Automated CAD System for Classification of Chest X-Rays using Xception Model

MSc Research Project
Data Analytics

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Automated CAD System for Classification of Chest X-Rays using Xception Model

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Abstract

WHO declared the Novel Cornoavirus a pandemic, on 11th March 2020 and it has continued to take a toll on well-being and health of people worldwide. An important step towards combating Covid-19 is early diagnosis and treatment of the infected patients, analysing the radiological images being one of the primary approaches. The author of this paper has designed an Automated CAD system to classify the Chest X-ray in to multiple classes of Covid-19, Pneumonia and Normal using the Deep learning approach. The dataset is taken from the Kaggle has train and test folders with more than 6432 images in it. This paper proposes Xception model with transfer learning to detect the Covid-19 with an accuracy of (training accuracy 94% and validation accuracy 92%). It also gives a high precision of 90.6%, recall of 90.5% and the F-1 score of 89.9%. The best model was saved as .h5 file and deployed using the flask in back-end on web application. Thus, the model proposed in this paper can be used for efficient and quicker diagnosis and treatement of Covid-19 patients which in turn reduces the pressure on the healthcare system and also strengthen the medical infrastructure.

***Keywords*—** Covid-19,Convolutional Neural Network(CNN), Xception , Confusion Matrix.

1 Introduction

Scientist all over the world started pondering over the sudden outbreak of Coronavirus in Wuhan city, a province of China in 2019 November. This disease is extremely communicable and is caused by the SARS-Cov-2 Virus. It has been declared as pandemic all over the world by WHO and termed it as Covid-19. As of 16th December 2021, 271 million cases have been confirmed positive and death of 5.32 million[1] recorded in WHO report. The countries which are badly impacted and have a high number of cases are United States, India, Brazil, UK and other countries follow the list. Covid-19 constitutes of a single-stranded genome RNA which has a range of 26.4 to 31.7 kb for Coronaviruses. Various research and studies have been conducted to analyse the public reactions and opinion that boomed over internet using the machine learning Liu et al. (2021) methods of emotional analysis, text mining and some thematic clustering.As the cases have increased rapidly worldwide, there has been a trend that identifies Pneumonia as commonly found symptoms among the positive cases of Covid-19 Yi et al. (2021). Pneumonia is accompanied by fever and cough that severely infects the respiratory duct and lungs Elliott et al. (2021), which not being diagnosed at an early stage grows rapidly and leads to life threatening ARDS (acute respiratory distress syndrome)Parhizkar Roudsari et al. (2020).The incubation time frame for the Covid-19 is 13 Days with some cases also showing asymptomatic with very minor headache. The combination of both the asymptomatic cases with the high incubation has made the task difficult for the medical practitioners over the world to diagnose the disease quickly at pre-stages.

The ubiquitous influence of Covid-19 was felt all over the world and forced countries to implement lockdown with individuals quarantined and leaving various industrial sectors crippled. Covid-19 has not only transformed the lives of human being but also hindered the various other facets of livelihood like education, tourism and transportation causing the overall growth economy to depreciate. The world opened with new normal and masks and sanitizers have become a part of daily lives. The most common and frequently used method of detecting Covid-19 is real-time reverse transcription-polymerase chain reaction known as RT-PCR test. RT-PCR method is very time consuming and it delays the whole process as the samples transportation itself takes half day. There are other methods of histopathological images like Chest X-ray and CT scans that help in diagnosis in a short time frame. Chest X-ray image is preferred more as compared to CT scans as it is cheaper cost effective for nation with limited resources and funds Rubin (2020). It has been difficult and hectic for radiologists to classify and detect the disease at an early stage using the Chest X-rays due to scarcity and inadequacy of trained and skilled specialist, so it has been of utmost importance to look for alternatives like intelligent systems and CAD based on machine learning and AI.

Computer has been used recently for diagnosis and research work in medical domain using machine learning, which is termed as CAD. These CAD systems are very effective and time saving as it classifies and detects the diseases at an early stage for proper treatment and diagnosis. Pathologist all over the globe have encouraged the use of such systems specially for classifying the histopathological images. Various medical Images Abdelhafiz and Nabavi (2019) were analysed by the radiologist using these CAD systems. These systems have been a milestone of medical imaging adding to competence of medical infrastructure of organisation and nation. Deep learning has played an important role is success of these systems as it is predominantly used for medical image classification. Last two decades has seen increase in the adaptation of Deep learning in medical infrastructure and applications. Deep learning method is opted mostly for the research in medical domain. Histopathological images like Chest X-ray, diagnosis reports and patient reports have exponentially increased data in medical domain. Deep learning

[1] Covid-19 Worldwide Data: https://covid19.who.int//

can be used to process huge amount of image data by extracting the important features and edges for its efficient implementation with number of iterations. Deep learning is further classified into three major types i.e., ANN, RNN and CNN. RNN and ANN are majorly used for the number and text data, on the other hand CNN is used mostly for image data Tiwari et al. (2020).

As discussed earlier that proper treatment of this disease can only be done by an early diagnosis, so we aim to design a system that will take less time for detecting Covid-19 for an early treatment to save the lives. This work will not only make medical infrastructure stronger but also it would help medical practitioners where lack of knowledge and diagnosis equipment's like RT-PCR and Antigen testing is not available.

1.1 Research Question

How to predict the Covid-19 from large dataset of Chest X-Rays and classify them as COVID-19, Pneumonia and Normal with higher accuracy using Xception Model?

2 Related Work

2.1 Medical Science and CAD

Computers have helped in creating a system for automated diagnosis of medical images, which is known as CADShin et al. (2016). These systems are used for lung cancer, leukaemia, blood cancer, breast cancer and other lungs diseases. In recent time CAD has also been used for classification of Chest X-ray images to detect Covid-19. A CAD system was used to detect the Leukaemia using the various CNN models like GoogleNet, VGG and AlexNet.Zaidi et al. (2021)introduced a customised CNN model with slightly modified parameters and some additional layers to achieve the desired results. It segmented the lung region to achieve a high efficiency. The model performed better using the entire Chest X-ray images reducing the noise as it achieved a accuracy of 86.7% in detecting the pulmonary disease. It was a good approach and can be implemented for Covid-19 classification as well. An automatic CAD system was developed for segmentation of pathological images of the lung cancer to improve the patient's diagnosisLi et al. (2021). These systems were also used to detect the breast cancer Wang et al. (2019)) using the CNN method by extracting the deep features. The selection of feature plays a crucial role in the results and accuracy in determining the disease.

2.2 Classification using CNN

Most of the research of Covid classification done is past are either binary or multi class classifications, depending upon the dataset. In the binary classification its about either suffering from covid-19 or not having it. Whereas multiclass classification it also detects other types of respiratory diseases such as viral or bacterial pneumonia.

Rodrigues et al. (2021) in his paper used deep learning approach to do binary as well as multi class classification. The author compared the various models based on five metrices of accuracy, sensibility, F1 score, precision and specificity. The author got an precision of 98% using the VGG models for the binary classification which was made between Healthy vs Covid and Pneumonia vs Covid but when it was used for multiclass classification i.e. Covid vs Healthy vs Pneumonia it gave an precision of 91.68%.De Moura et al. (2020) in his work used the densely convolution approach to classify the chest x-ray into normal, covid-19 and pathological. The dataset consisted of 648 pathological ,728 normal and 240 covid cases. Densenet-161 architecture was used for the classification of Chest X-ray and it achieved the accuracy of 79.86% and precision value of 87%. The model shows a promising results even lower quality of images, so results can be improved further by improving the image quality and increasing the dataset.Resnet50 CNN model based on residual was used by Rehman et al. (2021) in his paper to diagnose Covid-19 by classifying the chest x-ray.The dataset used in the study consist of 1824 images which are divided into 912 Coronavirus and non-covid images. The model attains a significant accuracy of 98% but still needs to be tested on a larger dataset and also with multiclass classification.

A larger dataset of 2905 Chest X-ray was taken by Ouchicha et al. (2020) to classify the Covid-19 from normal and viral pneumonia using CVDNet model.This model is designed on the basis of residual network with various kernel sizes at parallel positions to find global and local features. The model achieved a good accuracy of 97.20% in binary classification and 96.69 in the case of multiclass classification. A FractalCovNet model was applied by Munusamy et al. (2021)for segmentation using the U-Net for localising the lesion area. The same model was also used for the classificatoion and the results were compared with other deep learning architectures such as Xception, Resnet, DenseNet and VGG-16. The precision and Fscore for the FractCovNet was the best among all.Song et al. (2021)Collected a dataset of CT scans in China of 188 patients suffering from bacterial pneumonia and covid-19 images and combined it with 86 healthy persons to classify using a deep learning model DRENet. The model gave an accuracy of 95%, recall of 96% and precision of 79% when classifying covid-19 with bacterial pneumonia. The same model when used for multiclass classification gave a little less recall of 93% but precision value increased to 86%. So, in this case we can see a balance between precision and recall which is good for a model , but these results are on a very small amount of dataset due to which result may not be very significant when dataset is increased.

The classification of Chest X-ray for the medical diagnosis has been area of interest for quite long by the scientist and the research community all over the world but this pandemic of Covid-19 has highlighted its impact on societies and increased the interest of the researchers. There have been large number of works done on the lines of Covid-19 and its early diagnosis using the classification based on deep learning.

The technique used in this method would contribute to:

- Achieving higher accuracy on a large dataset of 6000 images as compared to previous work done on the same lines with very small dataset.
- Automated system design using flask in the backend.
- Medical diagnosis of Covid-19 at an early stage and boosting the medical infrastructure.
- Compare the various other approaches used previously to classify and diagnose the disease.
- The performance of model is tested on various parameters: precision,accuracy, F1 score and recall.

Researchers and radiologists have mixed feedback when it comes to use of technology in medical diagnosis. Some consider these methods to be efficient and an advantage to medical practitioners while some consider it to be misleading and in accurate. So, the work done in this paper cannot be considered as production ready, there are still lot of research and facets of the final product to be checked and evaluated. These models are heavily dependent on the resources of the local or virtual environment i.e. RAM and GPU on which deep learning algorithms are to be processed. This might hamper the desired outcome and also take a lot of time, so an alternative solution is to use transfer learning approaches wherever required. In this paper Pre-trained Xception model is used to save resources and get higher efficiency..

3 Methodology

This section of paper is all about the overall steps taken to achieve the desired result of research and its implementation. In this paper the, the Chest x-ray images have been classified into three classes i.e. Covid-19, Pneumonia and Normal using a pre-trained Xception architecture as research method starting from environment setup, data collection with some data pre-processing and finally deploying the model as web application.

3.1 Environment Setup

The implementation of this work is done using virtual as well as local environment. The whole code is divided into two parts one is designed to train a deep learning xception model to classify Chest X-ray and the second to deploy the trained model as web application. Fig[1]:The model is trained on one of the virtual machines from Google Colab environment using the Dell Inspiron 14-5000 running a windows-10 OS, which has Intel Core i7 10thGen processor and Nvidia graphic card. The trained model weight is the used to deploy on web using flask. Flask is implemented in the local environment running on open source Spyder IDE in Anaconda and uses the weights of model saved in h5 file. Python with libraries TensorFlow 2.1.6, Keras 2.1.1, Python Image Library, Flask and Numpy are used as the coding language.

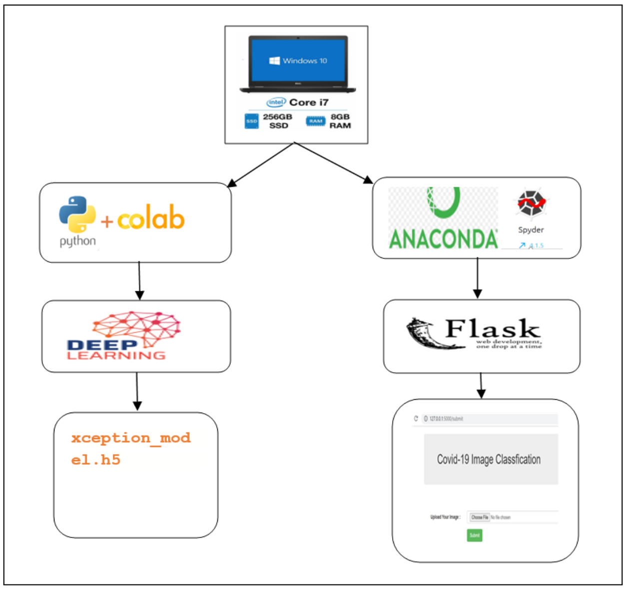

Figure 1: Environment Setup

3.2 Data Collection

The data is downloaded from open source Kaggle[2] website which consist of train and test folder where in test data comprises of 20% of total images. These folders consist of total 6432 Chest x-ray from various sources that consist of three classes shown in Fig[2] Covid-19, Pneumonia and Normal.

[2]COVID19-Classification Dataset: https://www.kaggle.com/bimsarananayakkara/kaggle-covid19-classification/data/

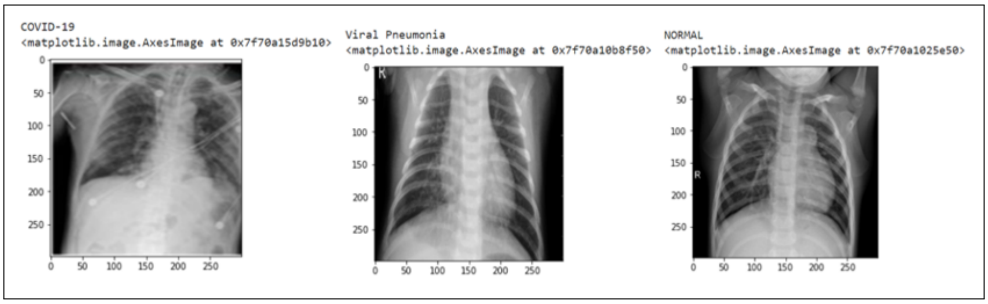

Figure 2: Dataset samples taken from code output of Chest x-ray showing Covid-19 in left Viral Pneumonia in centre and Normal cases.

3.3 Data Pre-processing

This step helps in improving the quality of data by enhancing the features and reducing unwanted noise. The data in this case are the Chest x-ray images which is pre-processed to train the model properly and get the best of results. Once the data is pre-processed it is converted into matrix which is important for processing the data further for training. ImageDataGenerator Class from Keras[3] is used to augment the images in this paper. All the images are normalized on a scale of (1/225) and also images are resized into 299x299 which is suitable for our my Xception model architecture. This function is also used for other augmentation techniques like rotation (±10 percent), horizontal flipping, zoom in (40%). This step helps in building a robust model which improves the accuracy and performance. A flow-from-directory method of the same ImageDataGenerator class is used to load the images directly from the dataset which have separate folder for each class.

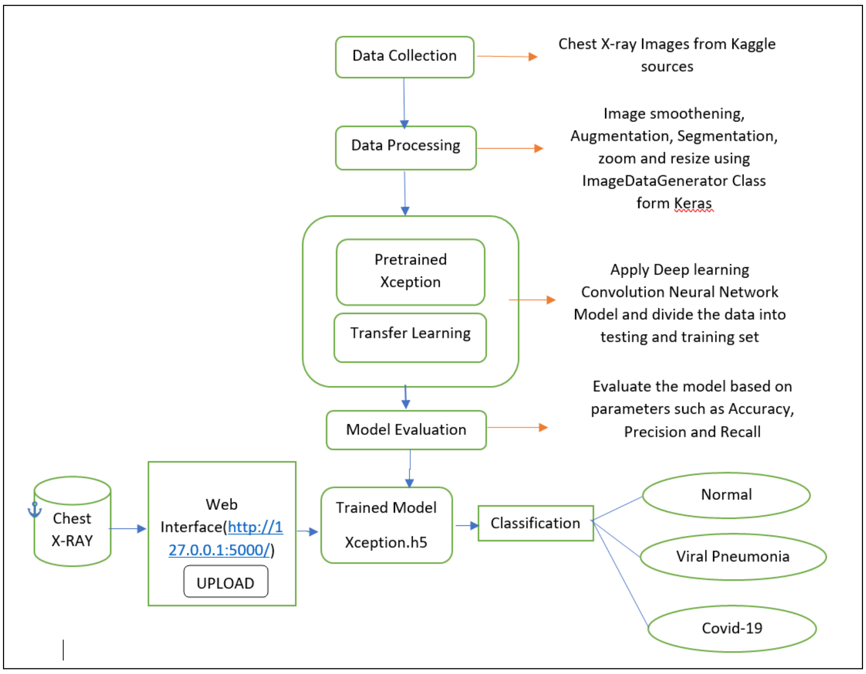

Figure 3: Flow chart diagram of proposed Methodology

[3]Keras: ImageAugmentationKeras|KerasImageDataGenerator(analyticsvidhya.com/

3.4 Model Preparation

Model preparation is one of the important stages in which key decisions need to be made in terms of model selection and approach. The best deep learning algorithm for image classification is CNN as its results have shown great accuracy and precision. It consists of various layers to implement sub sampling and reduce training overheads if any.in Fig[4] CNN consist of Convolutional layer, Pooling layer and Fully connected Layer with two important parameters dropout layer and activation function. Convolutional layer is used to extract feature from the images in the form of feature maps. Pooling layer is used for the dimensionality reduction of the feature map by sub-sampling or down sampling when the images are two large. Fully connected layers are used to combine all the information from the final feature maps and classify the images into various categories. There is an activation function between convolution and pooling layer which consist of a convolution value.

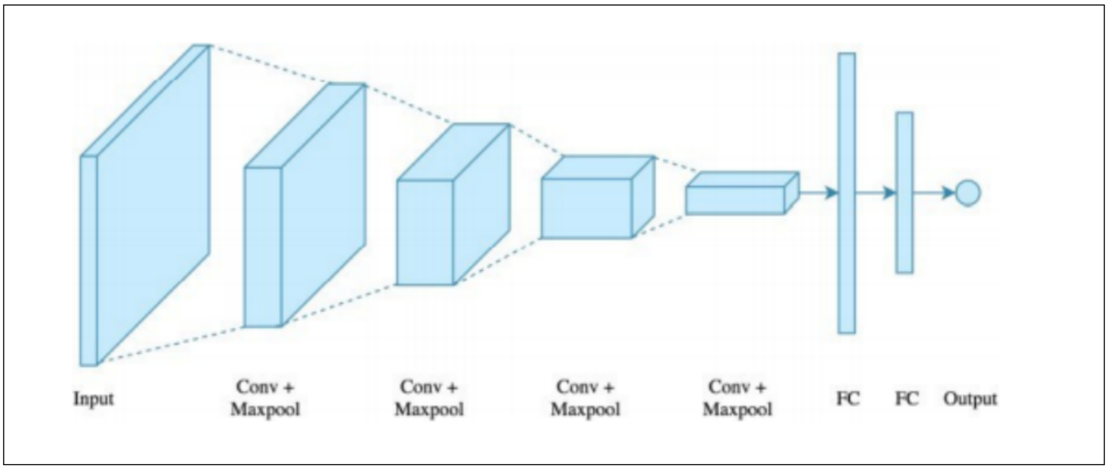

Figure 4: CNN Basic Architecture

In this paper, we have used a transfer learning approach by using pretrained xception model to prepare a base model for feature extraction and then those features are used in another model which is created. Transfer learning is a process in which knowledge gained by solving a previous problem is saved and used to solve a related problem. The resources and processing time required in transfer learning are very minimum as compared to the normal CNN architecture. This approach uses the previous model trained which also saves time for parameter tuning and optimizing the trained model.The FigureIsmail and Sovuthy (2019) depicted below gives an idea of the basic CNN architecture .

The performance of model is evaluated by using the various parameters like accuracy, precision and recall value achieved for each class. The weights of the model having the highest accuracy and precision is saved to develop a web application using flask.

4 Design Specification

Basic CNN model consists of convolution layer, RELU layer, input layer, pooling and fully-connected layer. Xception model is a special type of CNN model which was proposed by the Google.Inc Chollet (2017) and was also termed as 'Xtreme Inception'

INPUT Layer: The raw input image with pixel value is pushed using this layer. The image input format for any RGB image in this model has to be 299x299. In this layer model uses the pre-trained weights from the ImageNet dataset.

CONVOLUTION Layer: This layer is used to set some filters which helps in creating feature map.

RELU Layer: This layer helps in training the model efficiently by mapping the negative values with the zero and maintaining all the remaining positive values. This is also known as activation because the features which are activated are only transferred to the next layer.

POOL Layer: This layer is used to reduce the dimensionality of removing features which are not so important and in turn saving the resources.

FC Layer: This layer is used for the logistic and classification of data set. In out model softmax is used as activation function in this layer.

Exception model includes 36 conv layers and depth of 126 to extract the important features. The prediction or classification is done using the softmax function. The 36 Conv layers are structured into three sections of entry, middle and exit. There data passes through the entry flow which has eight convolution layers and then through the middle flow which has 8 times that is 24 convolution layers. The outer flow which is exit flow has four conv layers. Below Figure[5] shows the overall architecture of the pre-trained Xception model.

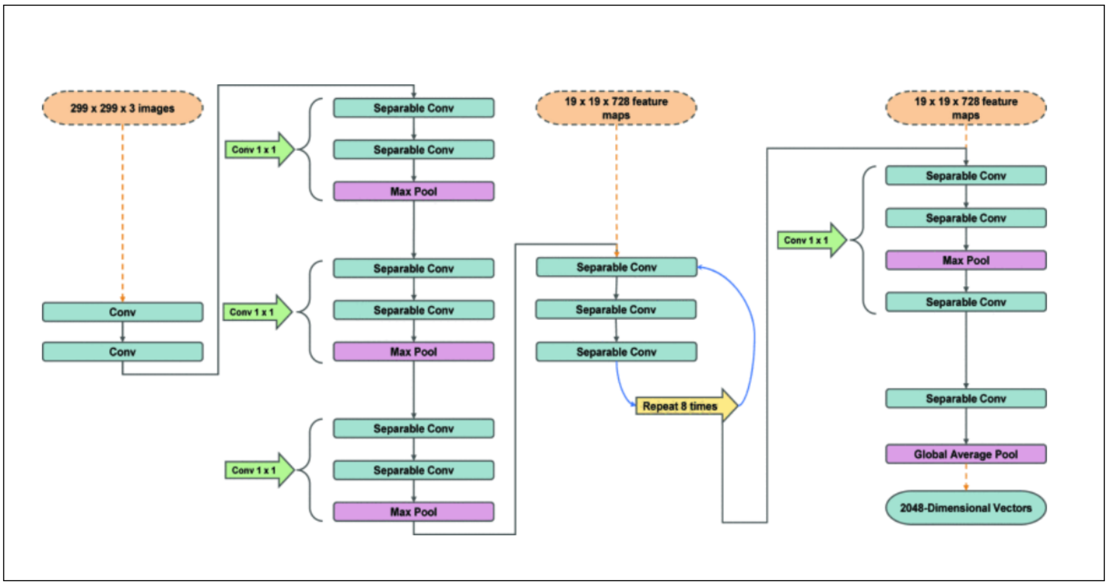

Figure 5: Xception Architecture

The Xception model follows the theory of Depthwise Separable Convolutions which are nothing but a slightly altered general convolutions that perform better and has a higher efficiency when compared on terms of computation time. This type of convolution comprises of two process that is Depth wise and other is Pointwise. In Depth wise, the computation is performed one by one rather than in channels. Suppose for image with RGB AxBxC, normal convolution is done by dxdxC, d being the kernel size but in this case of Depthwise it is done as dxdx1. The kernel size of pointwise is 1x1Xn and allows to form a shape of KxKxN similar to normal convolution. In case of Xception model, the convolution is performed in a reverse order as the depth wise convolution is performed after the pointwise convolution. The

Figure[5] above depicts that there are mainly 3 blocks- entry flow, middle flow and the exit flow.

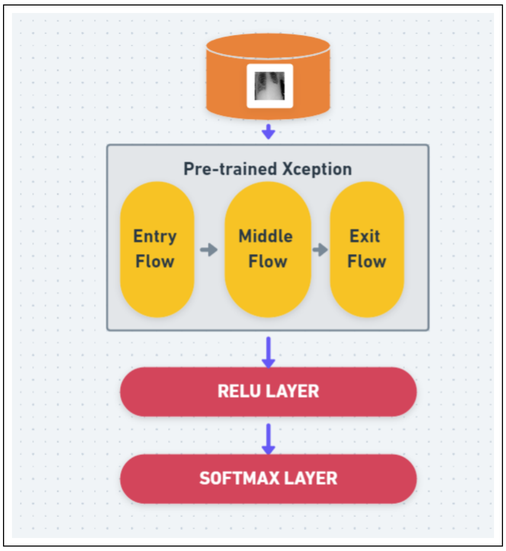

Figure 6: Proposed Model Architecture

In this paper the base model is instantiated and pre-trained weights trained using ImageNet dataset are loaded on it. Then the layers of the base model are freeze using trainable= False, so that a new custom model is created using the output from the base model layers. Train the new model created using the new dataset.The Relu activation function is used in the hidden layers and Softmax is used as the activation function in the outer layer to classify the images.The Figure[6] above shows the custom architecture of model used in this paper.

5 Implementation

The overall implementation of the research is done in two stages. The first stage is training the model using the pre-trained xception model and evaluating the model on the basis of various parameters. Once we have the model with the best parameter of evaluation, the next stage is to save the weights and develop a web-based CAD system using flask to produce a development model of the end product.

5.1 Model Training and Testing

Once the image is loaded using ImageDataGenerator Class from Keras to augment the images. The input layer of Xception model take the image in the form of 299x299 with the depth measure of 3. In this stage of the model, we train the base model using the pre- trained weight of ImageNet database. Below mention figure shows how the images passes through the various convolution network and pooling layers of the Exception architecture.

Once the images pass through pre trained Exception layer the model is freeze so that the information gathered for the coming training layers is not lost or destroyed. An extra layer is added on top of the layers freezed to that the old features extracted are used to make the classification of new dataset. A dense layer with 256 and relu as activation function is added to give the. Next an output layer is added to classify the model into 3 classes.The model gets trained with the 20 epochs and 40 steps per epoch with Adam Optimizer as learning function and crossentropy as loss function, to give the best of results. The trained model weight is saved in the form of h5 file using numpy library. In this paper the model weight is saved as Xception.h5. Figure[7] below shows both the training and deployment phase of the project.

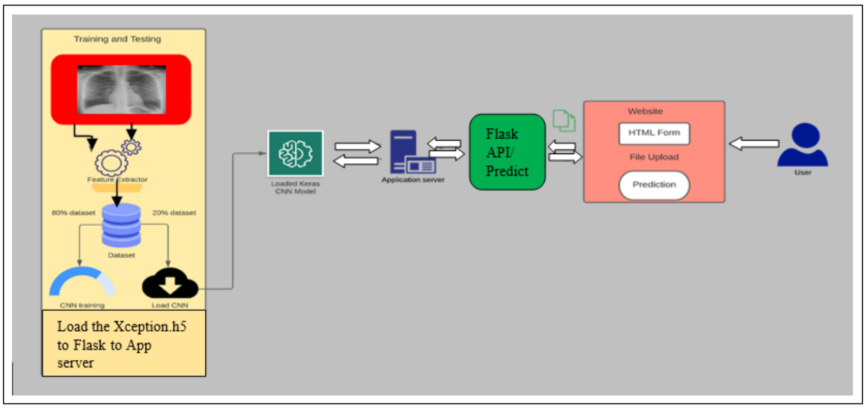

Figure 7: Implementation Diagram

5.2 Model Deployment Phase

In this phase we focus to develop as CAD system to predict the chest X-ray into Covid-19, Viral Pneumonia and Normal.Fig[8] below shows a web page which is designed using the HTML and CSS to provide a user with an Upload your Image option. There is a tab for choose file option to upload the image all the formats. Once the image is uploaded it gets stored in the locally hosted flask server.

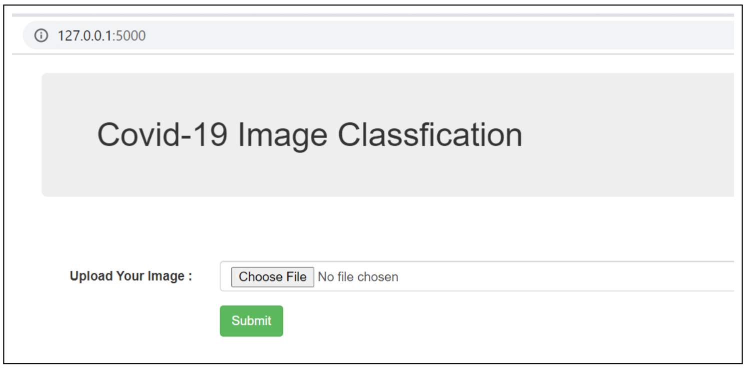

Figure 8: Automated CAD Webpage

The image stored is first modified into 299x299 format and scaled (img/255.0). The predict() function in flask pulls the stored image file and tries to extract the features. Then those images are passed through the trained xception model to classify the images as Covid-19, Viral Pneumonia or Normal. If any new image is uploaded it is picked up by the flask according to the current time in the back-end and the same process is iterated. The latest file according to the system current time is treated as new image and processed into the saved model.

6 Result and Evaluation

This section is used to evaluate the model performance of trained model. Confusion matrix was used as a cross-validation estimator with below mentioned four results shown in Figure[8]:

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

Figure 9: Confusion Matrix

TP (True Positives): It is a number which is used to depict the number of correct predictions made by the model about having a disease.

TN (True Negative): It is the number of instance where the model makes correct predictions about not having a disease.

FP (False Positive): A number of instances where in model predicted of having a disease but there is no disease. This is also termed as a case of Type-1 Error.

FN (False Negative): A number of instance where in model predicted of not having a disease but it had a disease. This is termed as Type-2 Error.

In this paper Accuracy, Recall, F-1 score and Precision are used as the parameter for evaluating the performance of the trained model.[4]

Accuracy: The ratio of correct predictions made out of total number predictions made by model. The accuracy in Fig[10] of validation data and training data are very close to each other means that model is learning fine. There is not a steep high or low at any point in the validation curve.

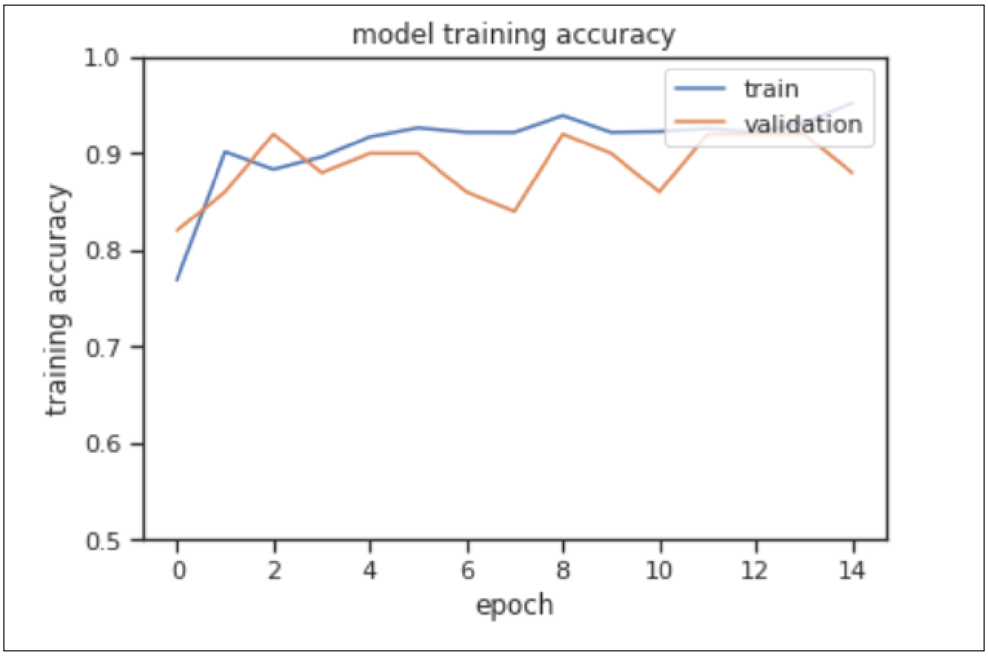

Figure 10: Accuracy Graph

[4] Evaluation metrics: `https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234/`

Logarithmic loss: It is generally used for the penalising the wrong predictions made by the model in multi-class classification. In the Fig[11] we can see that the train and validation loss graph get stabilised at a point and there is not much of gap between them. This shows that the model is good, there is no underfitting or overfitting.

Figure 11: Loss Graph

Precision: The ratio of correct positive predictions made out of total number of positive predictions made by model. In our case it can be interpreted as percentage of Covid-19/Pneumonia/Normal patients classified or predicted by the model by the total number (Correct-TP and Wrong -FP) predictions made of having a disease. Fig[12] shows that Covid has the highest precision value of 100%.

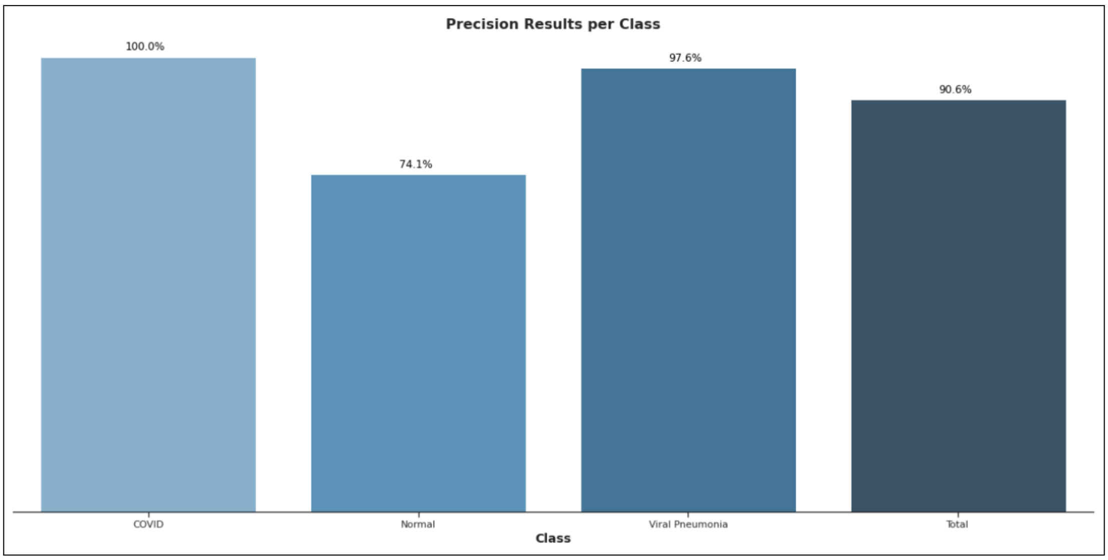

Figure 12: Loss Graph

Recall:It give the count of total number of correct positive predictions divided by all the samples of positive cases predicted or not predicted. In our case, it can be interpreted as percentage of patients that we classified correctly of Covid-19/Pneumonia/Normal out of total number of patient that were classified as having disease(correct-TP and wrong - FN). Both precision and recall value should be high for a model to work well.
Fig[13] shows that Covid-19 has a recall value of 87.1%.

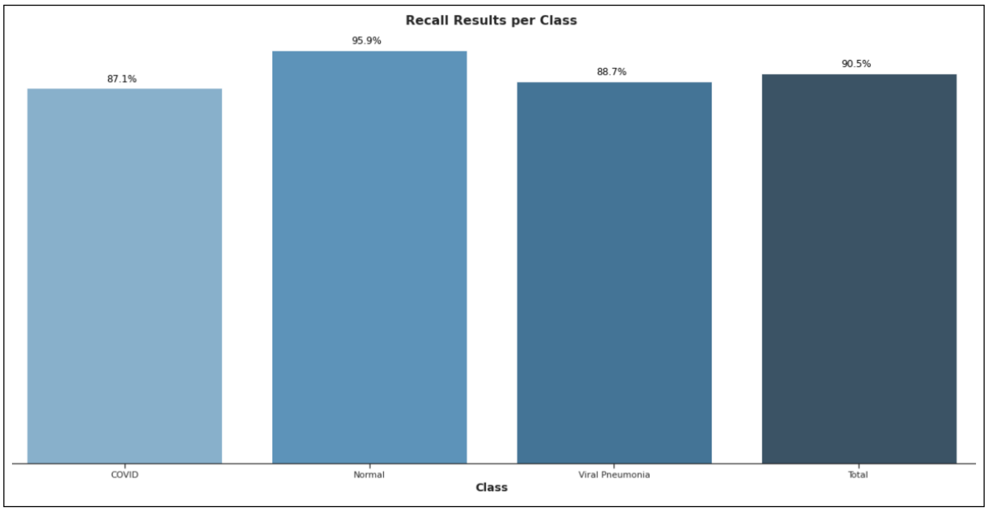

Figure 13: Loss Graph

F1 Score: It is used to measure the Precision and Recall value and balance them, at the same time it can be used to compare the training models. The more the F1 Score is the better the model performs. It also indicates how robust and precise a model is. It is calculated as harmonic mean of precision and recall.In this model the F1-score is the most important metric as we want to know the both precision and recall of the model. Fig[14] shows that for Covid F1-score is 93.1% and for overall it is 89.9%.

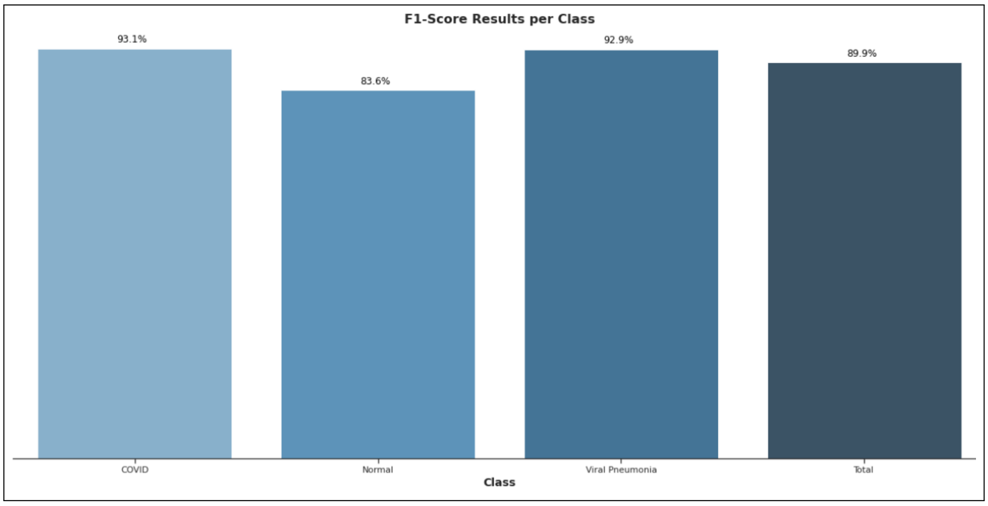

Figure 14: Loss Graph

Confusion Matrix:Fig [15] shows a multi-class confusion matrix showing the True and False prediction of the three classes Covid-19, Pneumonia and Normal. We can clearly observer that none of the Covid image were missed of not having the disease while some of the were predicted as not having Covid but they actually were suffering from Covid. None of the predictions showed Type-1 error while 15 of them showed type-2 error in case of Covid.

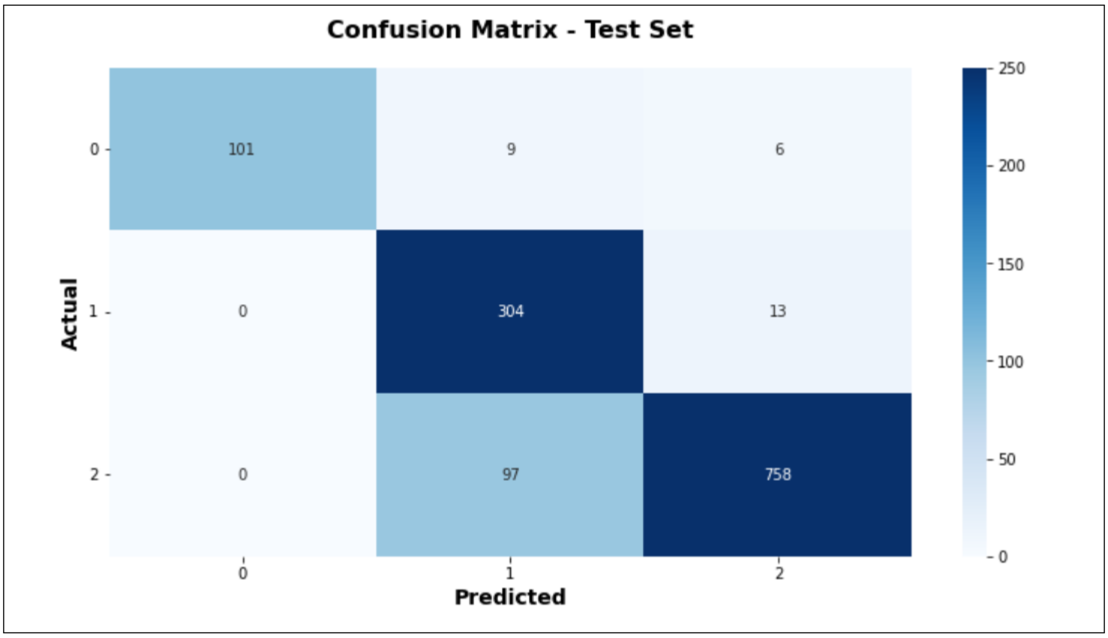

Figure 15: Loss Graph

6.1 Discussion

The evaluation parameters shows that the model achieves a high accuracy of 92% but when we solve a problem of classification such as disease classification checking accuracy as the only metrics does not makes sense always and other parameters such as precision or recall is also very important. There might be a scenario where in a classification model used for classifying Covid-19 or Pneumonia has a high accuracy but at the same time recall or precision is very low. There might be some situations where in a person is having a disease, but the model suggesting as everything normal, this would demand for a high recall value. In another instance there might be a scenario where a person is wrongly predicted to have a disease but in real, he has not and this may lead to a bad treatment. In such cases precision of model should be on a higher side.

The results in this paper depicts that the model is not only having a high accuracy but also is great when it comes to precision and recall value. A good recall value points to the fact that there are very small number of false negative predictions. This research is in line with reducing the false negative cases of so that it helps in making clinical decisions and has a recall value of 87.1% .The proposed model also shows a very high level of precision 100% for Covid-19 cases, which helps us in reducing the number of cases not diagnosed and treated. Achieving both high recall and high precision at the same time has been difficult as by changing certain parameters may achieve a high recall with all the patients suffering from disease detected but at the same time it may also lead us to the treatment of many patients not suffering from it. On the other hand in search for a high precision, to reduce any mistreatment, we may miss some of them who is suffering from the disease without treatment.[5]. So, with this discussion what we understand is that there is always a trade-off between Recall and Precision considering the main goal of project. So, a decision must be made what is more important to a classification problem, in some cases both may be important. In this paper, we may be interested in knowing

[5]Metrics Interpretation: https://www.analyticsvidhya.com/blog/2020/09/precision-recall-machine-learning/

about the patients who were not correctly classified as Covid-19 patients as they may be having some symptoms of other disease, which could help us in diagnosing them a get it treated at the earliest. Instead of focusing on the getting a balance between recall and precision the model should aim to achieve a high F1-score which is nothing but a balanced value indicating a good recall and precision

6.2 Comparative Analysis

In the below mentioned Table 1 a summarised comparison has been made between the proposed model and the other research work done in this field. It can be clearly observed that the proposed model outperforms the other model in terms of accuracy.

Table 1: Summary of related works compared

References	**Number of Images**	**Model**	**Accuracy**
Ouchicha et al. (2020)	2905	CVDNet	96.69%
De Moura et al. (2020)	616	DenseNet121	79.86%
Xu et al. (2020)	618	ResNet	86.7.02%
.Song et al. (2021)t	274	DRENet	93%
Rehman et al. (2021)	1824(2class)	Resnet50	98%
Ozturk et al. (2020)	1125	DarkCovidNet	87.02%
Proposed Model	**6432**	**Xception**	**93.98%**

From the above-mentioned table, we can clearly see that most of the works done are on a very small size of dataset. This work uses a bigger dataset of 6432 images and attains a decent accuracy of 93%whcih is fairly good. Ouchicha et al. (2020) in his model based on CVDNet achieved an accuracy of 96.69%, but it is still a small dataset when compared with work of art done in this project. We may apply the same CVDNet model on a bigger dataset and see if it changes. Xu et al. (2020) used deep learning methodology using location attention and Resnet achieving an accuracy of 86.7% which is a promising value but yet the number images used is very limited. Ozturk et al.(2020) used the DarkCovidNet which is not using any feature extraction, instead is uses it end- to-end architecture. This model gave an accuracy of 87.02% but the dataset used in this case was also very limited to 1125 images. A ResNet50 model used by Rehman et al. (2021) gave a very high accuracy of 98%, but the limitations of this model were that it was used for only binary classification of Covid or Non-covid whereas our model was used for multiclass comparison and also the dataset used was very limited.Our model has one more advanatage is that it does not requires too much of computational efforts as compared to other pretrained models discussed here. Though our model shows a very promising and significant result but its still needs to be clinically tested.

7 Conclusion and Future Work

The author has introduced an automated system for the quick and early diagnosis of Covid-19, so that it could help the medical practitioners and strengthen the medical infrastructure. The system used the pre-trained Xception model for training and the weights of the model is used to develop a web-based application. The model achieves a high accuracy, recall and precision value but there is still some more work to be done to make it production ready as larger dataset needs for training this model to get high performance on metrics scale. As, this Covid outbreak have kept whole whole world on its toes with different variants appearing every now and then, this work is definitely a step closer for early diagnosis and treatment of disease.

In future, this model can be run on a bigger dataset and also train the various other model and then compare the results to save the best model for deployment.Apart from training an individual model, hybrid model can also be trained to compare the results and performance.Before deploying the model also thrive for a clinical testing of these pilot projects so that it reduces the rate of error.

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