Thoracic Diseases Classification of Chest X-Ray Images employing Deep Learning Methods

Sarath Chandra Gollamudi
School of Computing
National College of Ireland
Dublin, Ireland
x19193581@student.ncirl.ie

Mansi Udani
School of Computing
National College of Ireland
Dublin, Ireland
x19186088@student.ncirl.ie

Shashikumar Madihalli Byrappa
School of Computing
National College of Ireland
Dublin, Ireland
x18173837@student.ncirl.ie

Abstract— **Chest X-ray is the most brisk and powerful test that has been valuable for quite a long time to help specialists to see indispensable organs. Focusing on the thrust, lungs, heart, bones, and the airways can be helpful in detecting abnormalities and different medical conditions. Identifying the diseases through chest x-rays that can only be done by specialized radiologists. To address this problem, the paper seeks to consequently diagnose thoracic ailments in chest x-rays utilizing deep convolution neural networks. The network identifies and locates specific forms of disease and seeks to align the automatic diagnosis method with different architectures. The VGG16 architecture and MobileNet architecture is utilized here for image classification. The efficiency and feasibility of both methods is shown through quantitative and qualitative studies, where accuracy of 87.89% is obtained for VGG16 architecture and 87.49% for MobileNet architecture on the NIH Chest X-ray dataset with 1,12,120 images each labeled with 14 different pathological findings.**

Keywords—Chest X-ray Images Classification, CNN, VGG16, MobileNet, Transfer Learning.

I. INTRODUCTION

Pulmonary disorders and diseases are one of the world's leading causes of hospitalization and death. According to a study in the U.S. by American Lung Association, pulmonary cancer remains the most dangerous cancer among all types of cancer for both men and women. Over 33 million people of America are confronting an interminable lung ailment. The chest radiograph (CXR) for lung cancer, pneumonia, tuberculosis and chronic obstructive pulmonary (COPD) are among the most common and requested radiation tests. Since in developing countries the qualified and experienced radiologists, are very less in number. So, radiologists and other physicians are in the desperate need of improving "computer-aided diagnosis / detection (CADx / CADe)" tools to better decipher and interpret X-ray images [1]. The ICU requires a large range of chest X-rays to be performed and deciphered each day. Detecting the diseases requires an expert who may not be always available, which may hinder detection. Developing strategies for artificial intelligence (AI) in detecting diseases that may help to rapidly diagnose pneumothorax and other diseases to identify and potentially evaluate it [2].

Specific segmentations of the lung fields may include rich structural details, for example, shape inconsistency, size estimation, overall lung volume and the average pulmonary length, to better assess such critical clinical problems by more automated diagnostics. For instance, identification of disease symptoms, segmentation and calculation [1].

Deep learning is a computing approach that learns from a vast spectrum of data including biological knowledge, brain-induced human algorithms, and neural networks. It is the new edge for large-scale business applications and an incredible confirmation of progress in nearly every area. We consolidate this information and apply AI as a tool conveyed to take care of the issues of healthcare, having wide intricacy and trouble in taking care [3].

As Lou et.al. pointed out, deep learning requires huge datasets, representing top notch quality of annotated information. It is not therefore possible to gather clinical pictures to be gathered under similar criteria. Rather, different datasets are collected through conflicting examining, imaging, and marking standard. In this manner, utilizing an external CXR dataset experiences flawed information in two folds. To start with, the CXR representations from various datasets have domain disparity. This is attributed by various factors that influence the image distribution, for example, unique imaging conventions, conflicting pre-processing strategies, various examining scans and so on. Although data-driven methods are heavily reliant on training data that accurately correlates to the distribution of the test sample, additional data from the original distribution cannot provide the internal dataset with value. Third, numerous CXR datasets with separate marking techniques are annotated, resulting in disparity between labels [4].

In most cases, regardless of whether information is accessible, it is either unstructured or needs appropriate labelling. To address this problem, radiologists annotate on the clinical pictures which ends up being a costly and tedious procedure. Sometimes, only a tiny portion of the x-rays can be labelled feasibly when there are several other unlabelled images. For directed students, for example, a convolutional neural system, just the small labels can be used for training. In the past, the question of data scarcity has come up, especially missing samples of disease categories at training, but by utilizing the accessible examples from a typical class to train a segment network [5].

The features created by this division model are utilized alongside the entire picture in the preparing of an illness classification system. This is a method of learning the

appropriation of information in a class and exploiting it in recognizing that class from others [5].

Fortunately, analysing the X-ray image can be formulated as a task of classification that allocates a specific category of disease to one image, along with a job that allows the position of the abnormality that needs to be annotated. Thus, "Deep Convolutional Neural Network (CNN)" methods could be used to implement a system with automatic image analysis [6].

II. Literature Review

Medical image processing has immense hegemony in the domain of health-care sector and especially in non-invasive therapy diagnostic exams. For clinical treatment, the obtained rehabilitative images which are MRI, CT scans, X-rays, and ultrasonic imaging are used. CT scan is one of the filtering mechanisms in medical imaging that uses enticing fields to collect images in the form of films. One of the cancers which we can identify in X-rays is lung cancer. In earlier researches people used a normal machine learning algorithm which is an SVM classifier, and accuracies are measured. In the paper [8] Lakshmanprabu S.K and Sachi Nandan Mohanty with his fellow colleagues performed research on classifying the lung cancer using CT scan images. As part of their research, they have used Linear Discriminate analysis and ODNN (Optimal Deep Neural Networks). The feature extraction from data and dimensionality reduction have performed on the images using the LDR technique. The output of the ODNN classifier is optimized with MGSA (Modified Gravitational Search Algorithm). The final output showed that the model can predict disease from the CT scans with an accuracy of 94.56% and gives the specificity and sensitivity of 94.2% and 96.2% respectively.

Modern hospitals obtain a wide range of imaging data for diagnosis and clinical planning. These large collections of data coupled with other sources of images (e.g. clinical manuals) and provides a new possibility to utilize a huge amount of image data to generate the computerized diagnostic tools. However, image's content and meaning can differ depending on its cell type, and as such the detection of the component of the image is a significant initial step. In this paper [9] Jinman Kim and Ashnil Kumar with their team have conducted research on medical image classification by developing a new method that utilizes an ensemble of various CNN architectures which are AlexNet and GoogleNet. This method extracts the higher quality features form the images data that comprises of 6776 training and 4166 testing images. The results showed that new classification method is good at prediction with the highest accuracy of 81.03%.

Classification of medical photos effectively plays an important role in facilitating clinical care and treatment. For example, an X-ray examination is one of the best approaches to pneumonia diagnosis which causes huge people to die every year. But the diagnosis of chest X-ray pneumonia involves qualified radiologists, which is an uncommon and expensive resource for certain regions. In earlier days researchers have used the traditional machine learning method SVM for image classification and there are a couple of disadvantages with this method. In modern times Deep Neural Network plays an important role to overcome those disadvantages. In the paper [10] Samir S. Yadav and Shivajirao M. Jadhav have used the CNN method to classify pneumonia disease in chest X-ray images with data augmentation and by using the two CNN models VGG16 and InceptionV3. The results have shown that the VGG16 performs well with an accuracy of 88.1% than InceptionV3.

In the 21st century, the disease which has created a huge impact on all over the world like never before is Coronavirus (COVID-19) which is one of the respiratory viruses that can cause respiratory illness, for example, the cold to major respiratory syndromes that are MERS and SARS. Many biomedical firms are tried and trying to implement the systems to identify the disease in a person with faster results. In this paper [11] Luca Brunese with his fellow colleagues performed research to implement an automatic detection system with a faster diagnosis from chest X-rays. This research has done in three steps which are checking the presence of pneumonia, differentiate between COVID-19 and pneumonia, and finding the disease patterns in X-rays using CNN VGG16. In total 6,523 X-rays were used for the analysis and the results showed that the model can detect the disease with an accuracy of 97% within 2.5 seconds.

One of the most dangerous causes of death across the world is the Breast cancer. Early diagnosis increases the odds of successful care as well as the chances of survival dramatically, but this phase is lengthy and sometimes leads to conflict among pathologists. Computer-assisted diagnostic systems gives the potential to increase the prediction accuracy of the diagnosis. In this paper [12] Alexey Shvets with his colleagues has implemented a computational approach focused on CNN for image classification of breast cancer histology using different neural network architectures. The results have shown that the model can predict the disease with an 87.2% accuracy for classification of 4 class task and 93.8% for classification of 2 class tasks with 97.3% of AUC and specificity and sensitivity at 88% and 96.5% respectively.

Diabetic Retinopathy is a diabetes-related eye disease. It is a clear result of damage to small blood vessels and retina neurons. It may cause blood vessel swelling and leakage, blocking blood from flowing through, and can also often contribute to the formation of irregular new cells in the retina. The key cause of Diabetic Retinopathy is elevated blood sugar levels in the retina called Diabetes Mellitus for a long period of time. In the paper [13] Navoneel Chakrabarty has conducted research to detect the Diabetic Retinopathy disease

in patients automatically from the images of Retina. After a thorough analysis of the data using the CNN model the results showed that the model can predict the disease with 91.67% accuracy.

The Uterine cervix cancer is among the most common clinical cancers and is the world's leading cause of death and morbidity among women. A cancerous tumour develops when the cells in the cervix expand and replicate with abnormal growth of cells and cell destruction. Computerized Pap smear cervical screening is among the most powerful imaging-based cancer detection techniques used to categorize the normal and irregular images of the cervical cells. Traditional methods of classification rely more on hand-crafted features and present limitations in large datasets. In the paper [14] Shanthi P B and Faraz Farugi with their colleagues have conducted research on the detection of Malignancy and Uterine Cervix Cell Images classification using Convolutional Neural Network (CNN). The model classifies different categories of cancer which are carcinoma, severe, moderate, mild, and normal. The model is applied on three sets of the data and the results have shown that all three sets of images give a good prediction accuracy of 99.97% for two class classification.

In recent years, the medical image sets are also growing rapidly with the increase in computer development diagnostic and image processing tools. The advanced system of digital processing and information storage benefits even for health research and medical treatments. Several algorithms had been developed for analysing these large data sets. Deep learning methods classification is among the powerful techniques for medical image processing. In the paper [15] Chaudhary and Arjun with their team performed research on the chest X-ray images dataset to classify different diseases from the images by using the CNN architecture with three ConVol layers and ReLu activation. The results have shown that the average prediction accuracy rate of 89.77% of overall diseases.

As discussed above most researchers have used different architectures for image classification. In this project analysis, we have used the VGG16 and MobileNet architectures for classifying the diseases from the images.

III. METHODOLOGY

The methodology used to implement the framework is the CRISP-DM Process Model. The phases of this model are discussed below:

Fig-1: CRISP_DM Methodology

A. Business Understanding

The development of this framework with good accuracy can be deployed in hospitals and health centers for quick identification of diseases. This will not only help to predict accurate results but also help reduce the work of a radiologist [7].

B. Data Understanding

The evaluation of the framework for detection of thoracic diseases on a Chest X-ray dataset available on Kaggle, contains 112,120 images but due to the short comings Google Collab only 90000 images have been considered for the analyzation. The abnormalities include pneumothorax, mass, cardiothoracic, infiltrate, pneumonia, nodule, pulmonary atelectasis, edema, fibrosis, hernia, emphysema pleural thickening and effusion.

C. Data Preparation

Class Imbalance: Classifying the images effectively with imbalanced data is highly important in few areas like finance, medical, etc. Moreover, highly imbalanced data will bias the learners after obtained results from deep learning techniques.

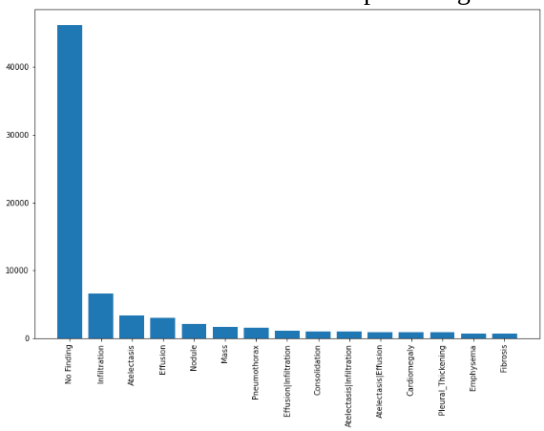


Fig-2: Before preprocessing data distribution of classes

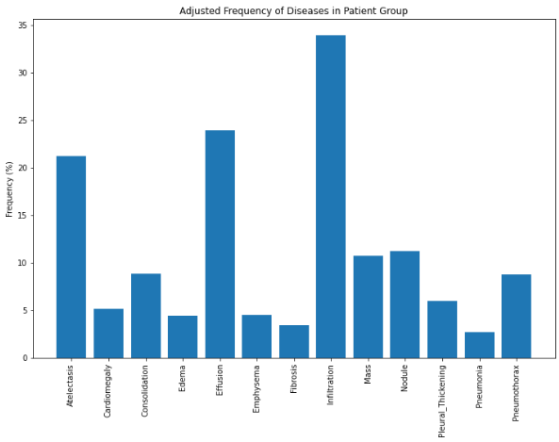


Fig-3: After preprocessing data distribution classes

From the datasets we have observed the class imbalance which will affect our classification of images. Also, with class imbalance it will increases the loss function that leads to reduce the accuracy of classification. Fig 1 shows that images which labeled for the different disease, from the fig 1 we found that “No Findings” has major number images and it will significantly affect our model and it may cause bias

result. After preprocessing of the data, we had eliminated "No Findings" from data that we can see in the above figure (fig 2).

Normalization: Normalization is rescaling pixel values in the range of 0-255 to 0 to 1. This process changes the intensity value of each pixel. This can be done by a ratio configuration of the rescale statement by multiplying each pixel for the desired amount. After running the dataset first reports the minimum and maximum pixel values is from the range of 0-255. Next, the iterator is prepared and a data generator. The next step is to build the data generator and to establish iterators. The train dataset includes 100 batches per epoch and 32 images in a batch. The first batch is taken from the data collection to validate that it comprises 32 images of 256 pixels and 1 channel in width and height, and that the current limit value is 0 and 9, respectively. It demonstrates the positive result of normalization.

One hot encoding: One hot encoding is performed on the disease's column, where 14 diseases are converted into 14 different columns with binary variables. This process of converting categorical data allows a state machine to compute at a faster rate.

D. Exploratory Data Analysis:

Exploratory data analysis is the critical part for the any data analysis which will help to identify relation between variables and insight of dataset. By visualizing dataset will help in critical decisions and business understanding.

a. Patient Gender:

Below chart represents the number patients according to the gender. From fig 3 it clearly shows that male patients are a greater number of counts compare to female patients. Approximately 48000 and 38000 male and female patients, respectively.

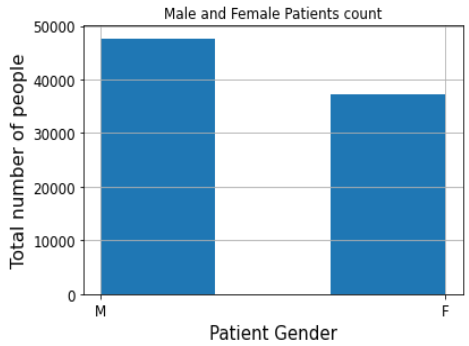


Fig-4: Patients count by gender

b. Patient Age:

Patient age is another important factor while treating diseases. By visualizing the patient age will help doctors to act very quickly according to the patient age. After plotting patient age with respect to the gender which shows in fig 4. Approximately majority of patients are belonging to age group between 30 to 70 both in male and female.

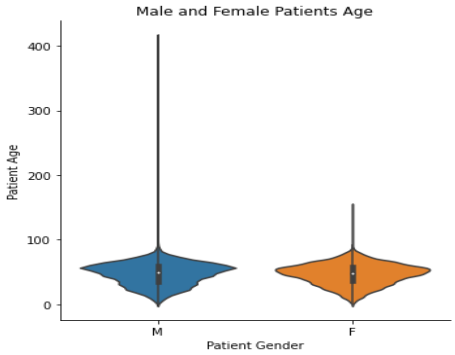


Fig-5: Patients age by gender

c. Percentage of patients with diseases:

Fig 5 represents the pie chart of different diseases with respective percentage. Highest percentage (25.02%) of patients belongs to infiltration and least percentage (0.33%) of patients belongs to hernia. This initial overview about diseases and percentage will helpful into look after patients to assist them with respective diseases.

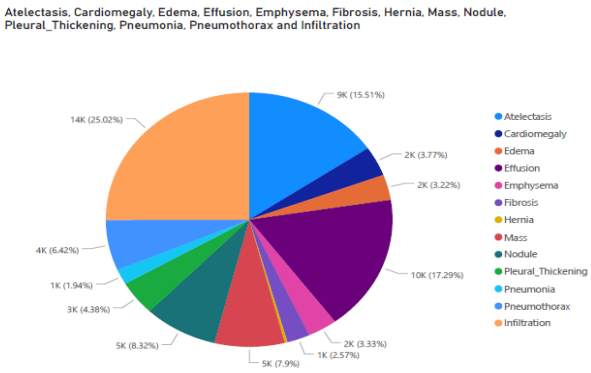


Fig-6: Total percentage of different diseases

D. Modelling

This phase is about implementing the deep convolution neural network. In this project analysis, two architectures are implemented to find out better prediction accuracy.

Activation Fucntion, Loss Function and Optimizer:

These functions are mainly representing in the form of mathematical equations which evaluate the neural network output. This function is tied to every neuron of the neural network to identify whether the network activated or not based on the neuron input, is it necessary for model prediction. For our analysis we used two non-linear activation functions named sigmoid and ReLU.

a) ***Sigmoid activation function:*** It is a type of non-linear activation function specially this used for make the prediction of probabilities since it limit the output to a range between 0 and 1. Sigmoid activation used to test the artificial neural networks [23]. This function determines the output from input and this output from node or neuron is used as input of next neuron until to get the final solution.

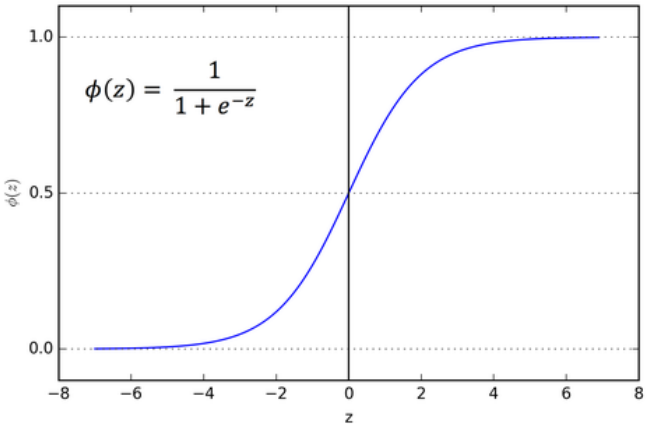


Fig-7: Sigmoid activation function

b) ***ReLU activation function:*** The full form of ReLu is rectified linear unit and activation function in mathematical term and graph are as shown below.

$$y = max\ (0, x)$$

ReLU is easy to compare since it all positive values are linear and negative values are zero. On the other hand, there is no complicated math involved, it is easy to compute the values. Because of this function it takes lesser time to train than to run the model [22].

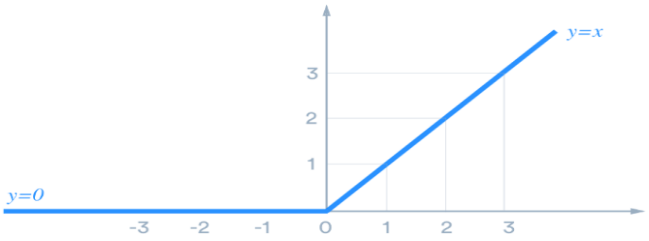


Fig-8: The ReLu activation function

Loss Function:

c) ***Binary crossentropy function:*** The loss function gives an answer in binary which are two choices (yes or no, 0 or 1). Below fig represents the simple understanding of Binary crossentropy function implementation in deep learning.

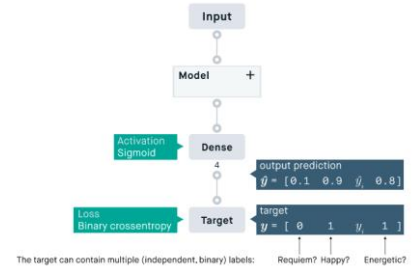


Fig-9: Binary Crossentropy loss in deep learning

Binary cross entropy loss function calculates the loss of the samples by following math formula [24]:

$$\text{Loss} = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i)$$

Where,

1. y^i is i-th scalar value in model output.
2. The target value is yi.
3. The number of scalar values is the output size in the model output.
4. This loss function is applied to every induvial classification problem with having a two possible output with probability of yi and (1−yi).
5. Sigmoid activation is only activation function compatible with Binary cross entropy loss with which we are using in project.

d) ***Mean squared error (MSE):*** The frequently used loss function in regression is MSE. It detect the average squared difference between the true and predicted values. The mathematical formula for this loss function defines below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where $\hat{y}$ is the predicted value and y is the true value

In this project we used MSE in ReLU activation function to determine the loss in the model.

Optimizer:

To change the attributes in neural network like weights and learning rate to minimize the losses optimizer algorithms are used.

Adam Optimizer: This method is applied on different parameters for each learning rate, depends on the estimates of first gradient and second gradient moments [20]. Adam as one more advantage such it is designed with combination of Adagrad which functions with the combination of sparse gradients and RMSprop, this also significantly works in online settings. As the advantage of all this combinations adam is used for wide range of takes [21].

F. Architecture:

Deep convolution neural network (CNN) has been the most significant achievement in the field of computer vision. It is also successful in image classification, sematic image segmentation, and target detection etc. [16]. CNN is typically consisting of the first layer as convolutional, followed by the pooling layers, and fully connected layers [17]. A simple architecture of CNN shown in fig 9.

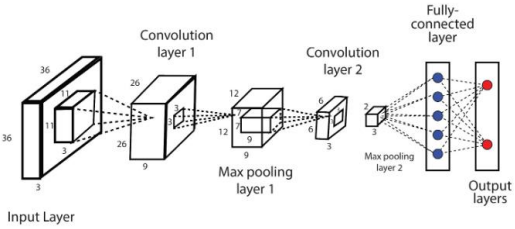


Fig-10: CNN Architecture

1) MobileNet Architecture: MobileNet architecture is the simplified architecture which uses depth wise separable convolution to build the lightweight deep CNN an effective

model for embedded vision and mobile applications [16]. MobileNet basically constructed with depth wise separable filters which is consists of point and depth wise convolution filters. This Depth wise filter carryout one convolution layer on every input channel whereas point convolution filter combines the depth wise convolution linearly with 1*1 convolution [16]. The architecture shown in the below figure (fig 10). The layers of VGG 16 has shown in fig 12.

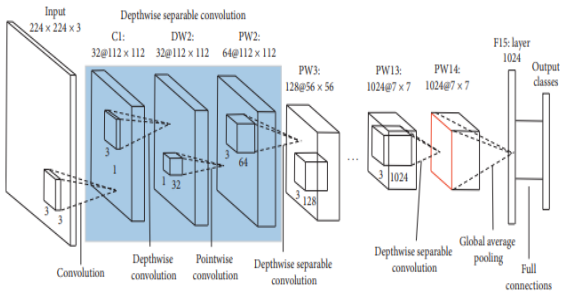


Fig-11: CNN Architecture

2) VGG16 Architecture: In this paper [18], VGG16 has been modified for very deep network and it is used to fit the small datasets. Specially made this change to make work of very deep model of small datasets. Kaur and Gandhi in their paper [19] used VGG16 for brain image classification. The special character of VGG 16 is it is capable of classifying images into 1000 classes. Specially in VGG16 last three layers are configured for these 1000 class. Figure 11 represents the architecture of the VGG 16.

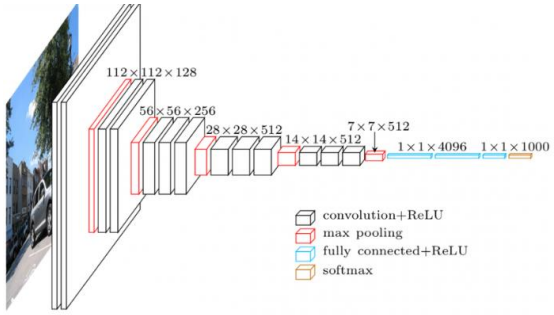


Fig-12: VGG16 Architecture

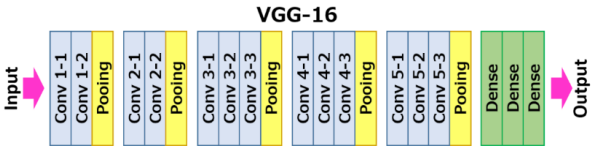


Fig-13: VGG16 Layers

IV. Evaluation

After removing the unwanted data which are NoFinding label images as shown in the data imbalance section the total data set is divided into 3 sets which are training set with 30982 images, test, and validation sets with 7740 images. The evaluation metrics of this project are performed using different parameters as discussed below.

Binary Crossentropy and ADAM (optimizer):

There are different loss functions that can be applied to compile the model are as follows Hinge, Huber, MSE(L2), Binary Crossentropy, and Categorical Crossentropy. For this project analysis, we have used binary crossentropy as a loss function to measure the performance of the model. The performance of the model is measured using loss, accuracy, and MAE. On the other hand, the weights of the model are updated on an iterative base while training the data by using the ADAM optimizer method despite the traditional stochastic gradient descent optimization algorithm. Below are the results of CNN architectures.

A. *MobileNet Architecture:*

The MobileNet architecture has developed with different layers in the following order: convolutional layer, average pooling, dropout, dense, and flatten layer. The final dense layer consists of 13 classification outputs. These output units will predict the disease pattern of one of the 13 diseases. This architecture has developed as a sequential model with a 'sigmoid' activation function and the summary of the model is as shown below.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
mobilenet_1.00_256 (Model)   (None, 8, 8, 1024)        3228864
_________________________________________________________________
global_average_pooling2d_1 ( (None, 1024)              0
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 13)                6669
=================================================================
Total params: 3,760,333
Trainable params: 3,738,445
Non-trainable params: 21,888
_________________________________________________________________
```

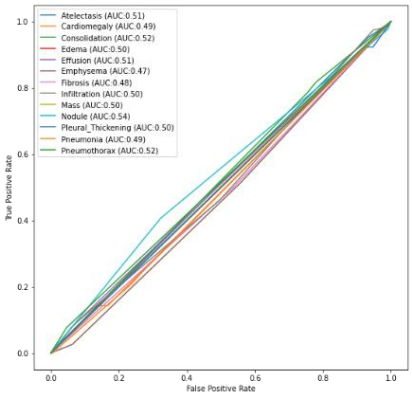
Screenshot-1: MobileNet Model

The model compilation is performed using the optimizer 'adam' and with loss function 'binary crossentropy'. On the other hand, the model is trained using training images with 5 epochs and a batch size of 32. The results have shown that there is no improvement in the val_loss after four epochs and the overfitting problem is controlled by using the early stopping method. The overall average training accuracy of the model is 87.45% with val_loss and val_mae of 0.33838 and 0.1378, respectively. Below is the training output.

```
Epoch 1/5
100/100 [==============================] - 1013s 10s/step - loss: 0.4189 - binary_accuracy: 0.8527 - mae: 0.2045 - val_loss: 0.3384 - va

Epoch 00001: val_loss improved from inf to 0.33838, saving model to xray_class_weights.best.hdf5
Epoch 2/5
100/100 [==============================] - 1023s 10s/step - loss: 0.3472 - binary_accuracy: 0.8711 - mae: 0.1979 - val_loss: 0.4167 - va

Epoch 00002: val_loss did not improve from 0.33838
Epoch 3/5
100/100 [==============================] - 1157s 12s/step - loss: 0.3410 - binary_accuracy: 0.8730 - mae: 0.1962 - val_loss: 0.4524 - va

Epoch 00003: val_loss did not improve from 0.33838
Epoch 4/5
100/100 [==============================] - 1119s 11s/step - loss: 0.3357 - binary_accuracy: 0.8745 - mae: 0.1955 - val_loss: 0.4631 - va

Epoch 00004: val_loss did not improve from 0.33838
<keras.callbacks.callbacks.History at 0x7f1f851cf860>
```

Screenshot-2: Training output

The ROC curve has generated with the final prediction output and test data and the AUC rate of each disease is as shown below.



Graph-1: ROC Curve

In the graph above, we could see the AUC rate of some diseases are above 50 percent and some diseases are below 50 percent. Finally, the model is used on all the test images to predict the percentage of the disease consists of the X-ray images. Below are the prediction output images.

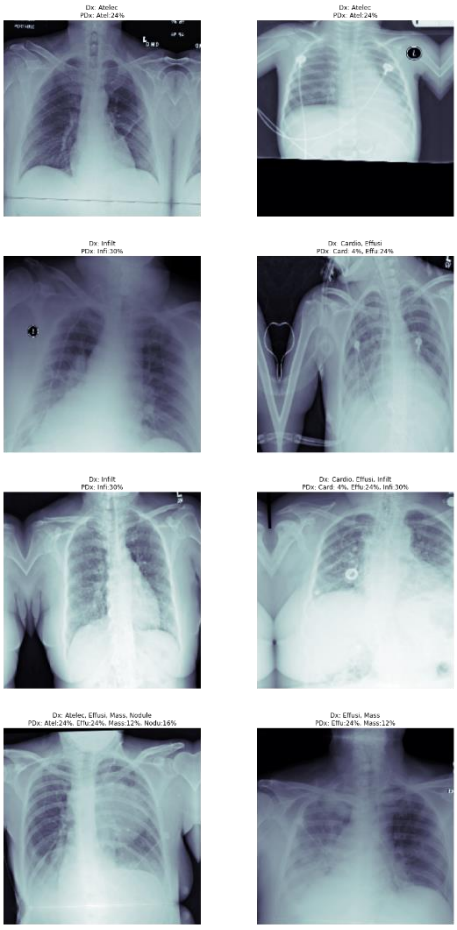


Fig-14: MobileNet model prediction output

B. VGG16 Architecture:

Firstly, the VGG16 architecture consists of 22 layers for this project analysis which are as follows: 13 Conv2D layers followed by 5 Max Pooling layers, flatten, 3 dense layers, and final SoftMax as an output layer. The kernel size of all the layer filters is 3*3 and the output shape of the first Conv2D is 256*256*64. We could see in the below screenshot that the size of the filters is gradually reducing from the topmost layer to the final layer. In the final SoftMax layer, the kernel size is given with 13 to classify different diseases. The ReLu is the activation function is used for VGG16 architecture.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 256, 256, 64)	1792
conv2d_2 (Conv2D)	(None, 256, 256, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 128, 128, 64)	0
conv2d_3 (Conv2D)	(None, 128, 128, 128)	73856
conv2d_4 (Conv2D)	(None, 128, 128, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 64, 64, 128)	0
conv2d_5 (Conv2D)	(None, 64, 64, 256)	295168
conv2d_6 (Conv2D)	(None, 64, 64, 256)	590080
conv2d_7 (Conv2D)	(None, 64, 64, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 32, 32, 256)	0
conv2d_8 (Conv2D)	(None, 32, 32, 512)	1180160
conv2d_9 (Conv2D)	(None, 32, 32, 512)	2359808

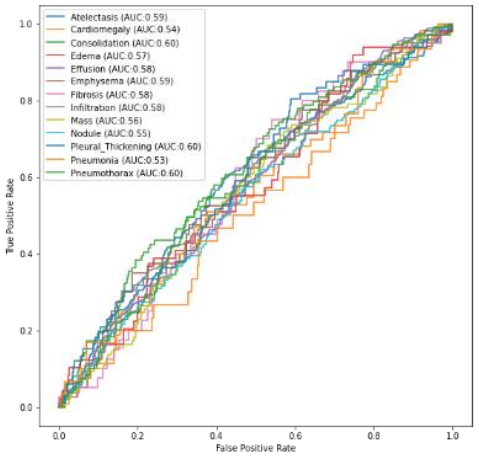
Screenshot-3: VGG16 Model

Secondly, the compilation of the model is performed by using the 'adam' optimizer and with the loss function 'binary crossentropy'. Then the model is trained using training images and with 3 epochs. The results have shown that the training accuracy rate of the overall model is 87.89% with val_loss and val_mae of 0.3416 and 0.1675, respectively. Below is the training output screenshot.

```
2922s 29s/step - loss: 0.3545 - binary_accuracy: 0.8751 - mae: 0.1704 - val_loss: 0.3448 - val_binary_accuracy: 0.8777 - val_mae: 0.1672
0.34477, saving model to sray_class_vggweights.h5
2889s 29s/step - loss: 0.3428 - binary_accuracy: 0.8789 - mae: 0.1663 - val_loss: 0.3428 - val_binary_accuracy: 0.8777 - val_mae: 0.1674
 to 0.34282, saving model to sray_class_vggweights.h5
2893s 29s/step - loss: 0.3461 - binary_accuracy: 0.8769 - mae: 0.1683 - val_loss: 0.3415 - val_binary_accuracy: 0.8777 - val_mae: 0.1675
 to 0.34146, saving model to sray_class_vggweights.h5
```

Screenshot-4: Training output

After training the model, the prediction percentage and AUC rate of the individual disease is generated by comparing the model output with the test images. Below are the ROC graph and prediction output images.



Graph-2: ROC Curve

In the graph above, we could see that the percentage of all individual diseases are more than 50%. This means that the overall model is performing well in predicting the disease pattern with the help of X-ray images. The model output images are shown below.

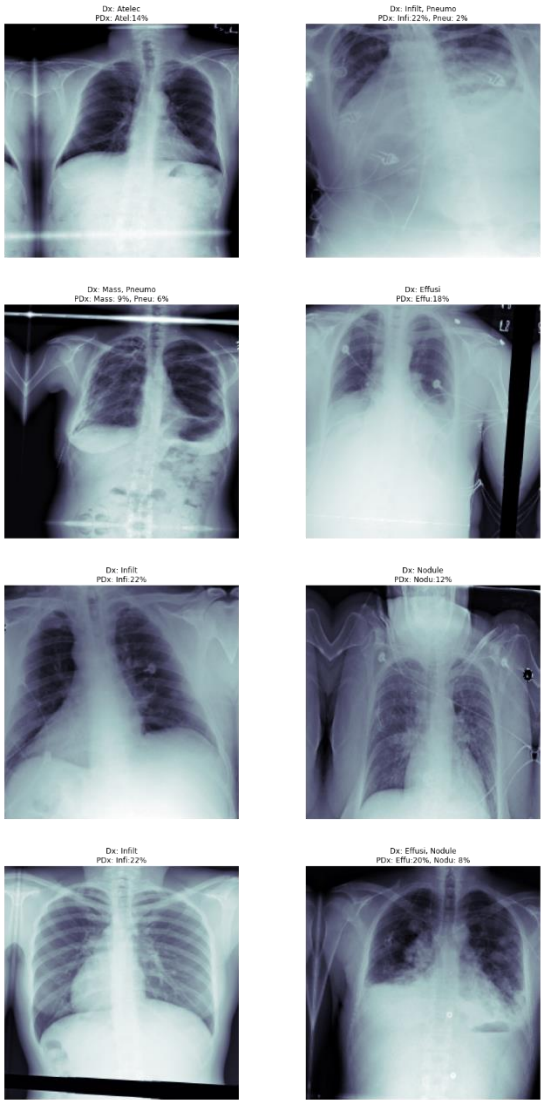


Fig-15: VGG16 model prediction output

Deployment: Deployment is focusing on the obtained results and the knowledge known. This knowledge should be of help where needed [7].

V. Conclusion And Future Work

Chest disease detection in X-Ray being one of the most important scientific problems of the last decades. To fix this problem, various traditional machine learning algorithms, pattern analysis, and the feature engineering methods are implemented. Yet in practical ways, most of the methods have struggled to produce successful performance. In this paper, the evaluation of the project is done by comparing two CNN architectures MobileNet and VGG16 performance and prediction accuracy percentages. These parameters are made for the best of our ability to allow a contrast in the context of the accuracy. Results of the analysis showed that VGG16 performs well over MobileNet with a good prediction accuracy rate of 87.89% and the VGG16 model can classify the disease based on the image patterns. Along with this, to decrease the loss and the model overfitting problem we have used early stopping technique and performs well on the two architectures. The future work involves the use of other CNN architectures like GoogLeNet and AlexNet by taking a large amount of images dataset to increase the prediction accuracy of the CNN.

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