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COV-Inception: COVID-19 detection tool using chest X-ray

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Abstract. Since the pandemic started, researchers have been trying to find a way to detect COVID-19 which is cost effective, fast and reliable way to keep the economy viable and running. This research details how chest X-ray radiography can be utilized to detect the infection. This can be for implementation in Airports, Schools and places of business. Currently Chest imaging is not a first-line test for COVID-19 due to low diagnostic accuracy and confounding with other viral pneumonia. Different pre-trained algorithms were fine-tuned and applied to the images to train the model and the best model obtained was fine-tuned InceptionV3 model with an accuracy=0.9950, precision=1, recall=0.9907, AUC=0.9935, F1-Score=0.9953 with a loss=0.0989.

1 Introduction

On March 11, 2020, the World Health Organization confirmed the worldwide pandemic of COVID-19. On July 28, 2020, the number of people infected with the new coronavirus worldwide exceeded 16.562 million, of which more than 654,000 people died, and more than 10.147 million were recovered. The actual number of infections may exceed the number of confirmed cases. The reverse transcription-polymerase chain reaction (RT-PCR) test is the standard for identifying COVID-19 patients, but this process is usually time-consuming, and the initial virus concentration is not high and easy false negatives occur. Therefore, computed Tomography (CT) and X-rays also play an important role in the auxiliary diagnosis process, and they are a powerful helper in the diagnosis and judgment of disease progression. CT and X-ray assessment of lung infections, further testing, isolation observation, and corresponding treatment are also important. CT scans can assist the detection of mutated COVID-19 than RT-PCR may detect false negative and it can also be used to quantitatively assist in evaluating the treatment effect through CT scans.

Artificial Intelligence (AI) in healthcare and medical image analysis has been widely used in many fields such as computer graphics, image processing, computer vision, and computer-aided design and has achieved extensive evaluation.

The combination of artificial intelligence technology, deep mining of big data, and optimization of computational models has been able to perform the medical image analysis with quite high accuracy and other performance metrics like sensitivity, specificity, precision, recall etc. AI has shown impressive improvement in also identifying the abnormalities in medical images.

Lung CT is extremely important for the treatment of new coronary pneumonia. Lung CT is not only an important means of diagnosing viral pneumonia, but also a powerful tool for judging the progress of the disease, changing nodes, and disease outcome. CT examination, early detection of changes in the condition, striving to intervene in time before the transition from moderate to severe, and interrupt the evolution of the disease to severe through life support treatment.

For mild patients, increasing the frequency of CT examinations can also detect potential changes in the condition in time and take corresponding measures as soon as possible. Although clinical doctors cannot wait to perform a lung CT every 2 or 3 days for patients with uncertain conditions, the current clinical practice cannot meet this demand.

The time required for reading and diagnosis is at least 10 to 15 minutes. The ability to effectively identify and segment COVID-19 lung CT and distinguish other types of pneumonia is the focus of the artificial intelligence models

Although chest X-rays are not as sensitive as CT images to chest abnormalities, their portability and economic benefits are better than CT imaging, so they are also widely used to study COVID-19 as a way to study patient infection. According to the literature, chest X-rays of COVID-19 pneumonia are different, but they may be bilateral, with lower lobes extending to the surface of the pleura. These functions help distinguish COVID-19 pneumonia from other pathological causes of lung disease. Many researchers have focused on this point and have applied it to machine learning.

Doctors/physicians must not be completely dependent on the machine learning model because the computer systems are never superior than human experts. After the emergence of the pandemic disease COVID-19, the citizen data scientists are getting their focus on this area and have developed many computer-aided COVID-19 diagnostic model using Artificial Intelligence (AI) and Machine Learning (ML) techniques.

This AI-driven approach has enabled the easy virus detection which is rapid, easy and at affordable costs. Since the RT-PCR kits are limited and costly at the same time with some error-rate in virus detection, adopting the AI-driven automated COVID-19 detection system which uses chest X-Rays (CXR) images will help the radiologists to detect the virus in the early stages which in turn will help the doctors to treat the suspected patients accordingly.

Although many of the automated detection system are built using the deep learning and machine learning techniques, this research has the following novel contributions:1)Detecting the age group having high chances of getting infected. 2)Improving the accuracy of detecting within a specific group due to higher fatalities.

2 Related Work

Between March 2020 and May 2022, multiple researches have been done using Machine learning to identify or diagnose COVID-19 from X-ray radiation of the chest.

Below are some of the articles that worked on chest X-Ray images for the COVID-19 Image prediction.

Cengil, Emine et al.[1] performed an analysis using Convolutional Neural Networks (CNN) and classification methods on X-Ray images and built a model that had an accuracy of 98.8%, 95.9% and 99.6% on the three different datasets they used for their analysis. The X-Ray images datasets consists of three classes (COVID, normal, pneumonia). Feature extraction methods like-AlexNet, 36 Xception, 37 NASNetLarge, 38 and EfficientNet-B039 methods were used for automated feature extraction which then after was passed to the classification algorithms- Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), k-Nearest Neighbor (KNN), Naïve Bayes (NB) and Decision Tree (DT).This paper details how some pre-trained algorithms are fine-tuned and achieved a higher performance metrics in detecting the COVID-19 for old-age group using chest X-Rays.

Wang, Linda et al.[2] designed a model called as COVID-Net by using deep convolutional neural network (CNN). The COVID-Net model had the best performance of 93.3% among the 3 architecture they used (VGG-19, ResNet-50, and COVID-Net) for building the model. Among all the architecture, VGG-19 obtained the sensitivity of 98% in detecting normal X-Ray images, ResNet-50 with 94% in detecting non-COVID-19 pneumonia and COVID-Net with 91% in detecting COVID-19 pneumonia. Thus, making the COVID-Net to be the best COVID-19 detector using Chest X-Ray images. Higher performance metrics were achieved using the COV-Inception model that helps in detecting the COVID-19 using the chest X-Rays.This paper details how some pre-trained algorithms are fine-tuned and achieved a higher performance metrics in detecting the COVID-19 for old-age patients using chest X-Rays.

Baltazar, Lei Rigi, et al.[3] worked on Chest X-Ray (CXR) images to detect the COVID-19 using transfer learning which is one of the machine learning techniques. They used five well-known architectures for developing the COVID detection system. There were-InceptionV3, Inception-ResNet, Xception, VGG19 and MobileNet. Stochastic Gradient Descent (SGD) was used an optimizer and categorical cross-entropy as a loss function for training and fine-tuning the CNN models. Three different detection ideas were adopted: two-class detection (Normal/Pneumonia), three-class detection (Normal/Non-COVID-19 pneumonia/COVID-19 pneumonia), and four-class detection (Normal/Viral pneumonia/Bacterial pneumonia/COVID-19 pneumonia). Two different strategy was used for different detection scenarios. First, the dataset was divided into training and test data in which 80% was training data and 20% test data. Second strategy divided the data into three parts: training, validation, and test data in which 70% was training data, 20% was validation, and 10% was testing data. model obtained by using InceptionV3 had best sensitivity of 86% and specificity of 99% with high positive predictive value (PPV) value of 91%. This research details COV-Inception, a COVID-19 detection tool that uses chest X-rays to predict the occurence of COVD-19 with accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

Mahmud, Tanvir, et al.[4] proposed a deep convolutional neural network (CNN) based architecture called CovXNet which uses Chest X-Ray (CXR) images of COVID-19 caused pneumonia and other traditional pneumonia (viral/bacterial) since they had significant similarity. Multiple classification algorithms like- XGBoost, Random Forest, Decision Tree, Support Vector Machine (SVM) k-Nearest Neighbor (KNN), GuassianNB, and Logistic regression were adopted to see which algorithms performs best in predicting the COVID-19 pneumonia in which XGBoost and Random Forest seemed to be performing best in detecting every type. Using two extensive experimentation datasets, the model obtained an accuracy of 97.4% for COVID/normal, 96.9% for COVID/Viral pneumonia, 94.7% for COVID/Bacterial pneumonia, and 90.2% for multiclass COVID/normal/Viral/Bacterial pneumonias. This paper details how some pre-trained InceptionV3 algorithms is fine-tuned and achieved a higher performance metrics in detecting the COVID-19 for old-age patients using chest X-Rays.

Hanafi Hanafi, et al.[5] developed an AI-driven model having 98% accuracy using deep Convolutional Neural Network (CNN) in combination with Autoencoder (AE) which was named as CAE-COVIDX. Accuracy, precision, recall, loss function, and confusion matrix were used for the model performance evaluation. Two task models were built in which for each task 60% data was used for training, 10% for validation, and 30% for testing. CAE-COVIDX was considered the best performing model after they run the experiment five times on traditional CNN, VGG-16 and CAE-COVIDX to ensure performance stability. This research achieved a higher performance metrics using COV-Inception in which data was divided into train, validation, and test batches using ImageGenarator function from tensorflow package.

J.L, Gayathri, et al.[6]] developed a model by integrating Convolutional Neural Network (CNN) with dimensionality reduction method named as Sparse Autoencoder and Feed Forward Neural Network (FFNN) for detecting the COVID-19 using CXR. Chest X-Ray image dataset having 504 COVID-19 and 542 non-COVID-19 images was used to train the model. Multiple pre-trained networks-InceptionResNetV2 having depth 164, ResNet101 with 101, Xception with 72, EfficientnetB0 with 82, and Darknet with depth 53 were used for feature extraction. When sparse autoencoder was not used, the single-CNN model using FFNN performed best on EfficientnetB0 pre-trained network with an accuracy=93.21% and AUC=0.9756 but when sparse autoencoder was implemented to the single-CNN model using FFNN, the model was able to predict the COVID-19 with 95.78% accuracy and had an AUC=0.9821 and was using the combination of Xception and InceptionResNetV2 pre-trained network. An AUC of 1 is considered as perfect classifier and a model with AUC less than or equal to 0.50 is considered worthless. So, the model with AUC=0.9821 is considered good classifier.This research details COV-Inception, a COVID-19 detection tool that uses chest X-rays to predict the occurence of COVD-19 with accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

Ackall, Gabriel, et al.[7] constructed a convolutional neural network (CNN) model that used xRGM-Net CNN to detect COVID-19 using chest X-ray images. An activation mapping technique called Score-CAM was implemented on the X-Ray images that creates a heatmap over an X-ray and helps in indicating which areas are most influential over the diagnosis. The model was built by using 2754 healthy X-Ray images and 439 COVID-19 X-ray images. The CNN model was trained with 90% data and 10% data was used for validation and testing. Three different algorithms were implemented to construct the model (AlexNet, VGG-19, and xRGM-NetV2). The best performing model achieved an accuracy=96.6%, sensitivity=93.6% and specificity=97.1% using xRGM-NetV2. This paper explains how different pre-trained algorithms like ResNet50, Inception-ResNetv2, DenseNet121, InceptionV3 etc. were fine-tuned and the best model COV-Inception obtained an accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

Khan, Murtaza Ali.[8] presents an automated and fast system that identifies COVID-19 from X-ray radiographs of the chest using image processing and machine learning algorithms. Initially, the system extracts the feature descriptors from the radiographs of both healthy and COVID-19 affected patients using the speeded up robust features algorithm. Then, visual vocabulary is built by reducing the number of feature descriptors via quantization of feature space using the K-means clustering algorithm. The performance of the proposed Support Vector Machine (SVM)-based classifier with the deep-learning-based convolutional neural networks (CNN). The SVM yields better results than CNN and achieves a maximum accuracy of up to 94.12%. This research made use of data augmentation that performs multiple operations on the image like rotation, flipping, blurring, contrast, padding, shifting etc. that generates different pattern images which in turn helps the model to get explored to every aspect of the images and train itself so that the model can make a better prediction.

Mahdi, Mohammed Salih, et al.[9] the suggested Schema of convolutional neural network (CNN) that can aid the doctors in hospital to improve the diagnosis of the five different classes (COVID-19, MERS SARS, ARDS and Normal). For evaluating testing set, the practical outcomes demonstrates the suggested Schema of CNN classifier with an accuracy of 98%. This research details COV-Inception, a COVID-19 detection tool that uses chest X-rays to predict the occurence of COVD-19 with accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

Chowdhury, Nihad K., et al.[10] proposed a Convolutional Neural Network (CNN) model based on COVID-19 detection system named as Parallel-Dilated COVIDNet (PDCOVIDNet) which take the chest X-Ray (CXR) images as input. The model used convolution parallel-dilation to extract the radiological features from the CXR images. Using the 2095 CXR images which had three different class (COVID, normal and pneumonia), the classification model under-goes five different methods-PDCOVIDNet, VGG-16, ResNet50, InceptionV3 and DenseNet21. The best performaing model that was able to detect COVID-19 was PDCOVIDNet with an accuracy=96.58%, precision=96.58%, recall=96.59% and F1-score=96.58%. This paper explains how different pre-trained algorithms like ResNet50, InceptionResNetv2, DenseNet121, InceptionV3 etc. were fine-tuned and the best model COV-Inception obtained an accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

While numerous approach have been made in detecting COVID-19 using the chest X-Rays and deep learning algorithms but a simpler and faster deep learning approach is proposed in this research paper. COV-Inception method performed the best among all the pre-trained deep learning algorithms with an accuracy of 99.5%, sensitivity of 99.07%, precision of 100%, AUC of 99.35% and F1-Score of 99.53% for old-age patients.

3 Data

The two different data sets were used for this study contains two types of images: "COVID" and "Normal". The data sets [24][25] were merged together for further analysis. The merged data set contains 32 variables and 1685 values. The variables which are given in the data set consists of Age, Gender, Survival, Temperature, Patient ID, Went-to-ICU,Intubated, needed-supplement, COVID-detection, finding, clinical notes, other notes, etc. Each variable is relevant information describing the patient and underlying factors. The data set contained 8 continuous variables and 24 categorical variables.

3.1 Data Visualization

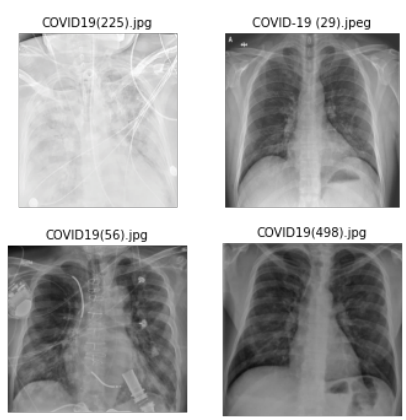

Fig. 1. Image showing 4 randomly selected X-Rays from the data set

Data visualization is one of the most important aspect in understanding and analyzing the data before you start building model using machine learning algorithms. It helps to determine trends, patterns and any relationship between the data. Different data visualization packages were used in this study. The packages includes-Matplotlib, Seaborn etc.

Matplotlib is an open source python package which is used for visualizing the X-rays and other graphs generated for the analysis. Matplotlib helps in creating stationary, animated, and interactive plots in Python environment.

Seaborn is also an open source package which is created on the top of Matplotlib package. It provides capabilities to create statistical graphs that helps in analyzing the data efficiently.

Missing Values- After analyzing the data set, it was found that there were missing values in it with some values being NULL and some being assigned as Unknown. Some variables have less missing values and some have more missing values. The study worked on handling those missing values by implementing data imputation strategies.

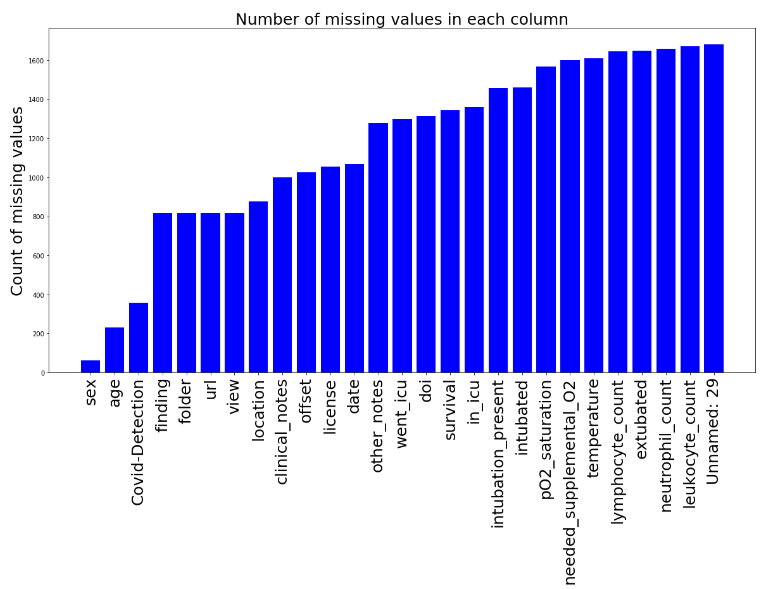

Fig. 2. Image showing missing data graphically from the data set

COVID-Detection (Positive/Negative)- After analyzing the COVID-Detection column in the data set, it was found that out of 1685 values, 357 values were missing values and 194 unclear values. From the remaining 1134 values, 602 of them were detected with COVID positive and 532 of them were COVID negative.

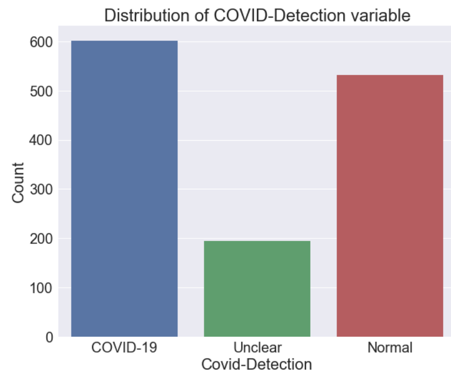

Fig. 3. Image showing covid positive/negative Status from the data set

Survival- After analyzing the Survival column in the data set, it was found that out of 1685 values, 1344 values were missing values. From the remaining 341 values, 256 of them survived and 76 of them did not survive.

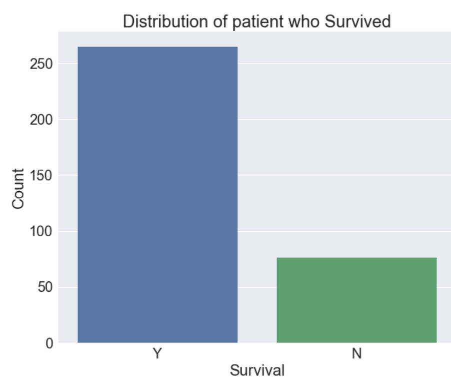

Fig. 4. Image showing survival of patients from the data set

Gender- After analyzing the Gender column in the data set, it was found that out of 1685 values, 689 values were missing values and 9 Unknown values. From the remaining 1017 values, 654 of them were Male and 363 of them were Females.

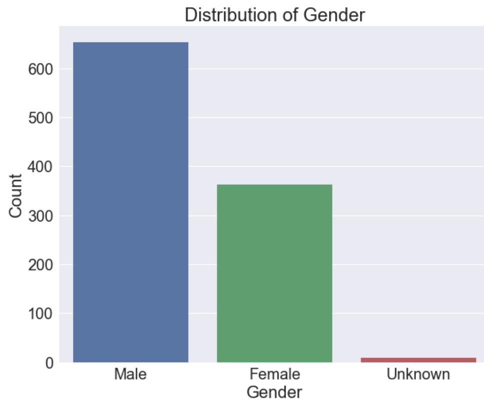

Fig. 5. Image showing grouping of gender obtained from the data set

Age- After analyzing the Age column in the data set, it was found that out of 1685 values, 230 values for Age were found to be missing which was handled using data imputation strategies.

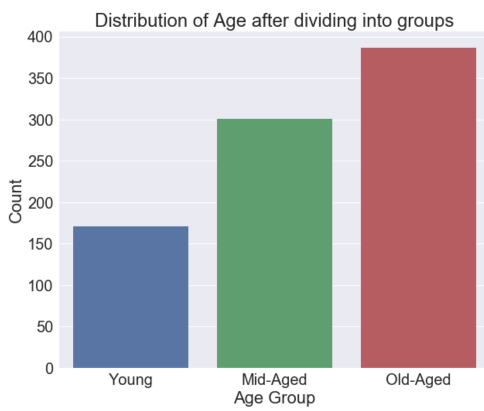

Fig. 6. Image showing Categories of Age column from the data set

The continuous nature of Age column was further converted into categorical which can help to focus on certain age group that needs more analysis. The minimum age was 18 years and the maximum age was 94 years with 55 years age as mean and median which indicates that the Age column has normal distribution. The age column was categorized into 3 categories: 0-40, 40-60 and 60-100 with 0-40 as Young-Aged, 40-60 as Mid-Aged and 60-100 as Old-Aged.

Went to ICU- After analyzing column regarding the patients that went to ICU in the data set, it was found that out of 1685 values, 1297 values were missing values. From the remaining 388 values, 277 of them went to ICU and 111 of them were not admitted in ICU.

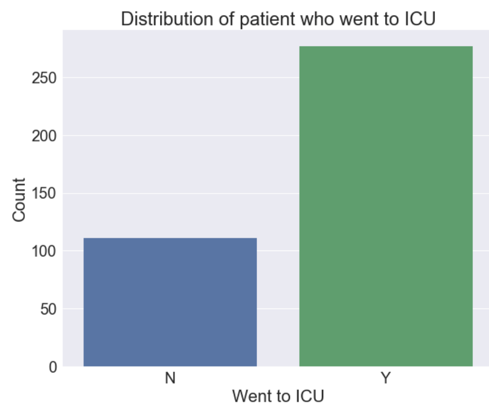

Fig. 7. Image showing patient who went to ICU vs NO ICU from the data set

Intubated- After analyzing column regarding the patients that were intubated, it was found that out of 1685 values, 1460 values were missing values. From the remaining 225 values, 130 of them were intubated and 95 of them did not undergo intubation.

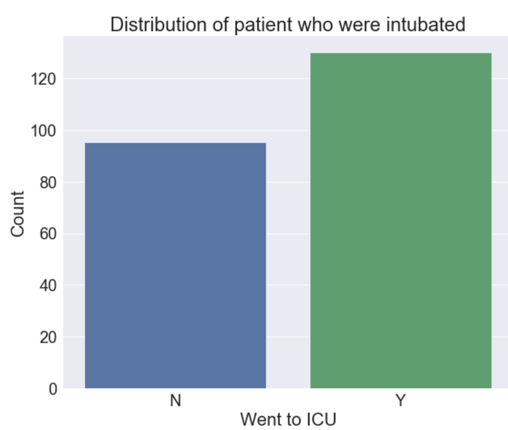

Fig. 8. Image showing patient who intubated vs. not intubated from the data

Chest X-Ray View- After analyzing column that informs about the view of X-ray in the data set, it was found that out of 1685 values, 819 values were missing values. From the remaining 866 values, 438 of them Posteroanterior (PA) X-Ray view, 344 of them were Anteroposterior (AP) X-Ray view and remaining 84 of them were lateral (L) X-Ray view.

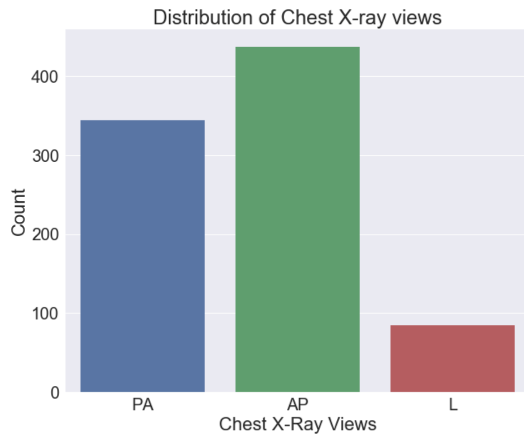

Fig. 9. Image showing type of view for X-ray from the data set

4 Methodology

4.1 Data Preparation

The study works on detecting COVID-19 in the patients for specific age group. To achieve this, the chest X-Ray images were divided into 3 groups: 0-40 years as Young, 40-60 years as Mid-Age and above 60 years are considered as Old-Age based on the metadata provided for the images. This article shows the image processing and recognition of COVID-19 for the Old-Age group patients.

4.2 Data Augmentation

Data Augmentation is a technique in which images are inputted and altering is done to the images. This operation on the images allows the training model to work on different aspects of the images and make prediction better when new image is given to the trained augmented model. Generally, below activities are used for data augmentation:

- Rotating
- Flipping (Horizontal and Vertical)

– Blurring
– Contrast
– Scaling
– Padding
– Cropping
– Shifting
– Translation (moving along X-Y direction)
– Color modification (brightening, darkening, etc.)
– Noising

Different open source data augmentation python packages from Keras used in computer vision are:

– Adversarial training/Adversarial machine learning
– Generative adversarial networks (GANs)
– Neural style transfer
– Reinforcement learning

Popular and advanced models for data augmentation are:

– ImageDataGenerator
– Skimage
– OpenCV

4.3 Convolutional Neural Network

A widely used deep learning approach, called Convolutional Neural Network (CNN) is used in this study. The first Convolutional Neural Network (CNN) was introduced in 1988, called LeNet, named after a french computer scientist, Yann LeCun- VP and chief AI Scientist at Meta (previously known as Facebook). Character and digit recognition was done using LeNet. Convolutional Neural Network (CNN) is a feed-forward neural network which is used in performing image recognition, computer vision which use a grid topology which performing the tasks. Nowadays, it is also known ConvNet.

The Convolutional Neural Network (CNN) cosists of 4 layers:

1. Convolution layer- A convolutional layer is the first layer in convolutional neural network (CNN). This layer works on extracting the features from the input images. It performs mathematical operation between image and filter of particular size (MxM).This filter of size (MxM) is slidded over the input image and a dot product is taken that is obtained between them. The output is called as a feature map which provides information about the corner and edges of the images.
2. Pooling Layer- A pooling layer in convolutional neural network (CNN) helps to decrease the size of convolved feature maps while preserving the important characteristics that can help in reducing the computational costs. In MaxPooling, largest value from a feature map is selected. Average pooling finds the average value of elements in predefined sized image section.Usually Pooling layer acts a bridge between convolutional and fully connected layer.

3. Rectified Linear Unit (ReLU) Correction Layer- ReLU correction layer converts all the negative values in the input to zeroes.
4. Fully connected layer-A layer which consists of weights and the biases along with the neurons is called as fully connected layer. It also helps in connecting neurons present on two different layers. Fully connected layers are usually placed before the output layer and form the last few layers of a convolutional neural network architecture.

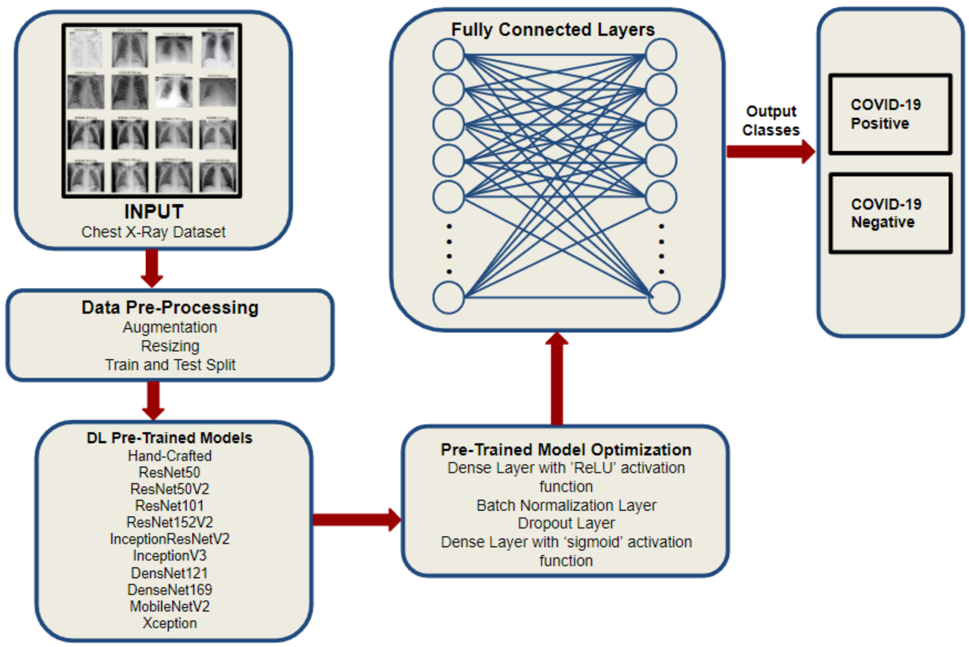

Fig. 10. Image showing COVID-19 Detection Model Architecture

Multiple deep learning models have been used for achieving high performance metrics. Some are pre-trained weight models and some are custom created models. The pre-trained deep learning models are used for making the predictions, feature extraction, and fine-tuning he models. In this article, the following models are used to perform image processing and predicting the COVID-19 using the chest X-Ray images:

1. **Sequential model using Conv-2D:** A CNN model using Sequential Conv-2D was built in which layers were added with following hyperparameters:
   (a) Convolutional layer- 32 filters where the size of each filter was 5 by 5, padding was 'SAME' and ReLU was the activation function.
   (b) Pooling Layer- A pooling layer was added with MaxPooling hyperparameter having pool_size of (2,2)

(c) Dropout layer- A layer with dropout=0.5 was added. This dropout layer helps prevent overfitting by randomly assigning zero to input units.
(d) Convolutional layer- 64 filters where the size of each filter was 5 by 5, padding was 'SAME' and ReLU was the activation function.
(e) Pooling Layer- A pooling layer was added with MaxPooling hyperparameter having pool_size of (2,2)
(f) Dropout layer- A layer with dropout=0.5 was added
(g) Flatten layer- A layer with flatten function having default values was added. The Flatten layers helps to convert a two dimensional array into one dimensional array.
(h) Dense Layer- A dense layer was added with 256 neurons and activation function set as 'ReLU'.
(i) Dense Layer- A dense layer was added with 1 neuron and activation function set to 'sigmoid'. This layer is then connected to the output (typically a classifier).

The custom model built using CNN method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=98.02%, Precision=98.13%, Recall=98.13%, AUC=98.64% and F1-Score=98.13%on test data with a loss of 1.23% .

The deep learning models with pre-trained weights were used for fine-tuning. These deep learning models were downloaded and some additional layers were added to the model. The additional layers that were added to each of the models are as follows:
(a) Dense Layer: A dense layer was added wirh 512 neuros and activation function is set as 'ReLU'.
(b) Batch normalization layer: A batch normalization layer was added. This layer efficiently provide the data flow between the layers of the neural network. It helps in regularization which means there is no need of dropout layer.
(c) Dense Layer:A dense layer was added with 1 neuron and activation function set to 'sigmoid'. This layer is then connected to the output (typically a classifier).

2. **ResNet50:** The pre-trained ResNet50 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned ResNet50 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9851, Precision=0.9906, Recall=0.9813, AUC=0.9901 and F1-Score=0.9859 on test data with a loss of 0.0852.
3. **ResNet50V2:** The pre-trained ResNet50V2 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned ResNet50V2 model built using

Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9901, Precision=1.000, Recall=0.9813, AUC=0.9949 and F1-Score=0.9905 on test data with a loss of 0.0480.

4. **ResNet101:** The pre-trained ResNet101 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned ResNet101 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9802, Precision=0.9905, Recall=0.9720, AUC=0.9916 and F1-Score=0.9811 on test data with a loss of 0.1217.
5. **ResNet152V2:** The pre-trained ResNet152V2 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned ResNet152V2 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9208, Precision=0.8824, Recall=0.9813, AUC=0.9870 and F1-Score=.9292 on test data with a loss of 0.2440.
6. **InceptionResNetV2:** The pre-trained InceptionResNetV2 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned InceptionResNetV2 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9208, Precision=0.8760, Recall=0.9707, AUC=0.9932 and F1-Score=0.9298 on test data with a loss of 0.1948.
7. **InceptionV3:** The pre-trained InceptionV3 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned InceptionV3 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9950, Precision=1.000, Recall=0.9907, AUC=0.9935 and F1-Score=0.9953 on test data with a loss of 0.0989.
8. **DenseNet121:** The pre-trained DenseNet121 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned DenseNet121 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.8812, Precision=0.9982 Recall=0.7850, AUC=0.9774 and F1-Score=0.8750 on test data with a loss of 0.3176.

9. **DenseNet169:** The pre-trained DenseNet169 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned DenseNet169 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9752, Precision=0.9811, Recall=0.9729, AUC=0.9939 and F1-Score=0.9765 on test data with a loss of 0.1264.
10. **MobileNetV2:** The pre-trained MobileNetV2 model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned MobileNetV2 model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9851, Precision=1.000, Recall=0.9720, AUC=0.9858 and F1-Score=0.9857 on test data with a loss of 0.1940.
11. **Xception:** The pre-trained Xception model was used and fine-tuning was done to it's architecture by adding more layers such as dense layer and batch normalization layer.The fine-tuned Xception model built using Sequential method was compiled using Adam's learning rate of 0.001, binary cross entropy loss on the precision and recall as the performance metrics. The compiled model was then fit to the validation data using 50 epochs. The model achieved an Accuracy=0.9901, Precision=1.000, Recall=0.0.9813, AUC=1.000 and F1-Score=0.9905 on test data with a loss of 0.0248.

5 Results

The chest X-Ray images of the patients are passed through multiple pre-trained deep learning models and different performance metrics like accuracy, precision, recall, loss, AUC, and F1-score were calculated. The pre-trained models used were fine-tuned by adding different layers which include dense layer, batch normalization layer, and an output layer.
The values that are used to generate the values of performance metrics comes from confusion matrix. The 4 terms are defined as below:

1. **True Positive (TP):** A condition where the actual value is **TRUE** and the predicted values is also **TRUE**
2. **False Positive (FP):** A condition where the actual value is **FALSE** and the predicted values is also **FALSE**
3. **True Negative (TN):** A condition where the actual value is **FALSE** and the predicted values is also **TRUE**
4. **False Negative (FN):** A condition where the actual value is **TRUE** and the predicted values is also **FALSE**

The different performance metrics are calculated by using above 4 terms and defined as below:

1. **Accuracy:** The accuracy is defined as the ratio between true predictions and all predictions made by the model.

$$\frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision:** The precision is defined as the ratio between true positives and all the positive(true positive and true negative) predictions made by model.

$$\frac{TP}{TP + FP}$$

3. **Recall:** The recall is defined as the ratio between true positives and all the samples are identified as positive by model.

$$\frac{TP}{TP + FN}$$

4. **AUC:** A metric obtained by plotting the true positive rate (TPR) and false positive rate (FPR) is called area under curve (AUC). It is used to identifying how well the model is able to classify.
   True Positive Rate is equivalent to Sensitivity and Recall and is defined as:

$$\frac{TP}{TP + FN}$$

   False Positive Rate is equivalent to 1-Specificity and is defined as:

$$1 - \frac{TN}{TN + FP}$$

5. **F1-Score:** The F1-Score is defined as the harmonic mean of precision and recall and is represented as-

$$\frac{2 * (Precision * Recall)}{Precision + Recall}$$

6. **Loss:** There are many types of loss defined but in this study binary cross-entropy loss, also known as Log Loss is used to measure the loss because the study is based on classification.

The below table shows the results obtained by using different pre-trained fine-tined models.

Method	Accuracy	Loss	Precision	Recall	AUC	F1-Score
Random Hand-created	0.9802	0.1235	0.9813	0.9813	0.9864	0.9813
ResNet50	0.9851	0.0852	0.9906	0.9813	0.9901	0.9859
ResNet50V2	0.9901	0.0480	1.000	0.9813	0.9949	0.9905
ResNet101	0.9802	0.1217	0.9905	0.9720	0.9916	0.9811
ResNet152V2	0.9208	0.2440	0.8824	0.9813	0.9870	0.9292
InceptionResNetV2	0.9208	0.1948	0.8760	0.9907	0.9932	0.9298
InceptionV3	0.9950	0.0989	1.000	0.9907	0.9935	0.9953
DenseNet121	0.8812	0.3176	0.9882	0.7850	0.9774	0.8750
DenseNet169	0.9752	0.1264	0.9811	0.9720	0.9939	0.9765
MobileNetV2	0.9851	0.1940	1.000	0.9720	0.9858	0.9857
Xception	0.9901	0.0248	1.000	0.9813	1.000	0.9905

The best model for classification were selected based on the performance metric called Recall. Since in this research it is important to diagnose the COVID-19 as positive for the patients who are being tested than diagnosing COVID-19 as negative, therefore, Recall was considered the critical performance metric. So, based on the Recall, the two models InceptionResNetV2 and InceptionV3 are performing same with 99.07%and best as well. But between these two models fine-tuned InceptionV3 performed better in terms on inference time. Therefore, the best model for classifying is fine-tuned InceptionV3 also called as **COV-Inception**.

6 Discussion

In this research, the subtlety of COVID-19 spread is observed carefully by analyzing the metadata obtained along with the chest x-ray images of the patients. These includes the patient's age, gender, clinical notes, chest x-ray image, if the patient went to ICU or not, if the patient was intubated or not, if the patient survived or not, view of the chest x-ray was taken such as anteroposterior (AP), posteroanterior (AP) and lateral (L) view and finally whether the patient was detected as COVID-19 positive or negative. To understand the severity of COVID-19 in a patient's body is very crucial because it helps in alleviating the effects. By predicting the COVID-19 in a patient's body, it will help in protecting the life of patients. The fine-tuned deep learning models with pre-trained weights used in this research help to predict the presence of COVID-19 in a patient's body by using features of the patient's chest X-Ray. The research can be extended to other applications as well.

In this study, fine-tuned deep learning models with pre-trained weights were used which help in finding the presence of COVID-19 in old-age group patients who are are more than 60 years of age. The models finds the patterns for the presence of COVID-19 in the chest X-Ray which in turn helps the doctor to know to severity. In healthcare industry, it is crucial to understand the patterns of any disease like COVID-19 because it helps in making the health policy and providing the medical support to the old-age patients which lead to lesser casualties as a result of COVID-19.

In this research, the most challenging task was to collect the chest X-Ray data set

that contains the images and metadata as well. The data was collected from different sources[24][25] and merged together. The chest X-Ray images were stored in two separate folders as COVID-19 and Normal with other two folders of train and test. The metadata as merged as well. Although the metadata had missing values for every attribute, the exploratory data analysis was done to find useful insights from the data that was collected for further analysis.The other attributes in the metadata was purposefully left and not included for further analysis because the research was focused on detecting COVID-19 in old-age patients. After analyzing the metadata,the research was then more focused on using the chest X-Ray for patients more than age of 60 years. The 1685 chest X-Ray images were used for building the COVID-19 detection tool that can predict the presence of COVID-19.
Multiple deep learning models with pre-trained weights were fine-tuned by adding some layers and the best performing model was selected. The model that performed the best in predicting the presence of COVID-19 was **COV-Inception** with a Recall of 99.07%. COV-Inception is a building on a InceptionV3 which is deep learning model with pre-trained weights. Recall was selected as critical performance metric because it was important to detect the presence of COVID-19 in the patients that are being tested than not detecting the presence of COVID-19.
This research is designed such that there are some personal information needed of the population to identify the presence of COVID-19. Therefore, anyone who would like to use the COV-Inception which is COVID-19 detection tool using chest x-rays should be above 60 years of age and must have a chest X-Ray to use this research. The individual cannot use anonymous information for their studies and should get consent from their sampled population before starting their study.
The future work on this research would include the increased number of chest X-Ray images for training the model. The increased number of images will help in training the model with variety of X-Ray which in turn help in the prediction on new data with better performance. Besides that integrating the cloud resources with model building will help in higher speed and lower run time in modeling.

7 Conclusion

The study focused on analyzing every age group (Young-Age, Mid-Age, and Old-Aged) and deep learning models were built by taking the Chest X-rays of specific age group (Old-Age group). The performance metrics which includes-Accuracy, Precision, Recall, F1-Score etc. of models were analyzed and strategies were made and implemented to improve the performance metrics.
By efficiently training through a relatively small set of specifics, our fine-tuned models show high performance in the classification of COVID-19 for specific age group which is Old-Age group in this research.
Since, the study was done using unbalanced data therefore, the critical perfor-

mance metric will be Recall of the model. Therefore, the study concludes that the model built using InceptionV3 performs the best with a F1-Score=0.9953, accuracy=0.9950, precision=1.000, recall=0.9907, AUC=0.9935 and loss=0.0989. The research has a conviction is that the proposed computer-aided diagnosis mechanism could outstandingly improve the diagnosis of COVID-19 cases.

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