USING DEEP CONVOLUTIONAL NEURAL NETWORKS DETECT COVID-19 FROM CHEST X-RAY IMAGES

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Abstract

Everyday life has been radically affected by the worldwide dissemination of COVID-19. The healthcare system in particular was almost overwhelmed to the point of collapse. The technology of artificial intelligence now allows for the development of very sophisticated systems, which can meet rigorous clinical accuracy criteria. Here, a specific kind of deep learning model called as CNN (Convolutional Neural Networks) was employed to identify pneumonia causedby the respiratory virus COVID-19. A total of 368 people who were diagnosed with COVID-19 had chest X-rays taken locally. Additionally, three open-source datasets were consulted. The efficacy was measured in four dimensions. In the early stages of training and testing, we used publicly accessible data. Second, both the training and testing data for the models came from both public and non-public domains. Third, the locally collected data was only utilized for testing, whereas the publicly available dataset was used for model training. By ensuring that the models aren't over fit to the training data, this technique verifies the accuracy of the detection methods and assesses how well they perform on novel data. As a fourth step, we utilized the local dataset for testing while training was done with the combined data. A cumulative detection accuracy of 98.7 percent was found, and most models performed similarly well when presented with novel data.

Index Terms—COVID-19, VGG16, Resnet 50, Inception V3,CNN(Convolutional Neural Networks)

Introduction

The SARS-CoV-2 virus, the causative agent of corona virus sickness 2019 (COVID- 19), has caused widespread destruction. In India, for instance, a recent outbreak of diseases has led many families to seek treatment at home rather than in one of the country's few ICUs. Numerous millions have died and countless others have had both temporary and permanent health issues as a result of this epidemic. Viral condition symptoms include high body temperature, dry cough, extreme tiredness, muscle and joint pain, impaired sense of taste and smell, and difficulty breathing. There may be other, less frequent symptoms (for example conjunctivitis and diarrhoea). Accurate diagnoses of infections are made using RT-PCR “real-time reverse transcription polymerase chain reaction”. CT scans and chest x-

rays (CXRs) serve an important role in confirming the presence of infection and determining the degree to which the lungs have been damaged. Clinical diagnosis of COVID-19 is mostly supported by CXR and CT scans. One of the most widespread forms of clinical diagnosis is the use of chest X- ray pictures. But, proper judgment requires for the use of specialized training and expertise. There aren't enough radiologists to go around, and the global COVID-19 epidemic is just adding to the pressure on medical professionals, therefore new, easily available solutions are needed. Artificial intelligence has progressed to the point where complex systems may be developed that can both manage massive amounts of data and satisfy stringent clinical accuracy criteria. By giving diagnostic references to radiologists, computer-aided diagnosis systems have the potential to enhance workflow, minimize diagnostic mistakes, and enhance workload situations throughout the medical hierarchy. There are several different strategies and fronts being used to combat COVID-19. Numerous components of responding to the pandemic have contactless alternatives that may be implemented with the help of artificial intelligence. Robotic systems for physical sampling, disinfection, and vital sign monitoring are a few examples. Also, verified cases not following quarantine standards are being aggressively identified using picture recognition and AI. We provide a method for automatically diagnosing COVID-19-related pneumonia in chest X-rays using AI (artificial intelligence). We employed three models: one hand- coded convolutional neural network, another that was pre-trained, and a third that was not (VGG16 and MobileNets). A major regional hospital's CXR images of verified COVID-19 patients were also gathered and examined by board- certified doctors over the course of6 months. The testing and training collection of images was expanded with the use of these images, making them more comprehensive than those found in the corresponding literature. The models were not only evaluated on the aggregated set, but also on the entirely different set of images that was utilized in the testing. Since some datasets include numerous images per individual, This approach showed some instances of the model being overfit to a small subset of CXR pictures.

I. Deep Learning Model

Currently, the most popular kind of artificial intelligence for solving classification issues is called deep learning. Numerous fields, most notably medicine, have found usefulness in its widespread and proven implementation. The models that briefed this research will be discussed in the following sections.

2D sequential CN

In the field of deep learning, CNN models are one subcategory. They are sortof feed forward neural networks, which excel at analyzing data in several dimensions. However, by sharing parameters and employing sparse connections, CNNs are able to preserve memory in comparison to multilayer perceptrons. In order for the different CNN parts to process the incoming images, they must first be converted into a matrix.

Convolutional layer

The convolutional layer is responsible for calculating the features of the various input patterns. The input matrix is subjected to a series of dot products (also known as convolutions). In this method, a feature map is generated from a kernel in the image processor that consists of many filters (i.e., motifs). Sub-windows of the input are convolved with the kernel using weights to create receptive fields. In this research, a 2D convolution layer was used (i.e., utilizing CONV2D class).

Pooling layer

By decreasing the amount of feature maps as well as network parameters, this down-sampling layer decreases the output volume. In addition, pooling aids generalization of the model by decreasing over fitting. The result of this process is a set of characteristics that hold up well during distortion and translation.

Dropout

In the world of neural networks, over fitting is a typical issue. Therefore, regularization is introduced into the network through dropout to enhance generalization. To do this, certain units, both visible and not, are arbitrarily disregarded. Thus, the network is taught to be able to process competing internal images.

Fully connected layer

Taking the feature map as input, this layer then uses an activation function to provide nonlinearly altered output. Characteristics from all phases are combined in this global process, which then yields a nonlinear collection of categorization features. In this stage, we employed the rectified linear unit (ReLU) to get around the vanishing gradient issue.

II. Pre-trained models

Mobile Nets

Mobile Nets model was chosen for this research because it is a CNN architecture that makes efficient use of limited resources and considers future mobile applications for disease detection. The number of parameters is drastically cut down by using depth-wise separable convolutions. Google released Mobile Nets under an open-source license to facilitate the creation of energy-efficient, space-efficient, and latency-tolerant mobile apps.

VGG-16

Among the various models available in the academic literature, VGG-16 stands out. It has been tweaked in a number of ways to lower its resource usage and increase its precision (e.g., VGG-19). In terms of computing, the VGG model has 19 layers, 3×3 filters, 1×1 convolution among convolution layers (for regularization), as well as max-pooling after the convolution layer; it is a spatial exploitation CNN. The type is well-liked for its straightforwardness.

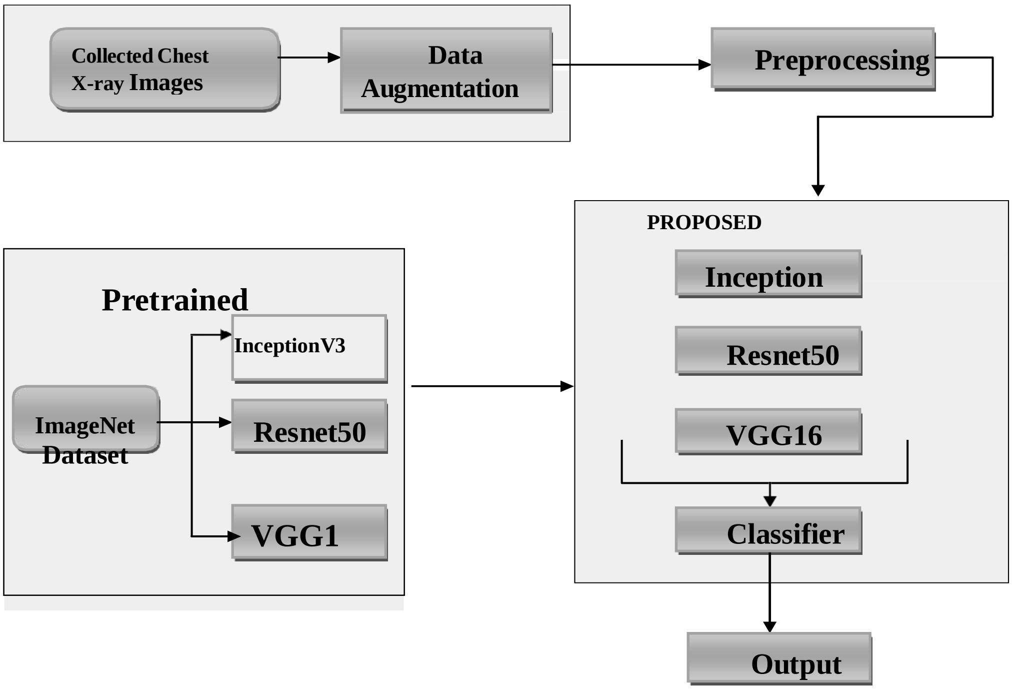
Related Works

The applications of the technologies employed in this article's tumor identification in image processing are reviewed in this part. Some of the most cutting-edge CNN architectures used for medical picture classification are assessed by Ioannis et al. [3]: Inception, Inception-ResNet-v3, Xception, MobileNet v2, and VGG19. Since there are few medical imaging datasets large enough to test for every possible flaw, the author resorts to transfer learning. A total of 1,442 X-ray data sets were included, including those of 714 patients with viral pneumonia as well as bacterial pneumonia, 224 patients with proven COVID-19 illness, 504 healthy controls, and additional patients who were relevant. According to the findings, MobileNet-v2 and VGG19 provide the highest accurate classification of the remaining CNNs. While VGG19's 98.75% accuracy is impressive, MobileNet-superior v2's sensitivity and specificity make it the superior technique (reaching 99.10 along with97.09 percent, respectively).People like Narin worked tirelessly to ensure that public hospitals no longer lacked access to COVID-19 test kits. To prevent further COVID-19 transmission and relieve stress on healthcare providers, it is suggested in [20] that an automated detection system be developed as a quickdiagnostic backup plan. To diagnose cases of corona virus pneumonia, the author examined a 100 chest X-ray images and made use of 3 diverse CNN-based models (ResNetV2, Inception-InceptionV3, ResNetV2) (50 COVID-19 images as well as 50 health images). Based on the collected reference data, we may conclude that pre-trained ResNet50 model outperforms the other two suggested models. InceptionV3's accuracy is 97%, whereas that of Inception-ResNetV2 is just 87%.A novel method for automatic COVID-19 identification in raw radiography pictures is presented by Ozturk et al. [21]. The YOLO real-time object identification system employs the suggested DarkNet model as its classifier. This model is comprised of seventeen convolutional layers. The authors use a multi-level filtering structure. The goal of this strategy is to correctly diagnose cases that fall into two- class (COVID/no-findings) and multi-class (COVID/no- findings/pneumonia) categories. For single binary classification the accuracy rate is 99.08 percent, whereas it drops to 87.02 percent when using more than two categories.Sethy and Behra describe a technique for detecting corona virus infections in X-ray images of patients utilizing deep features along with SVM classification. They employ SVM based classifiers instead of deep learning. The CNN model's completely linked layers serve as the source of the deep characteristics they're seeking. They then use SVM to sort the data into categories. Corona virus- affected X-ray pictures are categorized using SVM. COVID-19 X-rays, pneumonia X-rays, as well as standard X- rays are all used in the process. The author evaluates SVM's performance in identifying COVID-19 employing the deep functions of 13 distinct CNN models. SVM achieves optimal performance by making use of the rich characteristics of ResNet50. ResNet50and SVM both max out at 98.66% accuracy. A CNN model (COVID-Net) is given by Wang et al. [30]

for corona virus diagnosis from chest radiographs. Although there are only 76 photos of COVID-19 cases in COVIDx chest X-ray data set, 8066 normal images, and 5526 images of patients with pneumonia who do not have COVID-19 were used. PEPX design pattern, which is used in the construction of COVID-Net, is a lightweight residual projection extension. The 2.26 billion MAC operations needed to forecast a case with 92.4 percent accuracy is a decent trade-off between time and accuracy. Xu et al. [35] discover that this novel virus has distinctive CT imaging properties compared to existing viral pneumonias. In order to identify computed tomography images, calculate the likelihood of a COVID-19 infection, and aid in early identification, specialists have turned to several CNN models. The research comprised CT scans from 175 healthy participants, 219 COVID-19 infected participants, and 224 patients with influenza A virus pneumonia. To accomplish the objective of decomposing a set of images cubes into individual scenes, they use a 3D convolutional neural network (CNN) model built on top of the widely used ResNet-18 network architecture. Each picture block is labelled thanks to the author's employment of a 3D image categorization model. Our categorization system is geared toward identifying lung images with plaques based on their locations. Noisy or Bayesian algorithms not only classify the sickness (COVID- 19, influenza) but also calculate the total confidence score of CT cases. a case of viral pneumonia or an unidentified infectious agent). The proposed model showed remarkable overall classification accuracy across the three classes, at 86.7 percent. A deep learning method termed "VB Net" is proposed by Shan et al. [26] for autonomously segmenting and quantifying corona virus infection hotspots in computed tomography data. Combining features of the V-Net and bottleneck models resultsin the "VB Net" model. While V-Net is utilized for extracting global image properties, the bottleneck model employs convolution as well as up-sampling to combine fine-grained picture information. Data from 249 COVID-19 patients have been employed to train the system, while data from 300 newly afflicted persons were used to verify it. Faster display of COVID-19 CT images for training is provided using the author's "in loop (HITL)" approach, which iteratively builds training examples. Drawing the revised model after the third iteration of the suggested manual loop approach takes just 4 minutes. The deep learning model achieved 91.6 percent accuracy in subdividing the whole 300-point verification set, as measured by the Dice correspondence coefficient. In this study, we assessed very deep convolutional networks for large-scale picture categorization (up to 19 weight layers). It was shown that representation depth improves classification accuracy, and that using a traditional ConvNet architecture (LeCun et al., 1989; Krizhevsky et al., 2012) with significantly increased depth, state-of-the-art performance on the ImageNet challenge dataset can be attained[10]. A human-in-the-loop (HITL) strategy has been adopted to help radiologists for infection region segmentation, which dramatically reduced the total segmentation time to 4 minutes after 3 iterations of model updating. This allowed for quick manual delineation of training samples and potential manual intervention of automatic results. Between automatic and manual infection segmentations, the average Dice similarity coefficient revealed 91.6% agreement, and the mean estimation error of percentage of infection (POI) was 0.3% for the entire lung. The study of follow-up CT scans and the correlation between infection distributions in the lobes and segments and clinical results were just a few of the potential applications that were mentioned.[9]

Methodology

All of the problems with the existing setup are suggested to be addressed by the new model. In this study, we employ three widely used pre-trained deep learning architectures for



“Fig. 1. Block Diagram for proposed work”

classifying chest X-ray images as either "COVID-19" or "non- COVID- 19." Deep learning models like VGG16, InceptionV3 and ResNet50, find extensive application. Figure 1 offers a high-level summary of the study's methodology, outlining the deep learning approach presented using a conventional, minimally-invasive workflow for preprocessing chest images and then applying a transfer-learned classification model. A deep model is trained once the data has been cleaned and prepared. The fully-connected classifier, for instance, will be trained alongside the augmented model component in our experiment (by a process of fine-tuning wherein the frozen model utilized for feature extraction has its upper layers unfrozen)

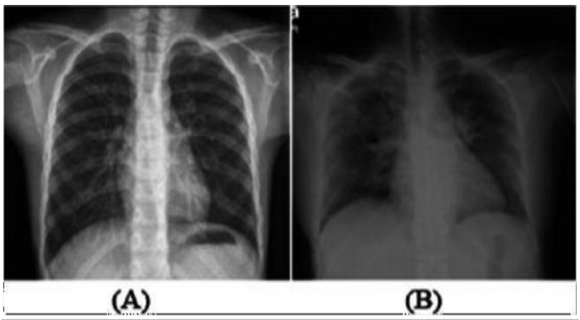
Dataset Creation

Chest X-rays may be used to evaluate a patient's lung health because of the harm COVID-19 does to the epithelial cells that lining our airways. This article refines the three proposed classification models utilizing chest X-rays instead of CT images. Despite the greater radiation exposure, longer scanning periods, and higher costs associated with CT scans, X-rays provide a number of benefits. Hospital infections and the requirement for PPE may be reduced if portable X-ray machines are tested in isolation rooms. In addition, analyzing images from chest X-rays might be a more convenient alternative to the PCR technique. They may help with a wide range of issues, from detecting the illness to isolating and prioritizing high-risk individuals to doing targeted tests to uncover false-negative PCR results. But radiologists and clinicians have a hard difficultyvisually distinguishing enough information between viral pneumonia patients due to their similarity and overlap. The deep learning models may provide a precise answer. We conducted an experiment in which we used three different augmentation procedures on our gathered chest X-ray images for decreasing false positives and negatives number. A total of 5000 images were utilized to create the dataset for this research."Chest X-Ray Images (Pneumonia)" as well as "Covid-19 Radiography Dataset" repositories on Kaggle were mined to get the requisite 3,000 images for a typical chest X-ray.623 chest X-rays Images from the COVID-19 radiography data set may be found in the Covid-19 repository on GitHub. Therefore, we used image enhancement to get the total to 2000.The contents of the Normal and COVID-19 subfolders of the prepared dataset are listed in Table 1 below.

	Without Data Augmentation	With Data Augmentation
COVID -19	623	2000
Normal	3000	3000
Total of images	3623	5000

Table 1 Content of our prepared dataset

Two sample chest X-rays from our compiled dataset are shownin Figure 2.



“Fig. 2 (A): Chest X-ray image of a healthy person.(B): COVID-19 chest X-ray image”

I. Data Augmentation

In most cases, for deep learning models, a large quantity of training data is necessary. Because introduction of deep learning, image augmentation technology was more popular in the field of computer vision. Due of the disease's recent appearance, COVID-19 lacks a Publicly accessible dataset large enough to construct a reliable model. Since data augmentation is a very effective method for artificially generating a large dataset, it is the only option we have. Horizontal flips, random rotation along with random noise at an angle between 10 and 10 degrees are the three methods we use to improve the quality of the original. The term "image noising" describes the method our model use to learn how to decipher signal from noise in visual data. As a result, the model will be less sensitive to changes in the starting conditions

II. Data Preprocessing

The X-ray images may be adjusted during preliminary processing of the data. This is because different algorithms need unique sets of input images. The images must be scaled such that they match the model specifications. All of the input photographs were of varying sizes before being processed and having their dimensions standardized to 224×224.

III. Transfer Learning Approach

There was not enough data to reliably train a CNN model from start, therefore automated COVID-19 X-ray picture identification may not be possible. To address this issue, we use a standard technique known as "transfer learning" to fine-tune threewidely-used pre-trained models using data at hand.

Modifications to the initial, pre-trained framework are necessary for the vast majority of deep learning applications. We feed fresh data containing novel classifications into a preexisting network. A new job may be performed as soon as the network is updated.

There are primarily two approaches of reusing models that have already been trained. In the first approach, a pre-trained model is utilized for extracting features to feed into a newly trained classifier; however, the pre-trained model's weights are not transferable to the current job at hand. A new classifier may be learned by feeding new data into the convolutional basis of the already-trained network. The second approach involves teaching the network to do a novel task. As a result, the network uses the learned model's weight as input to the next training exercise. Due to hardware constraints during COVID- 19 images acquired, we only made minor adjustments to the last CNN layer and used the pre-trained model as the feature extractor.

COVID-19 Detection using VGG16:

VGGnet framework, or "Very Deep Convolutional Networks forLarge-scale Image

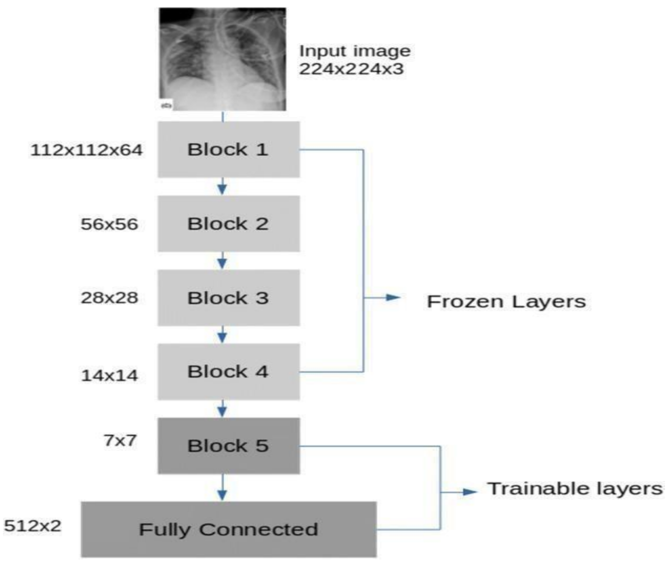
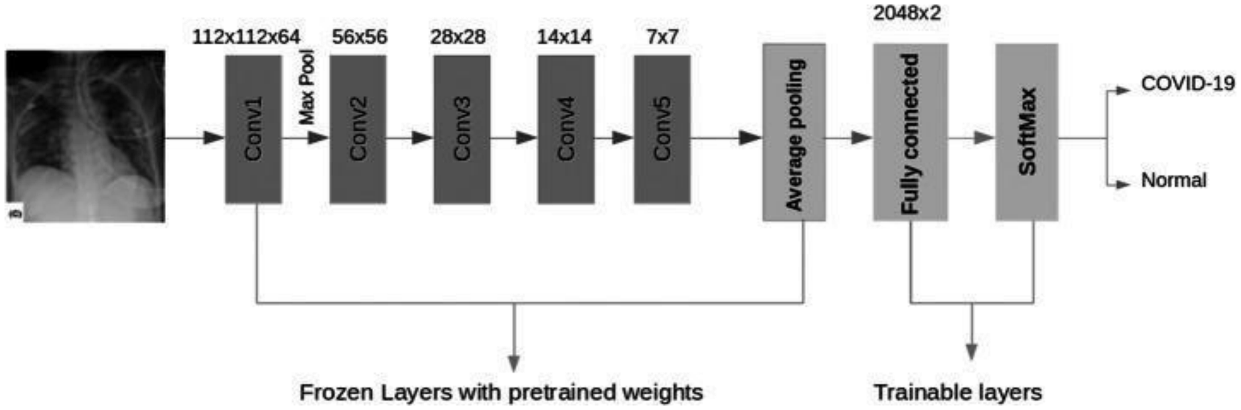


Fig.3 Proposed VGG-16 Architecture

Recognition," is responsible for this. Networks in the VGG series are distinguished by their use of stacked convolutional layers of size 3 by 3, with increasing depthas the series progresses. In order to decrease the volume, a maximum pooling is used. The suggested architecture for VGG16 is shown in Fig. 3, with the frozen and trainable layer inparticular being highlighted.

COVID-19 detection using ResNet5:

The ResNet-50 CNN has 50 layers, making it more complex than the VGG16 network. ResNet50's model size is reduced from 104 MB to 102 MB by using global average pool in place of fully linked layer. Residual block learning is where ResNet really shines. This implies that there should be a direct connection between each layer and the layers that are the following two or three hops away.



“Fig. 4 Proposed Resnet50 Architecture”

COVID-19 detection using inceptionV3*:*

By performing 1 ×1, 3 ×3, and 5× 5 convolutions in similar network module, therefore initial module serves as a "multi- level feature extractor." The results of these filters, including thenumber of channels used, are then sent to the layer below. Whencompared to Resnet and VGGnet, Inception architectures need less processing resources (since using this framework requires less memory). However, the results showed that it performed very well.

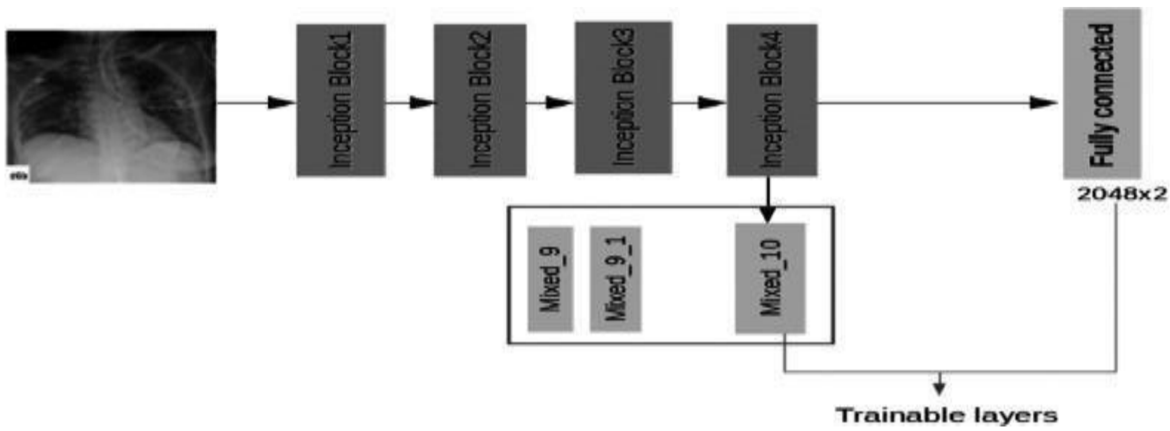


Fig. 5. Proposed InceptionV3 architecture

Results Analysis

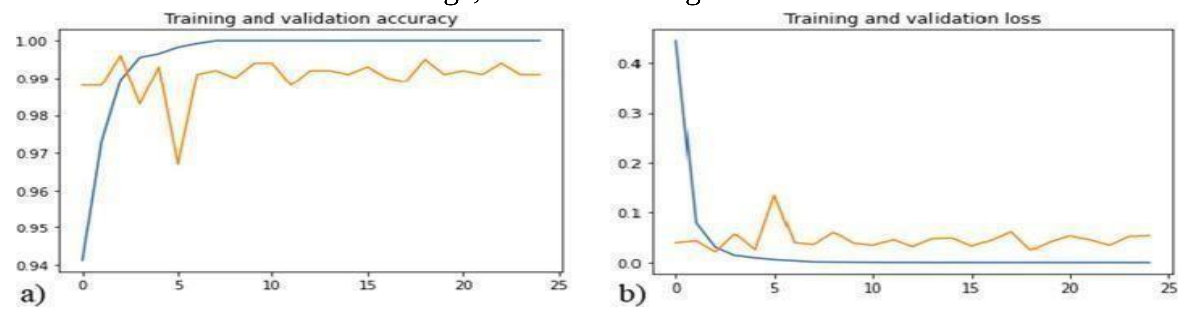
I. Experimental Results

The underlying layers' activation function is represented using rectified linear units. A (224, 224, 3) is the input shape. All of the models are tuned for a total of 25 iterations. Our parameters for the loss function, ADAM, are as follows: batch size = 32, learning rate = 0.0001. A cross-entropy loss function was applied to all models. We split the dataset (mentioned in Sec. 3.1) in half, using the first half for training purposes (around 80% of the total) and the second half for validation purposes (20% of the total). The F1 score is the culmination of the following six performance metrics: precision, recall, specificity, accuracy, sensitivity. The final results are shown below.

II. Training Results

The suggested models' training outcomes are recorded and shown in Figs. 6, 7, and

8. Validation data is shown in orange, whereas training data is shown in blue.



“Fig. 6. Plots of (a) Training and validation accuracy and (b) Training and validation loss by” using training epochs-InceptionV3

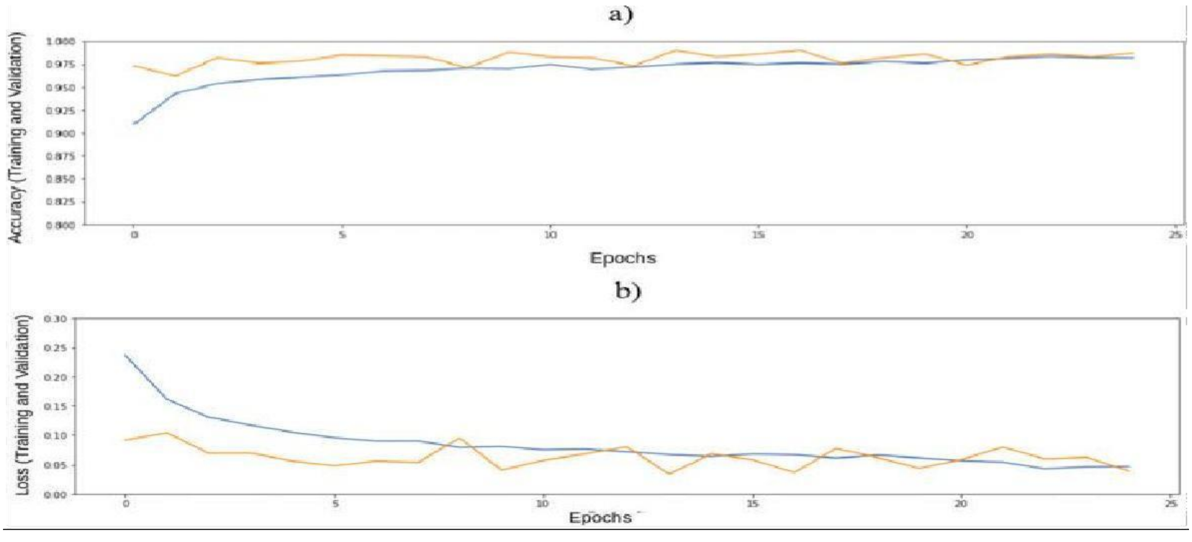
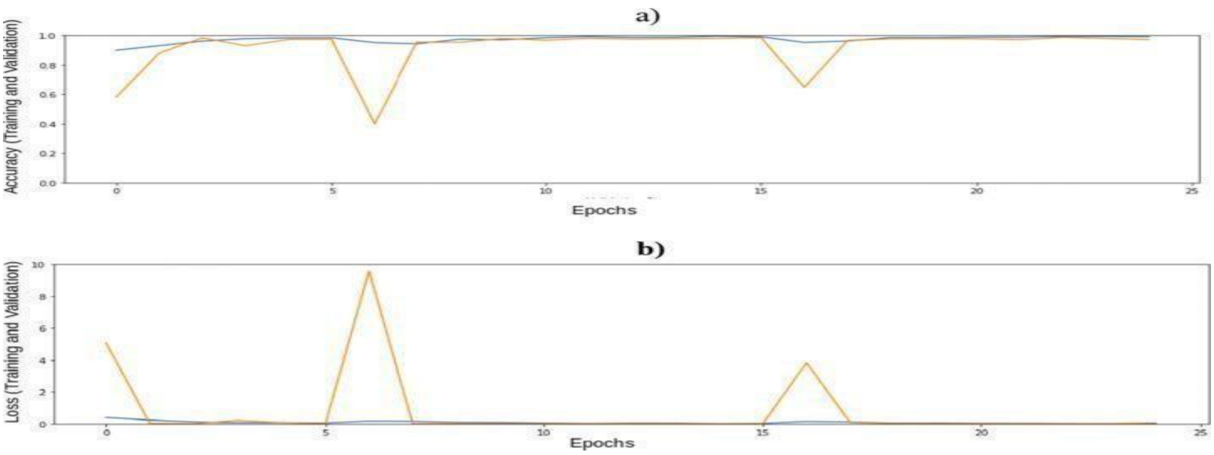


Fig.7. Plots of (a) Training and validation accuracy and (b) Training and validation loss by using training epochs-VGG16“



"Fig. 8. Plots of (a) Training and validation accuracy and (b) Training and validation loss by using training epochs-Resnet50"

Training accuracy for the three models reaches as high as 97% while training loss is limited to 0.1, as seen in every image. In the world of medical diagnostics, this is appositive indicator for accurate classifications to be made.

III. Performance Criteria

Using the aforementioned criteria— precision, recall, specificity, accuracy, sensitivity and ultimately F1 score—we may evaluate the efficacy of a classification model. A model might be assessed according to specificity and sensitivity. In fact, they see extensive use in the medical field.

Definition of the terms

First, we need to distinguish between four types of target-classified items before we can assess the classifier's performance:

- True Positive (TP)
- True Negative (TN)
- False Positive (FP) and
- False Negative (FN).

1) **TP:** It occurs when incorrect category is marked as "positive" by the model. The term "positive class" here indicates a person with COVID 19.

2) **TN:** It occurs when a negative class is successfully predicted by the model. A patient who does not have COVID 19 belongs to the "negative class" in this context.

3) **FP:** (Type 1 Error): It happens when the incorrect category is marked as "positive" by the model. An incorrect assumption was made about a patient with COVID-19.

4) **FN:** (Type 2 Error): Whenever a model makes a wrong prediction for a class that has a negative value. The assumption that a patient does not have COVID-19 was

incorrect. We must first disclose the metrics by which we judged the quality of the pre trained models.

- ***Classification accuracy*** = TP + TN / (TP + TN + FP + FN): this is measured by how often images are accurately identified.
- ***Sensitivity*** = TP / (FN + TP): Evaluation of the model's performance in identifying favourable occurrences. Since COVID-19 falls into the positive category, the percentage of X-ray images properly predicted as COVID-19 may be measured using sensitivity.
- ***Specificity*** **=** TN/ (FP + TN): The rate at which true negatives are identified is called "specificity."

- ***Precision*** = TP/(TP + FP): It is defined as the ratio between actual and predicted number of positive classes. Accuracy refers to the percentage of true COVID-19 infections among those patients who were expected to have a positive result. Precision is essential.
- ***Recall*** = TP / (FN + TP): The percentage of positive individuals that were properly diagnosed is known as the recall rate. The goal is to raise it to its highest feasible level.
- ***F1 score*** = 2 * (precision * recall)/ (precision + recall): It is difficult to provide fair comparison between two models that either have high recall but poor accuracy or low recall whereas excellent precision. The F1-score is often utilized for such a purpose. It permits simultaneous evaluation of both accuracy and recall. In practice, we substitute the Harmonic Mean for the Arithmetic Mean. As a consequence, we place even more emphasis on punishing outlying values.

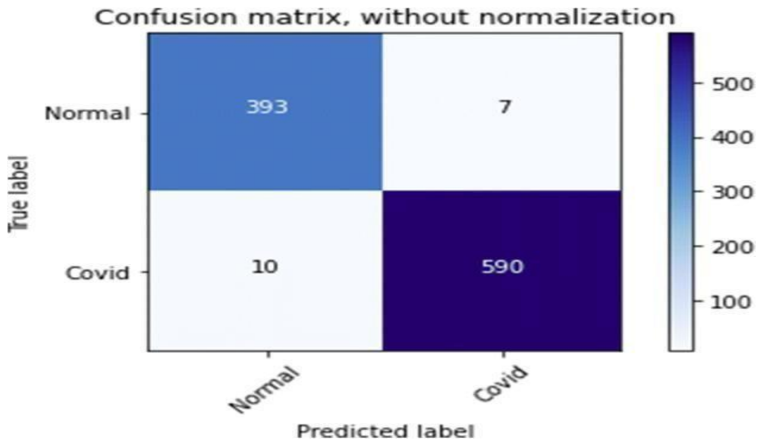
Results

Table 2 displays the VGG16, Resnet50, and InceptionV3 accuracy, sensitivity, precision, specificity, recall, along with F1 score. It reveals that when compared to the suggested fine-tuned version of Resnet50, the two fine-tuned versions of InceptionV3 along with VGG16 perform better across all six metrics. As can be observed in the third to last column of Table 2, both optimized versions perform similarly in terms of accuracy, F1 score, and recall.

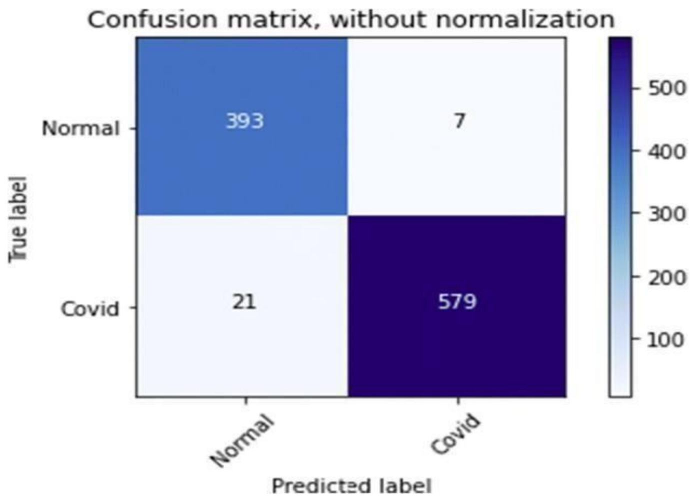
Modified version of	***Accuracy***	***Recall***	***Precision***	***Specificity***	***sensitivity***	***F1 Score***
InceptionV3	98.10 %	98.00 %	98.00 %	98.00 %	99.25 %	98.00 %
Resnet50	97.20 %	96.00 %	97.00 %	97.00 %	98.25 %	97.00 %
VGG16	98.30 %	98.00 %	98.00 %	98.33 %	98.25 %	98.00 %

Table 2 Classification report for Resnet50, InceptionV3 and VGG16

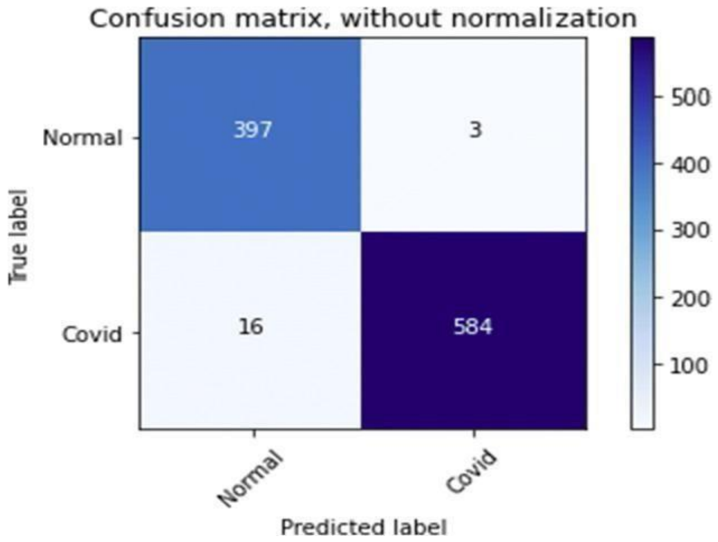
When compared to optimized InceptionV3, updated VGG16 model performs marginally better in terms of specificity and accuracy. In contrast to VGG16, the tweaked InceptionV3 achieves higher sensitivity. This leads us to the conclusion that InceptionV3, with its many improvements, is the best option.The confusion matrix between these 3 models is provided. Figures 9, 10, and 11 illustrate confusion matrices for InceptionV3, ResNet50, along with VGG16 models, respectively, using a dataset of 1000 test images.



“Fig. 9 The confusion matrix of the proposed VGG16 model



“Fig. 10 The confusion matrix of the proposed Resnet50 model”



“Fig. 11. The confusion matrix of the proposed InceptionV3 model”

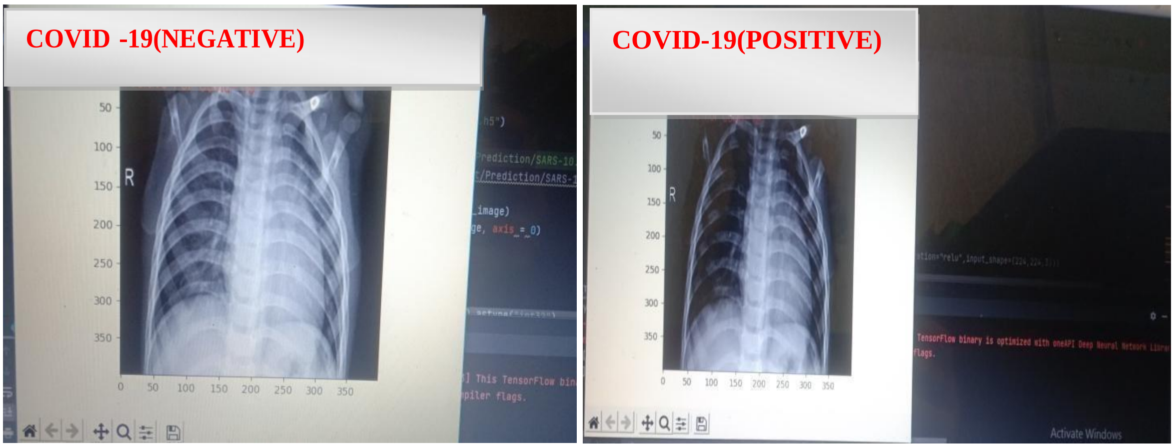


Fig. 12. Output Result

Discussion

With a sensitivity and specificity of around 98%, all three models have shown favorable outcomes. InceptionV3 outperforms Resnet50 and VGG16, but only by a small margin.Our findings demonstrate that an effective CNN model can be built utilizing a mixture of data augmentation and transfer learning techniques using Resnet50, VGG16,and InceptionV3.The findings show that recall rate and accuracy of COVID-19 instances is a good observation. There were fewer false-negative results (FN) because of the high recall rate. It's important to note that FN prediction has serious risks to both patients and society as a whole since it allows sick people to go about their regular lives without taking anyprecautions against spreading the disease. Considering that decreasing FN COVID-19 occurrences is central to this work in order to improve clinical decision assistance, this discovery is noteworthy. The findings of automated

COVID-19 diagnosis applying chest X-ray images are summarized in Table3 as well as compared to the suggested model

"Stud y	*Architecture*	*Accuracy*	*Number of parameters in Million*
Narin et al. [20]	InceptionV3	97 %	26
Sethy and Behra [25]	Resnet50	95.38 %	36
Ioannis et al. [3]	VGG19	98.75 %	143
Ozturk et al. [21]	DarkNet	98.08 %	1.1
Ioannis et al. [3]	Xception	85.57 %	33
Fine-tuned InceptionV3	InceptionV3	98.10 %	21
Fine-tuned VGG16	VGG16	98.30 %	15
Fine-tuned Resnet50"	Resnet50	97.20 %	23

Table 3 Comparison of the most commonly used automatic diagnosis of COVID-19 that are based on chest X- ray images to our fine-tuned models

Common models with the same number of parameters are considered in Table 3. (around 25 Million). Comparing the accuracy of the models in Table 3 to that of our three improved models, theresult is clear. For other five performance indicators, we do not have any data at this time. A future piece will focus on this topic. Compared to our optimized models and the models in Table 3, the VGG19 model has 143 million parameters, or roughly 7 times as many. The increased computing effort required by this model is offset by its improved accuracy (98.75 percent). The fine-tuned VGG16 model is already 0.5% less accurate than the VGG19 model, thus there is no use in expanding our models to include more parameters.The clinical support function of the deep learning model created for identifying COVID-19 in x-rays is expected to grow if the model proves to be accurate. The study's shortcomings may be mitigated by doing further analyses if more data becomes available (symptomatic as well as asymptomatic patients).

Conclusion

The new corona virus must be identified as quickly as possible in order to stop its spread. In this study, we automate the identification of COVID-19 in patient chest X-rays using a deep transfer learning-based technique. The suggested classification model has demonstrated an accuracy of more than 98% when used to the detection of COVID-19. Our research suggests that using it to help doctors make clinical decisions is consistent with the laws of nature. This research paper shows in depth how to implement deep transfer learning algorithms for speedy COVID-19 detection. The global healthcare system is at peril from COVID-19, which is responsible for millions of deaths every year. Computer-aided analysis has the potential to save lives through early screening and appropriate therapy since doctors have less time to devote to each patient while treating a large number of people in the field or in an emergency. Our optimized models show impressive efficiency in identifying COVID-19 pneumonia, and they were trained fast using a limited sample of pictures. We are certain that the suggested CAD approach will significantly enhance the COVID-19diagnosis. Clinical diagnostic procedures can effectively include cutting-edge methods for deep learning and medical image processing. Combining the use of quantitative image analysis technologies with the expertise of the doctor can increase the sensitivity and specificity of the diagnosis while speeding up interpretation. In pandemic time, when current health careresources may be insufficient to deal with the disease load and the need for preventative activities, this will be of great assistance. The purpose of deep learning research is to create increasingly precise world representations and models that can autonomously acquire these representations without the use of labeled training data. Recent discoveriesin several disciplines inspired some of these renderings. For example, researchers may use deep learning algorithms to explore temporal and spatial relationships. To reliably forecastcitywide traffic, they propose a deep hybrid spatiotemporal neural network. Combining the three models shown here and training all the layers might be explored further as a creative approach to producing better results in future research.

REFERENCES

[1] Ai T et al (2020) Correlation of chest CT and RT- PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. Radiology: 200642 [PMC freearticle][PubMed]

[2] Ali A, Zhu Y, Zakarya M. A data aggregation-based approach to exploit dynamic spatio- temporal correlations for citywide crowd flows prediction in fog computing. Multimed Tools Appl. 2021 doi: 10.1007/s11042-020-10486-4. [CrossRef] [Google Scholar]

[3] Apostolopoulos ID, Mpesiana TA (2020) Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Phys Eng Sci Med43(2):635– 640 [PMC free article] [PubMed]

[4] Axell-House DB, Lavingia R, Rafferty M, Clark E, Amirian ES, Chiao EY (2020) The estimation of diagnostic accuracy of tests for COVID-19: A scoping review. J Infect 81(5):681– 697 [PMC free article] [PubMed]

[5] Lalkhen AG, McCluskey A (2008) Clinical tests: sensitivity and specificity. Contin Educ Anaesth Crit Care Pain 8(6):221–223

[6] Narin A, Kaya C, Pamuk Z (2020) Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849 [PMC free article] [PubMed]

[7] Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR (2020) Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput Biol Med 121:103792 [PMC free article] [PubMed]

[8] Romero Lopez A, G-i-Nieto X, Burdick J, Marques O (2017) Skin lesion classification from dermoscopic images using deep learning techniques,. (2017) 13th IASTED International Conference on Biomedical Engineering (BioMed), pp 49–54.10.2316/P.2017.852-05326.

[9] Shan F et al (2020) Lung infection quantification ofcovid-19 in ct images with deeplearning. arXiv preprint arXiv:2003.04655

[10] Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[11] Wang L, Lin ZQ, Wong A. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Sci Rep.2020;10(1):1–12. doi: 10.1038/s41598-019-56847-4. [PMC free article] [PubMed][CrossRef] [Google Scholar]

[12] Xu X, Jiang X, Ma C, Du P, Li X, Lv S, Li L (2020) A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering 6(10):1122–1129 [PMC free article] [PubMed]