Employing transfer learning techniques for COVID-19 detection using chest X-ray

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ABSTRACT

Coronavirus 2 (SARS-COV-2) is a global emergency that continues to terrify the globe at an alarming rate. Some nations are still combating the virus, attempting to discover infected individuals early on to prevent the infection from spreading. In terms of identifying the pattern in the pictures, radiological patterns have been shown to have greater accuracy, sensitivity, and specificity. Publicly available datasets are used for the implementation. The data is divided into three categories: COVID, normal, and pneumonia patients. Transfer learning is a type of deep learning that allows pre-trained models to be used and achieves high accuracy by detecting various anomalies in limited medical datasets. An image dataset of 1109 pictures was used in this work, and training was done using two distinct models, ResNet50 and InceptionV3, to distinguish the patient categories. For ResNet and InceptionV3, the proposed model has an accuracy of 97.29 and 98.20, respectively, with a sensitivity of 100% for InceptionV3 and a specificity of 99.41% for ResNet50. With a 98.20% accuracy, complete sensitivity, and high specificity, this study presents a deep learning model that gives diagnostics for multiclass classification and attempts to discriminate COVID-19 patients using chest X-ray photos. Other illnesses can also be detected using the proposed model.

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1. INTRODUCTION

On January 30, 2019, World Health Organization (WHO) declared coronavirus a health emergency as Wuhan became the epicenter of the epidemic [1]. As of June 13th, 2020, the total number of cases was reached to 7,573,699 people. It was given the name coronavirus because the virus resembled a crown [2], and it belongs to the coronaviridae family [3]. Alphacoronavirus, betacoronavirus, and gammacoronavirus are three members of the coronaviridae family, all of which are derived from the bat species "rousettus leschenaulti" [4]–[6]. The virus is thought to have originated in a human seafood market, and the virus's ability to reproduce and mutate fast allows it to find new hosts quickly [7]. Coughing, sneezing, droplets, and aerosols can all be used to spread this [8], [9]. Coronavirus 2 (SARS COV-2) is the virus, and COVID-19 is the disease [10]. Symptoms include fever, headache, muscular discomfort, sore throat, dyspnea, and tiredness. Figure 1 depicts the global increase in confirmed cases, fatalities, recoveries, and active cases, with the United States of America, Brazil, Russia, and India at the top of the list with the most active cases.

Figure 2 depicts the twenty nations with the highest number of active cases. The sensitivity of reverse-transcription polymerase chain reaction (RT-PCR) can be as low as 60-70%, which implies that it may initially indicate a negative COVID-19 but still reveal abnormalities on a chest computed tomography (CT), such as peripheral focal or multifocal ground-glass opacities [11]–[13]. COVID-19 is shown to be negative in research utilizing the RT-PCR test but is subsequently found to be positive by repeated swab testing [14].

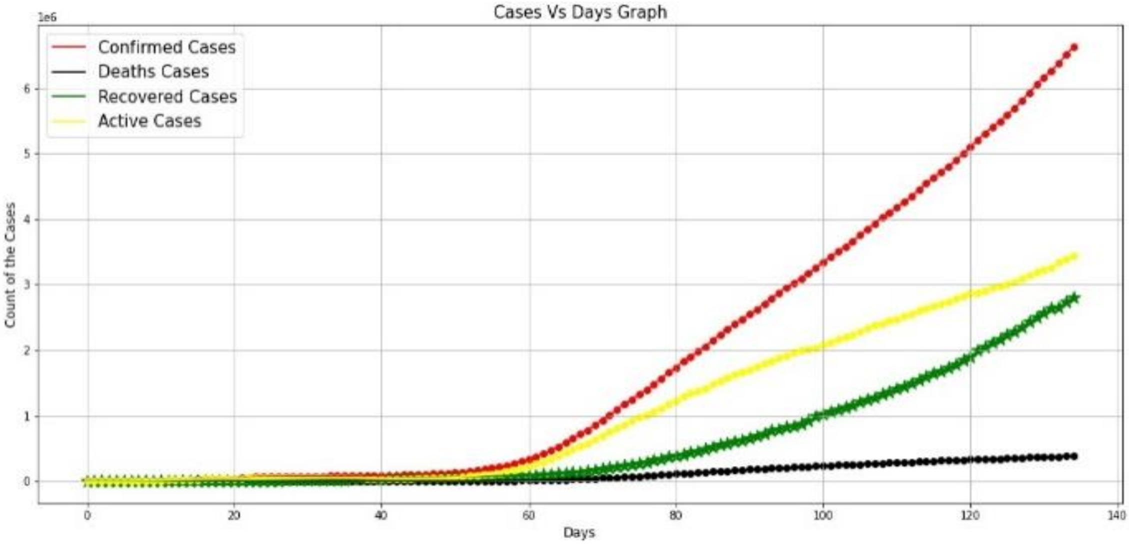


Figure 1. Growth in cases globally

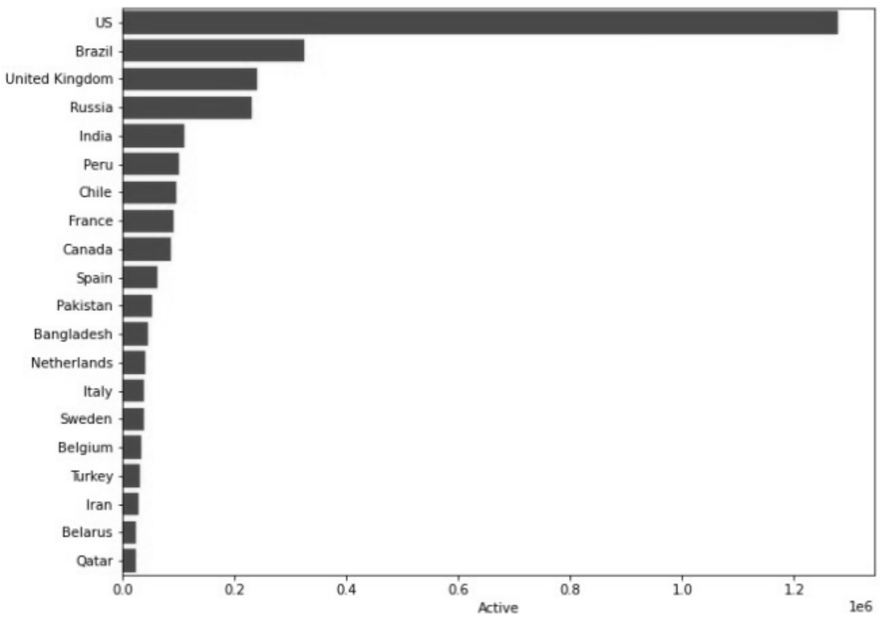


Figure 2. Top twenty counties with maximum active cases

Due to the sheer scarcity of RT-PCR kits and the possibility of false-negative findings, chest CT diagnosis was chosen as a valid stand-alone method for detecting COVID-19 [15], [16]. This implies that asymptomatic persons who have been exposed to COVID-19 pneumonia patients in the early stages of the disease should have CT scans [17]. Several studies show that radiological testing provides consistent findings in clinical situations [18]–[20]. CT scans can be very effective in detecting COVID-19. CT scans have a reduced risk of missed diagnosis due to their great sensitivity [20], [21].

Machine learning may be utilized for anything from detection through diagnosis, prognosis, and risk calculation [22], [23]. Deep learning is an effective approach for detecting comparable ground-glass opacity (GGO) in the early stages of radiological imaging [24]. To identify Pneumonia, a CNN was utilized for feature extraction and training of data on chest X-ray images [25]. Because of its ability to conduct an alternative dataset with the information obtained from one dataset, transfer learning with CNN is favored.

For normal and COVID, visual geometry group 19 (VGG19) and dense convolutional network (DenseNet) show almost identical performance of 89 and 91%, respectively [26]. COVID-Net, developed by Wang *et al.* [27], has a positive predictive value of 90.5% for normal cases, 91.3% for non-COVID cases, and 98.9% for COVID-19 cases, which is higher than the scores obtained by VGG-19 and ResNet50. In the identification of COVID-19 instances, NN had a 97.82 % accuracy rate. Transfer learning [28] is a discipline concerned with training and evaluating a new dataset. ResNet50, InceptionV3, and Inception-ResNetV2 are three distinct convolutional neural networks used in this article. According to research by Narin *et al.* [29], the pre-trained ResNet50 has the greatest accuracy of 98%, compared to 97 and 87% for InceptionV3 and Inception-ResNetV2.

Support vector machine (SVM) is utilized to differentiate COVID patients' X-ray pictures from those of other groups [30]. Song *et al.* [31] built a deep pneumonia deep learning algorithm to analyze CT scans to detect COVID-19 patients. The model has a high level of accuracy, with a 99% AUC and a sensitivity of 93%. Wang *et al.* [27] employ an internal and externally validated modified Inception transfer learning model. Internal validation was 89.5% accurate, whereas external validation was 79.3% accurate [25]. COVID-19 is detected utilizing a segmented 3D lung area using poorly supervised deep learning. Zheng *et al.* [32] algorithm has a 90% accuracy rate. Xu *et al.* [33] present a convolution neural network (CNN) model for detecting COVID-19 that has an accuracy rate of 86.7%, demonstrating that deep learning approaches are a good strategy for frontline clinicians.

2. MATERIAL AND METHOD

The existence of COVID-19 is anticipated utilizing online X-ray pictures of patients to carry out the study. The reason for using X-ray pictures for the experiment is that they are digital and can be taken in as little as 10-15 minutes, making it easy for a doctor to see them digitally. The X-ray pictures of patients are taken from the Cohen *et al.* [34] dataset accessible on the GitHub repository, while the X-ray images of pneumonia and normal people are taken from Pham [35]. As indicated in Table 1, the dataset contains 262 samples of COVID-19 patients, 424 samples of normal people, and 423 samples of pneumonia patients. Figure 3 shows sample pictures, especially shown in Figure 3(a) shows COVID, Figure 3(b) shows pneumonia, and Figure 3(c) shows normal. The dataset is partitioned into 2-categories by the prediction model: training and testing samples. For training, 80% of the total pictures are chosen at random from the dataset, while 20% are utilized to test the model. For both training and testing, these pictures are resized to fit the size requirements of various CNN models. Because of the limited availability of data, one of the scheme's disadvantages is the small size of COVID-19 X-ray pictures.

Table 1. Total number of images used for 3 different classes

S.No	Label	Count
1	COVID	262
2	normal	424
3	pneumonia	423

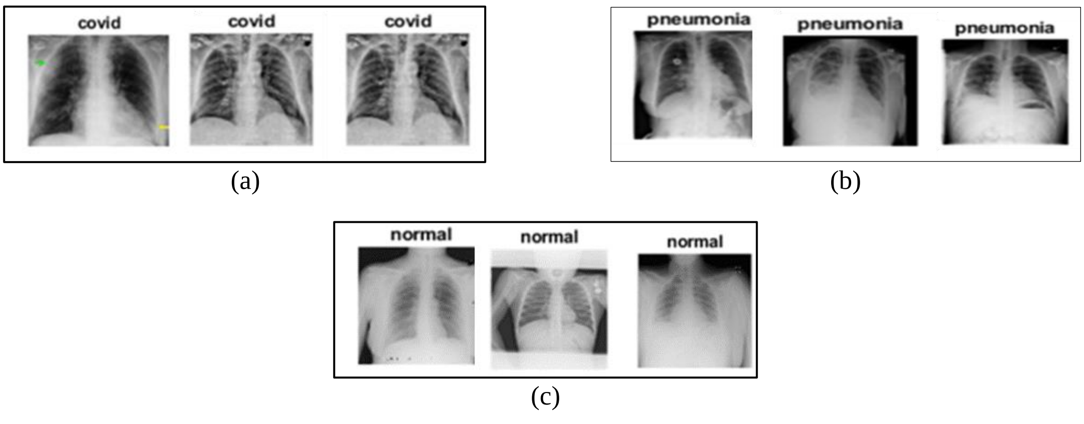


Figure 3. Sample image dataset with three categories: (a) COVID, (b) pneumonia, and (c) normal

2.1. Convolution neural network

Artificial neural networks are used in deep learning to replicate the behavior of neurons in the human brain [36]. CNNs are used in deep learning to learn a certain pattern from pictures or text that may be used to predict or categorize other activities. CNN has many levels, such as an input-output and hidden layer, and a pooling layer [37]. This neural network approach may be used to recognize medical picture patterns in grey-scale imaging in general [38]. To extract features from pictures, two pre-trained CNN models termed ResNet50 and InceptionV3 are utilized.

2.2. ResNet50

ResNet is a 50-layer CNN model that was trained on the ImageNet dataset and can classify 1000 item categories. It has excellent image classification performance and may be used to extract features from pictures for classification purposes [39]. Rectified linear unit is utilized as an activation function in the ResNet network [40]. ResNet has been found to perform effectively with medical pictures in several studies [41], indicating that it is being utilized here for categorization. For detecting the existence of COVID-19 illness in a patient's X-ray, the last three layers are modified as shown in Figure 4 by adding a fully linked layer, a soft max, and a classification layer.

Figure 4 is the deep learning system model developed in this work for detecting COVID-19. It can extract various characteristics from the X-ray images given to it. The backbone of the proposed architecture is a RestNet50 and InceptionV3, which accepts a sequence of chest X-rays as input and produces characteristics from these images. Finally, all the feature maps are mapped into the soft-max function.

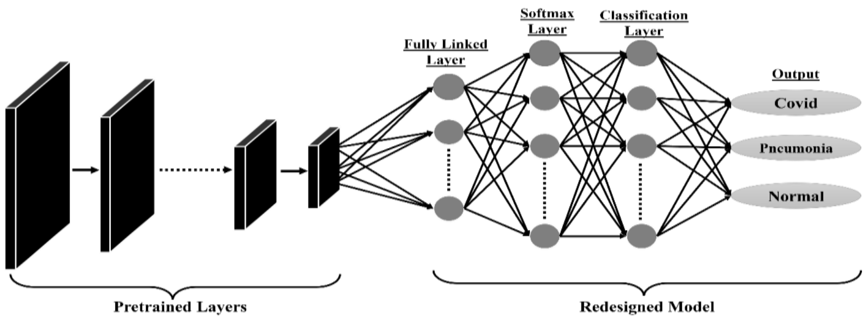


Figure 4. The proposed model

2.3. Inception

It's a 48-layer pertained CNN model that can categorize pictures into 100 different categories [42]. There are several variants of the inception net, including v-1, v-2, v-3, and v-4, each with its own set of benefits and drawbacks. Szegedy *et al.* [43] presented it as GoogleNet. InceptionV3 is trained on the ImageNet Dataset and delivers high picture classification accuracy. Inception-V3 allows pictures with a resolution of 299×299 [44], thus X-Ray images are scaled to 299×299 and then fed into this pertained model for training on a fresh dataset. Fully linked, softmax, and classification layers are added to the last three layers.

3. RESULTS

The section describes the environmental setup used in the proposed work. It also explains the results of the research and compares the proposed work. The performance is evaluated by calculating various parameters such as accuracy, specificity, F-score, sensitivity, and precision.

3.1. Environmental setup

All tests in this study were carried out on a MATLAB R2020a computer with 4 GB of RAM and an Intel ® core CPU. The tests are carried out using X-ray pictures of numerous patients that may be found on the internet. COVID, pneumonia, and normal are the three classifications utilized for categorization, with 262, 424, and 423 pictures in each class, respectively. To begin, all three classes are divided into two datasets, one for training and the other for testing the model.

Images are pre-processed after the data has been divided since some of the images were difficult to discern, had reflections on them, and were rotated by any angle. All the images used in the testing and testing were scaled to 224×224 for ResNet50 and 299×299 for the InceptionV3 network. For training, 20 images were utilized at a time, referred to as batch size, and Adam gradient descent was used for optimization. One by one, ResNet50 and InceptionV3 were loaded. Following that, the model was built by specifying different parameter values such as gradient descent, batch size, and epochs. Finally, this model was trained on a training dataset before being utilized for testing purposes. ResNet50 obtained a 97.29% accuracy, whereas InceptionV3 achieved a 98.20% accuracy. The planned work's workflow is visualized in Figure 5, which depicts the entire flow chart from beginning to end.

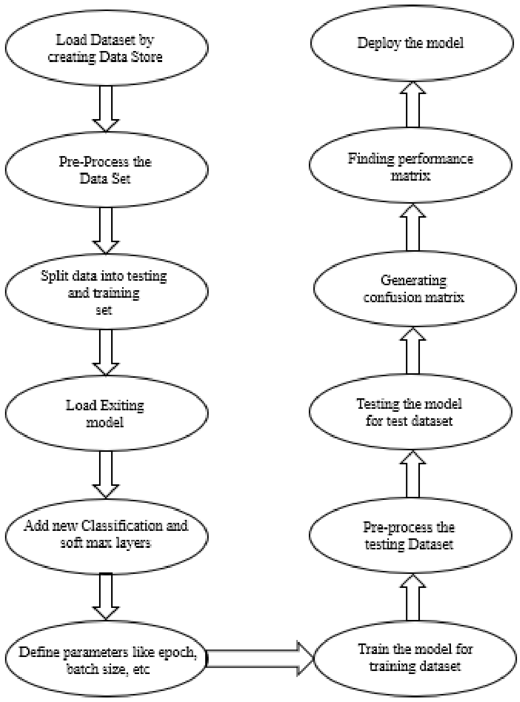


Figure 5. Workflow of the proposed model

3.2. Result and comparison

The performance is evaluated by calculating various parameters. These parameters depend on the true positive and negative values. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) data connected to the COVID class are used to calculate the performance of the suggested task. Table 2 shows the outcomes of these values for both models.

Table 2. TP, TN, FP, and FN values related to the COVID class

Model	TP	TN	FP	FN
ResNet50	47	169	1	5
InceptionV3	53	166	4	0

Five criteria: accuracy, sensitivity, specificity, F-score, and precision values, as given in Table 3 are used. The percentage of cases anticipated correctly is referred to as accuracy. Precision refers to positive predicted values and is defined as the ratio of genuine positive instances for COVID, as well as the total of TP and FP values, and F-score is a measure of the test's performance for positive cases in COVID. In (1)-(5) are used to calculate these values [45].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

$$F - Score = \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

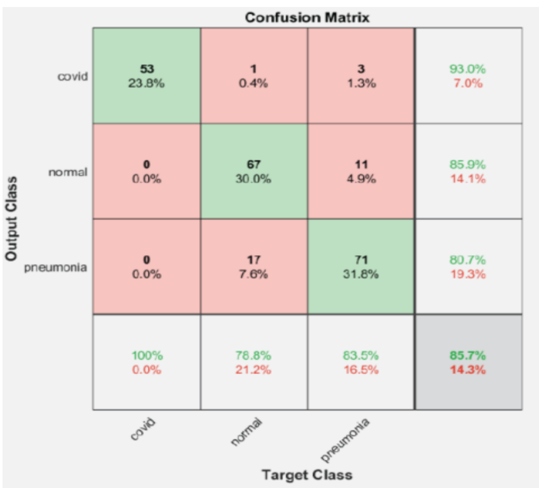
Because this study is based on COVID-19 instances, the model's accuracy is calculated in terms of the COVID class. Table 3 indicates that the accuracy of the Inception-v3 model (98.20%) is higher than that of the ResNet50 model (97.29%). Other performance measures such as sensitivity, specificity, F-score, and accuracy are also shown in Table 3. The results are highly encouraging since both models attain an accuracy of higher than 95%, which is regarded as excellent.

Table 3. Various performance measures

MODEL	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-Score (%)	Precision (%)
ResNet50	97.29	90.38	99.41	94.00	97.90
InceptionV3	98.20	100.00	97.64	96.36	92.98

A confusion chart comprising all three classes is given in Figure 6, especially Figure 6(a) shows ResNet50 and Figure 6(b) shows Inceptionv3 for both models. According to the ResNet confusion matrix, 47 COVID images are accurately predicted, whereas 5 images of COVID patients are predicted as pneumonia, and none are predicted as normal. As a result, the COVID class has an excellent accuracy value. Table 4 compares the suggested architecture to other current works in terms of accuracy, sensitivity, specificity, and model utilized by these approaches. Using both models, the table demonstrates that the suggested approaches produce superior outcomes than the comparative procedures.

(a)



(b)

Figure 6. Confusion matrix by (a) ResNet50 and (b) Inceptionv3

Table 4. Comparison with existing work

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
De-Trac ResNet18 [46]	95.12	97.91	91.87
Inception [36]	86.13	12.94	99.70
COVID-Caps [47]	**98.30**	80.00	98.60
Proposed work (ResNet50)	97.29	90.38	**99.41**
Proposed work (InceptionV3)	98.20	**100.00**	97.64

4. CONCLUSION AND FUTURE WORK

This study offers a deep learning model that gives diagnostics for multiclass classification and seeks to differentiate COVID-19 patients using chest X-ray pictures with a 98.20% accuracy, complete sensitivity, and good specificity. These tests are carried out on CPU systems that are commonly available and may be utilized without requiring a great deal of technical knowledge. This model can be used by countries with a shortage of RT-PCR kits and remote areas where radiologists or experts are scarce to use as an assistive intelligence tool for initial screening, and it can also be used by countries with a shortage of RT-PCR kits and remote areas where radiologists or experts are scarce.

The publicly accessible dataset is currently limited, and a larger database would make this model more robust. Furthermore, this model may be turned into a cloud model for improved and quicker outcomes. Radiologists would save time and effort because of this. This research may be expanded by comparing the accuracy of different deep learning models and obtaining even better results.

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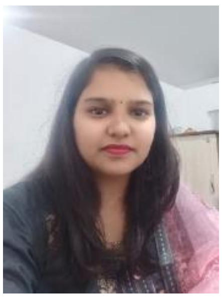

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