19 infects the upper respiratory zone also the lungs. On the magnitude of a worldwide contagion, the number of demises and cases has been aggregated every day. Chest X-ray (CXR) images have lately been utilized to monitor the Covid19 disease, which has shown to be beneficial for monitoring the diversity of lung disorders. Deep learning (DL) based techniques were utilized to categorize Covid19 and usual CXR images in this article with fine-tuning, deep feature extraction of pre-trained convolutional neural networks (CNN). A pre-trained deep CNN model (ResNet50, Xception, and VGG19) was utilized to extract deep features. We also evaluated and tested the accuracy of each model. An open-access dataset of 300 COVID and 200 NonCOVID CXR images was used to examine the model's performance with 70% images for training, 25% for testing, and 5% for validation. The study's performance was calculated using classification accuracy. The outcomes of the trials suggest that DL can detect Covid19 from CXR images. The model correctly classified 81.91%, 92.02%, and 93.09% of binary class situations. As a consequence, when compared to other models, the VGG19 model has the best accuracy (i.e., 93.09%) for identifying CXR images.**

Keywords*—*Covid19, Convolutional Neural Networks, Deep Learning, Feature Extraction, Chest X-Ray Analysis.

I. INTRODUCTION

Covid19 is formally called Severe Acute Respiratory Syndrome coronavirus 2 (SARS-CoV-2) [1]. By the end of November 2019, Covid19 was initially observed in Wuhan, Hubei Province, China [2]. The WHO acknowledged the contagion of a public health crisis on 30th January 2020. This is owing not only to its rapid transmission from person to person but also the fact that most diseased persons aren't resistant to it [3]. The Covid19 virus can cause respiratory disease, fever, and cough, as well as severe pneumonia in some people [4]. Its intensity can be influenced by several factors including a weakened immune system, chronic conditions such as asthma, aged people, and smoking [5]. Antibiotics, cough medication, fever reducers, and pain relievers are frequently required depending on the organism that caused the disease. The patient may need to be taken to the hospital depending on the symptoms in severe situations, the patient may need to be committed to an intensive care unit (ICU) to utilize a mechanical ventilator to help them breathe [6]. Because of its great transmissibility and lethality, the Covid19 pandemic can be classified as severe [7]. The number of persons who require ICU hospitalization and long-term mechanical ventilation has a significant influence on the healthcare system [8].

The Covid19 virus infects humans and a variety of animals including bats, cattle, and cats [9]. "Fig. 1" depicts the propagation of the nCoV19 virus. Coronaviruses belong to the Coronavirinae subfamily of the Coronaviridae family which is part of the Nidovirales order. The subfamily Coronavirinae is divided into Alpha (α), Beta (β), Gamma (γ), and Delta (δ) coronavirus based on phylogenetic connections and genomic architecture. Only animals are infected by α and β viruses. γ and δ viruses infect birds and in rare cases mammals such as rats and bats. In humans γ and β cause respiratory sickness but in animals they cause stomach trouble [10].

Early Covid19 cases in Wuhan's epicenter were linked to animal markets and seafood indicating animal-to-human spread. The person-to-person spread of this disease has caused a considerable rise in the number of affected persons [11], [12]. Following that the WHO declared the nCoV19 eruption an epidemic on 11th March 2020 when the number of confirmed cases touched approximately 0.12 million with over 4000 demises [13]. According to the European Centre for Disease Prevention and Control's statistics as of 14th June 2020 [14], Covid19 has become a severe public health crisis over the world with an estimated 7.76 million cases worldwide. As of the 16th December 2020, there were roughly 7.38 million global corona

ISBN # 978-969-23372-2-9

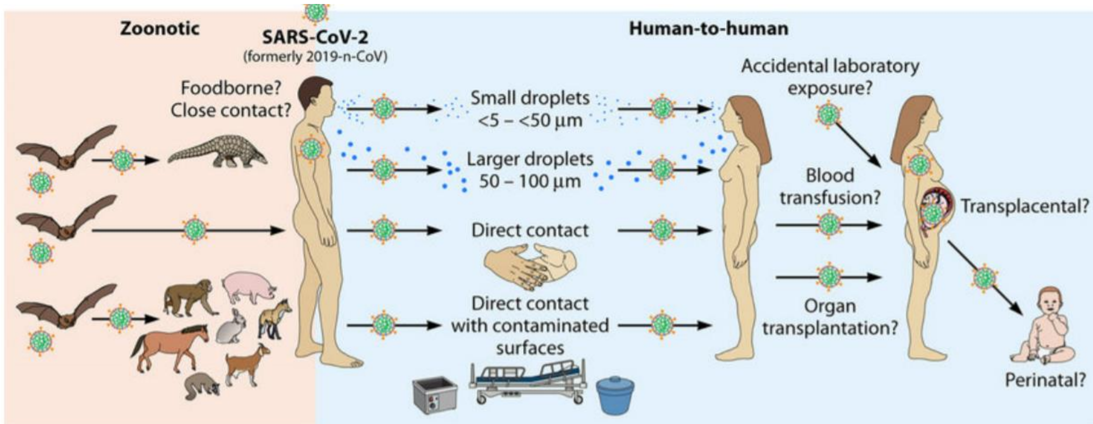


Fig. 1. nCoV19 Disease Spread

virus cases with 1.6 million documented fatalities [15]. Early diagnosis is critical in this situation for proper treatment and perhaps reducing stress on the healthcare system. In this regard, AI-based technologies can be used to detect Covid19 and other kinds of pneumonia at a low cost and with high accuracy [16]. The CXR and computed tomography (CT) scan are the main imaging diagnostic tests for covid19. The CXR is the most common radiographic test and it is still effective since it is less expensive, quicker, and exposes the patient to less radiation than a CT scan [17]. The goal of this research is to detect covid19 using solely CXR images. Despite the CT scan being the gold standard for pneumonia diagnosis we only employed CXR imaged because of their lower cost, faster results, and widespread availability as CT scan equipment are still few and expensive [18]. Our main objective is to get the highest feasible recognition rate. To do so, we used CXR images from the open-source GitHub repository [19] to create a database.

In this article, Fine-tuning, and deep feature extraction of pre-trained CNN models were used to classify Covid19 and usual CXR images using DL-based techniques. A pre-trained deep CNN model (ResNet50, Xception, and VGG19) was utilized to extract deep features. We also compared and tested the accuracy of these models. An open-access dataset of 300 COVID and 200 NonCOVID CXR images was applied to analyze the model's performance with 70% images for training, 25% for testing, and 5% for validation. The study's performance was measured through classification accuracy. The outcomes of the tests suggest that DL has the potential to detect Covid19 using CXR images. The following is an overview of the paper's structure. Section II looks at some related works. The problem statement is then described in Section III. Our proposed methodology is detailed in Section IV. Performance analysis is discussed in detail in Section V. The acquired results are described in Section VI. Section VII then wraps up the existing research and discusses some potential future projects.

II. RELATED WORKS

This section describes some significant works in the literature that address one of the following issues that have a direct impact on the development of this work.

Maghdid et al., [3] propose AI tools that radiologists or healthcare practitioners can utilize to swiftly and accurately diagnose Covid19 patients. The unavailability of a publicly accessible dataset of CT, and CXR images, however, makes the development of such AI technologies difficult. The goal of this research is to compile a large dataset of CT scan and CXR images from various sources as well as to develop a simple but effective Covid19 detection technique based on transfer learning algorithms. On the prepared CT scan and CXR images dataset, a simple CNN and an improved pre-trained AlexNet model were used. The results of the studies reveal that using a pre-trained network can deliver accurateness of up to 98% and using an improved CNN can offer accuracy of up to 94.1%.

Jain et al., [20] examined the PA view of CXR images for healthy and covid19 affected individuals. They compared the performance of DL-based CNN models after cleaning up the images and using data augmentation. They compared the accuracy of the Xception, InceptionV3, and ResNet models. 6432 CXR scan samples were attained from the Kaggle repository to analyze the model's performance with 5467 being used for training and 965 for validation. In contrast to further models, the Xception model has a peak accuracy of 97.96% for identifying CXR images. This study emphasizes exclusively possible approaches for classifying covid19 affected individuals.

Sethy and Behera [21] proposed using x-ray images to identify covid19 diseased individuals using a DL-based methodology. Through the deep feature, the support vector machine (SVM) differentiates covid19 affected CXR images. The methodology can help doctors diagnose patients who have been infected with the coronavirus. For detecting Covid19 suggested classification model, ResNet50 plus SVM attained accuracy, F1-score, FPR, Kappa, and MCC of 95.52%, 95.38%, 90.76%, and 91.41%, respectively (ignoring MERS, ARDS, and SARS). In comparison to other classification models, the ResNet50 with the SVM classification model is superior. The outcome is based on data from the Kaggle, GitHub, and Open-i repositories as well as their certified CXR images.

Horry et al., [22] show how covid19 identification may be performed utilizing CXR images using pre-trained DL models. Propose an image pre-processing methodology that is semi-automated to build a reliable image dataset for constructing and testing deep learning models. Create a deep learning experimental framework in which we use the processed dataset to compare many popular and widely available DL models families such as VGG, Inception, Xception, and Resnet. The experimental results show that these models are suitable for the currently available dataset and that models with simpler networks such as VGG19, perform better, with up to 83% precision.

Salman et al., [23] develop a DL algorithm for identifying covid19 infection on high-resolution CXR, easing radiologists' jobs and causal to the widespread's management. 260 images from the GitHub and Kaggle repositories were utilized for model building, validation, and testing. The images are made up of 130 covid19 (excluding MERS, SARS, and ARDS) and 130 usual CXR. In the dataset, the model has a sensitivity and specificity of 100% an accurateness, PPV, and an NPV of 100%. The model was able to match the performance of an expert radiologist on 260 images.

Kumar et al., [24] presented ResNet152 with pneumonia and covid19 patients using CXR images to do ML-based categorization of the derived deep feature. SMOTE is utilized to balance the normal and covid19 patient data points that are unbalanced. By evaluating CXR this non-invasive and early prediction of nCoV19 can also be utilized to anticipate the virus's transmission in asymptomatic individuals. The model has a 97.3% accuracy on Random Forest and a 97.7% accuracy on XGBoost predictive classifiers.

Bukhari et al., [25] demonstrate 278 CXR images that were evaluated using ResNet50 deep neural networks architectures. These digitized CXR images were split into three categories: covid19, pneumonia, and normal. The data set contains 89 radiological images of lungs infected with covid19, 93 images of lungs with no radiological abnormalities, and 96 images of a patient with pneumonia caused by other infections. 80% of the images in this dataset were used for training, while 20% were used for testing. On lung CXR images, a pre-trained ResNet50 design was used to identify cases of covid19 contagions. According to the findings, computer vision-based algorithms had a detection accuracy of 98.18% and an F1-score of 98.19.

Kassania et al., [26] compare various DL-based feature mining frameworks for automatic covid19 categorization. DenseNet, ResNet, MobileNet, Xception, InceptionV3, VGGNet NASNet, and InceptionResNetV2 were chosen from a pool of deep CNN to achieve more accurate features, which is a key factor in learning. The extracted features were then served into a series of ML classifiers to determine whether the subjects were covid19 cases or controls. To promote a stronger generalization capacity for unknown data, this strategy eschewed task-specific data pre-processing approaches. A publicly accessible covid19 dataset of CT and CXR images was used to authenticate the suggested technique's performance. With a classification accuracy of 99%, the DenseNet121 feature extractor with the bagging tree classifier had the best results. With an accurateness of 98%, the second finest learner was a cross of the Resnet50 feature extractor trained by LightGBM.

Minaee et al., [27] demonstrate how deep learning models can be used to identify covid19 infected patients from CXR images. A dataset of 5k CXR from openly accessible datasets first. A board qualified radiologist found images that exposed the presence of covid19 ailment. Four protuberant CNN, including ResNet50, ResNet18, DenseNet-121, and SqueezeNet were trained to classify covid19 disease in the examined CXR images using transfer learning on a subset of 2k radiograms. On the remaining 3k images we tested these models and the majority of them had a sensitivity, and specificity of 97%, 90% respectively.

Rahimzadeh and Attar [28] trained numerous deep CNN using the proposed training approaches for classifying CXR images into 3 classes: covid19, normal, and pneumonia created on 2 open-access datasets. To produce the best potential results, the data comprises 180 CXR scans of people diseased with nCoV19. Also, propose a concatenation of the Xception and ResNet50V2 networks to create a NN.

By merging several features extracted by 2 vigorous networks, this network was able to attain maximum accurateness. The network's average accuracy for identifying covid19 instances is 99.55%, with an algebraic accurateness of 91.4%.

Hall et al., [29] investigate the utility of CXR images in the analysis of covid19 infection. The researchers gathered 135 covid19 CXR and 320 viral and bacterial pneumonia CXR for the study. Resnet50, a pre-trained deep CNN, was optimized using 10-fold cross-validation on 102 covid19 cases and 102 added pneumonia cases. Pre-trained VGG16, and ResNet50 and as well as our own customized CNN were adjusted or trained on a balanced set of pneumonia, and covid19 CXR yielding an overall accuracy of 90.7%, a covid19 true positive rate of 0.8, and an AUC of 0.97. On a test set of 33 covid19 and 208 pneumonia patients, a collaborative of the 3 kinds of CNN classifiers was utilized. The total accurateness was 94.5%, with a true positive, and true negative rate of 0.97, and 0.95 with 6% for a true negative rate and an AUC of 0.99 for covid19.

Ioannis et al., [30] used a CNN named MobileNet that was trained from scratch to evaluate the significance of the retrieved features for the classification purpose. MobileNetV2, which has been shown to deliver extraordinary outcomes in related tasks, is trained using a dataset of approximately 4k CXR images corresponding to 6 disorders. The findings imply that training CNNs from the ground up could disclose important biomarkers linked to covid19 disease with classification accurateness of 87.66% for the 7 classes. Furthermore, this approach detects covid19 with an accuracy, sensitivity, and specificity of 99.2%, 97.4%, and 99.42% respectively.

Asnaoui et al., [31] analyze contemporary Deep CNN designs for automatic binary categorization of pneumonia images using fine-tuned kinds of the DCNN that includes (DenseNet201, Xception VGG19, VGG16, InceptionV3, InceptionResNetV2, MobileNetV2, and ResNet50). A CXR and CT dataset with 5856 images were used to test the study (4273 cases of pneumonia and 1583 normal cases). As a result, fine-tuned types of MobileNetV2, ResNet50, and InceptionResnetV2 determine highly sustaining performance with a rate of growth in training and validation accuracy of 96%. DenseNet201, Xception, VGG19, VGG16, and InceptionV3 in contrast to CNN have poor accuracy of 84%.

Narin et al., [32] propose three distinct CNN-based models for detecting nCoV19 infected using CXR images (ResNet50, InceptionV3, and InceptionResNetV2). These 3 models ROC examines and confusion matrices are provided and investigated using 5-fold cross-validation. In comparison to the other two proposed models, the pre-trained ResNet50 model delivers the maximum accuracy of 98%.

Many state-of-the-art CNN models were utilized in our earlier study to identify nCoV19 utilizing CXR images. However, covid19 lacked sufficient data. As a result, to address the concerns raised by our previous work, the suggested study was re-run with more data and DCNN models to categorize nCoV19 diseased patients. The proposed model is inspired by all of the preceding studies and stabs to attain better competence standards on a bigger dataset so that it can be used for clinical reasons.

III. PROBLEM STATEMENT

Novel covid19 is currently affecting numerous countries around the world, including Pakistan. Several nations, including the United States, Germany, Italy, and others are dealing with its spreading in the community transfer phase, which means that one infected person can infect up to 100 individuals. As a result, the problem's remedy is to recognize sick people and place them in quarantine to prevent further transmission. Existing diagnosis processes for identifying the infected individual are time demanding, which slows down diagnosis rates when dealing with a high number of cases. As a result, to address this problem, we created a model that can accurately classify covid19 positive and negative cases that are well advanced in time. So, assuming the challenge, the aim is to use an automated ML-based model to categorize persons as covid19 positive or negative. The model uses CXR images as an input parameter, which reveal the disease's early signs.

IV. MATERIAL AND METHOD

The dataset used and the method used are enlightened in the succeeding section.

A. Dataset

The data for this study came from an open-source GitHub repository that included CXR images of covid19 afflicted and normal patients. This dataset was gathered to investigate several approaches of proficiently identifying corona-virus contagions using computer vision procedures rather than to entitlement the diagnostic ability of any DL model. As shown in Table 1 the gathered dataset comprises 500 total CXR images, including 300 COVID and 200 NonCOVID CXR images. This dataset is separated into a training (70%), testing (25%), and validation (5%) set of covid19 and normal CXR images. The infected and normal CXR images are shown in “Fig. 2”.

ISBN # 978-969-23372-2-9

TABLE 1 SUMMARY OF THE INPUT DATASET

Category	Training sample	Testing sample	Validation sample
COVID	210	75	15
NonCOVID	140	50	10

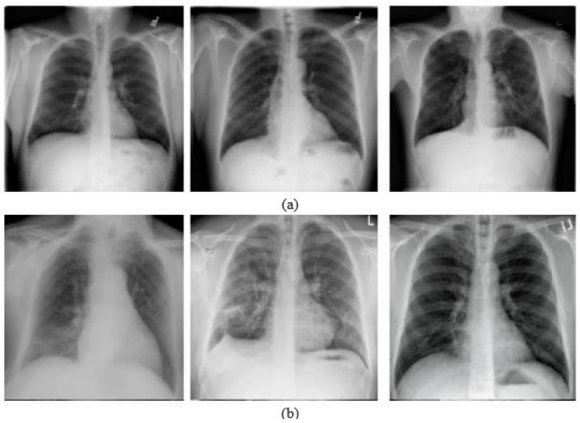


Fig. 2. Representative CXR images (a) Normal, (b) nCoV-19

B. *Deep Transfer Learning Architecture*

Deep learning (DL) is a sub-branch of machine learning (ML) that is inspired by the brain's structure. DL approaches have sustained to exhibit outstanding performance in the field of medical image processing as well as in many other fields in recent years. It is hoped that by applying DL procedures to medical data, relevant results might be mined [33]. Deep neural networks (DNN) have been utilized successfully in a variety of fields including medical data classification, recognition, and lesion segmentation [34]. With the use of DNN signal and image data from medical imaging modalities such as CT, MRI, and CXR were analyzed [35].

CNNs are a type of DNN that can be used to resolve computer vision challenges. For CNN to function, the images delivered as input must be predictable by computers and transformed into a process-able arrangement. As an outcome, images are renovated to matrix design first. Based on image inconsistencies and hence matrices, the system recognizes which image fits which label [36]. During the training stage, it acquires the significance of these variations on the label and then uses them to generate forecasts for different images. To conduct these procedures meritoriously CNN has 3 layers: a convolutional layer, a pooling layer, and a fully connected (FC) layer. Both the convolutional and pooling layers are elaborate in the feature extraction procedure. The classification process on the other hand takes place in the FC layer. The next sections look at these strata in order.

1) *Convolutional layer*

CNN's elementary layer is the convolutional layer. It is accountable for determining the pattern's features. The input image is passed through a filter in this layer. The feature map is made up of the values that arise subsequently filtering. This layer adds some kernels to the pattern that slide past it to collect high and low-level features. The kernel is an M×M shaped matrix that is modified with the pattern matrix as input. The stride parameter specifies the number of steps to move the input matrix over [37].

2) *Pooling layer*

The pooling layer is the next layer succeeding the convolutional layer. The pooling layer is usually engaged in freshly established feature maps to diminish network parameters and the number of feature maps by executing mathematical calculations. We employed global average pooling in this work. A global average pooling layer is only applied earlier to the fully connected (FC) layer and shrink's data to a specific dimension. The dropout layer is the other transitional layer that is engaged. This layer's major goal is to avoid network divergence and overfitting [38].

3) *Fully connected layer*

The most crucial layer in CNN's model is the fully connected (FC) layer. This layer works in the same way as a multi-layer perceptron. On an FC layer, the activation function rectified linear unit (ReLU) is normally utilized while the softmax activation function is often used to forecast output images in the FC layer [39].

C. *Proposed Algorithm*

The method for taking the suggested concept into practice is described further below. We start with the CXR images sample and pre-process it by scaling all of the images to 256×256 pixels and retaining 25% of the data for testing, as shown in "Fig. 3". The remainder of the pre-processed dataset is divided into two sets with the training set accounting for 70% and the validation set accounting for 5%. We train ResNet50, Xception, and VGG19 individually using the training dataset, accompanied by model validation. The test set is used as input, fully trained and verified models predict the outcome in terms of probability. For further processing, these projected probabilities are collective. The Covid19 positive and negative instances are predicted using the probability gained after the ensemble.

D. *Experimental Setup*

The suggested deep transfer learning models are trained using Anaconda Navigator (Jupyter Notebook) version 5.3.0. The suggested model is implemented on a Dell Inspiron Core(TM) i5-8250U CPU (8 CPUs) operating at 1.6 GHz with 16 GB RAM and Microsoft

ISBN # 978-969-23372-2-9

Windows 10 Professional (64-bit). The source of the regularizers is Keras. The performance was precise to the Graphics Processing Unit (GPU). By enhancing the cross-entropy function with Adam optimizer (β_1=0.89 and β_2=0.997) CNN models (ResNet50, Xception, and VGG19) were pre-trained with initial random weights. For all experiments, the learning rate, no. of epochs, and batch size was set at 1×10^{-5}, 500, and 32 correspondingly. All datasets were alienated into two separate datasets at random with 75%, 20%, and 5% utilized for training, testing, and validation accordingly.

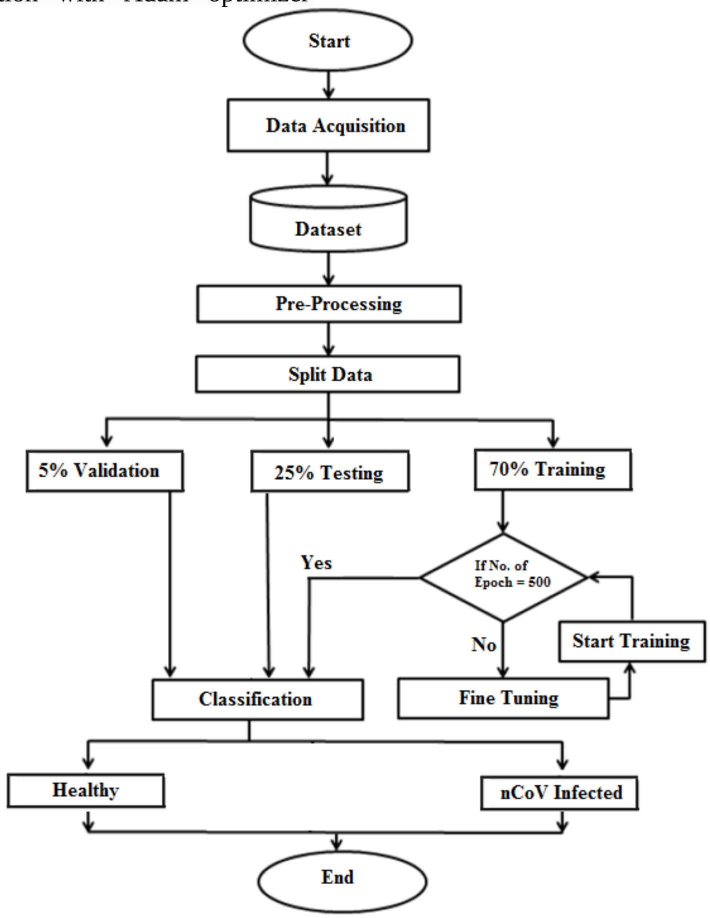


Fig. 3. Flowchart of the Proposed Model

V. PERFORMANCE ANALYSIS AND COMPARATIVE STUDY

Computing is done in Python-3 for investigating the performance of the suggested model and is tested and trained using Google Colab (cloud-based) coding platform. The proposed model's performance is assessed by plotting the confusion matrix (CM) for test and validation samples, and the relative investigation determines the model's importance.

A. *Performance Metrics*

The following are a few key measures that can be used to assess the effectiveness of the suggested model to that of other models.

1) Accuracy

As shown in "(1)" accuracy is expressed as the proportion of samples properly identified out of a total number of samples [40].

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

where True Positive = TP, True Negative = TN, False Positive = FP, and False Negative = FN.

A greater accuracy rating indicates that the model is effective.

2) Precision

Precision is well-defined in ML as the ratio of a definite class of data exactly forecast by a model to the total amount of samples in that class [41], as shown in "(2)". The class of COVID-19 positive people in the suggested model is taken into account.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

ISBN # 978-969-23372-2-9

3) *Recall*

The recall is the proportion of true positive samples properly forecasted. It is calculated in the proposed model as a fraction of COVID-19 positive samples right predictions [42]. "(3)" can be used to calculate the value.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+ FN}} \tag{3}$$

4) *F1-Score*

The F1-score, which is specified as the harmonic mean of the model's recall and precision as shown in "(4)" is a technique of combining the model's precision and recall [43].

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+ Recall}} \tag{4}$$

VI. EXPERIMENTAL RESULTS

Table 1 shows the findings of the experiment. Over the 20 experimental runs, we calculated the average Precision, Recall, and F1-score for each classifier. Table 1 provides the averages of 20 test cycles expressed as percentages. It's helpful to think about learning curves while interpreting these outcomes. Typical CXR images were associated with covid19 afflicted participants in the analysis. Accuracy matrices are used to evaluate ResNet50, Xception, and VGG19 [44], [45]. The findings were then compared to decide which model was the best. "Fig. 4" depicts the accuracy and loss training curves for each transfer learning model.

To estimate the effectiveness of each model, we evaluated the CM and AUC of ROC. A confusion matrix, also known as a table of confusion is a 2×2 table that displays four basic parameters: FN, FP, TN, and TP. "Fig. 5" depicts the efficacy of each transfer learning (TL) approach in binary classification as a CM to differentiate covid19 CXR from healthy images. As demonstrated in "Fig. 5" the VGG19 model has better classification success criteria such as accuracy, precision, F1-score, and recall are used to assess each transfer learning model's classification accuracy. The metrics listed above are the most often used metrics in ML. As shown in Table 2 all suggested models have an accurateness of better than 80%. In contrast with two different proposed models, the pre-trained VGG19 model delivers the maximum classification accuracy of automatic covid19 classification with 93.09% accuracy. The F1-score is a metric for determining how accurate a test is. The ROC curve is a two-dimensional graphical diagram that indicates the association between the sensitivity (true positive rate) and the specificity (false positive rate). The substitution between specificity and sensitivity is represented by the ROC curve. The ROC curve of each TL model is presented here, with a true positive rate on the y-axis and a false positive rate on the x-axis, as illustrated in "Fig. 6". We also measured the AUC, which is a metric for how fine a parameter can distinguish among the COVID and NonCOVID sets. The designed AUC of ROC of three distinct models ResNet50, Xception, and VGG19 were 81.91 %, 92.02 %, and 93.09 %, respectively, as shown in "Fig. 6". These numbers are regarded as "good" in the realm of medical diagnosis.

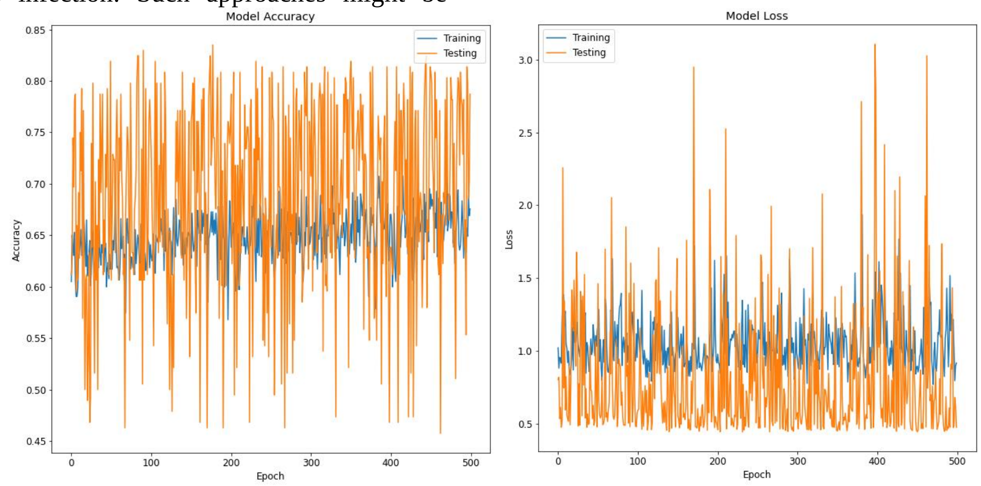
Our proposed pre-trained deep CNN models particularly VGG19 can address the aforementioned drawbacks. In less than 3 seconds the proposed models in this study can detect a covid19 positive instance. With the minimal patient data, we had our proposed models attain an accuracy of more than 80%. In comparison to recent methodologies suggested by the state-of-the-art our projected models accomplished auspicious and inspiring results in the identification of covid19 from CXR images. Data suggest that DL will play a significant role in combating the covid19 epidemic in the coming years. More patient data must be added to the training dataset to validate our model. Our developed models based on CXR images attempted to advance covid19 recognition in this investigation. The presented models have the potential to greatly reduce doctor workload.

TABLE 2 MODEL PERFORMANCE MATRIX COMPARISON

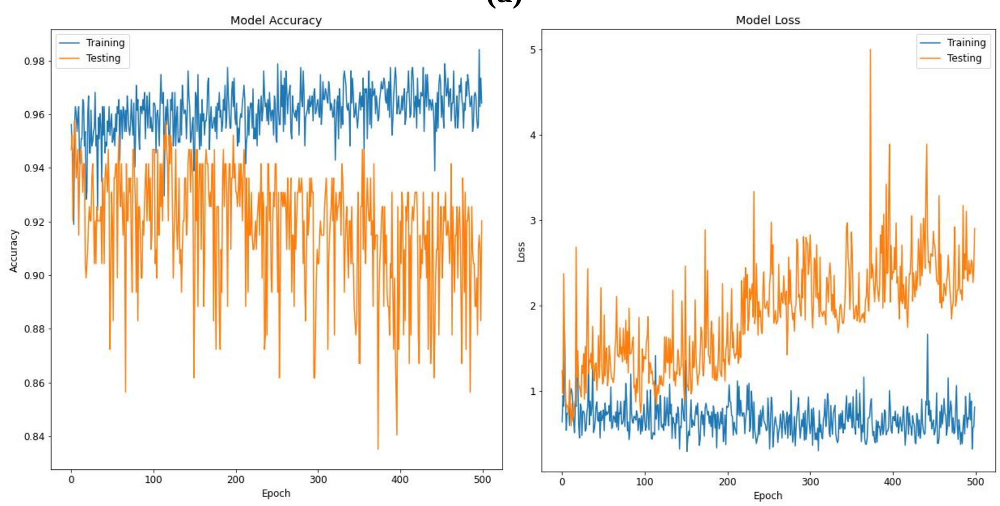
Model	Accuracy %	Precision %	Recall %	F1 Score
ResNet50	81.91	90.80	75.24	82.29
Xception	92.02	96.15	86.21	90.91
VGG19	93.09	87.76	98.85	92.97

VII. CONCLUSION AND FUTURE WORKS

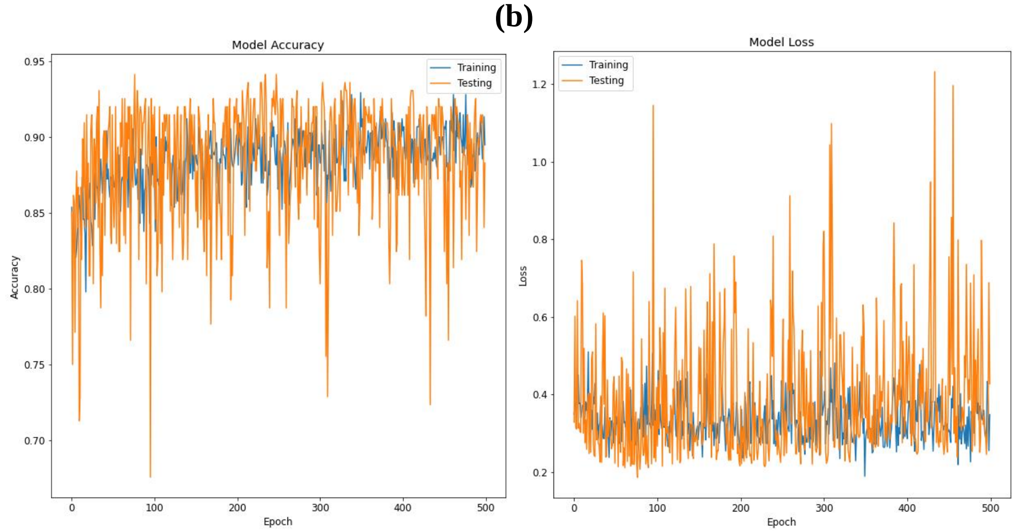
The covid19 epidemic is spreading at an alarming rate. With the growing sum of instances, majority testing of cases may become necessary. We used different CNN models in this study to try to characterize Covid-19 afflicted patients based on their CXR scans. We also determined that out of the 3 models the VGG19 model has the best accuracy and is the most suitable for use. We effectively categorized covid-19 images, demonstrating the potential for using such algorithms to automate diagnosis duties shortly. The great accuracy observed could be cause for concern because it could be due to over-fitting. This may be validated by comparing it to novel data that will be released soon. Recently, the omicron virus is the next threat to the human race. It spread 70 times faster than covid19. Our focus is to cope with this virus as well. This technique of transfer learning can work well with the dataset of omicron as well. In the future, we can use the vast dataset of chest X-rays to validate our suggested model. For any practical application of this project, it is also recommended that medical professionals be consulted. We don't want to develop a perfect detection technique instead; we want to look into the most cost-effective approaches to battle against this infection. Such approaches might be explored for additional investigation to demonstrate their real-world use.



(a)



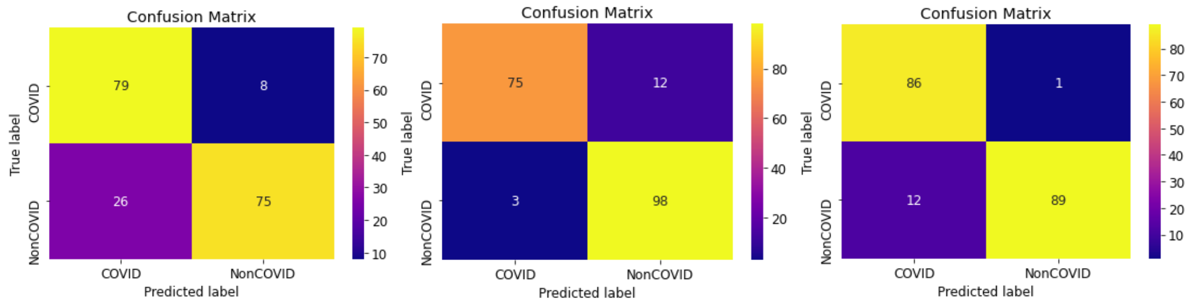
(b)



(c)

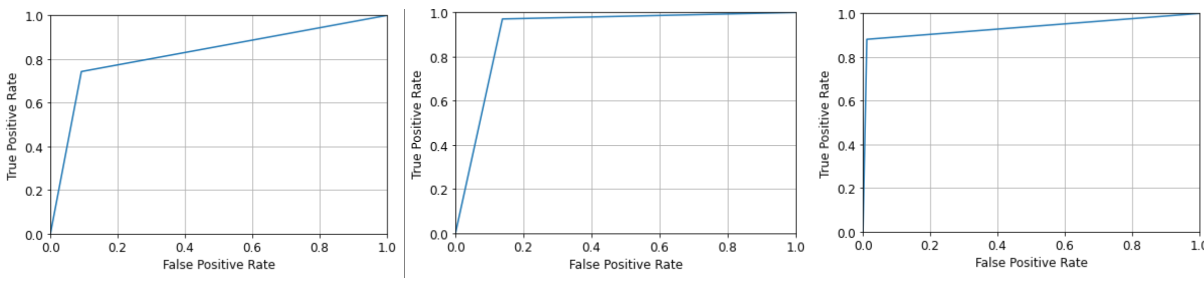
ISBN # 978-969-23372-2-9

Fig. 4. Accuracy and Loss Curve of models, (a) ResNet50 (b) Xception (c) VGG19



(a) **(b)** **(c)**

Fig. 5. Confusion Matrix of models, (a) ResNet50 (b) Xception (c) VGG19



(a) **(b)** **(c)**

Fig. 6. ROC Curve of models, (a) ResNet50 (b) Xception (c) VGG19

REFERENCES

[1] W. H. Organization, "Coronavirus disease 2019 (COVID-19): situation report, 73," 2020.

[2] A. S. Kwekha-Rashid, H. N. Abduljabbar, and B. Alhayani, "Coronavirus disease (COVID-19) cases analysis using machine-learning applications," *Appl. Nanosci.*, pp. 1–13, 2021.

[3] H. S. Maghdid, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq, S. Mirjalili, and M. K. Khan, "Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms," in *Multimodal Image Exploitation and Learning 2021*, 2021, vol. 11734, p. 117340E.

[4] W. Guan *et al.*, "Clinical characteristics of coronavirus disease 2019 in China," *N. Engl. J. Med.*, vol. 382, no. 18, pp. 1708–1720, 2020.

[5] D. M. Musher and A. R. Thorner, "Community-acquired pneumonia," *N. Engl. J. Med.*, vol. 371, no. 17, pp. 1619–1628, 2014.

[6] K. Tolksdorf, S. Buda, E. Schuler, L. H. Wieler, and W. Haas, "Influenza-associated pneumonia as reference to assess seriousness of coronavirus disease (COVID-19)," *Eurosurveillance*, vol. 25, no. 11, p. 2000258, 2020.

[7] G. Grasselli, A. Pesenti, and M. Cecconi, "Critical care utilization for the COVID-19 outbreak in Lombardy, Italy: early experience and forecast during an emergency response," *Jama*, vol. 323, no. 16, pp. 1545–1546, 2020.

[8] M. Sharma, B. Sharma, A. K. Gupta, D. Khosla, S. Goyal, and D. Pandey, "A Study and Novel AI/ML-Based Framework to Detect COVID-19 Virus Using Smartphone Embedded Sensors," in *Sustainability Measures for COVID-19 Pandemic*, Springer, 2021, pp. 59–74.

[9] A. Manish, P. Pandey, N. Garg, and T. Masood, "Novel severe acute respiratory syndrome corona virus. A review of current status and strategies in India."

[10] P. C. Y. Woo *et al.*, "Discovery of seven novel Mammalian and avian coronaviruses in the genus deltacoronavirus supports bat coronaviruses as the gene source of alphacoronavirus and betacoronavirus and avian coronaviruses as the gene source of gammacoronavirus and deltacoronavi," *J. Virol.*, vol. 86, no. 7, pp. 3995–4008, 2012.

[11] F. Wu *et al.*, "A new coronavirus associated with human respiratory disease in China," *Nature*, vol. 579, no. 7798, pp. 265–269, 2020.

[12] C. D. Coronavirus, "Available via the Internet at http://www. health. gov. on. ca/en/pro/programs/publichealth/coronavirus/docs/2019_case_definition. pdf," *Toronto, Canada Public Heal. Ontario*, 2020.

[13] T. Zebin and S. Rezvy, "COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization," *Appl. Intell.*, vol. 51, no. 2, pp. 1010–1021, 2021.

[14] R. R. Pasupuleti, P.-C. Tsai, V. K. Ponnusamy, and A. Pugazhendhi, "Rapid determination of remdesivir (SARS-CoV-2 drug) in human plasma for therapeutic drug monitoring in COVID-19-Patients," *Process Biochem.*, vol. 102, pp. 150–156, 2021.

[15] W. H. Self, D. M. Courtney, C. D. McNaughton, R. G. Wunderink, and J. A. Kline, "High discordance of chest x-ray and computed tomography for detection of pulmonary opacities in ED patients: implications for diagnosing pneumonia," *Am. J. Emerg. Med.*, vol. 31, no. 2, pp. 401–405, 2013.

[16] G. D. Rubin *et al.*, "The role of chest imaging in patient management during the COVID-19 pandemic: a multinational consensus statement from the Fleischner Society," *Radiology*, vol. 296, no. 1, pp. 172–180, 2020.

[17] H. Zunair and A. Ben Hamza, "Synthesis of COVID-19 chest X-rays using unpaired image-to-image translation," *Soc. Netw. Anal. Min.*, vol. 11, no. 1, pp. 1–12, 2021.

[18] B. A. Mohammed and M. S. Al-Ani, "Follow-up and Diagnose COVID-19 Using Deep Learning Technique."

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

ISBN # 978-969-23372-2-9

arXiv2006.11988, 2020.

[20] R. Jain, M. Gupta, S. Taneja, and D. J. Hemanth, "Deep learning based detection and analysis of COVID-19 on chest X-ray images," *Appl. Intell.*, vol. 51, no. 3, pp. 1690–1700, 2021.

[21] P. K. Sethy and S. K. Behera, "Detection of coronavirus disease (covid-19) based on deep features," 2020.

[22] M. J. Horry *et al.*, "X-ray image based COVID-19 detection using pre-trained deep learning models," 2020.

[23] F. M. Salman, S. S. Abu-Naser, E. Alajrami, B. S. Abu-Nasser, and B. A. M. Alashqar, "Covid-19 detection using artificial intelligence," 2020.

[24] R. Kumar *et al.*, "Accurate prediction of COVID-19 using chest X-Ray images through deep feature learning model with SMOTE and machine learning classifiers," *MedRxiv*, 2020.

[25] S. U. K. Bukhari, S. S. K. Bukhari, A. Syed, and S. S. H. Shah, "The diagnostic evaluation of Convolutional Neural Network (CNN) for the assessment of chest X-ray of patients infected with COVID-19," *MedRxiv*, 2020.

[26] S. H. Kassania, P. H. Kassanib, M. J. Wesolowskic, K. A. Schneidera, and R. Detersa, "Automatic detection of coronavirus disease (COVID-19) in X-ray and CT images: a machine learning based approach," *Biocybern. Biomed. Eng.*, vol. 41, no. 3, pp. 867–879, 2021.

[27] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. J. Soufi, "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning," *Med. Image Anal.*, vol. 65, p. 101794, 2020.

[28] M. Rahimzadeh and A. Attar, "A new modified deep convolutional neural network for detecting COVID-19 from X-ray images," *arXiv e-prints*, p. arXiv-2004, 2020.

[29] L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, "Finding covid-19 from chest x-rays using deep learning on a small dataset," *arXiv Prepr. arXiv2004.02060*, 2020.

[30] I. D. Apostolopoulos, S. I. Aznaouridis, and M. A. Tzani, "Extracting possibly representative COVID-19 biomarkers from X-ray images with deep learning approach and image data related to pulmonary diseases," *J. Med. Biol. Eng.*, p. 1, 2020.

[31] K. El Asnaoui, Y. Chawki, and A. Idri, "Automated methods for detection and classification pneumonia based on x-ray images using deep learning," in *Artificial intelligence and blockchain for future cybersecurity applications*, Springer, 2021, pp. 257–284.

[32] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks," *Pattern Anal. Appl.*, pp. 1–14, 2021.

[33] M. A. Zaki, S. Narejo, S. Zai, U. Zaki, Z. Altaf, and N. u Din, "Detection of nCoV-19 from Hybrid Dataset of CXR Images using Deep Convolutional Neural Network," *Int. J. Adv. Comput. Sci. Appl*, vol. 11, no. 12, pp. 699–707, 2020.

[34] M. Kim *et al.*, "Deep learning in medical imaging," *Neurospine*, vol. 16, no. 4, p. 657, 2019.

[35] J.-G. Lee *et al.*, "Deep learning in medical imaging: general overview," *Korean J. Radiol.*, vol. 18, no. 4, pp. 570–584, 2017.

[36] P. Deepan and L. R. Sudha, "Deep Learning Algorithm and Its Applications to IoT and Computer Vision," *Artif. Intell. IoT Smart Converg. Eco-friendly Topogr.*, vol. 85, p. 223, 2021.

[37] V. Rajesh and U. P. Naik, "Quantum Convolutional Neural Networks (QCNN) Using Deep Learning for Computer Vision Applications," in *2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, 2021, pp. 728–734.

[38] H. You *et al.*, "MC-Net: Multiple max-pooling integration module and cross multi-scale deconvolution network," *Knowledge-Based Syst.*, vol. 231, p. 107456, 2021.

[39] J. Li, Y. Pei, A. Yasin, S. Ali, and T. Mahmood, "Computer Vision-Based Microcalcification Detection in Digital Mammograms Using Fully Connected Depthwise Separable Convolutional Neural Network," *Sensors*, vol. 21, no. 14, p. 4854, 2021.

[40] A. Nalumansi *et al.*, "Field evaluation of the performance of a SARS-CoV-2 antigen rapid diagnostic test in Uganda using nasopharyngeal samples," *Int. J. Infect. Dis.*, vol. 104, pp. 282–286, 2021.

[41] M. A. Zaki, S. Narejo, M. Ahsan, S. Zai, M. R. Anjum, and N. u Din, "Image-based Onion Disease (Purple Blotch) Detection using Deep Convolutional Neural Network," *Image (IN).*, vol. 12, no. 5, 2021.

[42] D. Chicco, N. Tötsch, and G. Jurman, "The Matthews correlation coefficient (MCC) is more reliable than balanced accuracy, bookmaker informedness, and markedness in two-class confusion matrix evaluation," *BioData Min.*, vol. 14, no. 1, pp. 1–22, 2021.

[43] H. Zhang, L. Zhu, S. Xu, J. Cao, and W. Kong, "Two brains, one target: Design of a multi-level information fusion model based on dual-subject RSVP," *J. Neurosci. Methods*, vol. 363, p. 109346, 2021.

[44] M. Gour and S. Jain, "Automated COVID-19 Detection from X-ray and CT Images with Stacked Ensemble Convolutional Neural Network," *Biocybern. Biomed. Eng.*, 2021.

[45] Z. Mousavi, N. Shahini, S. Sheykhivand, S. Mojtahedi, and A. Arshadi, "COVID-19 detection using chest X-ray images based on a developed deep neural network," *SLAS Technol.*, 2021.

ISBN # 978-969-23372-2-9