Using Chest X-ray Images to diagnose and distinguish COVID-19 Pneumonia, Viral Pneumonia, and Lung Opacity.

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MSc Data Analytics

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Using Chest X-ray Images to diagnose and distinguish COVID-19 Pneumonia, Viral Pneumonia and Lung Opacity

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Abstract

Diseases caused by coronaviruses are ubiquitous all over the world and have the potential to negatively impact not just human health but also the global economy. Coronavirus is a common respiratory virus that can cause pneumonia and can spread rapidly. The novel coronavirus COVID-19 is currently being fought around the globe. The globe was caught off guard by the disease's rapid spread. Even if a diagnostic kit for COVID-19 did exist, it would likely have a high false-negative rate (i.e., it would return a negative result even if the patient was infected with COVID-19), making it unavailable in most parts of the world. As a result, early diagnosis of COVID-19 is essential for reducing mortality and morbidity associated with the virus. Pneumonia symptoms are universal, and COVID-19 is no different. A chest X-ray is the gold standard for making a pneumonia diagnosis. As a result, detecting COVID-19 and the other anomalies it created has significantly boosted the demand for radiologists. In this paper, we propose a multi-class convolutional neural network model that uses transfer learning to automatically diagnose pneumonia and distinguish between COVID-19 and non-COVID-19 pneumonia. Input chest X-ray images into the model, and it can turn radiographic patterns into useful information and track structural changes in the lungs due to disease. Our model was developed using the COVID radiography dataset. We trained our model with 3 main alogorithms (Densenet121, InceptionV3 and Xception). The Xception model performed better than the other model in terms of Precision, recall and F1-score, with a classification accuracy of 88%. The simulation findings show that the suggested model is effective, can identify chest images rapidly and reliably, and aids doctors as a second reader in making a final choice.

1 Introduction

Located on either side of the heart, the lungs are important components of the respiratory system. In the process of gas exchange, they serve as an essential part of the respiratory system, drawing oxygen from the surrounding air and transferring it to the bloodstream. When bacteria, viruses, or parasites assault the lungs' tissue, an infection can arise. There are many diseases that can cause an infection, including pneumonia and the world's most feared coronavirus.

Inflammation and even enlargement of the lung tissue are symptoms of pneumonia. Lung alveoli fill up with fluid or pus as a result of this condition. When it comes to diagnosing pneumonia, doctors typically consult the patient's medical history and do several diagnostic procedures such as blood and sputum testing and pulse oximetry measurements. As previously mentioned, the chest X-ray is a critical diagnostic tool. If you're 65 or older, or younger than 2, or have a preexisting medical condition, you're at an increased risk of developing pneumonia. Children as young as two years old, those with weakened immune systems, and those over the age of 65 are at particular danger. There are an estimated 450 million cases of pneumonia in the world each year, according to the World Health Organization (WHO) (Ruuskanen et al., 2011)

This unique SARS-CoV-2 coronavirus was initially discovered in Wuhan, China, in December of 2019, and it is widely referred to as the "coronavirus." Both the health of people and the health of economies have been harmed as a result of the sickness. As a result, the World Health Organization (WHO) has designated it a global pandemic (Lai et al., 2020) (Sohrabi et al., 2020). Although the condition was first referred to as novel coronavirus-infected pneumonia (NCIP), it was later renamed COVID-19 (Corona Virus Disease 2019) by the WHO (Microbiol, 2020). At a rate of 6.14 percent globally, COVID-19 had a harmful impact on many people and resulted in numerous fatalities. In addition, COVID-19 is 96% similar to coronaviruses found in bats, which caused the SARS pandemic that occurred between 2002 and 2003. A few multinucleated giant cells are seen in both SARS and COVID-19, but COVID-19 is more dangerous than SARS, and the number of deaths in the current outbreak has already eclipsed that in the SARS pandemic (Mason, 2020).

For COVID-19, the primary trait is its ability to bind to human lung type 2 alveolar cells, which is similar to viral pneumonia (non-COVID-19) (Andersen et al., 2020). There is no way to do a COVID-19 test because the diagnostic kit is not available everywhere. However, even if the kit is available, the false-negative rate (which indicates that a person is not infected with COVID-19) is significant. Covid-19's morbidity and mortality rates can be reduced by early identification. It was for all of these reasons that researchers set out to devise new diagnostic techniques. For COVID-19 and pneumonia patients, X-rays are performed to evaluate the health of their lungs. But a specialized radiology should examine chest X-rays or computed tomography (CT) scans to detect structural alterations in the lungs. To diagnose COVID-19 and other anomalies induced by the pandemic, the demand for radiologists has risen significantly. In addition, the diagnosing process is lengthy and susceptible to human mistake.

Contrarily, computer advancements have a significant impact on a wide range of fields including medicine. (Khairat et al., 2018) Computerized systems are used in medicine as a second reader to prevent medical errors and save time during interpretation, diagnosis, and treatment of patients. Spatio-temporal correlation patterns can be used by Convolutional Neural Networks (CNNs) for classification and feature extraction in medical imaging, making them a dominating method in computer-aided diagnostic systems. This research include COVID–19 image classification (Sahlol et al., 2020), breast cancer detection (Li et al., 2017), lung lesions identification (Setio et al., 2016), detection of hand osteoarthritis (ÜRETEN et al., 2020), and categorization of tumors in the brain (Deepak & Ameer, 2019) in medical imaging. Diverse, labeled datasets are necessary for a successful CNN model.
Aside from that, it's crucial to have high-quality photographs and the right network in place. Data augmentation and transfer learning, on the other hand, can be employed in circumstances where there isn't enough data (Iandola et al, 2016) (Krizhevsky, Sutskever, and Hinton, 2012). Pre-trained models can be applied to new situations by modifying the model's structure and re-trained using new datasets, and this process is called transfer learning. Annotated data is critical in areas where it is scarce. Because it is difficult to get annotated medical data, this is a significant advantage of transfer learning (Anwar et al., 2018).

An automatic computerized CNN-based multiclass model for detecting viral pneumonia, COVID-19, Lung opacity and normal patients from chest radiographs has been developed in this study. The model uses X-ray pictures of the lungs to track the structural changes that occur as a result of the disease. Randomly selected COVID-19 chest images were also used to test the model's performance (Chowdhury et al., 2020) (Rahman et al., 2021). The model can act as a second set of eyes for radiologists, minimizing the amount of variation in their interpretations of pictures due to variances in their level of experience.

Research Question

Using a deep-learning model, how successfully can a chest x-ray image be used to differentiate various types of pneumonia?

Objectives

The project main aim and objectives are to:

- Examine the current level of research on other scientists' approaches to the challenge of identifying and diagnosing Covid-19 pneumonia from x-ray pictures.
- Create and put into place a method to handle the issue of identifying and diagnose Covid-19 pneumonia using x-ray pictures.
- Analyze the proposed system's accuracy
- Getting more accuracy when compared to previous research.

2 Related Work

In medical terms, Covid and Pneumonia image classification has been a major shift in the field of machine learning. For image categorization, various deep learning architectures and algorithms have demonstrated enormously promising findings and opinions. In some cases, using human power and technician abilities to examine images has yielded significant results; however, the time, effort, and stress involved were significant, and the results, when examined by human power alone using microscopic instruments and other means, have shown errors due to the urgency of the results. To solve this issue, data scientists have been working tirelessly to identify the best algorithms and approaches for deep learning that can classify photos and provide a substantial solution.

2.1 Image Classification

Image classification is an example of a work that falls within the scope of computer vision. A procedure in which an input, such as a picture, is fed into and a class or probability of the class to which the input belongs is computed. Types of terrain used to identify specific locations Image categorization is used to do this. Target classes are defined or inputted, and then the model is trained based on the weights, while on the other hand, a collection of photos are kept concealed for testing them on the learned model (Widiawati et al., 2016). The classification of an image is based on the accuracy or outcomes achieved following the examination.

2.2 Convolutional Neural Network (CNN)

Deep learning models, such as CNN, are used to automatically and adaptively learn spatial hierarchies of features from low- to high-level patterns when processing data with a grid pattern, such as pictures. Convolution, pooling, and fully connected layers make up the basic building blocks of a CNN. CNNs can be constructed in a variety of ways. It is this fully linked layer that transfers the extracted features into final output such as classification. The first two layers are responsible for feature extraction using convolution and pooling. A convolution layer is essential to CNN, which is a stack of mathematical operations, such as convolution, a specific sort of linear operation. An array of numbers, or a 2D grid, is used to hold the values of pixels in digital images and a feature extractor, called kernel, is applied to each image location. This makes CNNs particularly efficient for image processing, since a feature can be found anywhere in a 2D grid of numbers. Hierarchical and progressively more sophisticated features can be recovered as one-layer feeds into the next. Backpropagation and gradient descent are two optimization algorithms for minimizing output-to-ground truth label differences that can be used to improve kernel performance. This process is called "training."

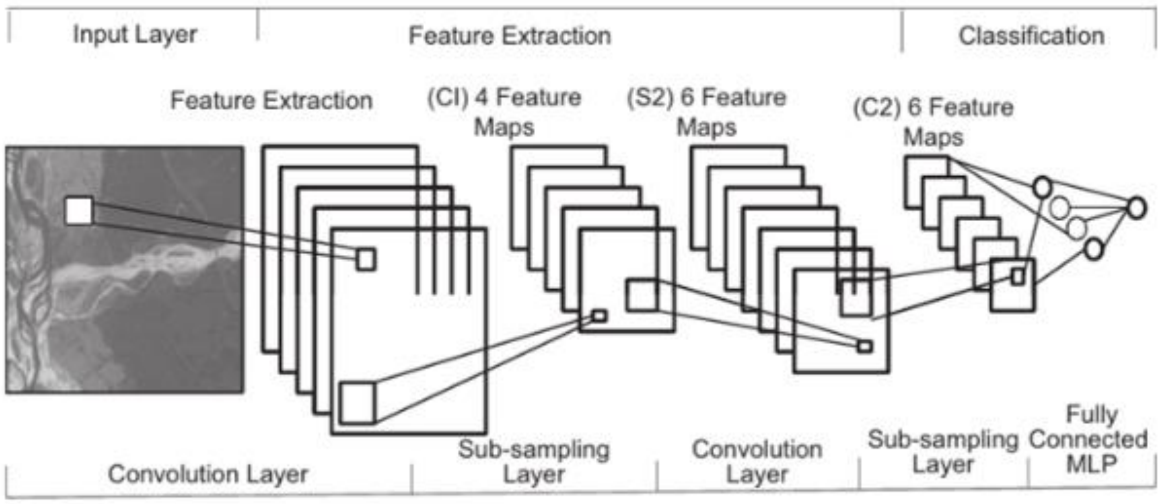

Figure 1. CNN architecture (Kumar et al., n.d.)

2.3 Deep Learning Based Pre-trained CNN Models

The use of machine learning to diagnose COVID-19 using chest CT or X-ray scans has been investigated in numerous studies. Depending on the level of deep architecture deployed, these projects can be classified into a variety of subcategories. After that, we'll take a look at a few common deep architectures research projects.

For the diagnosis of COVID-19 from chest CT scans or X-ray pictures, DL-based models are often regarded as the gold standard. One of the most distinguishing features of many categorization models is how deeply they use deep architecture (ResNet, VGG, and Dense Convolutional Network) (DenseNet, for example).

CNNs (Yamashita et al., 2018) are now the most often used deep architecture for picture categorization. A CNN-based approach was described in (Ozturk et al., 2020) for the detection of COVID-19 cases from chest X-ray images. The binary classifiers COVID-19 and non-COVID-19 were the first to be suggested. Lung infection, COVID-19, and Non-COVID-19 were the results of a multi-category classification algorithm. According to their research, their recommended model categorization accuracy rates are 98 percent and 87 percent. COVID-19 patients were identified using X-ray chest pictures and classifier models (Elaziz et al., 2020) from two separate sources. Researchers then came up with a variety of CNN-based comparison methods. Accuracy ratings of 96% and 98% were achieved using the proposed model for the first two datasets. The authors (Shi et al., 2021) also looked at a number of CNN-based COVID-19 detection algorithms.

The ResNet architecture (He et al., 2016) performs well on a wide range of datasets when it comes to picture categorization. The authors (Keles et al., 2021) developed a ResNet architecture to detect COVID-19 in chest X-ray images using deep transfer learning. Pneumonia and 350 chest X-ray images for normal circumstances were used in addition to the 210 COVID-19 chest X-ray photos. Over 95.5% of the cases were correctly classified.

The architecture proposed by (Huang et al., 2017) is called DenseNet. When a new layer is added to DenseNet201, all of the previous layers' inputs and feature maps are transferred to the new layer. Studies have used CT scan pictures to automatically detect COVID-19 patients (Zhu et al., 2021) (Zhu et al., 2021) (Sun et al., 2020). The DenseNet-201 architecture was also presented by the authors (Jaiswal et al., 2020) to characterize the suspected case as COVID-19 or normal based on the CT scan image of the patient. CT scans from 2,492 patients were used to train a suggested classifier model. The classification was right 86% of the time. Proposals to automatically identify COVID 19 patients utilizing portable on-device technologies were made by the authors of (Li et al., 2020). It is also possible to track the case's progress with the new system proposed. For the construction of the classifier model, the authors made use of DenseNet architecture and deep transfer learning. The proposed system's maximum categorization accuracy has been reported to be 88%.

For the automatic recognition of COVID-19 cases utilizing CT volumes, the authors (Zheng et al., 2020) suggested a 3D deep CNN-based approach. According to the authors' suggestions, pre-trained UNet (Ronneberger et al., 2015) may be used to generate 3D lung masks that could be categorized. Classes were accurately assigned to ninety percent of the students. A number of tests were carried out using COVID-19 CT scan images. Prior to performing a classification job, the authors in (Fan et al., 2020) (Wu et al., 2021) proposed two segmentation strategies for removing noisy data from an input image.

Even though it uses a lot of memory, the VGG deep architecture has a high classification accuracy rate. COVID-19 and normal CT images from 592 scans were categorized by (Shah et al., 2020). This led to the creation of the CTnet-10 model, which is based on binary classifiers. This model has an accuracy of 82%, while the pre-trained VGG-19 model has an accuracy of 94.54%. (Dansana et al., 2020) proposed a VGG-based model. Classifiers for COVID-19, pneumonia, and normal pictures were proposed by the authors. There are a total of 360 photos in the dataset. To create feature maps, they proposed using X-ray images, which would subsequently be vectorized and categorized using the VGG-16 architecture. Deep transfer learning was used, and they kept the ImageNet-trained VGG-16 weights. There should be a separate output layer for each of the three categorization outcomes, they said. The accuracy rate of categorization is 91%.

Table: 1 Examination of previous works

Paper	**Algorithm**	**Result**	**Dataset**	**Authors**
Automated detection of COVID-19 cases using deep neural networks with X-ray images	Darknet	Deep model for early COVID-19 case detection proposed utilizing X-ray imaging. obtained accuracy for binary and multi-classes of 98.08% and 87.02%, respectively. The radiologists can spot the troubled areas on chest X-rays with the aid of proposed heatmaps.	COVID-19 X-ray image database	Tulin Ozturk, Muhammed Talo, Eylul Azra Yildirim, Ulas Baran Baloglu, Ozal Yildirim, Rajendra Acharya
Deep Learning-based Detection for COVID-19 from Chest CT using Weak Label	pre-trained UNet	0.959 ROC AUC and 0.976 PR AUC. There was an operating point with 0.907 sensitivity and 0.911 specificity in the ROC curve. When using a probability threshold of 0.5 to classify COVID-positive and COVID-negative, the algorithm obtained an accuracy of 0.901	COVID-19 X-ray image database	Chuansheng Zheng, Xianbo Deng, Qiang Fu, Qiang Zhou, Jiapei Feng, Hui Ma, Wenyu Liu, Xinggang Wang

COVID-MobileXpert: On-Device COVID-19 Patient Triage and Follow-up using Chest X-rays	COVIDMobileXpert	a portable deep neural network (DNN)-based smartphone application that can forecast radiological trajectory and screen for COVID-19 cases using chest X-rays (CXR).	ChestX-ray8 COVID-19 Image Data Collection. RSNA Pneumonia Detection Challenge.	Xin Li, Chengyin Li, Dongxiao Zhu
Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning	Pre-trained DenseNet201 model	use the automatic COVID-19 diagnosis and detection tools built within pre-trained deep learning architectures. The suggested model produces 96% correct categorization outcomes.	SARS-CoV-2 CT scan dataset	Vijay Chahar, Aayush Jaiswal, Neha Gianchandani, Dilbag Singh
Adaptive Feature Selection Guided Deep Forest for COVID-19 Classification with Chest CT	deep forest model	Their method yielded results for accuracy (ACC), sensitivity (SEN), specificity (SPE), AUC, precision, and F1-score that were, respectively, 91.79%, 93.05%, 89.95%, 96.35%, 93.10%, and 93.17%.	CT images dataset	Liang Sun, Zhanhao Mo, Fuhua Yan, Liming Xia, Fei Shan, Zhongxiang Ding, Wei Shao, Feng Shi, Huan Yuan, Huiting Jiang, Dijia Wu, Ying Wei, Yaozong Gao, Wanchun Gao, He Sui, Daoqiang Zhang, Dinggang Shen
Deep Learning on Chest X-ray Images to Detect and Evaluate Pneumonia Cases at the Era of COVID-19	InceptionResNetV2	On the COVID-19 blind test set, the InceptionResNetV2 model detected the least number of false negatives for pneumonia (0.7%).	SARS-CoV-2 CT scan dataset	Karim Hammoudi, Halim Benhabiles, Mahmoud Melkemi, Fadi Dornaika, Ignacio Arganda-Carreras, Dominique Collard, Arnaud Scherpereel
Pneumonia Classification Using Deep Learning from Chest X-ray Images During COVID-19	AlexNet	Accuracy, sensitivity, and specificity for the suggested model were 94.43%, 98.19%, and 95.78% respectively.	novel-corona-virus-2019-dataset, covid19-radiography-database covid-chestxray-dataset, novel-corona-virus-2019-dataset	Abdullahi Umar Ibrahim, Mehmet Ozsoz, Sertan Serte, Fadi Al-Turjman & Polycarp Shizawaliyi Yakoi
Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks	ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2	ResNet50 model has 96.1% accuracy, the best classification performance.	COVID-19 image data collection	Ali Narin, Ceren Kaya & Ziynet Pamuk
CoroDet: A	CoroDet	Using a 22-layer CNN	COVID-R	Agata Giełczyk, Anna

deep learning based classification for COVID-19 detection using chest X-ray images		architecture, classification accuracy for two classes was 99.1%, three classes was 94.2%, and four classes was 91.2%.	dataset	Marciniak, Martyna Tarczewska, Zbigniew Lutowski
CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization	A novel deep neural network architecture is proposed based on depthwise dilated convolutions.	With 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, extensive experiments using two separate datasets produce highly good detection performance.	SARS-CoV-2 CT scan dataset	Tanvir Mahmud, Md Awsafur Rahman, , Shaikh Anowarul Fattah

3 Research Methodology

CRISP-DM is a well-established data mining methodology that was used in this study. It refers to a data mining method that is applicable across different industries. The order in which the steps are completed can be reversed in this method. The Chest x-ray pictures data collection was used in this research problem to identify the various kinds of pneumonia. As the input requirements of deep learning architectures change, so too do data reprocessing stages. It was therefore possible to train the models on the pre-processed data before evaluating it for its ability to predict pneumonia diagnoses based on test data.

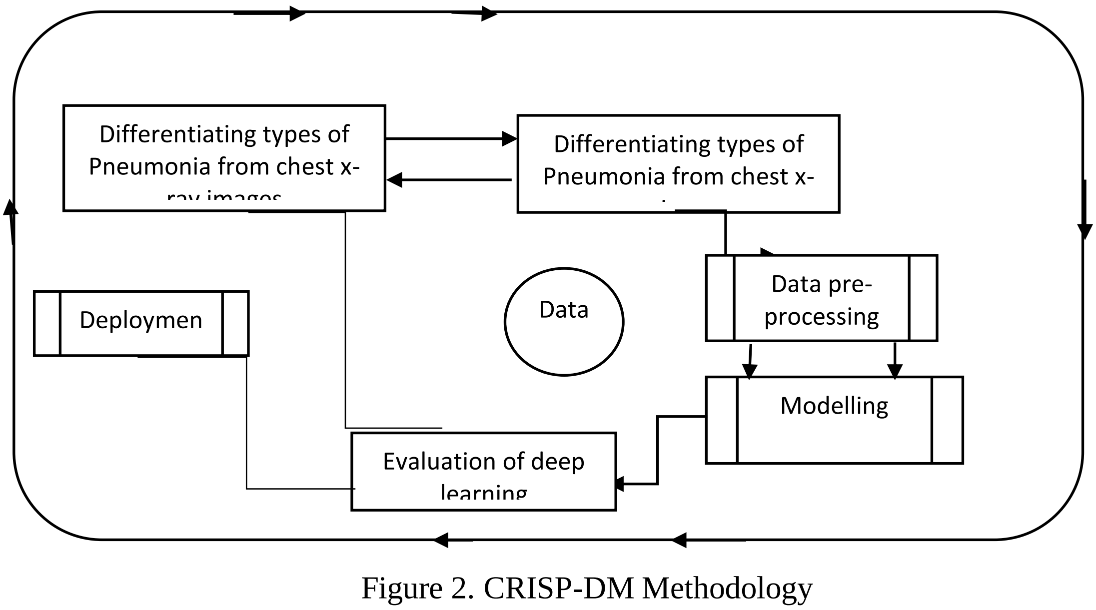

Figure 2. CRISP-DM Methodology

Figure 2 clearly depicts the approach used in this study, which follows a modified CRISP-DM methodology. During the data pre-processing step, all of the pre-processing tasks like resizing, reshaping, and transforming photos into NumPy arrays were completed. Afterwards, the dataset was divided into training and test data sets, and models were trained on them in the modelling portion before being evaluated on the test data set. CRISP-DM's process had been successfully followed by this project.

4 Design Specification

Using a two-tier framework, the suggested research study was to be conducted. Research conducted by researchers affiliated with Qatar University and the University of Dhaka (Bangladesh), as well as colleagues from Pakistan and Malaysia, in conjunction with medical practitioners and hospitals, has been incorporated into the database layer for this project. On the other hand, the python environment and jupyter notebook served as the client layer. Pre-processing and implementation of deep learning architectures and their assessment, as well as the necessary visualizations for presenting the findings, were all done on the same platform.

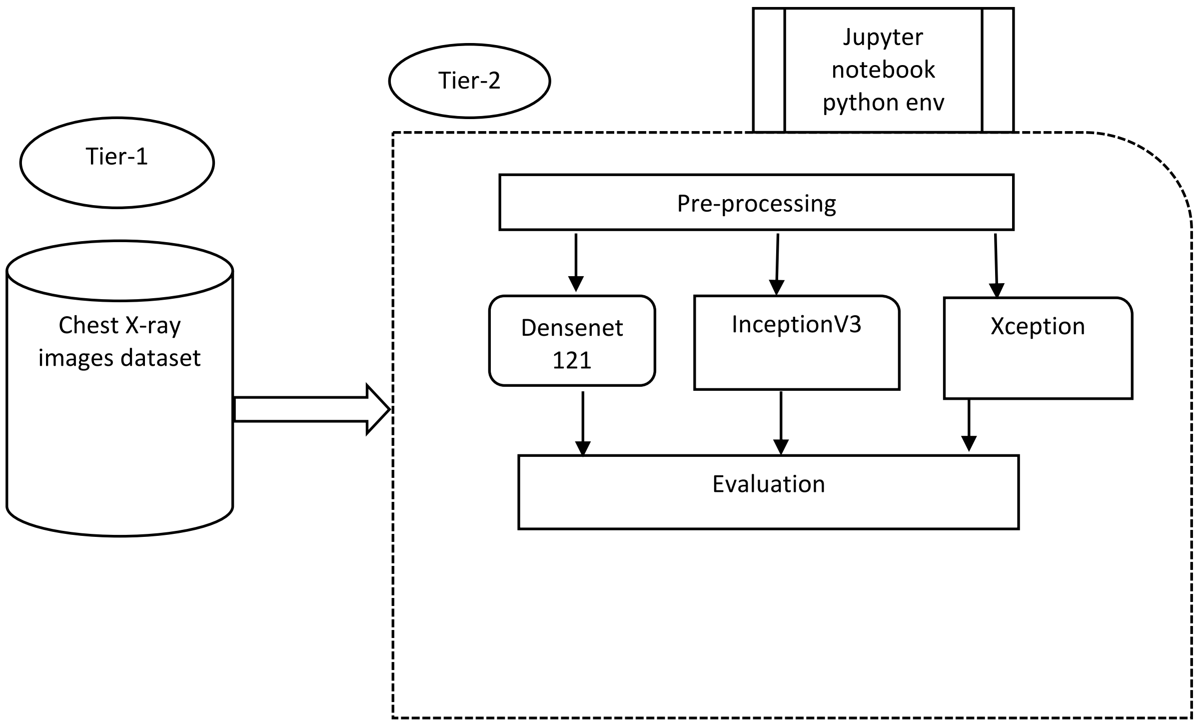

Figure 3. Two-tier framework

Anaconda3 2021.11 and python 3 (64-bit) were used to implement the study project, both of which were published by Anaconda, Inc. of version 2021.11. The configuration manual outlined all of the necessary libraries and packages to be installed before the tasks could be completed effectively. There were four subfolders (Covid, Viral Pneumonia, Lung Opacity, and Normal Samples) in the data, all of which had to be compressed into a zip folder before use.

A lot of algorithms have been used to classify x-ray images as COVID-19 or viral pneumonia. We would be comparing the accuracy of our proposed model with the accuracy of previous models researched. We would also use new models Densenet 121 and Xception that hasn't been used to classify chest x-ray images COVID-19, viral pneumonia, and lung opacity and compare there accuracy with models that have previously been used such as InceptionV3

5 Source of Data

Covid Pneumonia may be detected utilizing Chest X-rays and deep learning models in comparison to normal samples, hence we plan to employ this dataset for our research. Research teams from Qatar University in Doha and the University of Dhaka in Bangladesh, along with collaborators from Pakistan and Malaysia, assembled the data. 3616 COVID-19 positive cases, 10,192 normal, 6012 non-COVID lung infection, and 1345 viral pneumonia images are included in the collection as well each classes masked images.

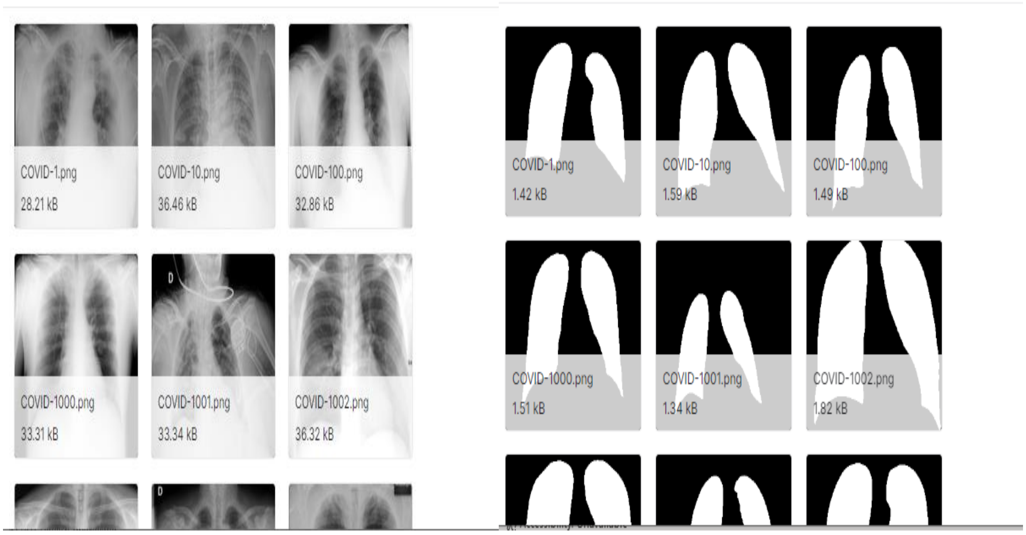

Figure 3. Covid sample chest x-ray images (Unmasked and Masked)

Figure 4. Lung Opacity sample chest x-ray images (Unmasked and Masked)

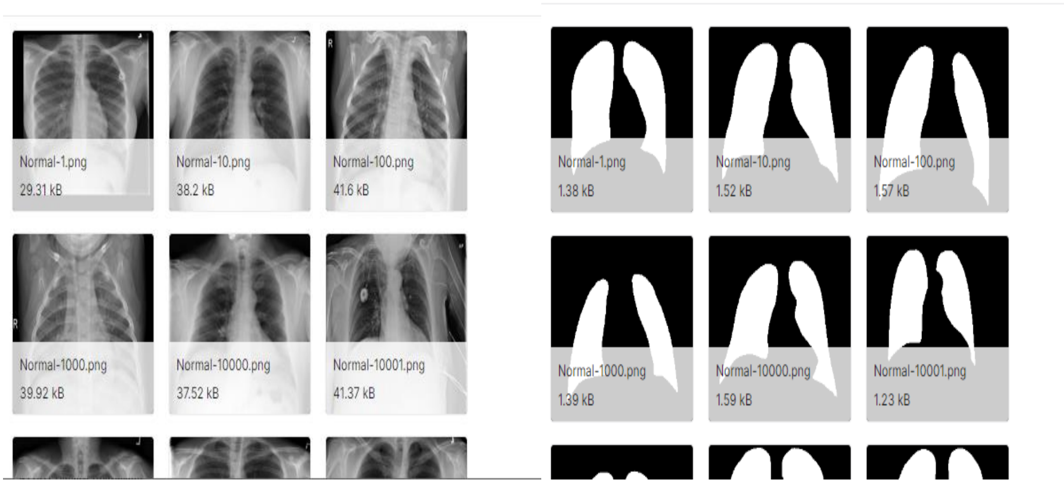

Figure 5. Normal sample chest x-ray images (Unmasked and Masked)

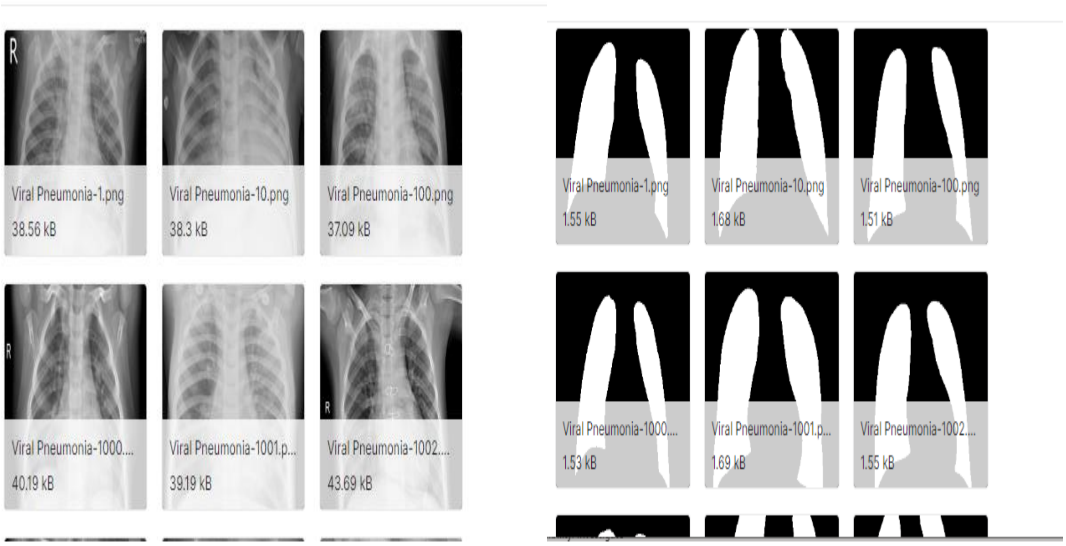

Figure 6. Viral Pneumonia sample chest x-ray images (Unmasked and Masked)

6 Implementation

6.1 Dataset Pre-processing

The pre-processing step involved resizing the image from the dataset to 224 by 224. Resizing images is a critical pre-processing step in computer vision. Principally, deep learning models train faster on small images. A larger input image requires the neural network to learn from four times as many pixels, and this increase the training time for the architecture. During Pre-processing, we also created an image data frame that had all of our photographs and their labels (Covid, Normal, Lung Opacity, and Viral Pneumonia). We also checked for outlier and missing data but found none.

We used 80 percent of the dataset for training and 20 percent for testing, resulting in two subsets. Regardless of which method was run, we used the same sample size split. We augmented the training data for each algorithm run with some additional information. The photographs were rotated, flipped horizontally and vertically, and the width and height of the images were shifted in various ways. In order not to confuse our model, we only augmented the training images and not the test ones. We used three distinct algorithms to train our model (Densenet121, InceptionV3, and Xception)

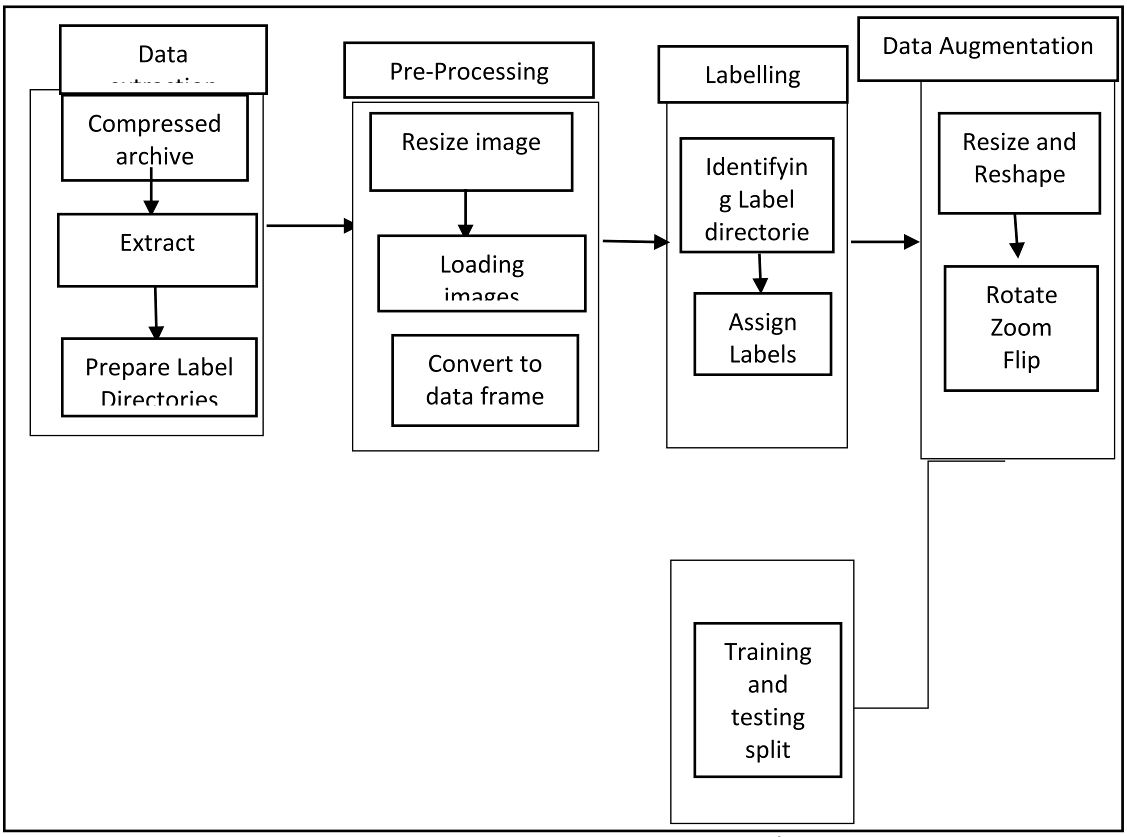

Figure7: Data pre-processing diagram

6.2 Random Forest

This random forest classification was used as a test to see if the classification would be successful or not. As a preliminary step, the data was run through a random forest classifier to see how it fared.

A random forest is made up of a slew of different decision trees, all working together in harmony. During the learning process, nodes were divided using a random selection of data's features. A node, a branch, and a leaf always make up a decision tree. Test results or outputs are represented by a node, and each leaf represents a different class label. It is classified by every single tree in a random forest (Zhou et al., 2014) and the final result is a fusion of the voting results of all the trees. There are two steps to this procedure: first, select one set of train data, and then choose replacement n times throughout the entire set (Bosch et al., 2007). Node testing and subsampling of the train data are two ways in which unpredictability can be supplied into random forest classification.

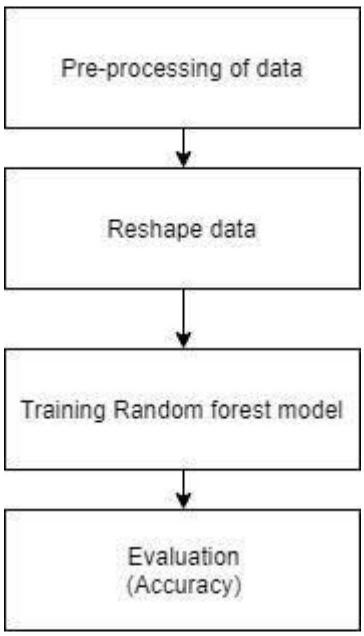

Figure 8. Random forest classifier modelling

Data that is in the form of images and is therefore four dimensional must be transformed to two dimensions before being fed into the random forest classifier. The random forest classifier achieves a 67% percent accuracy rate.

6.3 Densenet 121

DenseNet (Dense Convolutional Network) tries to make deep learning networks increasingly deeper and more efficient to train by employing shorter connections between layers. First-layer neural networks are connected to second-, third-, and fourth-layer neural networks, for example; second-layer neural networks are connected to third-layer neural networks, for example. Layers can communicate with each other more effectively this way. For the system to remain feed-forward, each layer gets input from all preceding layers and transmits its own feature maps to all subsequent layers. Like Resnets, it does not integrate characteristics by summation but rather by concatenation. There are only I inputs and feature maps from the previous convolutional blocks in the ith layer. Following 'I-i' layers are all provided with their own feature maps. The network now has '(I(I+1))/2' connections instead of only 'I' connections as in normal deep learning setups. In other words, because no irrelevant feature mappings need to be learned, it uses fewer parameters than typical convolutional neural networks and is hence faster. Additional to the essential convolutional and pooling layers that make up the DenseNet, there are two other key components. Dense blocks and transitional layers make up the majority of the structure.

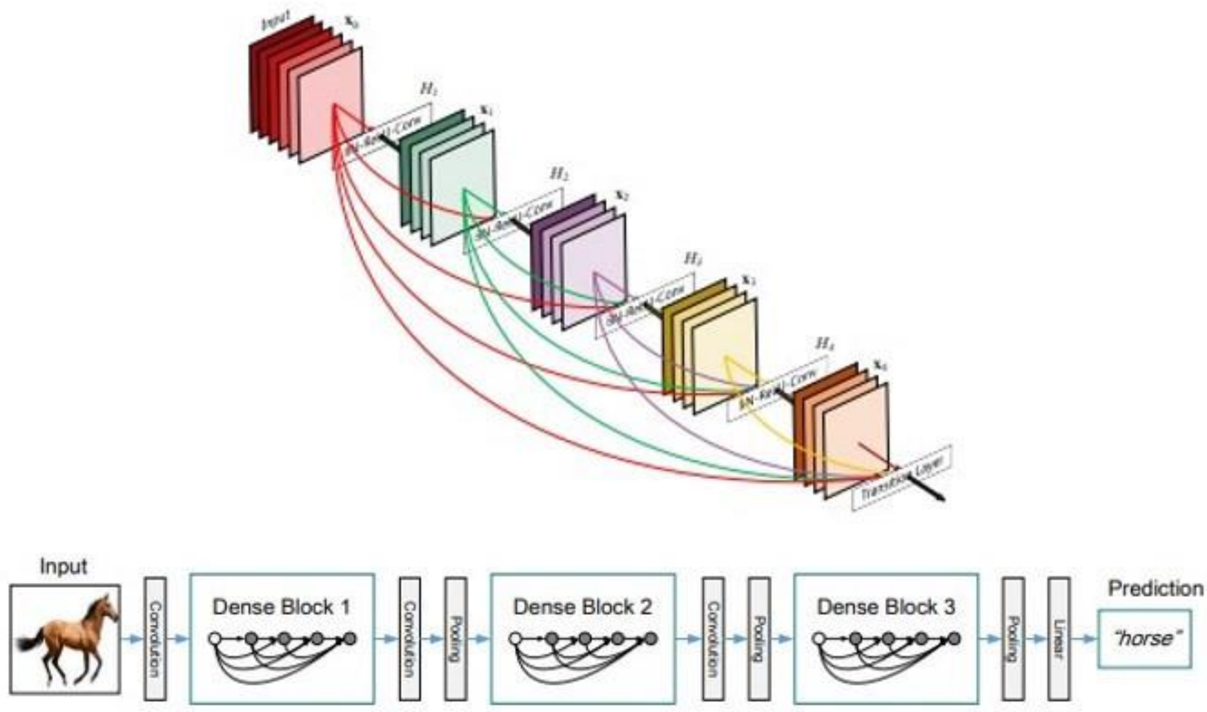

Figure 9. Architecture of Densenet 121 (Sarkar, 2020)

After the data has been pre-processed, the inception architecture for the chosen dataset has been pre-built. Once the Keras library model is imported, the output layers are added, and the model is completed. The model is then compiled with the optimizer and loaded into the Densenet model. Check-pointer is used to save the finest models. When the model has a batch size of 12, it is run for 5 epochs. Implementing the Densenet 121 architecture resulted in an accuracy rate of 86%.

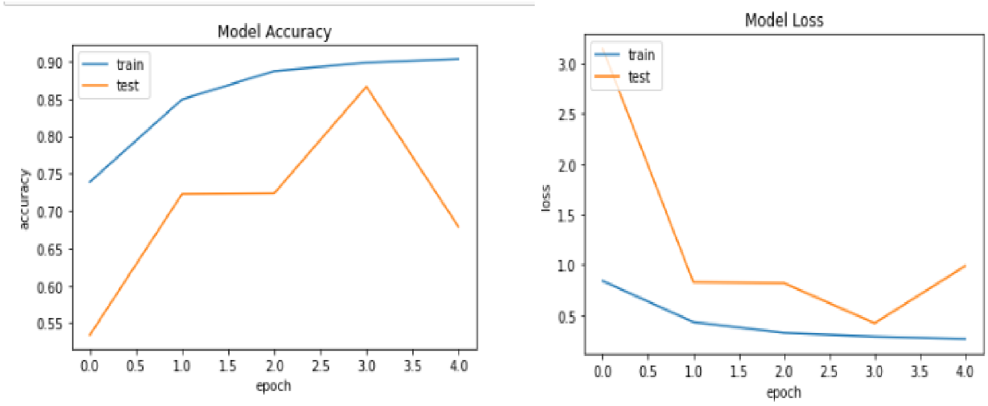

Figure 10. Densenet 121 Model Accuracy and loss

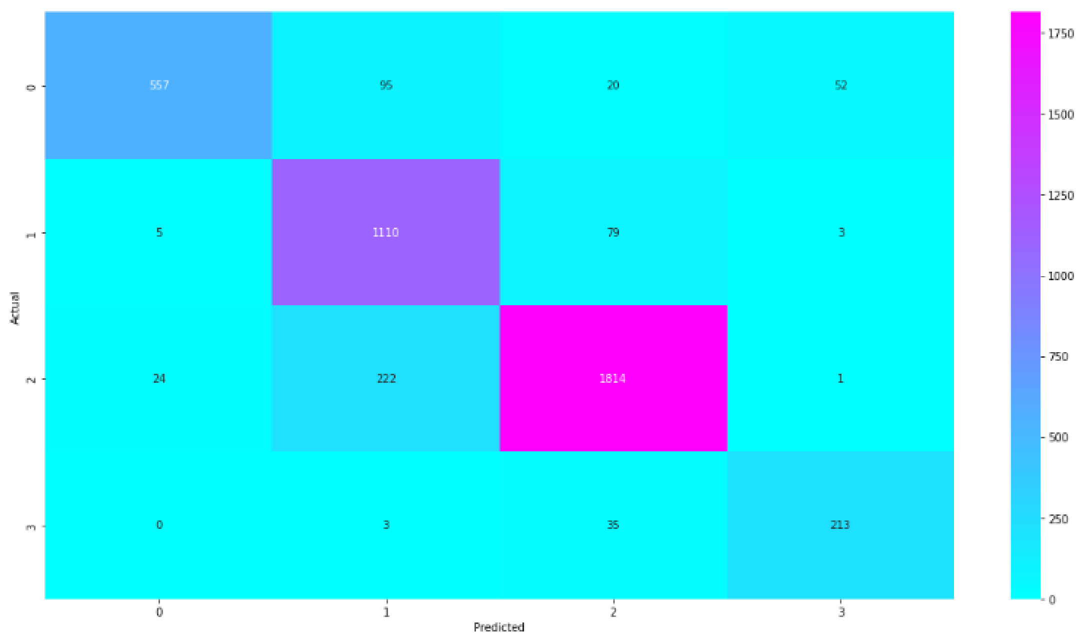

Figure 11. Densenet 121 Confusion Matrix

6.4 Architecture of Inception V3

It will take a few days to model and evaluate this deep neural network on a low-configuration machine. End layers of inception can be trained anew for new categories using transfer learning. It is possible to retain the preceding layers in place while replacing the last layer and retraining the last layer (Mittal et al., 2018) A dataset with 100 classes will have 100 nodes in the final layer of an Inception v3 architecture, which is the same as the dataset's number of categories (Xiaoling Xia et al., 2017). When comparing Inception v3 to Versions 1 and 2, factorization is the most significant improvement. Inception-key v3's advantage is its network computing power and non-linearity, which allow it to rise in network depth (Zhang et al., 2018). Nearly 44 layers and 21 million variables make up this design (Varaich & Khalid, 2019)

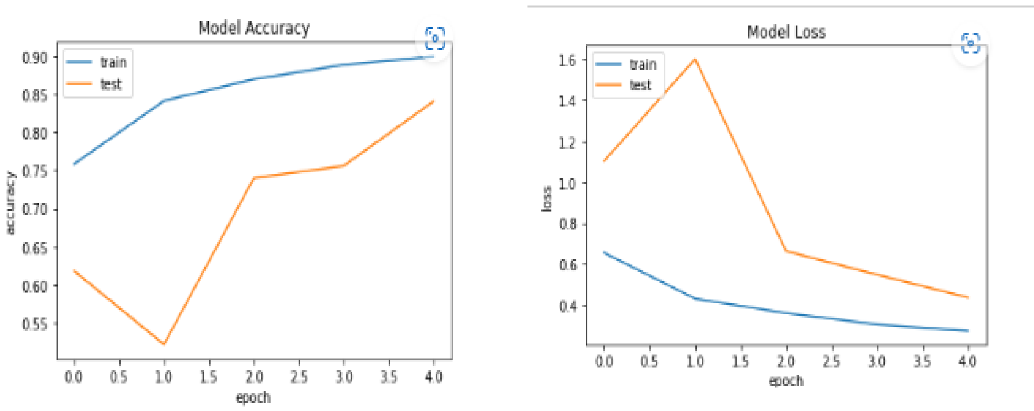

Figure 12. InceptionV3 Model Accuracy and loss

The spatial correlations, which are to be mapped differently from the cross-channel correlations, exist in this design between pixels of individual channels and are referred to as "spatial correlations." Figure 13 depicts the area under the receiver operating characteristic curve, which is not as good as what has been provided by the other models. The better the model, the closer the yellow line on the graph is to 1.0. Getting the hypothesis is the goal of this model's schedule. It is customary in other CNNs to map the cross-channel correlations first, followed by the spatial correlations. This is not the case in inception v3 (Varaich & Khalid, 2019). Smaller parts of the image can be covered by 3x3 filters, whereas larger sections are covered with 5x5 filters in Inception's model. Pooling tower is then used to acquire information by reducing input maps' dimensions.

After the data has been pre-processed, the inception architecture for the chosen dataset has been pre-built. Once the Keras library model is imported, the output layers are added, and the model is completed. The model is then compiled with the optimizer and loaded into the inception model. Check-pointer is used to save the finest models. When the model has a batch size of 12, it is run for 5 epochs. Implementing the Inception v3 architecture resulted in an accuracy rate of 84%.

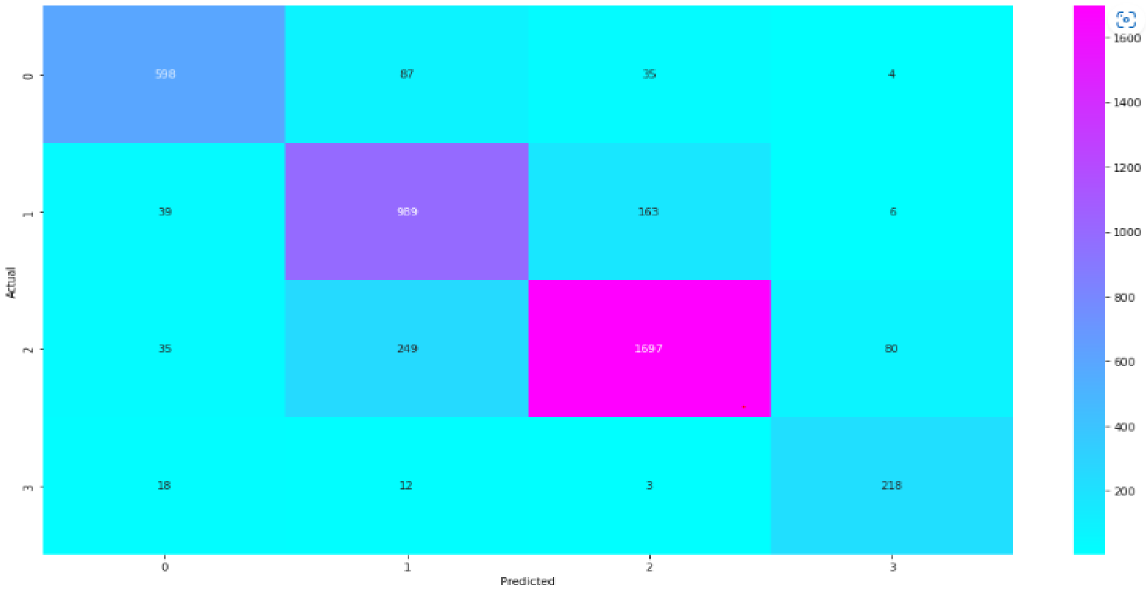

Figure 13. InceptionV3 Model Confusion Matrix

6.5 Architecture of Xception model

Xception design is inspired by Inception v3 and was proposed by popular author Francis Cholett of keras, a library of deep learning. There are 36 levels of the Xception architecture, compared to 44 levels and almost 21 million learnable parameters in the inception (Varaich & Khalid, 2019). Inception v3 designs follow the Depth-wise separable convolution to detect spatial correlations, but Xception architectures take this to a new level by rewriting the Inception v3 algorithm. There are multiple spatial convolutions utilized in Inception v3, whereas just one spatial convolution is used in Xception. The global average pooling layer is used as a replacement for the fully connected layer in order to reduce the number of layers. Also, a function known as softmax is utilized to arrive at the forecast outcome.

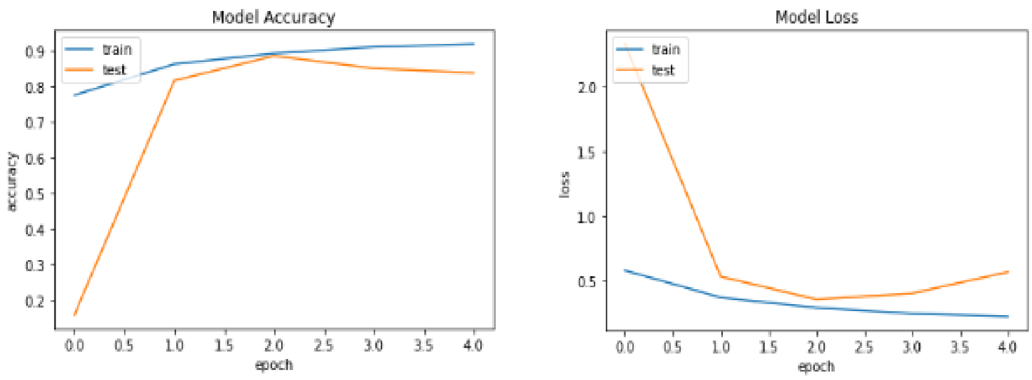

Figure 14. Xception Model accuracy and Loss

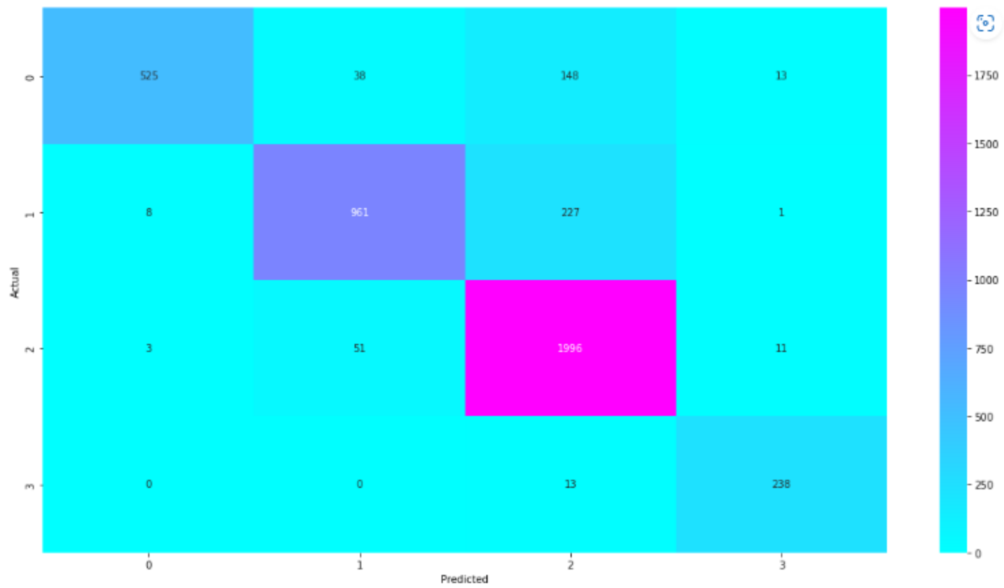

Figure 15. Xception Model Confusion Matrix

All of the 14 convolutional layers, with the exception of the first and last, feature linear skip links. The 36 layers are grouped into three categories: entering flow, middle flow, and exit flow. An 8-layer entry flow, four-layer end flow, and three multiples of 8 (24 total) for the middle flow make up the 36-layer pattern (Lo et al., 2019)). Figure 13 shows the Confusion matrix for Xception architecture

The data flow procedure will then be schematically distributed amongst them all. The Xception model uses depth-wise separable convolution to decrease the operational cost of convolutions. The model is imported once the data has been pre-processed.

which is pre-built by adding output layers later. which is subsequently. After compiling the model, we obtain the exception model, which is run with a batch size of 12 and an epoch interval of 5, we had an accuracy of 88%.

7 Evaluation

Deep learning models Densenet 121, InceptionV3, and Xception were used to classify chest X-ray images of distinct types of pneumonia. Classification accuracy, precision, recall, and F1-score were all used as evaluation metrics in this study. The model's accuracy is measured by the percentage of images it correctly classifies as Covid, Lung Opacity, Normal, or Viral Pneumonia. If the person is having covid-19 he is going to positive and in the same way with out is represented as negative. The accuracy of an image classification model was evaluated by comparing its performance against that of a deep learning model. The evaluated statistics reveal a lot about the quality of the data collection, the performance of the models used, and the quality of the analysis.

7.1 Comparison of Models

While comparing how accurate each model were, we found out that the Xception model performed better than the other models. All models were ran with 5 epoch, with the Xception model having an accuracy of 88% compared to the Densenet 121 and InceptionV3 model with 86% and 84% respectively. The precision for the Xception model was also higher than other models for each of the classes. The InceptionV3 model performed poorly to other models in terms of precision, recall, F1- score and confusion matrix.

Table 2: Comparison Between models.

Model	**Model Accuracy**	**Precision**	**Recall**	**F1-Score**
Xception	88%	91%	86%	88%
Densenet 121	86%	86%	86%	85%
InceptionV3	84%	80%	84%	82%

By seeing the above table we can easily understand that Xeception model is having greater accuracy when compared to other models with Accuracy 88%, Precision 91%, Recall 86% and F1-score 88%. Where as the InceptionV3 got less accuracy with 84%.

7.2 Discussion

With the problem of image sizes and resolutions by the dataset, these images need to resize to match the input requirement of the model used. While considering various architectures used, the Xception model performed better than other models. All models were ran using an epoch of 5 with various changes to the input size to match the model. According to our evaluation metrics used such as classification accuracy, precision, recall, F1-score and confusion matrix, the Xception model performed better than the Densenet 121 model and the InceptionV3 model. The Xception model can be said to be adequate and reliable in classifying various Pneumonias.

When comparing the papers in the literature review, the model suggested in this study receives the greatest validation accuracy, as well as the highest validation recall and validation precision, only by looking at performance metrics. However, despite the model's somewhat worse performance in the test images, it is still a good competitor.

8 Conclusion and Future Work

Three major models were used in the study for individual modelling purposes. Implemented deep learning models included Densenet 121, Inception v3, and Xception architectures. These models performed better than other models covered in the literature review. .

Due to this research's primary goal of examining previously unexplored image classification structures in the medical imaging sector, In the study, three models were chosen and applied after a thorough examination of the literature on the subject. The selected models were chosen not only because of the architectural uniqueness but also because of the time and resources available for this study endeavour. The objective is to get more accuracy when compared to previous studies with implementation of 3models. We get high accuracy for the xception model with 88% and less accuracy for the inceptionv3 with 84%. We have done 5epoch for each model. With implementation of these techniques machine learning models will going to have better performance.

As part of our future work, we may have utilized alternate segmentation methods to improve the accuracy of our model, such as removing the dataset's background or using grayscale or RGB images. We might have experimented with various algorithms like AlexNet and GoogleNet to see if we might increase our accuracy. To perform an object detection task rather than just image classification, we could have used algorithms like fast-RCNN or faster-RCNN or even YOLO (you only look once). Additionally, we could have evaluated the performance of our model against more established machine learning models like support vector machines, or decision trees. We can also use ensemble technique to get the better accuracy by combining all three models. Due to lake of time and limited computer resources we have done only 5epochs. There are certain techniques which can be used to detect and diagnose the disease at primary stage.

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