Detection of Covid-19 from Chest X-Ray Images using Transfer Learning based Deep Convolutional Neural Network

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ABSTRACT
The infectious coronavirus disease (COVID-19) has persisted in having devastating consequences for the lives of human beings all across the world. A fast, affordable COVID-19 screening procedure is needed to identify and isolate affected people, preventing the spread of the disease and ensuring appropriate medical treatment. Recent research reveals that deep learning-based screening of COVID-19 from chest x-ray images may be an alternative to commonly used real-time reverse transcription-polymerase chain reaction (RT-PCR) in circumstances where RT-PCR has time and availability limitations. Therefore, the automatic detection of COVID-19 cases through deep learning is garnering popularity. In this paper, we introduces a novel methodology for automated detection of COVID-19 instances from chest x-ray images, employing a fine-tuned deep convolutional neural network (CNN) approach with transfer learning. We employed three pre-trained deep CNN architectures, specifically Inception V3, DenseNet-121, and MobileNet. These deep CNN architectures were trained using a publicly accessible dataset of COVID-19 chest x-ray images, which was obtained from the Kaggle platform. Data augmentation, such as rotation and zooming, has been used to increase the size of the dataset in order to boost model performance. According to the experimental results, a fine-tuned modified Inception V3, DenseNet-121, and MobileNet model provides an overall accuracy of 98.71%, 98.85%, and 96.70%, respectively. The DenseNet-121 model outperforms state-of-the-art models for COVID-19 diagnosis in terms of overall accuracy, precision, recall, and F1-score metrics. The proposed model can predict from Chest x-ray images with higher precision, making it a faster option than the traditional RT-PCR technique.

General Terms
Covid-19, chest x-ray, RT-PCR, convolutional neural network, transfer learning.

Keywords
Novel coronavirus detection, biomedical image classification, deep learning, pre-trained model, feature extraction.

1. INTRODUCTION
COVID-19 emerged in December 2019 in Wuhan, China, and it has since spread around the world, causing a pandemic situation. As a direct result of it, thousands of individuals have already lost their lives, and millions of instances have been confirmed all across the world. As of July 12, 2023, the World Health Organization (WHO) has reported approximately 767 million confirmed cases of COVID-19 worldwide, with around 6.9 million fatalities [1]. In individuals who are infected, the most frequent symptoms include fever, cough, inflammation and breathing difficulty, loss of taste, fatigue, body aches, and nasal blockage. In order to detect Covid-19, the RT-PCR method is widely employed. However, this technique has its drawbacks, including prolonged processing time, typically ranging from 6 to 9 hours, and significant cost implications. Moreover, RT-PCR exhibits limitations in terms of sensitivity, leading to a relatively high rate of false-negative results. This highlights the need for more efficient diagnostic approaches in the ongoing pandemic battle [2]. However, rapid screening of covid-19 is the first and most important priority for pandemic control. To address this issue, deep learning-based techniques are frequently employed to analyze radiological imaging techniques such as chest X-rays to detect and diagnose COVID-19 automatically, which can speed up the analysis process [2-6].

Many investigations into the employment of artificial intelligence in the identification and classification of COVID-19 have been reported recently. Transfer learning based Deep Convolutional Neural Networks (CNNs) has successfully demonstrated their superiority over conventional techniques for COVID-19 identification. Siddhartha and Santra [2] developed COVIDLite, a method for classifying COVID-19 that combines white balance, Contrast Limited Adaptive Histogram Equalization, and a depth-wise separable convolutional neural network. In both binary classification and multi-class classification, the proposed method had a higher accuracy of 99.58% and 96.43%, respectively. Hussain et al. [3] has reported a 22-layer CNN model named CoroDet for automatic detection of COVID-19 utilizing raw chest X-ray and CT scan images. Batch normalization has been employed to improve the stability of the model and the Adam optimizer is being used to update weight and cross-entropy as the loss function. CoroDet model yielded classification accuracy scores of 99.1% for two classes, 94.2% for three classes, and 91.2% for four classes. Moreover, the accuracy of CoroDet was compared to that of ten other COVID identification techniques and showed its superiority over other model. Ozturk et al. [4] proposed a deep CNN architecture named DarkCovidNet consist of 17 convolutional layers along with different filtering in each layer to deliver reliable features

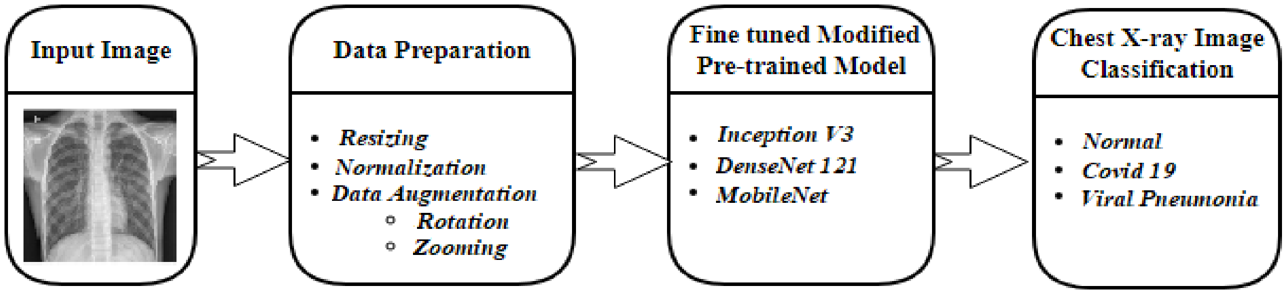

Fig 1: Overview of the methodology

for binary classification (COVID vs. no findings) and multiclass classification (COVID vs. no findings vs. pneumonia) for automated COVID-19 detection from raw chest radiographs. The study used the DarkNet model as a classifier for the YOLO (you only look once) real-time object identification system. For binary classes, the model provided classification accuracy of 98.08%, and for multi-class scenarios, it produced accuracy of 87.02%. In another study, a model named CoroNet was reported by Khan et al. [5] which use Xception as base model with a dropout layer and two fully-connected layers added at the end to automatically detect COVID-19 infection from chest X-ray images. The model trained end-to-end on a dataset prepared by collecting COVID-19 and other chest pneumonia X-ray images from two different publically available databases. On the provided dataset, they demonstrated CoroNet as being computationally less expensive and obtained encouraging results of 95% accuracy. In order to identify COVID-19-infected patients from chest X-ray images, Das et al. [6] developed a weighted average ensemble strategy leveraging DenseNet201, Resnet50V2, and Inceptionv3 deep CNN architectures. The prediction accuracy for the proposed approach is 91.62%. They used a dataset comprising 538 images of COVID-positive patients and 468 images of COVID-negative patients to train their model. However, it is important to note that the data size may not be sufficient to ensure robust generalization for the proposed approach. In order to enhance the reliability of the model and broaden its applicability, a larger and more diverse dataset should be considered. This would enable the model to better handle variations and complexities that may be encountered in real-world scenarios, ultimately leading to more accurate and reliable results. Additionally, a GUI-based program was created for general public use. Sitaula and Hossain [7] combined pre-trained VGG-16 with the attention module to develop a deep learning model for COVID-19 chest x-ray image classification. They fine-tuned the model and diligently trained it. The classification accuracy of the proposed framework was 79.58%. Umair et al. [8] implemented a transfer learning technique with fine tuning for the detection and classification of COVID-19. They employed four pre-trained models namely VGG16, DenseNet-121, ResNet-50, and MobileNet and trained on the dataset of 7232 (COVID-19 and normal) chest X-ray images. They were collected a dataset of 450 chest x-ray images for validating the performance of the proposed method in terms accuracy, precision, recall, F1-score, On the blind test set, VGG16, ResNet-50, DenseNet-121, and MobileNet achieved test accuracies of 83.27%, 92.48%, 96.49%, and 96.48%, respectively. Class-specific heat map images were created using the Grad-CAM technique to highlight the features obtained from the radiographic images. For the objective of minimizing errors, various optimizers were applied. Both in terms of accuracy and prediction, DenseNet-121 fared better than the other three models implemented in this work. Sarki et al. [9] presented their work using transfer learning-based CNN models (VGG16, InceptionV3, Xception) on publicly available chest x-ray dataset. Image pre-processing was performed using morphological operation to increase the model efficacy. They utilized their pre-trained CNN models for both binary (COVID and Normal) and multi-class classification (COVID, Normal and Pneumonia). They reported a binary classification accuracy of 100% and a multi-class classification accuracy of 87.5%.

This research introduces a multi-classification approach for the detection of COVID-19 through the utilization of Chest X-ray images. The model exhibits the ability to differentiate between normal patients and two specific diseases, namely COVID-19 and viral pneumonia. In order to enhance the prediction accuracy, we made the strategic decision to leverage transfer learning as opposed to directly implementing a Convolutional Neural Network (CNN) during the classification stage. Three separate pre-trained models named the Inception V3 model [10] , DenseNet-121 [11], and MobileNet [12] are utilized in this investigation. The main contribution of this research is the development of a COVID-19 disease diagnosis model that leverages the power of transfer learning. To achieve state-of-the-art performance, we modified the pre-trained CNN model and fine-tuned it. This enabled us to achieve cutting-edge outcomes, enhancing the capacities of COVID-19 diagnosis and potentially facilitating more precise and effective detection of the disease. The modified fine-tuned Inception V3, DenseNet-121 and MobileNet model provides an overall accuracy of 98.71%, 99% and 97% respectively. In terms of overall accuracy, precision, recall, and F1-score metrics, the DenseNet-121 model is demonstrated to be superior to state-of-the-art models for COVID-19 diagnosis.

2. MATERIALS AND METHODS

Deep learning techniques have become vital elements in the field of intelligent medical diagnosis systems. A detailed methodology has been proposed, consisting of three main phases: data collection, data preparation, and fine-tuning of a pre-trained deep CNN model employing chest x-ray images, for the specific objective of identifying occurrences of COVID-19. These three phases collectively form the foundation of the framework designed to identify and classify COVID-19 cases accurately. In the initial data collection phase, relevant and diverse chest x-ray images were gathered to build a robust dataset. Subsequently, in the data preparation phase, the collected data underwent various preprocessing steps to ensure it was suitable for training the deep CNN model effectively. To make the deep CNN model more adept at COVID-19 detection, fine-tuning was performed, involving modifications and optimization of the pre-trained model using the prepared dataset. This initiative was taken to enhance the performance of the model and adapt it specifically to the task at hand. The effectiveness of the proposed framework was then thoroughly evaluated using blind test data, which represented data that the model had never seen before during training or fine-tuning.

This evaluation process was essential to validate the model's ability to generalize and accurately identify COVID-19 cases beyond the dataset it was trained on. Fig. 1 provides an overview of the entire methodology, visually illustrating the different stages involved in the COVID-19 detection and classification process. The presented approach demonstrates the significant impact of deep learning methods in addressing complex medical challenges like COVID-19 diagnosis and showcases the potential for further advancements in intelligent medical diagnosis systems.

2.1 Dataset Collection

A COVID-19 dataset that is open-source and publicly accessible has been acquired from Kaggle [2]. The dataset includes a total of 1823 chest X-ray images, which are organised into the following three categories: normal (668 photos), covid (536 images), and viral pneumonia (619 images).

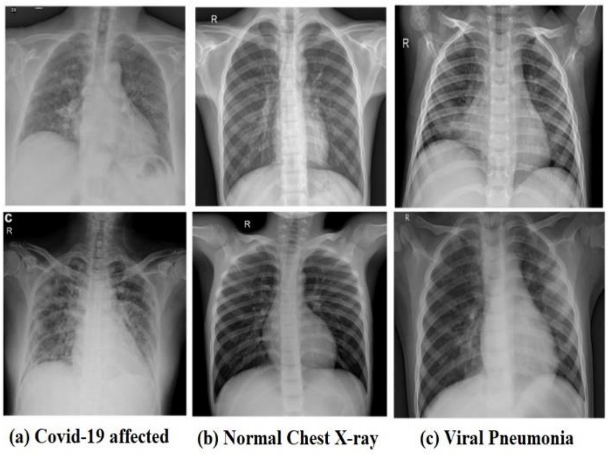

Fig 2: Sample images from dataset

2.2 Dataset Preparation

The images within the dataset went through a scaling process for uniformity, resulting in their dimensions being adjusted to 224×224. The normalization process was subsequently applied to the image in order to aid the convergence of the proposed model. After resizing and normalizing, data augmentation strategy was used to enlarge the dataset and add variability. Specifically, the number of images was raised by rotation and zooming, which are most common and effective augmentation approach. Here, the augmentation was carried out using a simple augmenter. The likelihood value is 70% after flipping the images to the right and left with a maximum rotation angle of 10 degrees. Additionally, with the likelihood of 30%, we magnified the images by zooming them in by 1.1 to 1.6 times. We now have a total of 3608 chest X-ray images following the augmentation process. Total number of dataset image before and after augmentation is shown in Table 1.

2.3 Transfer learning based Modified Pre-trained CNNs

CNN analyses and classifies visual characteristics in images. It has a multi-layered architecture that was developed to do particular tasks such as object detection, image classification and segmentation by analysing specific inputs and carrying out the task. The fundamental principle of CNN is the extraction of local features from input image at higher layers and incorporates them into lower-layer features that exhibit greater complexity. This architectural design of CNN, while effective in capturing intricate patterns, comes at the cost of computational demands, necessitating substantial computational resources. Additionally, the training process of CNNs requires a huge amount of data and time due to the multilayered nature of the network, further contributing to the computational burden. Both the amount of training time and the quantity of the dataset needed are significantly reduced using transfer learning [13]. Retraining the last layer enables you to preserve the knowledge that the model had gained during its first training and apply it to a smaller dataset, producing classifications that are extremely precise [14, 15].

COVID-19 detection and classification were conducted in this paper using pre-trained deep CNN architectures named Inception V3, MobileNet, and DenseNet-121. The deep CNN architecture of Inception V3, MobileNet, and DenseNet-121 has been modified and fine-tuned. As initialization, we used the weights of the pre-trained network (Kumar and Mallik 2022) and removed the output layers from the pre-trained architecture. Furthermore, we added the GlobalAveragePolling2D, dense layer with 512 neurons, dropout layer with a value of 0.4 and a classification layer with three classes using softmax function at the end of the base deep CNN models. In order to optimize the performance of the proposed pre-trained model for COVID-19 detection and classification, we employ a technique known as layer freezing. The learnt representations are successfully isolated and preserved by selectively freezing the layers. However, in this work, we allow the last ten layers to remain unfrozen, enabling us to update their weights using the dataset. This strategic approach ensures that the proposed model adapts to the specific characteristics of the data, enhancing its overall efficacy. The input layer is given an image with dimensions of 224×224. The adam optimizer having learning rate 0.0001 is used in this work to compute the loss function, which is sparse categorical cross-entropy We have successfully trained the model using an augmented training dataset. The training process was carried out on a span of 20 epochs, with a batch size of 32. Table 2 presents the training parameters of the CNN models.

Table 1. Total number of chest X-ray images

Class Name	Total Number of Images (Before Augmentation)	Total Number of Images (After Augmentation)
Covid	536	1114
Normal	668	1272
Viral pneumonia	619	1222

Table 2: Training parameters of deep CNN models

Parameters	Value
Image Size	224×224
Batch Size	32
Epoch	20
Optimizer	Adam
Loss function	Sparse Categorical Cross-Entropy
Learning rate	0.0001

3. RESULTS AND DISCUSSION

In this section, we evaluate the effectiveness of modified fine-tuned deep CNN employed to a dataset of Chest X-ray images for COVID-19 identification. The entire training and testing of the pre-trained CNN architecture was performed on a personal computer running the 'Windows 10' operating system (CPU: Intel core i5 @ 2.7GHz 64-bit, RAM: 12.00 GB, and free-space on SSD: 100 GB). We employed the Adam Optimizer, a stochastic optimization procedure based on first order gradients, for the training phase. The presented model incorporates the sparse categorical cross entropy loss as its cost function. We trained the modified CNN architectures using 80% of the dataset images and remaining 20% is used for validation purposes. Accuracy as well as precision, recall, and F1 score value was used to assess the training performance of the models in this work. The training accuracy has been evaluated on the training dataset of the model. The validation accuracy, on the other hand, was calculated using a validation dataset that was never used for training. The modified pre-trained Inception V3, DenseNet-121 and MobileNet model was trained for 20 epochs and achieved impressive performance metrics. Inception V3, DenseNet-121, and MobileNet achieved training accuracies of 100% and validation accuracies of 98.71%, 98.85%, and 96.70%, respectively. DenseNet-121 has achieved slightly higher validation accuracy among the other two modified CNN. DenseNet-121 exhibits a superior performance in terms of validation loss, as it achieves a significantly lower value of 0.0470, indicating its ability to minimize errors. In comparison, Inception V3 and MobileNet demonstrate higher validation losses of 0.0565 and 0.1423, respectively. The precision, recall, and F1 score values are shown in Table 3 and the accuracy score for the CNN models is shown in Table 4. According to Table 3 and Table 4, DenseNet-121 outperforms the other two pre-trained models in terms of accuracy and validation loss.

Table 3: Precision, recall and F1- Score of deep CNN models

Pre-trained Model	Class	Precision	Recall	F1-Score
Inception V3	Covid	1.00	1.00	0.99
	Normal	0.98	0.98	0.98
	Viral Pneumonia	0.98	0.98	0.98
DenseNet-121	Covid	0.99	1.00	1.00
	Normal	0.98	0.99	0.99
	Viral Pneumonia	0.99	0.98	0.98
MobileNet	Covid	0.98	0.99	0.99
	Normal	0.97	0.96	0.96
	Viral Pneumonia	0.96	0.96	0.96

Table 3: Accuracy score of deep CNN models

Pre-trained Model	No. of Epochs	Training Accuracy (%)	Validation Accuracy (%)	Validation Loss (%)
Inception V3	20	100	98.71	0.0565
DenseNet-121		100	**98.85**	**0.0470**
MobileNet		100	96.70	0.1423

During the training phase of the deep CNN models, both the training characteristics and the validation characteristics are recorded. The training of the three deep CNN models is converged in the proposed approach after 15 epochs, and no improvement over sparse categorical cross entropy loss has been seen for 5 further epochs. The accuracy curve have been depicts in Figure 3, Figure 5, Figure 7, and loss curve have been depicts in Figure 4 and Figure 6, Figure 8 of modified inception V3, DenseNet-121 and MobileNet model respectively.

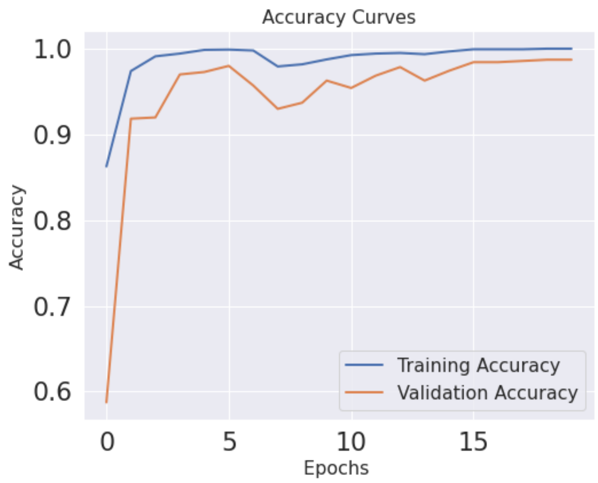

Fig 3: Accuracy curve of modified Inception V3 model

Fig 4: Loss curve of modified Inception V3 model

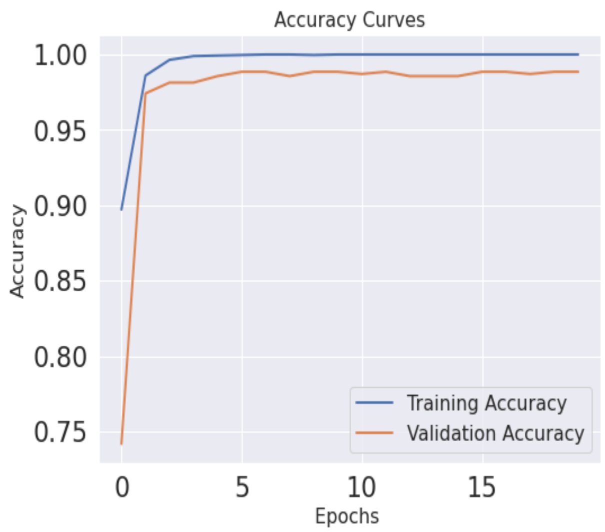

Fig 5: Accuracy curve of modified DenseNet-121 model

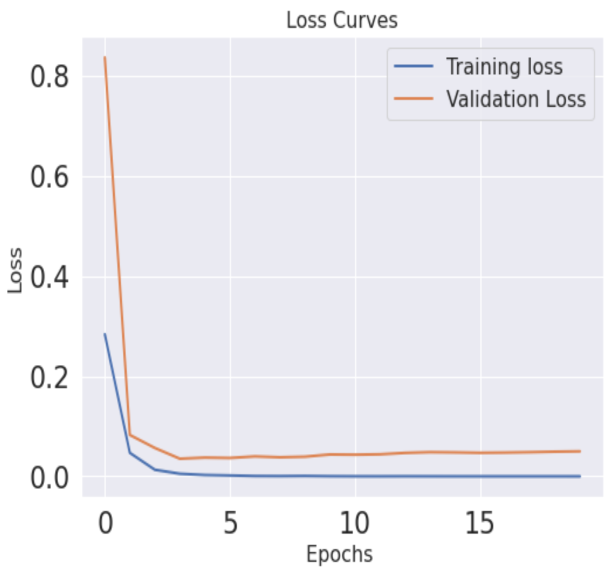

Fig 6: Loss curve of modified DenseNet-121 model

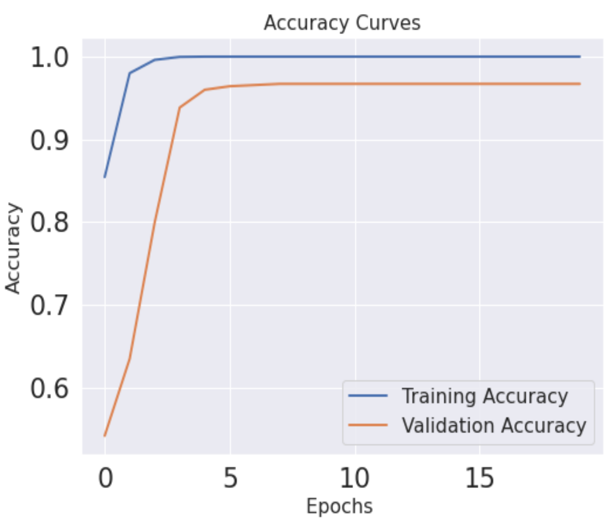

Fig 7: Accuracy curve of modified MobileNet model

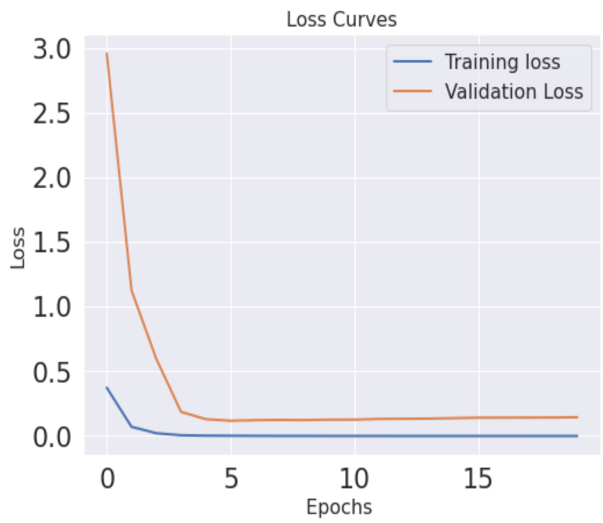

Fig 8: Loss curve of modified MobileNet model

The confusion matrix for the pre-trained CNN model is fairly good. The confusion matrices for the Inception V3, DenseNet-121, and MobileNet models are shown in Tables 5, Table 6, and Table 7, respectively. The confusion matrix shows that all three models accurately classify the covid-19 patient. Inception V3 and MobileNet successfully categorize 198 out of the 199 examples of covid, and DenseNet-121 correctly classifies every case. The performance is noticeably good enough in the other two classes (Normal, Viral Pneumonia).

Table 5: Confusion Matrix of Inception V3 model

		Predicted Label		
		Covid	Normal	Viral Pneumonia
Actual Label	Covid	197	1	1
	Normal	0	242	4
	Viral Pneumonia	1	5	247

Table 6: Confusion Matrix of DenseNet-121 model

		Predicted Label		
		Covid	Normal	Viral Pneumonia
Actual Label	Covid	199	0	0
	Normal	0	243	3
	Viral Pneumonia	1	4	248

A comparison with recent works on COVID-19 case detection using chest x-ray images was performed. The comparison with recent works is shown in Table 8. The DenseNet-121 model produces outperforms previous work with 98.85% accuracy.

Table 7: Confusion Matrix of MobileNet model

		Predicted Label		
		Covid	Normal	Viral Pneumonia
Actual Label	Covid	198	0	1
	Normal	1	235	10
	Viral Pneumonia	4	7	242

Table 8: Comparison with the existing work

Related work	**Dataset Description**	**Model**	**Accuracy (%)**
Das et al. (2021)	COVID (538 images), Non COVID (468 images)	DenseNet201	91.11
		Inception V3	90.43
Siddhartha and Santra (2020)	COVID-19 (536 images), Viral pneumonia (619 images), Normal(668 images)	CovidLite	96.43
Presented Work	Covid19 (536 images), Viral Pneumonia (619 images), Normal(668 images)	Inception V3	98.71
		DenseNet121	98.85
		MobileNet	96.70

4. CONCLUSION

In this paper, we reported a transfer learning based deep learning approach for automatic detection of COVID-19 from chest x-ray images because the COVID-19 pandemic is still ongoing globally, necessitating smart automatic coronavirus screening to combat the pandemic situation. After assessing the models, it was discovered that the DenseNet-121 architecture obtained the highest accuracy among the three fine-tuned deep CNN models (Inception V3, DenseNet-121, and MobileNet). Finally, we compared the performance of the suggested method against earlier research in the field. The proposed models are anticipated to be helpful for clinical applications to identify COVID-19 cases using chest x-ray images. In the future, increasingly critical and diverse chest x-ray image datasets will be used for model training to increase its robustness.

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