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***Abstract*— In this study, the Traditional Convolution Neural Network (TCNN) and state-of-the-art approaches were applied to the datasets of Chest X-ray and CT scan imaging modalities and trained them concurrently. The TCNN's performance for detecting COVID-19 infected tissues was determined through a comparison examination using state-of-the-art approaches. The accuracy of the models has been improved by lowering the model's losses and overfitting. Finally, the training data size has been enhanced utilizing various picture augmentation methods such as flip-up-down, flip-down-left-right, and so on. VGG19 and InceptionV3 were tested in this work, and accuracy scores of 97 percent (X-ray images) and 96 percent (CT-scan images) were obtained. The model's loss functions, Precision, Recall, and F1-Score, were extracted and interpreted in the study. We examined the researchers' modified DL models and discovered that they were 65 percent accurate on X-ray data and 62 percent accurate on CT scan images. Experiments have demonstrated that when the number of sample images rises, the VGG19 and InceptionV3 perform well.**

Keywords*— COVID-19, State-of-art, Traditional Convolution Neural Network (TCNN)

I. Introduction

SARS-CoV-2, also known as COVID-19, is an infectious disorder detected in China in December 2019 and soon became a global pandemic [1]. This virus has a high transmission rate since it spreads from person to person through droplets, gossip, or sneezing. This virus has a strong survival rate and will survive in the atmosphere for a couple of hours to a few days [2]. It is more common in older and adults with pre-existing conditions; asymptomatic signs (cough, headache, shortness of breath or trouble coughing, and running nose) are only apparent in 40-45% of people [3]. The virus is brand new, and scientists all over the world are working on a cure. Currently, there are no unique drugs available to avoid or cure COVID-19. Although traditional diagnosis has gotten much easier, it still poses a substantial risk to medical professionals. Furthermore, it is costly, and only many diagnostic test kits are accessible. A medical imaging technique-based screening method, is less risky, quicker, and more generally available than traditional screening methods. In comparison to CT imaging, X-ray imaging has been frequently used for COVID-19 screening because it takes less imaging time, is less expensive, and X-ray scanners are generally available, particularly in remote regions [4]. For radiologists, a larger-scale visual inspection of X-ray images is time-consuming and uncomfortable. It might result in an incorrect diagnosis because of a lack of prior knowledge about the virus-infected regions. Therefore, there is an urgent need to develop automated ways for obtaining a more quick and exact COVID-19 diagnosis as a result of this situation.

Machine learning (ML) and deep learning (DL) techniques are extensively used in several medical fields for disease recognition. It's crucial for recognizing and screening life-threatening illnesses [5]. Artificial Intelligence (AI) and machine learning (ML) are currently being utilized to differentiate suspected COVID-19 triggers and symptoms from Chest Radiography or Chest Computed Tomography (CT) Scan [6]. Furthermore, scientists, doctors, physicians, and healthcare practitioners worldwide are creating and modeling current ML or DL-based algorithms for early diagnosis and screening at the start of this global pandemic. It is difficult to identify a dependable and useful model for real-life application from theoretical alternatives due to a lack of research. However, because DL-based techniques are widely utilized in medical imaging, finding the most effective model can be difficult because each model's computational complexity and effectiveness differ. To put it another way, COVID-19 detection is currently being carried out using a range of cutting-edge methods. Nonetheless, analyzing the performance of these methods is critical because the model's performance, overfitting, and effectiveness are all vital factors in effectively detecting a serious disease like COVID-19. This study aims to create a model that can categorize COVID-19-infected tissues using the most common methodologies, such as chest X-ray and CT-scan pictures, and compare the performance of state-of-the-art methods in terms of COVID-19 detection.

The significant contributions of this proposed study can be outlined as follows:

- With the reduction of overfitting and losses, the detection accuracy has been enhanced, and the training data size has been increased by employing various image augmentation methodologies.

- The performance of the six most powerful pre-trained deep CNN models, namely VGG-16, VGG-19, Inception-V3, Xception, CNN, and Modified CNN, has been comprehensively compared. Finally, a Doctor has evaluated the efficacy of the proposed study model.

Section 2 discusses the literature review, section 3 illustrates the research methodology, section 4 delineates results analysis, section 5 explains discussions, and section 6 describes the conclusions and future work.

II. RELATED WORK

Several novel ML models are proposed to detect COVID-19 infection from Chest X-ray images. However, the primary issue with these ML models is that they are trained and tested on limited datasets.

In paper [7] suggested a deep learning approach for categorizing COVID-19 that is iteratively pruned. Although the dataset contains various images, the COVID cases are only 121 and 165 training image data. Ucar et al. in paper [8], the authors analyzed two enormous datasets for their experiment. Still, unfortunately, just 76 COVID examples are present among 5949 pictures in one dataset, indicating that the authors' hypothesis was incorrect. The other dataset only has 45 COVID cases. Panwar et al. in the paper [9] employed a small dataset of 337 pictures and 192 X-rays of covid patients. The authors, however, used picture augmentation to increase the number of photos. These experiments only present a small quantity of data for training and assessing ML models, which may not perform well when applied to a larger dataset or when the potential dataset varies.

A deep learning algorithm was used to detect Coronavirus in [10], where the authors employed a dataset consisting of three categories: Covid-19, Pneumonia, and X-ray pictures. The Fuzzy Color approach was used in image preprocessing to restructure the photos, and the structured images and original images were stacked. Following the training of the dataset, deep learning techniques such as MobileNetV2 and squeezeNet were used. The support vector machine (SVM) is also employed to combine the efficient qualities with a perfect classification rate of 99.27% for the regular x-ray and pneumonia datasets and 100% for the covid-19 dataset. The paper [11] provided a method for screening COVID-19 using an Automatic System (ACoS) based on Chest X-ray pictures (CXR) to determine the Normal condition, Suspected point, and COVID-19 infected site. The propound system has been separated into two phases: Normal Vs. Abnormal and Covid-19 Vs. Pneumonia instances.

Furthermore, throughout the validation process, the system utilized 258 CXR images, with each category consisting of 86 photos, and accuracy of 98.062 percent for phase-I and 91.329 percent for phase-II. This article [12] proposed a deep learning strategy to automatically determine and localize covid-19 instances with high accuracy to aid doctors. The dataset (chest X-ray picture) was obtained from a freely accessible public source, and the Xiangya Hospital was divided into two groups: training and testing. The suggested framework's two separate processes are the Discrimination-DL and the Localization-DL. Discrimination-DL is used to elicit COVID-19 lung features using 3548 chest X-rays, while Localization-DL is used to train using 406-pixel images. Finally, the results showed that COVID-19 Discrimination-DL had an accuracy of 98.71 percent, whereas Localization-DL had an accuracy of 93.03 percent. In paper [13] provide a successful technique for detecting COVID-19 instances utilizing a mixed dataset (X-ray and CT-scan) acquired from several sources using deep learning and transfer learning algorithms. A bespoke pre-trained model AlexNe and a traditional convolution neural network (CNN) were used in this paper, with 98 percent and 94.1 percent accuracy for the pre-trained and CNN models, respectively.

In the paper [14], a software system for weakly supervising covid-19 was constructed utilizing deep learning approaches and CT scan images (3D). In this study, 499 CT scan images are utilized for training, and 131 CT scan photos are used for testing. The outcome was a ROC accuracy of 0.959 and a PR accuracy of 0.976, with the operating point determined by the sensitivity (0.907) and specificity (0.976). (0.911). Using an exclusive GPU, the approach processed the CT volumes of a single patient in only 1.93 seconds. The authors of the study [15] began their research with the notion that utilizing deep learning algorithms might detect covid-19 contaminated features in CT scan pictures. Based on this probability, 453 pathogen-confirmed COVID-19 CT images are collected, 217 of which are used for training the dataset, and the inception migration-learning model is used to build the model, which helped to elicit distinguishing features such as accuracy 82.9 percent, specificity 80.5 percent, and sensitivity 84 percent. The external dataset testing approach yields 73.1 percent accuracy, 67 percent specificity, and 74% sensitivity. To detect COVID-19 situations, an enhanced deep learning technique is provided as an alternative.

The suggested method comprises data augmentation, preprocessing, stage I and stage II deep network model creation [16]. In the case of COVID-19 detection, the proposed system achieved an accuracy of 97.77 percent, a recall of 97.14 percent, and a precision of 97.14 percent. However, 5-fold cross-validation produced a promising result with an accuracy of 98.93% in COVID-19 detection. In this dissertation [17], a Machine Learning technique is suggested to categorize Chest X-ray pictures as COVID-19 or non-COVID-19 utilizing new Fractional Multi-channel Exponent Moments (FrMEMs) and a parallel multi-core computational framework to extract the features. A customized Manta-Ray Foraging Optimization was used to determine the most important attributes. The described system was evaluated on two COVID-19 x-ray datasets, yielding accuracy of 96.09 percent and 98.09 percent, respectively.

In our research, we created a dataset of 3200 images by combining all of the datasets, which included 2000 images of COVID-19 negative cases and 1200 images of COVID-19 positive cases. We also considered some basic machine learning models, such as VGG19, VGG16, EfficientNET, InceptionV3, ResNet, Xception, and CNN, and used our dataset for training and testing. Besides, we compared the performance of these models in terms of performance metrics such as accuracy, sensitivity, and specificity. Finally, the models that perform well on X-ray and CT scan data have been identified as a gold standard for classifying COVID-19 infected lungs.

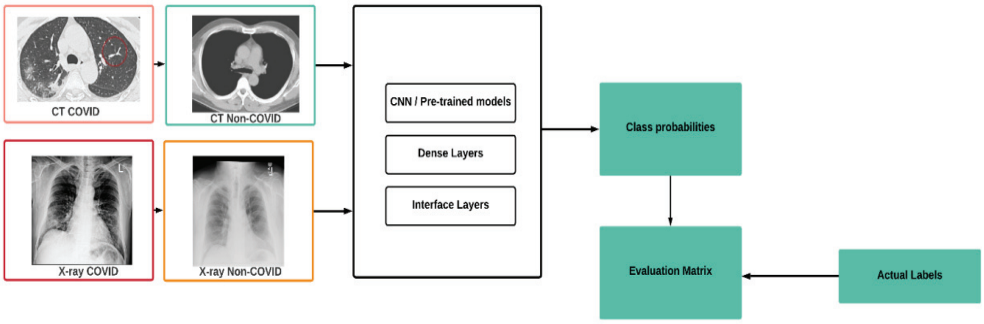
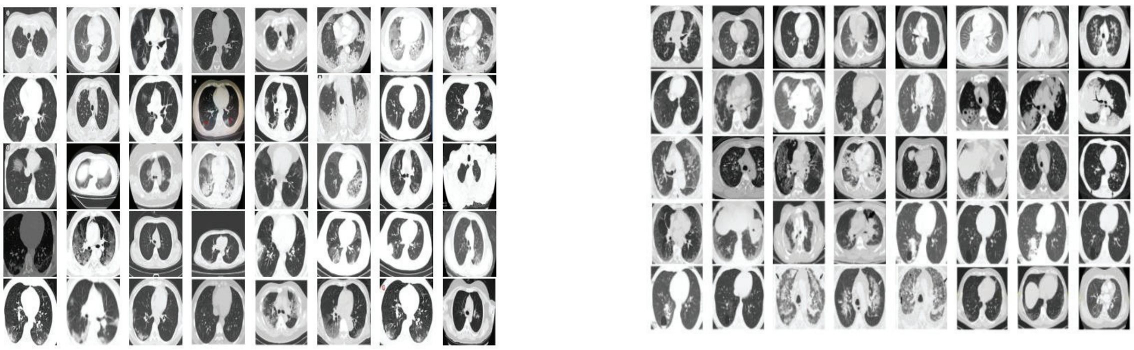
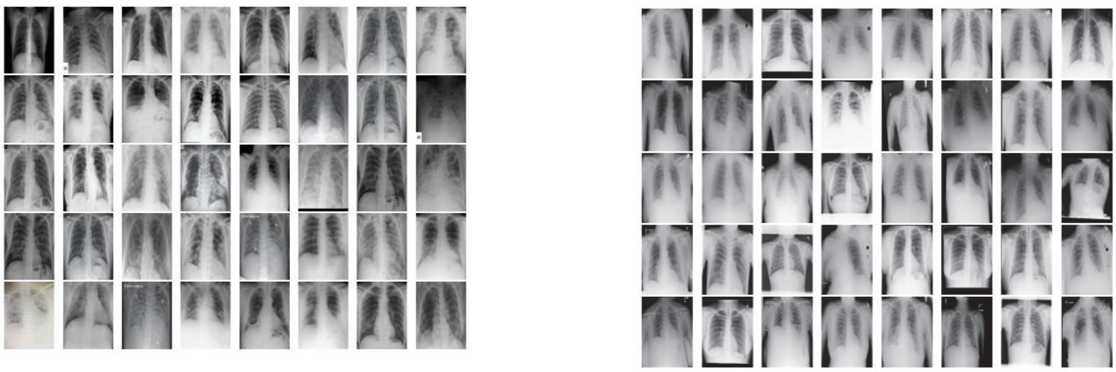


Fig. 1. Proposed Research Architecture and Conceptual Visualization



(a) (b)

Fig. 2. (a) Positive case COVID-19 above CT scan images (b) Negative case COVID-19 on CT scan images



(a) (b)

Fig. 3. (a) Positive case of COVID-19 infected Xray images (b) Negative case of COVID-19 infected Xray images

III. Research Methodology

The Research Methodology is classified into several phases: Data Preparation, Image Augmentation, and the Interpretation of the Proposed Algorithm (IPA). The IPA is further subdivided into three parts: Traditional Convolutional Neural Network (TCNN), Pre-Trained Deep Learning Architectures and DarkCovidNet Architecture. Fig. 1 shows the overall research model.

A. Data Preperation

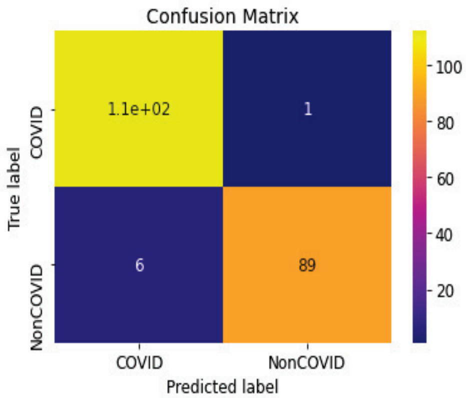
In this work, the suggested models were tested using numerous imaging modalities, such as CT-scan and Chest-X-ray, to see how well the model can categorize diseases from various types of datasets. Fig. 2 and Fig. 3 sample images for this research. The batch size under consideration is 32, and the file height and width are 224 X 224 pixels. Simultaneously, clinical photos must be scaled to a specific shape before being supplied into the algorithms [18]. If the dimension size is 500 or larger and the batch size exceeds 32, the system may crash due to RAM usage (Google Colab free trial version is around 13 GB). One option is to consider a smaller dimension with a larger batch shape [19]. The batch size of 32 indicates that the error gradient will be computed using 32 samples from the training dataset before re-equipping the model weight. In this study, batch size 32 was chosen because it is easier to put one batch of training data into memory with small batch sizes (e.g., when utilizing a Graphics Processing Unit (GPU)) [20]. The data has so been prepared in this manner.

TABLE I. CLASSIFICATION REPORT ON X-RAY BASED IMAGES (RAW IMAGES)

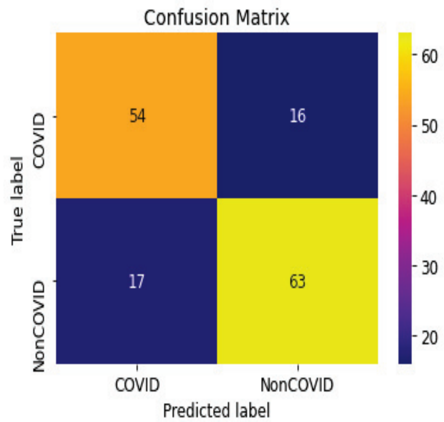
Algorithm	For the case of "0."				For the case of "1."			
	Dataset Category	P	R	F1	P	R	F1	Accuracy Score
InceptionV3	X-Ray	0.92	0.97	0.94	0.83	0.60	0.70	0.91
RESNET	X-Ray	0.80	0.92	0.86	0.88	0.73	0.80	0.83
VGG19	X-Ray	0.95	0.99	0.97	0.99	0.94	0.96	0.97
Xception	X-Ray	0.96	0.86	0.91	0.89	0.97	0.93	0.92
CNN	X-Ray	0.52	0.81	0.63	0.33	0.11	0.16	0.49
ModifiedCNN	X-Ray	0.77	0.33	0.46	0.62	0.92	0.74	0.65

TABLE II. CLASSIFICATION REPORT ON X-RAY BASED IMAGES (RAW IMAGES)

Algorithm	For the case of "0."				For the case of "1."			
	Dataset Category	P	R	F1	P	R	F1	Accuracy Score
InceptionV3	CT	0.92	0.99	0.96	0.99	0.93	0.96	0.96
RESNET	CT	0.66	0.91	0.77	0.89	0.59	0.71	0.74
VGG19	CT	0.75	0.77	0.76	0.79	0.78	0.78	0.77
Xception	CT	0.72	0.94	0.81	0.93	0.68	0.78	0.80
CNN	CT	0.53	0.46	0.49	0.55	0.62	0.58	0.54
ModifiedCNN	CT	0.67	0.46	0.54	0.60	0.78	0.68	0.62



(a)



(b)

Fig. 4. (a) Representing the Confusion matrix for VGG-19 above X-ray images (b) Demonstrating the Confusion Matrix for InceptionV3 on top of CT scan images.

B. *Image Augmentation*

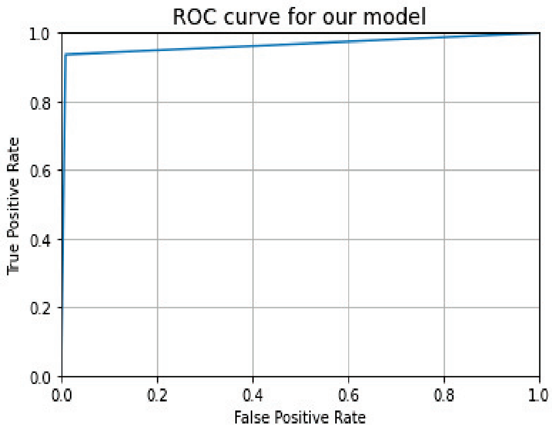
A significant amount of data is necessary to obtain reliable findings using deep learning technologies. Because gathering medical image data can be time-consuming and costly, data is most likely required for medical image analysis. Image augmentation, which employs a variety of methodologies, increases the dataset's size and the sample size. Working on critical medical photos is a very dependable strategy because, in most circumstances, the model's accuracy does not improve with insufficient data. With augmentation, over-fitting can be avoided, and the precision of suggested models can be enhanced [21]. The Image Augmentation approach incorporates a variety of rotations (45 degrees, 135 degrees, 225 degrees, 315 degrees), spins, shears, and flips (Flip left-right, Flip up-down, Flip up-down-left-right), comparison, and saturation.

C. *Interpretation of the Proposed Algorithm*

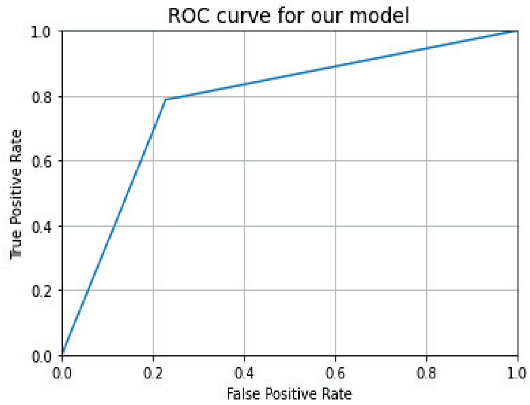
This section interpreted the concentrated algorithms selected for diagnosing the COVID-19. Simply put, The Traditional Convolutional Neural Network (TCNN), Pre-Trained Deep Learning Architecture, and DarkCovidNet Architecture have been illustrated in this section (Modified CNN). We have experimented with different types of pre-trained models since the medical image is relatively complex; it is essential to know which models have higher computational costs. Researchers have already developed an advanced algorithm for this particular work, for example, the DarkCovidNet Architecture.

Traditional Convolutional Neural Network (TCNN): The convolutional neural network (CNN) is a type of feed-forward neural network that can categorize and extract characteristics from the human brain. The four interconnected layers of the CNN are: the convolutional layer, the ReLU activation layer, the subsampling layer, and the fully-connected layer [22]. Because overfitting is a possibility in CNN, the Pooling methods used sub-sampling methods in addition to overfitting to reduce the number of parameters [23]. CNNs are employed in medical picture detection and recognition because of their high precision. The CNN employs a hierarchical model that starts with a funnel-shaped network and then outputs a fully connected layer with all neurons coupled and the output processed.

VGG Model: VGG19 is a transfer learning model with 19 layers [24]. Transfer learning has several advantages, including reduced training time and improved neural



(a)



(b)

Fig. 5. (a) ROC-AUC on VGG-19 classifier above X-ray images (b) ROC-AUC on InceptionV3 classifier above CT scan images

network performance. The overall number of parameters in the VGG19 model is 20,074,562; the number of trainable parameters is 50,178; the number of non-trainable parameters is 20,024,384.

InceptionV3 Model: In 2015, [25] constructed the InceptionV3 network. The main idea behind this network, Inception modules made up of convolutional and pooling layers. Inception V3 is a widely used image recognition model that has been found to achieve higher than 78.1 percent accuracy on the ImageNet dataset. This approach has been investigated for identifying COVID-19 based on its efficacy. Total params: 21,905,186, trainable params: 102,402, and non-trainable params: 21,802,784 are revealed in the InceptionV3 model's trainable parameters and summary.

DarkCovidNet Architecture: DarkCovidNet was proposed in this study because researchers use it to undertake COVID-19 categorization research [26]. The YOLO (You Only Look Once) real-time object identification approach employs the DarkCovidNet. This architecture is designed for entity identification and is one of the most advanced ways available. The DarkNet classifier is used to detect the COVID-19 based on this successful design. We concentrated on fewer layers and filters than the original DarkNet topologies. From eight to sixteen to thirty-two filters, we gradually raised the number. To understand the DarkCovidNet's principles, which use Maxpool to generate 19 convolutional layers and five pooling layers, it's helpful to have a basic understanding of the DarkCovidNet. These are basic CNN layers with a variety of filter, size, and stride parameters. There are several DarkCovidNet summaries available: 1,164,434 total params, 1,164,434 total trainable params, and 0 total non-trainable params.

IV. Result and discussions

A. *Model Classification Report (MCR)*

The Model Classification Report (MCR) segment used several state-of-the-art methodologies to demonstrate the model's empirical ramifications. The accuracy of the classification algorithm's predictions is evaluated using a classification report. In this study, two different datasets, such as chest X-ray images and CT scan images, are used to assess the proposed model's prediction capacity. On VGG19 (X-ray volume), we found 97 percent accuracy and a 96 percent performance score on InceptionV3 (CT scan volume). Table. 1 and 2 demonstrate the Precision (P), Recall (R), F1-Score (F1), and Accuracy (A) for recognizing Positive and Negative COVID-19 cases, which are represented by "0" and "1" respectively.

B. *Performance Evaluation*

Confusion Matrix, Receiver Operating Characteristic Curve (ROC)-Area under the ROC Curve (AUC), and Loss Function Measurement are the three evaluation methodologies discussed in this section. This study included these widely used performance metrics since simply determining the model's correctness may not be enough; if the model is not assessed correctly, overfitting may occur. The binary classification in terms of COVID-19 classification is included in the acquired dataset, as shown in Fig. 4 (a) and 4 (b). Besides, Fig. 5 (a) and Fig. 5 (b) shows the AUC-ROC curve for the model VGG19 and Inception V3.

C. *Discussions*

After completing the literature study and comparison analysis, it can be said that the comparative research work utilizes VGG19 and InceptionV3 classifiers with an accuracy of 97 percent (X-ray pictures) and 96 percent (CT-scan images) found the maximum efficacy of COVID-19 infected tissues. Various models have been utilized with pinpoint precision in earlier studies to locate COVID-19-infected tissues based on CT scans and X-ray images. Compared to the perspectives of employing VGG19 and InceptionV3, their accuracy levels are rather poor. After comparing study articles, it was discovered that the accuracy of the models is higher with a smaller dataset. It is critical to work with a large dataset when applying Deep Learning algorithms to diagnose any ailment in medical imaging. On the other hand, the indicated study studies promise promising accuracy based on other image modalities, such as chest X-ray and CT scan, where their datasets are rather small, in the comparative analysis part. Even though the existing research articles employed their own proposed models, which included state-of-the-art procedures, their accuracy on top of CT scan and X-ray pictures cannot compare to that of our concentrated models (VGG19 and InceptionV3).

Furthermore, the previously published papers make no mention of the loss-function or overfitting of their models. The difficulties have been satisfactorily handled in this research work. COVID-19 datasets cannot be used with state-of-the-art techniques in medical imaging, resulting in overfitting and model generalizability issues. In addition, six different strategies are used in this work to address hyperparameters tuning, and the results are compared to find the optimum method for determining COVID-19 infected tissue using CT scan and X-ray volumes.

V. Conclusion

The goal of this research is to successfully apply the model to aid doctors in diagnosing the illness. The anticipated approaches are tested and quantified using an experiment based on several factors like performance, precision, sensitivity, specificity, and F1-score. In comparison to alternative methodologies, the proposed strategy has shown promise. In terms of COVID-19 classification from X-Ray and CT-scan based pictures, the suggested research used a variety of state-of-the-art techniques. On VGG19, the accuracy of chest X-ray pictures exceeded 97 percent. On top of the InceptionV3, however, 96 percent accuracy is revealed in CT-scan-based images. The performance of the various models was determined by discussing some of the most important processing methods utilized in medical image analysis at the time of development. As a result, in the future, a more enriched dataset will be used to diagnose COVID-19 (positive and negative cases) more precisely by representing a comparison with pneumonia and lung cancer situations. Data fusion techniques will eventually be used to address medical image computing.

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