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Deep Learning Techniques for Detection of COVID-19 using Chest X-Rays

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Abstract: The COVID-19 pandemic situation keeps on ruining and affecting the wellbeing and prosperity of the worldwide population and due to this situation, the doctors around the world are working restlessly, as the coronavirus is increasing exponentially and the situation for testing has become quite a problematic and with restricted testing units, it's impossible for every patient to be tested with available facilities. Effective screening of infected patients through chest X-ray images is a critical step in combating COVID-19. With the help of deep learning techniques, it is possible to train various radiology images and detect COVID-19. The dataset used in our research work is gathered from different sources and a specific new dataset is generated. The proposed methodology implemented is beneficial to the medical practitioner for the diagnosis of coronavirus infected patients where predictions can be done automated using deep learning. The deep learning algorithms that are used to predict the COVID with the help of chest X-ray images are evaluated for their prediction based on performance metrics such as accuracy, precision, Recall, and F1-score. In this work, the proposed model has used deep learning techniques for COVID-19 prediction and the results have shown superior performance in prediction of COVID-19.

Keywords: COVID, X-ray images, transfer learning, radiology, deep learning, diagnosis

1. INTRODUCTION

COVID'19 has influenced many nations in a very little amount of time. The coronavirus has given a devastating blow to the entire world which is detrimental to the health condition of many people and continues to intimidate the world. This newly identified virus is extremely dangerous and pathogenetically different from SARS-CoV, MERS-CoV, avian influenza, influenza, and other various common respiratory viruses [1]. Although the diagnosis process has become relatively rapid, the financial issues arising from the cost of diagnostic tests affect both the patients as well as the GDP of the country, particularly in countries with private health systems, or restricted access to health systems. So far, due to the lack of availability of public images of COVID-19 patients, detailed studies reporting solutions for automatic detection of COVID-19 from X-ray (or Chest CT) images are not available [2]. Medical predictions are not accurate a lot of times and their uncertainty always has been seriously underestimated [3]. In March 2020, there has been an enormous increase in COVID cases which consequently, lead to a rapid increase in the x-ray dataset. This helps us

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to analyze the medical images and recognize potential trends that help in the automatic diagnosis.

The Automated and Early Covid-19 diagnosis can be helpful for the countries to immediately refer the patient to quarantine, rapid intubation, or severe cases in specialist hospitals, and control the spread of the disease. The model can detect the COVID from x-ray images or CT images using image classification with the help of various deep learning techniques [4]. Due to a gradual increase in cases, the testing of COVID has become the most difficult situation and it also takes more time. To overcome this situation, a model is designed, by which the coronavirus can easily be predicted with the most appropriate deep learning techniques which have the highest accuracy. The effectiveness of the deep learning technique proposed is pre-trained fully convolutional neural networks with regard to their expertise in the automatic diagnosis of Covid-19 from thoracic X-rays.

The use of machine learning techniques for automated medical diagnosis has recently gained prominence by being an adjunct method for clinicians [5]. Researchers are increasingly applying the recent advancements of deep learning to the analysis of chest X-ray images to increase performance and relieve the burden of radiologists. Deep learning, allows end-to-end models to be built to achieve promised results using input data without the need for manual extraction of features. The rapid rise of the COVID-19 epidemic has required the need for expertise in this field. The interest in designing automated detection systems based on machine learning techniques has increased. A weakly-supervised classification and localization system proposed for the computer-aided diagnosis of common thoracic diseases developed 121-layer dense convolutional neural networks [6]. For many image processing applications, such as image analysis, image classification, and image segmentation, deep learning techniques have demonstrated high efficiency. Image classification is achieved through a descriptor extracting the import features from the images, and then these features can be used using classifiers in the classification task. In this research work, four major convolution neural networks namely ResNet50, VGG16, InceptionV3, Xception are used for evaluating the performance against coronaviruses detection.

2. LITERATURE SURVEY

COVID is one of the major causes of death nowadays. Ali et al. [7] had proposed a deep transfer learning technique-based approach for COVID-19 detection using Chest X-ray images. They have classified the images from the three datasets used for implementation into four classes namely COVID-19, Normal (healthy), viral pneumonia, and bacterial pneumonia. Five pre-trained convolutional neural network models were used in this study – ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2. The performance analysis showed that the ResNet50 convolutional neural network model showed the highest accuracy in all the three datasets.

A deep convolutional neural network design for the detection of coronavirus cases in humans from chest X-ray (CXR) images is called COVID-Net with the help of an open-source, available to the general public COVID-19 dataset. Through this method, they gained deeper insights into critical factors that are related to the COVID-19 cases, which helped doctors with an improvement in screening. The obtained model is a successful one as it has a success ratio of 95.9% in detecting the COVID-19 virus and it can also identify non-COVID accurately from a person's chest X-ray. But also, a slight problem would be that the detection decisions are taken only by COVID-Net [8]. They adapted DeTraC (Decompose, Transfer and Compose) – a deep CNN architecture that depends on a class decomposition approach for the classification of COVID-19 images. The experimental results showed that DeTraC had high accuracy and with high sensitivity and specificity respectively [9].

The first-ever data collection of COVID-19 images are made accessible to researchers. They have collected CXR image data, which is about 542 chest X-ray images from about

262 Covid-19 patients from 26 different countries. Frontal and lateral view imagery has been collected and all the metadata such as when did the patient experience first symptoms and what was his intensive care unit (ICU) status, intubation status, or his survival status [10]. Suat Toraman, Talha Burak Alakus, and Ibrahim Turkoglu proposed a novel artificial neural network for detecting COVID-19 from the Chest X-ray images and also to classify the dataset images into COVID-19, and pneumonia X-ray images using capsule networks. The results displayed using capsule networks will not only lead to higher accuracy but at the same time can be effectively used for classification in a limited dataset too [11].

The following study attempts to give insights on the feasibility of using a deep learning-based decision tree classifier for detecting COVID-19 from chest X-ray images. This proposed classifier consists of three binary decision trees. The first tree classifies the chest X-ray images as normal and abnormal. The second tree identifies the abnormal images with signs of tuberculosis and the third does the same thing for COVID-19. The average accuracy achieved by the proposed classifier was found to be 95%. [12]. A deep learning model was used for detecting Coronavirus, which is a sub-branch of artificial intelligence. The dataset used for this research consists mainly of three classes that are coronavirus, pneumonia, and normal X-ray imagery. Fuzzy Color techniques were used to restructure the data classes that would be used as a pre-processing step and the images that were structured with the original images were stacked. In the following step, deep learning models like MobileNetV2, Squeeze Net were used to train the stacked dataset and the Social Mimic optimization method was used to process the feature sets obtained by the models. Subsequently, all the features were combined and categorized using SVM that is Support Vector Machines [13].

In this research paper, the authors used a dataset of X-ray images from patients that have diseases similar to Coronavirus (Covid-19) like pneumonia. Incidents from daily news and cases were utilized for the automatic detection of the Covid-19. The purpose of this study is to evaluate the performance of state-of-the-art convolutional neural network architectures that are suggested over the past years for medical image analysis and classification. Particularly, the method called transfer learning was implemented. It is shown in the paper that even for small medical image datasets detection of various abnormalities is an achievable target with the help of transfer learning, and it often yields remarkable results. The outcome of the research proposed that Deep Learning with X-ray imaging may extract quite noteworthy biomarkers related to the Coronavirus disease, with the highest accuracy, highest sensitivity, and highest specificity which is quite remarkable [14].

A deep learning-based lung CT diagnosis system [15] was developed that detects the patients with the presence of COVID-19. The results of the experiment show that the trained model can identify the COVID-19 patients from others accurately with high sensitivity and an excellent AUC. Besides, the obtained model is capable of distinguishing the coronavirus patients and pneumonia-infected patients with an astonishing high AUC and recall. Furthermore, the trained model is of great help to assist doctors in diagnosing coronavirus disease since it can also localize the main lesion features, especially the ground glass opacity (GGO). Also, the diagnosis is super-fast. The diagnosis of a patient just takes about 30 seconds. So, the conclusion obtained from this research is that the established models can achieve a rapid and accurate classification of coronavirus, therefore allowing the identification of patients.

The authors of this paper compared the Deep learning-based feature extraction frameworks for the automatic classification of coronavirus. To achieve the most accurate feature, algorithms such as Xception, VGGNet, ResNet, MobileNet, InceptionV3, InceptionResNetV2, DenseNet, and NASNet were used in the accurate classification of the virus. The features were extracted and then fed into several machine learning classifiers to distinguish the subjects as a case of coronavirus or not. The approach used to avoid task-specific data pre-processing methods supports a better generalization ability for unseen data. The performance of the proposed method collaborates on a freely available dataset of chest

X-ray and CT images of coronavirus patients. The best performance was achieved by the DenseNet121 feature extractor with a Bagging tree classifier which was a classification accuracy [16].

In this report, the authors implemented a deep convolutional neural network architecture for the detection of cases of coronavirus in humans from chest X-ray (CXR) images, called COVID-Net, accessible to the general public dataset of COVID-19 with the aid of an open-source. In addition to this, they researched how COVID-Net can use an explanatory capacity approach to make predictions. They gained greater insights into crucial factors linked to the COVID-19 cases through this approach, which allowed doctors to enhance screening. The model obtained is a good one as it has a high success ratio in COVID-19 virus detection and can also reliably distinguish non-COVID from the chest X-ray of a human [17]. But also, a slight problem would be that only covid-net is taking the detection decisions. Mahesh Gour and Sweta Jain introduced a novel stacked convolutional neural network for the automatic analysis and diagnosis of the COVID-19 from the Chest X-ray images of the dataset. The authors obtain different sub-models from VGG19 and create a new 30 layered CNN model called CovNet30 [18]. For the training and creation of our model, have used heterogeneous online sources for data collection. Our dataset includes images under 2 categories - COVID-19 chest X-ray images and normal Chest X-ray images [19,20]. During the development of classification models, the initial stage included the merging of the following GitHub repositories and Kaggle resources which maybe have been updated even in our implementation. We would like to acknowledge them for their contributions to this research work and also making the data sources publicly available.

2.1. GitHub Repositories

The links are provided below:

- https://github.com/ieee8023/covid-chestxray-dataset
- https://github.com/shervinmin/DeepCovid
- https://www.dropbox.com/s/09b5nutjxotmftm/data_upload_v2.zip?dl=0
- https://github.com/CSSEGISandData/COVID-19

2.2. Kaggle Repositories

The links are provided below:

- https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
- https://www.kaggle.com/bachrr/covid-chest-xray?select=images
- https://www.qmenta.com/covid-19-kaggle-chest-x-ray-normal/

The reason behind creating the new dataset is that researchers till now have used a smaller number of COVID chest X-ray images which is not enough to validate or justify that the model will be accurate in any study. So, A huge dataset has been used i.e. a greater number of images compared to other researchers' datasets and is getting better accuracy for some algorithms in our model. A heterogeneous online data collection sources have been used for the training and development of our model. The initial stage involved combining the dataset from various credible sources during the creation of classification models and also making the data sources publicly accessible [21, 22].

3. DATASET COLLECTION

The dataset is generated by collecting a set of chest x-ray images of COVID -19 from heterogeneous online public sources like GitHub, Kaggle, and certain data sources mentioned in multiple research papers. In the new dataset created, there are 4539 number of COVID-19 chest X-Ray images and 5961 number of Non-COVID-19 chest X-Ray images, used for training and testing using deep learning models. A total of 10500 images was collected, in that 8400 was used for the training phase of the model and the rest 2100 was used for the testing phase of the model. The training of models also includes data argumentation (image data generator) for increasing the dataset size for both training and testing [23, 24].

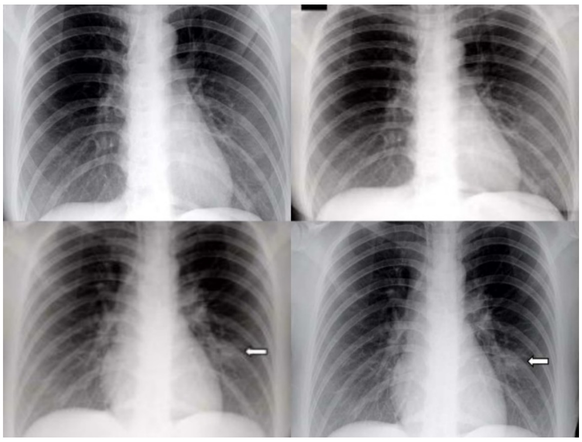

Fig. 3.1. X-ray Images of COVID infected patients.

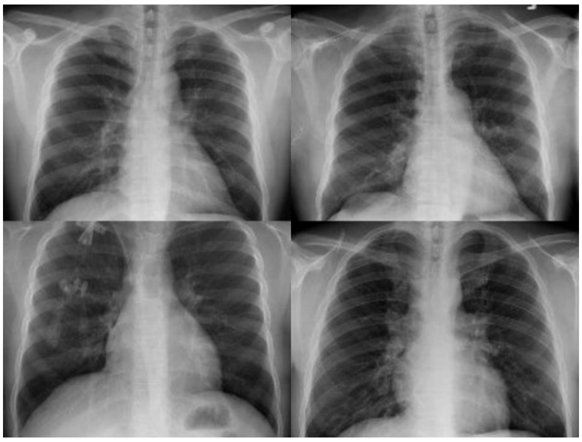

Fig.3.2. X-ray Images of Normal patients.

After Data Argumentation 8736 training images were generated and 2220 testing images.

4. METHODOLOGY

Diagnostic imaging modalities, such as chest x-ray images are playing an important role in confirming the primary diagnosis from the Polymerize Chain Reaction test for COVID-19. Convolutional Neural Networks are algorithms that are used to predict the class of images [25]. In our proposed work, deep learning techniques have been applied like VGG16, Resnet50, InceptionV3, and Xceptionfor covid-19 prediction. Preprocessing of data has been implemented to establish the same size for all data and to normalize the images in the dataset. Different techniques such as Image Resizing, Image Data Generator, Data Labelling, and Data Normalization has been applied to the dataset.

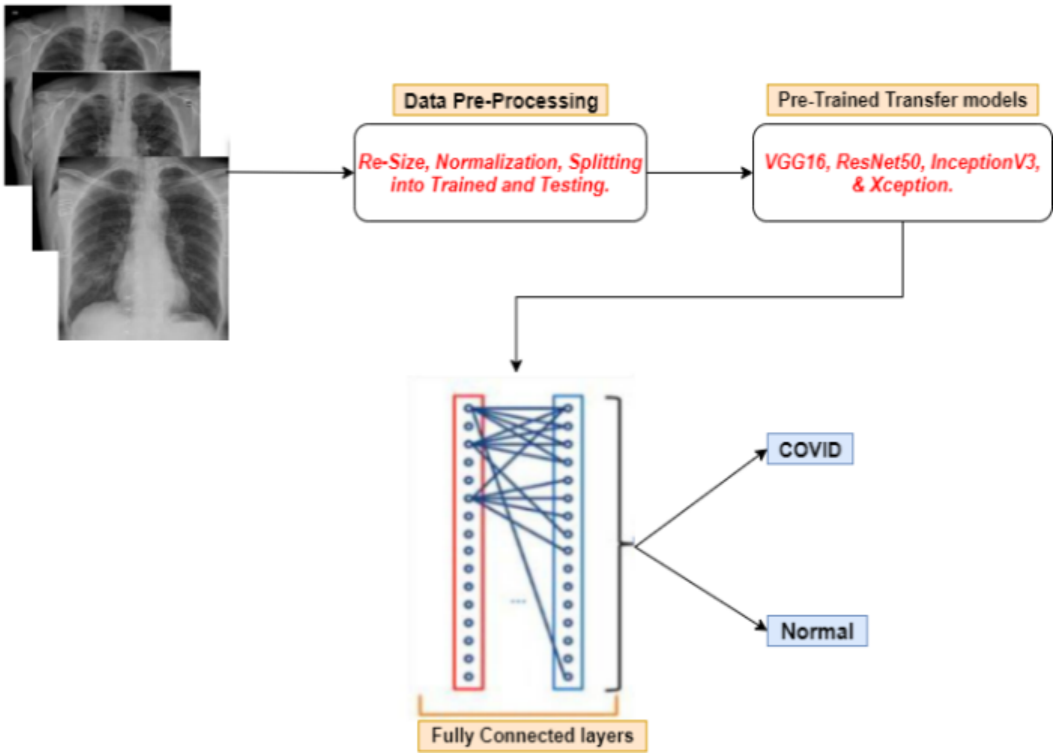

Fig. 4.1. Block Diagram of the model.

. The dataset is prepared for the training and testing phase by applying the required preprocessing. Then, the data is split into an 80:20 ratio for training and testing the dataset to predict the outcome of the chest x-ray image. The deep learning models are trained for 500 epochs with a batch each consisting of 32 images. The requirement of the model is to recognize the necessary features from the training phase and after training make the predictions and classify the images. In this work, the implementation of all the architectures included the addition of three custom layers in the pre-trained models for training the dataset. The first layer (flatten layer) was used to flatten out the input features. The next layer is the Dropout layer, which buried the problem of overfitting. A dense layer with a softmax activation function is used as an output layer.

4.1 VGG16

VGG16 technique is a deep learning predictive model that is based on the ability of imitation effects shown by multiple small filters in a sequence with respect to large filters [26]. For interpreting the effect of depth on accuracy a simple CNN with a small convolution filter of size 3x3 with stride and padding of 1 along with a 2x2 max-pool with a stride of 2 for 16 layers was used.

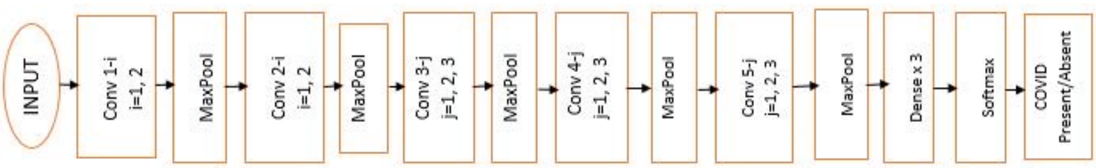

Fig. 4.1.1. Architecture of the VGG model.

It shows improvement over Alex Net by substituting large kernel sized filters with multiple 3x3 kernel sized filters one after another. The algorithms were specifically trained for image localization. The input to the first Convolutional layer is an image after pre-processing the dataset. The image is passed over a stack of layers where small size filters of 3x3 have been used and pooling is also been applied after every convolutional layer. A 1x1conv filter had also been used for the conversion of input channels to linear. To help us extract the generic low-level descriptors or patterns from the chest X-ray image data, then froze the weights of the earlier layers of the pre-trained backbone. The first few layers learn very basic and generic characteristics that generalize to almost all types of images in the convolutional networks that are used in this research work. The features became increasingly more unique to the dataset on which the model was trained. The objective of fine-tuning is to adapt these specialized features rather than overwrite the generic learning, to work with the newly fed COVID-19 dataset. VGG16 is an improvement over AlexNet, which used to be a state of art model until the introduction of VGG16 that reduced the image size very drastically using convolution to avoid without needing SGD (stochastic Gradient Descent) necessarily and to increase the number of channels to make the image while reducing height and width of the image simultaneously. This improves the computational speed and accuracy of our model without going through a deep neural network.

4.2 ResNet50

Resnet50 is a deep learning pre-trained model, which is trained on the ImageNet dataset. The backbone of this architecture involves introducing an identity shortcut connection that will enable us to skip multiple layers. It is the short name for the residual network and it introduces the concept of residual layers.

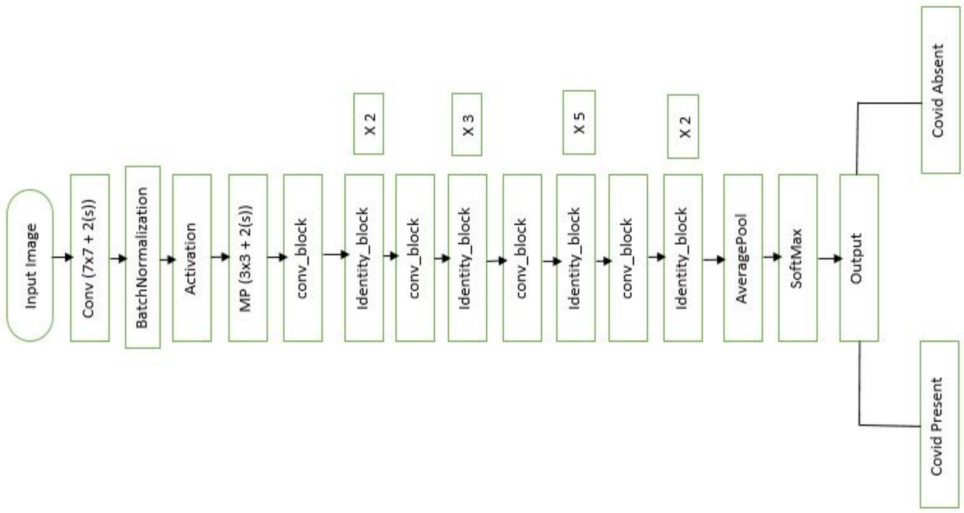

Fig. 4.2.1. Architecture of the ResNet50 model.

ResNet50 architecture is pretty similar to ResNet18, the main difference being having more layers. ResNet50 network each 2-layer block in the 34-layer net is replaced by a 3-layer bottleneck block leading to a 50-layer model. The idea behind this is to skip layers and establish direct short connections to prevent saturation of accuracy [27]. The insertion of short connections will lead the network to turn into its residual counterpart. As the network gets deeper and more complex, it avoids the distortion that happens in the model during training. The shortcut connections perform identity mappings and the outputs obtained are added to the outputs of other stacked layers. One of the advantages of the architecture includes helping the network to create a path, which will help us simplify the gradient updates for the preceding layers.

4.3 InceptionV3

InceptionV3 architecture aims to assist in image analysis and object detection. It is a type of neural network model of convolution. It consists of several stages of convolution and full pooling. It increases the depth and width of the network and improves the involvement of computing resources inside the network while keeping computation operations unchanged [28].

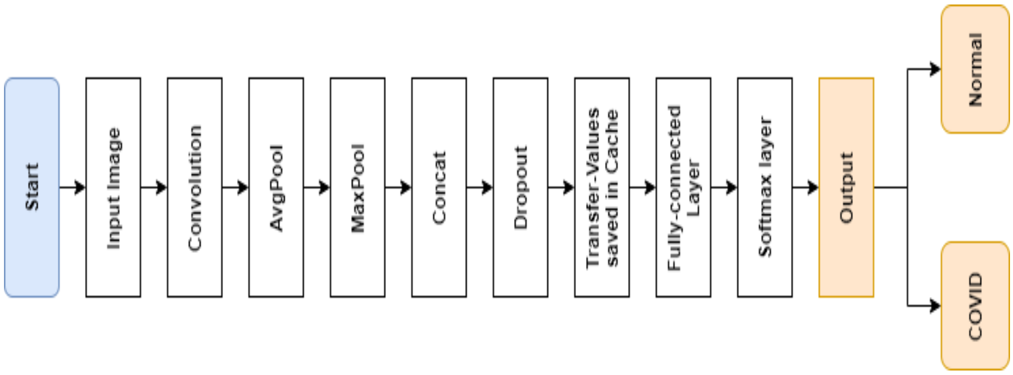

Fig. 4.3.1. Architecture of the InceptionV3 model.

In general, it has 48 layers and uses inception modules consisting of a concatenated layer with convolutions of 1 x 13 x 3 and 5 x 5. Reducing the number of channels in the image is the basic concept of the 1x1 convolution. Thus, it also decreases the number of parameters. The size of the matrix is usually not affected by 1x1 convolution; however, if the input matrix is multi-channel, the channel number of the 1x1 convolution method output matrix is equivalent to the number of 1x1 convolution filter channels added. This architecture's key benefit is that it enables one to reduce the number of parameters and increase the speed of training. Another benefit of this architecture is that it enables the user to perform the localization according to their parameters and helps us to recognize with better accuracy.

4.4 Xception

Xception is a 71-layer deep convolutional neural network. It involves Depth Wise Separable Convolutions instead of standard Inception modules. It is an extension of the Inception architecture. A pre-trained version of the network trained on more than 10 lakh images from the ImageNet database can be loaded. In this model, the initiation of convolution modules is replaced by depth-wise separable convolutions. Point-wise convolution layers obey the depth of wise convolution layers. For a large range of images, the network is capable of learning-rich feature representations and is able to perform a little better than the Inception network. The input image was first sent through the entry flow in this analysis, then eight times through the middle flow, and finally through the exit flow that includes a SoftMax Layer.

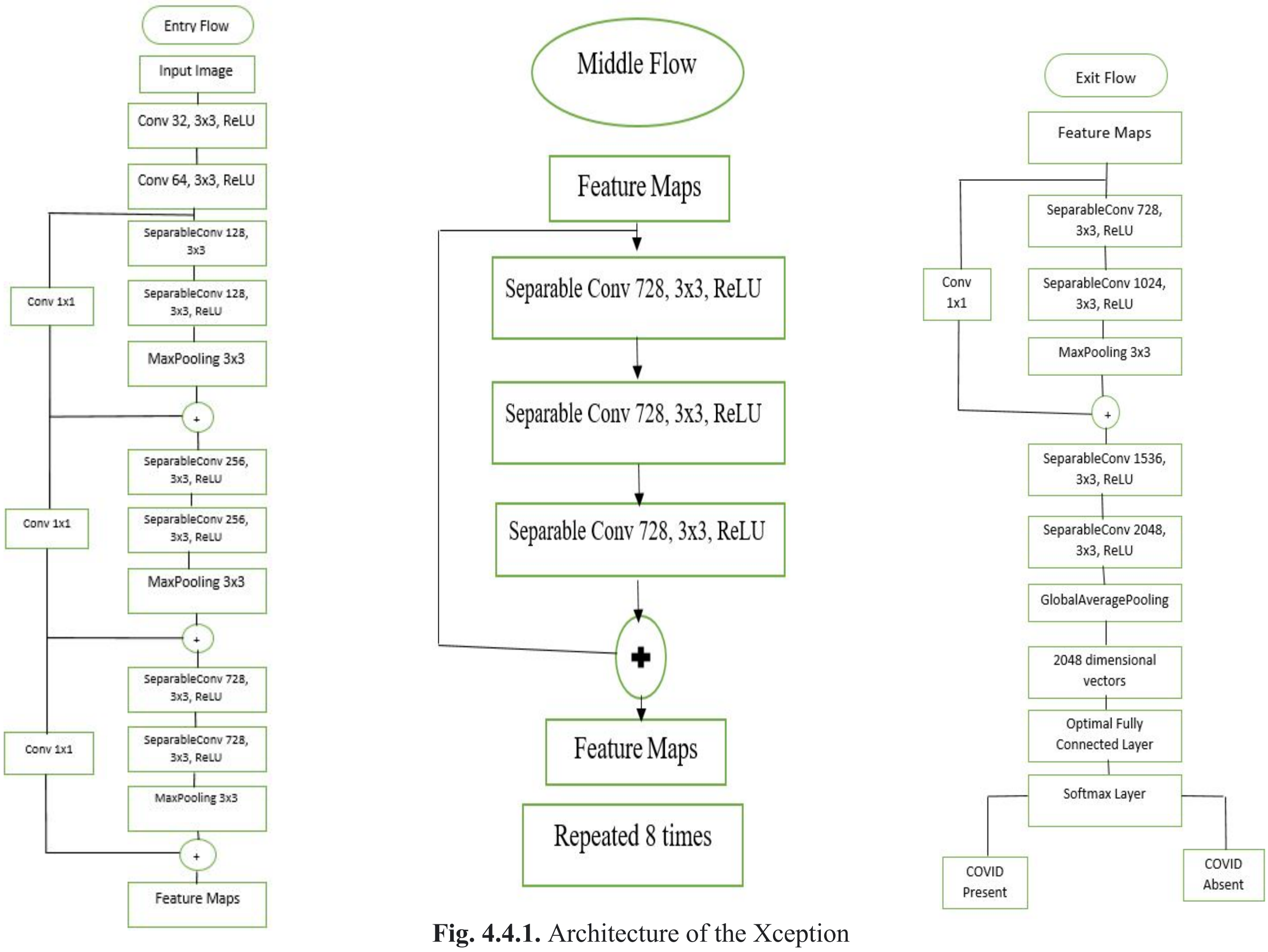

Fig. 4.4.1. Architecture of the Xception model.

5. COMPUTATIONAL EXPERIMENTAL SETUP

In this research paper, the proposed architecture is to demonstrate the pipeline model that assembled would optimize the outcome and evaluate all model results, then compare model accuracy, training time, and model loss of the VGG16, ResNet50, InceptionV3, and Xception algorithms on the dataset while training. The classification model is evaluated in terms of precision, recall, and F1-score and is applied to the dataset after data set collection and using different data preprocessing techniques [29].

Transfer Learning modules from deep learning were implemented. Several Machine learning libraries such as TensorFlow 2.3.2, Sklearn, Seaborn, Numpy, Matplotlib, and OpenCV are used to incorporate all Transfer Learning, and the training and testing procedures are carried out on the Google Colab platform. All the experiments presented in this paper have been performed on Google Colaboratory with the use of GPU, Tesla K80 Graphical Processing unit with 12GB GDDR5 VRAM hardware from the online cloud service that is available for free. The CNN models (ResNet50, VGG16, InceptionV3, and Xception) pre-trained on the ImageNet dataset are used with random initialization weights, and adaptive moment estimation (ADAM) optimization of the cross-entropy function has been performed. There has been a random division of data into two separate datasets (train & test) of 80 % and 20% for training and testing, respectively. For all experiments, the batch size of 32, a learning rate of 0.00001, and a number of epochs of 500 were respectively used. These are some of the results after applying all the algorithms.

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5.1 VGG16

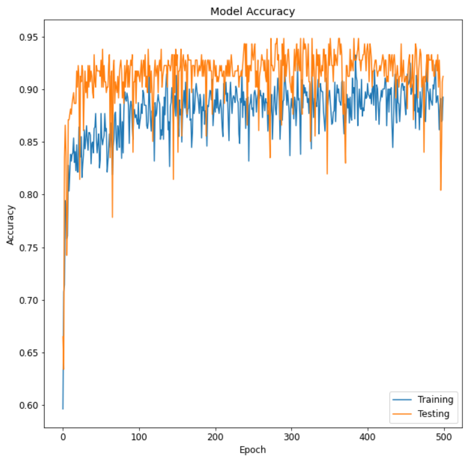

Fig. 5.1.1. Epoch Vs Accuracy

In Fig. 5.1.1. In this Model Accuracy, the x-axis indicates the Epoch and the y-axis indicates the Accuracy of training and testing of data which displays the graph of our dataset.

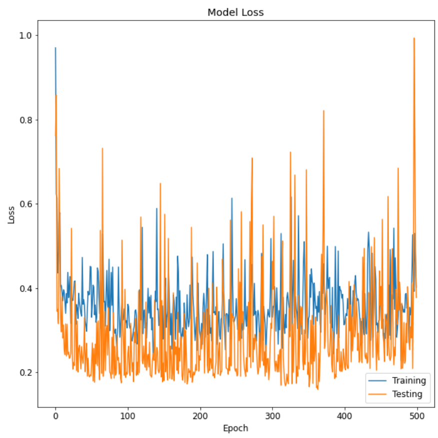

Fig. 5.1.2. Epoch Vs Loss

In Fig. 5.1.2. In this Model Loss, the x-axis indicates the Epoch and the y-axis indicates the Accuracy of training and testing of data which displays the graph of our dataset.

5.2 ResNet50

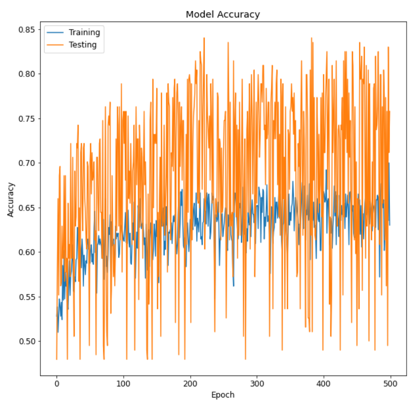

Fig. 5.2.1. Epoch Vs Accuracy

In Fig. 5.2.1, The graph displays the model accuracy of Epoch with respect to Accuracy for the ResNet50 model.

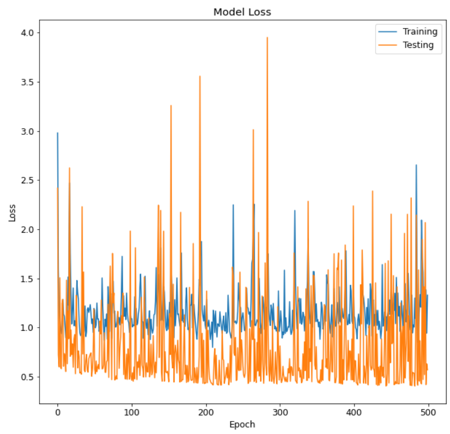

Fig. 5.2.2. Epoch Vs Loss

In Fig. 5.2.1, The graph displays the model Loss of Epoch with respect to for ResNet50 model.

5.3 InceptionV3

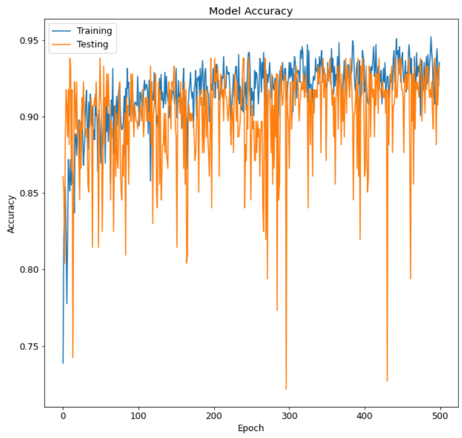

Fig. 5.3.1. Epoch Vs Accuracy

In Fig. 5.3.1. In this Model Accuracy, the x-axis indicates the Epoch and the y-axis indicates the Accuracy of training and testing of data which displays the graph of our dataset for the InceptionV3 model.

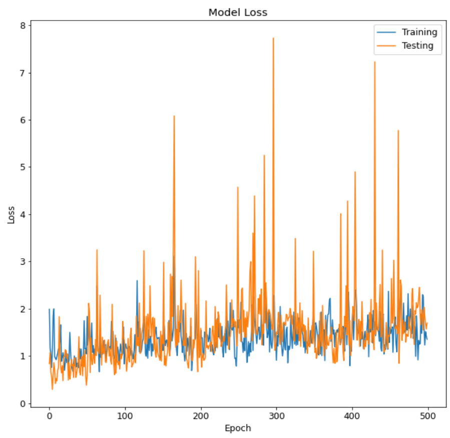

Fig. 5.3.2. Epoch Vs Loss

In Fig. 5.3.2. In this Model Loss, the x-axis indicates the Epoch and the y-axis indicates the Accuracy of training and testing of data which displays the graph of our dataset for the InceptionV3 model.

5.4 Xception

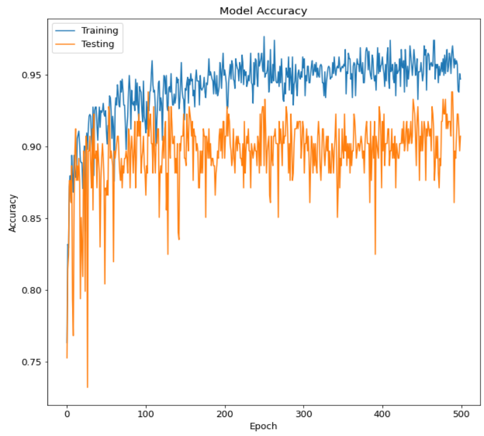

Fig. 5.4.1. Epoch Vs Accuracy

In Fig. 5.4.1, the graph displays the model accuracy of Epoch with respect to Accuracy for the Xception model.

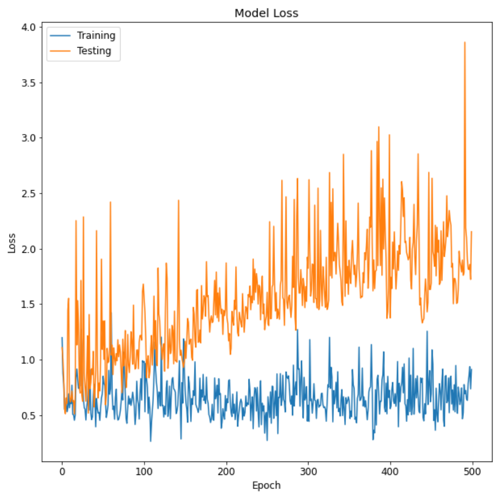

Fig. 5.4.2. Epoch Vs Loss

In Fig. 5.4.2, The graph displays the model loss of Epoch with respect to Loss for the Xception model.

If true positive is categorized as the number of Covid-19 chest x-ray images; false negative is the number of Covid-19 chest x-ray images misclassifies as normal; false positive is the number of normal chest x-ray images misclassified as Covid-19; the true negative is the normal number of chest x-ray images. In the convergence graph field, it is a standard measure to check how quickly the model is able to classify the data. Accuracy, recall, F1-score, accuracy is defined and the following equations will describe them.

$$\text{Precision} = \frac{TP}{TP+FP}. \tag{5.1}$$

$$\text{Recall} = \frac{TP}{TP+FN}. \tag{5.2}$$

$$\text{F1-score} = \frac{2*(Precision*Recall)}{Precision+Recall}. \tag{5.3}$$

Accuracy: It is defining as the number of true positives and true negatives by the number of true positives, true negatives, false positives, and false negatives.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}. \tag{5.4}$$

Table 5.1. Classification Report of all algorithms.

Algorithms	Precision	Recall	F1-Score	Accuracy
VGG16	0.90	0.89	0.89	0.91
ResNet50	0.83	0.82	0.82	0.83
InceptionV3	0.96	0.96	0.96	0.96
Xception	0.91	0.91	0.91	0.92

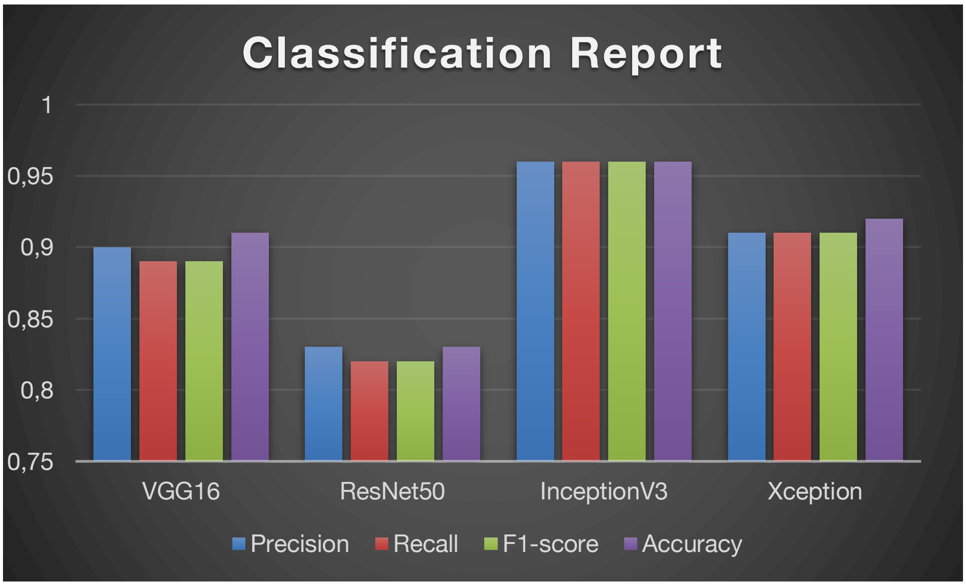

Fig. 5.5.2. Classification Report

In the above Table. 5.1, the precision, recall, F1-score and accuracy performances are listed after processing via various algorithms. The algorithms are trained and probed on the chest x-ray image dataset of the pre-trained models. In the above figures, the model accuracy and model loss of the trained models are given. It can be said that for the initiation, the highest model training accuracy is obtained for inceptionV3 and the training is carried out for 500 epochs. It can be analyzed that from the model loss figures that the loss values are reduced in all pre-trained models, and with the help of the confusion matrix, a comparison of all algorithms is listed out based on performance from the classification table. After comparing the Precision, recall, f1-score, and accuracy from the above table, the inceptionV3 gives the best results in both the training and testing phase and shows better output than the other three models.

6. CONCLUSION

Early prediction of coronavirus is vital to prevent the spread of the disease among other people. So, the use of deep learning algorithms for the diagnosis of COVID-19 has become a major concern during this pandemic considering the accuracies and f1 score of the present algorithms. Keeping that in mind, we came up with better accuracies for the algorithm compared to the one which is present. We collected a huge dataset of x-ray images from different reliable sources and combined them to form one. Large datasets could lead us to identify coronavirus infection more accurately and reliably when training and testing the model. In an effort to identify the Covid19 affected patients more accurately and precisely we have implemented four different algorithms and compared each among themselves for better results. Out of the four models VGG16, ResNet50, InceptionV3, and Xception. InceptionV3 showed better results among other algorithms and also with the previously proposed algorithms with an F1 score of 96% whereas the previously proposed InceptionV3 algorithm has a score of 94.8%.

Further, current research work can be enhanced by improving the efficiency of the model and also by reducing the training time with an improved version of the present code. Finally, the current model can be deployed across various devices such as mobile phones such that patients can scan their X-rays and can get the prediction.

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