Anomaly identification in chest radiography

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

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Anomaly identification in chest Radiography

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Abstract: COVID-19 is a recently identified coronavirus that causes mild to moderate respiratory sickness in many people. However, the new disease has a significant impact on the elderly and those with underlying health problems. To understand the process of evolution of the model, several outcomes from studies on the issue were studied. Computer vision can perform tasks like object recognition and picture classification, which may be used to classify and identify lung images. The goal of this study is to employ deep learning techniques to categorise and detect COVID-19-affected medical lung pictures. This work suggests using deep learning methods such as VGG-16 and ResNet-50 in identifying and classifying the anomalies present in medical lung images. Various classes of data were modelled from binary classification with anomaly dataset, three label classification and four label classification. Models trained on balanced class of anomaly dataset yielded highest result on common test data, VGG-16 model had an accuracy of 81% with recall value of 91%, ResNet-50 had an accuracy of 86% with recall of 81 for covid cases.

1 Introduction:

Coronaviruses are an RNA virus family that infects both mammals and birds. In people and birds, they cause lung infections that can be minor or fatal. Some cases of the common cold (which can be infected by a variety of viruses, primarily rhinoviruses) are mild, whereas others are more deadly strains that cause SARS, MERS, and COVID-19 in humans. The COVID-19 virus can induce pneumonia in both lungs, producing fluid buildup and inflammation, as well as breathing difficulties. Shortness of breath, cough, and other persistent symptoms are caused by fluid collecting in the lungs' air sacs, which reduces the ability of the lungs to take in oxygen, resulting in shortness of breath, cough, and other symptoms. A chest CT scan can be used to diagnose, detect, and predict coronary artery disease (COVID-19). Computer vision is a branch of artificial intelligence (AI) that enables computers and systems to extract valuable information from digital photos, videos, and other visual inputs, such as photographs, movies, and other visual inputs.

To identify one image from another, machine learning algorithms such as Convolution Neural Networks (ConvNet/CNN) take an image as input and assign weights and biases to aspects of the image. These algorithms are based on the structure of the human brain's visual cortex and can help detect problems in covid patients' respiratory systems. To undertake data processing and finally recognize images, computer vision requires a large amount of data. Convolution Neural Networks help a machine learning or deep learning model "perceive" by reducing images down to pixels and assigning tags or labels to them. It uses the labels to do convolutions to make predictions about what it's "seeing." To put a stop to something. The neural network conducts convolutions and checks the accuracy of its predictions over a series of iterations. In the beginning, a Convolution Neural Network recognizes hard edges. A Convolution Neural Network recognizes hard edges and fundamental forms first, then fills in the gaps as it iteratively makes predictions to interpret single images. Hospitals all throughout the world are working to treat those who have been affected by the epidemic or other causes. Computer vision can assist caregivers in recognizing and signaling sickness by examining chest radiography or a large amount of data, allowing them to make better informed judgments. The high accuracy achieved by models on Covid data is concerning because the outcome may be influenced by overfitting and can be validated using additional data.

The research question is to see how effective and reliable deep learning system are at detecting anomalies in chest radiography of covid patients. The goal of this proposal is to explore and examine the employment of a machine learning model that best differentiates scan types, as well as evaluate criteria. Anomalies can be seen in COVID-19 infected images caused by pneumonia or lung injury, and these anomalies can be identified and diagnosed with a high degree of accuracy using various machine learning methods. The application of a machine learning model to radiography data would aid clinicians in more efficiently evaluating radiography. Combining computer-assisted diagnosis with radiologist diagnostics systems reduces doctors' effort, improving the accuracy and quantitative analysis of results(saha p ,et al,2020).

2 Research question:

"How efficient and reliable are deep learning algorithm as VGG-16 and ResNet -50 in identification of chest radiography affected by covid?"

Sub question: *"How does data categorization of lung images impact the results in covid classification?"*

The goal of this study is to assess the efficiency of transfer learning algorithm in assessing the identification of lung impacted by covid and how the model behaves with different mode(class) of data as input.

3 Literature review

The author presented two methods for lung disease diagnosis: a deep neural network (DNN) based on the fractal characteristic of images and a convolutional neural network (CNN) methodology that directly uses lung images. According to the results categorization, the given CNN architecture surpasses the DNN technique with an accuracy of 83.4 percent and a sensitivity of 96.1 percent. According to the study, the offered technique can almost detect hazardous zones with a high accuracy of 83.84 percent (Hassantabar et al , 2020).

ASNetLarge claimed the highest score in COVID-19 sample classification when compared to other models. The author also suggests that binary classification (COVID-19 and non COVID-19) is better than multi class classification (COVID-19 vs other classes), implying that grouping other diseases together as non-COVID-19 samples allows models to learn COVID-19 features and patterns more efficiently (Punn N.s,Agarwal s,2021).

A VGG16-based CNN model was trained with ImageNet and fine-tuned with chest X-ray data in this work. A histogram equalisation approach and a bilateral filter are used to generate two sets of filtered pictures from the source photographs. This work use the transfer learning approach to create a novel model for identifying and categorising COVID-19-infected pneumonia. The CNN model correctly identified three subgroups of patients with 94.5 percent accuracy and correctly identified COVID-19 infected pneumonia cases with 98.1 percent accuracy (Heidari M et al , 2020).

Model ResNet50V2 achieved 98.49 percent accuracy on more than 7996 test pictures in a single image classification step, using a dataset of CT scan pictures from 282 healthy people and 95 COVID-19 patients. The system first runs an image processing algorithm, evaluating the view of the lung and discarding CT pictures of the lung that are not clearly visible, reducing processing time and false detections. About 234 of the 245 cases were correctly identified by the algorithm. (Rahimzadeh, M et al,2021).

To identify and detect infection caused by Covid-19, chest X-ray images were collected from three different open sources, and a deep learning architecture CNN model was used for prediction. The author proposes that CNN based method showed high performance in COVID-19 detection, but that CNN decision should not be taken into account until clinical tests confirm the findings(Ahmed Z et, al,2021).

Multiple pretrained convolutional neural network-based models (ResNet50,ResNet101,ResNet152,inceptionV3 and inception resNetV2) were used in the detection of coronavirus pneumonia infected patients using chest radiographs. Three different binary classifications with four classes (COVID-19,normal,viral pneumonia, and bacterial pneumonia) were used, along with five fold cross-validation, and the ResNet50 model provided the highest classification performance of 96 percent The author also suggests that multi-class classification produces better results(Narin A et ,al ,2021).

The model is trained using 330 chest X-ray images separated into two classes: 'COVID-19' and 'Normal.' The proposed model was trained for 25 epochs with 10 steps each epoch, model was trained with batch size of 32, to avoid over fitting of model the author employed data augmentation which includes random cropping and random horizontal flipping (Faysal Haque et ,al,2020).

Deep learning based model CNN known as NCOVnet with 24 layers composed of convolutional,ReLU, and max pooling layers, was used in detecting COVID patients with limited amount of data they were able to achieve 97 percent true positive rate, author proposes use of more sample data to train data to get higher accuracy, layer in this model were part of pre trained VGG16 model The VGG16 model has been trained on over 20,000 distinct categories(Panwar H et al,2020).

The ResNet50 and ResNet101 models were used in two stages to classify lung X-ray pictures of pneumonia, viral caused cases, and normal healthy cases. The trained ResNet50 model had a 95% accuracy, while the Deep ResNet101 model had a 97% accuracy. The author recommends using the ResNet101 network to produce a solid classification report. A dataset of 1200 photos was increased to 1800 images to improve adaptability and minimise model overfitting. The author also offers a greater number of COVID-19 scans from other databases, and the work may be enlarged(Jain G et al,2020).

A dataset was created with three classes of COVID-19, normal, and pneumonia lung X-ray images, each with 364 images. An image contrast enhancement algorithm was used for preprocessing, and deep learning models such as AlexNet, VGG19, GoogleNet, and ResNet were used to extract features from this data set. Two meta heuristics techniques, binary swarm optimization and binary grey wolf optimization, were used, and the combined features were categorised using a Support vector machine with a 99 percent accuracy(Canayaz M ,2020).

H.Moujaid et al.(2020) offer VGG16 as an efficient model for classifying photos with an accuracy of 96 percent and a precision of 91 percent on a dataset of 1583 healthy and 4273 pneumonia images. The author also suggests maximizing 0- a4dataset by merging different datasets for greater accuracy. The InceptionResNetV2 model was 94% accurate.

Using deep learning-based approaches, COVID-19 and normal (healthy) chest X-ray pictures were classified using deep feature extraction, fine-tuning of pretrained convolutional neural networks (CNN), and end-to-end training of a constructed CNN model. Support Vector

Machines (SVM) classifiers were used along with various kernel methods for deep feature classification. The dataset contained 180 COVID-19 and 200 normal X-ray images, and a classification accuracy of 94.7 percent was achieved using deep feature extracted from ResNet50 model and SVM classifier with linear kernel function, which was the highest among all other models author experimented upon(Ismael, A.M., Şengür, A., 2021).

Lung segmentation and image classification of COIVD-19 infected and normal chest ct imaging (ct) images were performed using two different models, both of which contained AlexNet architecture, 8 layer deep, useful for image classification, and another model was a hybrid structure containing Bidirectional Long Short-Term Memories (BiLSTM) layer, the first architecture had an accuracy of 98.14 percent and the second hybrid architecture had an accuracy of 98.70 percent, dataset contained Due to the limited sample size, image augmentation was used on the infected dataset. The author states that because the proposed study performs image segmentation automatically, it contributes to high accuracy, CNN was used for feature extraction, and BILSTM is used for classification. The author also points out the disadvantage of learning studies, stating that the ability to generalize is dependent on the size of the train data, and recommends the use of larger datasets(Aslan M et al ,2021).

The author proposes three stages of detection to increase model accuracy: data augmentation, COVID-19 detection using a pre-trained CNN-based model, and abnormality localization in CT images. ResNet18, ResNet50, ResNet101, and squeeze net were among the pre-trained designs studied. Data augmentation was conducted because to the restricted amount of photos. The data collection included around 300 COVID-19 infected individuals and 300 non-infected individuals. The dataset was separated into 70% train and 30% test sets, and the model was trained. The ResNet18 transfer learning model had a higher accuracy of 99.82 percent on train and 99.4 percent on test, with a validation score of 97.32 percent. The author also presents a CNN model based on transfer learning that works well with less data and has a quicker learning process(Aahuja S et al ,2020).

Deep transfer learning (DTL) technique was used to build COVID 19 infected images, 10 fold cross validation technique was used to prevent overfitting, which is a procedure to evaluate model performance, dataset was divided into 6:4 ratio, classification model achieved train and test accuracy of 96 percent and 93 percent respectively, author also points out optimal selection of hyper parameter were not considered and proposes the use of genetic algorithm, non-discriminant analysis The top-2 smooth loss function with cost-sensitive characteristics dealt with noisy and unbalanced datasets(Pathak Y et al,2020).

Several deep learning-based feature extraction techniques, such as DenseNEt, Xceptionnet, Resnet, Incpetion V3, Mobile net, and others, were used in the proposed study. Extracted characteristics were input into machine learning classifiers to categorise people into COVID-19 or normal classes. The suggested model DenseNet 121 with bagging classifier had a 99 percent accuracy, while the hybrid ResNet50 with LightGBM had a 98 percent accuracy. The author also mentions the limitation of the proposed study's data size and suggests the use of extra data in Figure 2.2, which compares the accuracy of several models. Densely linked convolutional network (DenseNet) is a Resnet architecture variant. Residual blocks are a concept in ResNet design that involves connecting the input of the first block to the output of the following block in order to train a deeper recognition network(Kassania S,H et al,2020).

After evaluating 17 different pre-trained neural networks, the author determined that Darknet-19 was the best deep learning neural network for detecting COVID-19 pneumonia on chest radiographs. The author used an open source dataset that included 85 COVID-19, 2772 bacterial, 1493 viral pneumonias, and 1,576 images of healthy subjects. All 17 pre-trained networks have the same learning rate of.0001, validation frequency of 5, epochs value of 8, and batch size of 64. Resnet50 and Darknet-19 were two models that were evaluated in terms of model fitting and performance. The Darknet model had a better fit and greater accuracy of 96 percent than the ResNet50 model. Darknet is an open source framework for detecting objects in real time (Elgendi M ,et al,2020).

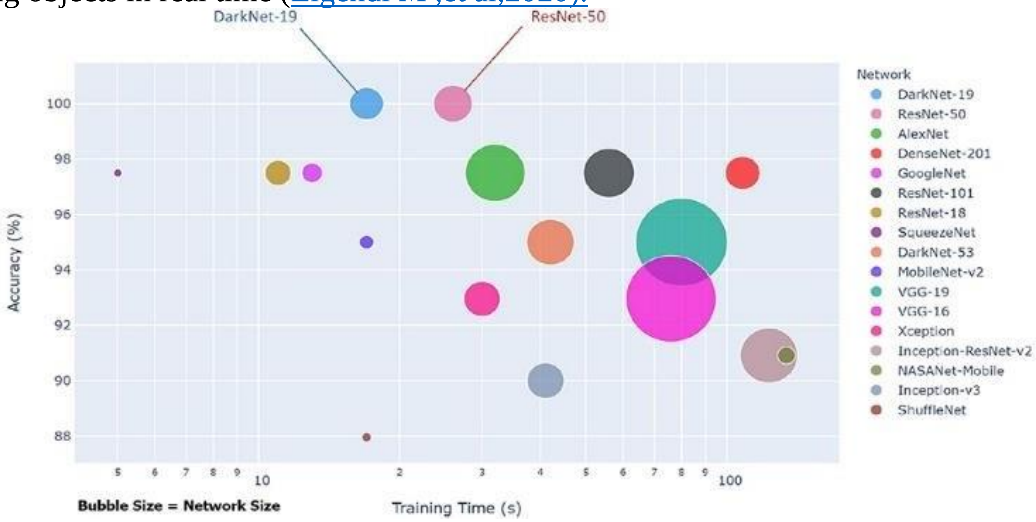

Fig.1. Overall performance of 17 pre trained neural networks for Covid_19 detection source:(Elgendi M ,et al,2020)

The goal of this paper is to employ several deep learning approaches to distinguish between COVID-19 and non-COVID 19 CT scan pictures. For the COVID-19 diagnostic, a self-developed model called CTnet-10 was created, with an accuracy of 82.1 percent. DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19 are some of the other models we tested. In comparison to all other deep learning models, the VGG-19 showed to be superior, with an accuracy of 94.52 percent. Using 592 labelled images and 74 validation images, the CTnet-10 model network was created using supervised learning. The CTnet-10 model had an accuracy of 82.1 percent. The pre-trained VGG16 network was put to the test with 73 pictures, yielding an accuracy of 89 percent between COVID-19 infected and non-infected CT scans. We may get an accuracy of up to 93.15 percent via picture augmentation and fine-tuning. We got 53.4 percent accuracy with the Inception V3 model. The ResNet model, which did not include a top layer, was then employed. Sixty percent accuracy was achieved(shah v et al, 2021).

A total of 1000 photos were picked, with 500 being conventional pneumonia X-rays and the remaining 500 being COVID infected X-rays. These pictures were utilized to train the DenseNet-161 Network, using an 80:20 training/testing ratio. We discovered that we can distinguish pneumonia from COVID-infected chest X-rays with 99 percent accuracy. To verify the findings, researchers used supervised learning to train the VGG-16 network with 970 tagged pictures. The pre-trained VGG-16 network was put to the test with 270 pictures, yielding a 98 percent accuracy between pneumonia infected, TB infected, and non-infected X-rays, VGG-16 was the deep learning model used to classify pneumonia, tuberculosis, and normal, and it had a 95.9% accuracy rate. Author also points out to limitation as the number of labelled data points that could be obtained, As a result, the dataset size and number of data points utilized were reduced. There is a risk of overfitting as a result of this. If the dataset size is raised, better results can be produced (Shelke A ,et al.2021)

Images of pneumonia from the National Institutes of Health and the Kaggle library were utilized. VGG-19 and ResNet-50 were compared to fine-tuned CNN models that were built from scratch on chest X-ray pictures, The first set of tests used VGG-19 and ResNet-50, pretrained models, to distinguish pneumonia pictures from normal chest X-ray images acquired at high resolution from the anterior to posterior (AP/PA). ResNet-50 was chosen above ResNet-101 to compensate for the low resources available to author. The picture was shrunk to smaller sizes using normal techniques before being fed into the convolutional neural network for classification.VGG-19 gave an accuracy of 97.3 and ResNet-50 gaev an accuracy of 97.3(Murali s, et al,2021)

4 Research Methodology:

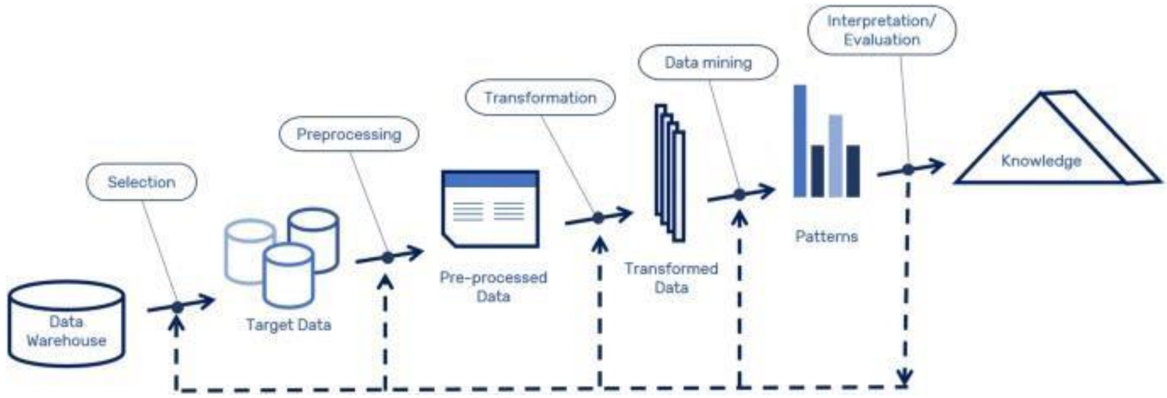

Fig.2. KDD-DM life cycle(source-net)

Knowledge discover in databases methodology has been employed in this research, the process involves storing of data, preprocessing and transformation, applying data mining model to transformed data and interpretation of result, at any given step process findings can be improved by moving into previous steps. Figure 2. defines the pictorial representation of the process.

4.1 Ethics:

Datasets are open to the public and can be used for non-profit purposes. All photographs and reports are anonymized, making it difficult to deduce personal information about any patient from them.

4.2 Dataset:

The objective of this research is categorize lung images infected by covid and also to determine and understand the best way of training model, for this purpose the dataset was collected from Kaggle repository, dataset was amalgamated form different sources (Rahman T et al, 2020), dataset consist of 3616 COVID-19 positive instances , as well as 10,192 Normal, 6012 Lung Opacity (Non-COVID lung infection), and 1345 Viral Pneumonia images. Fig .3 represents a pictorial representation of data used for modelling.
Link: www.kaggle.com/tawsifurrahman/covid19-radiography-database/code

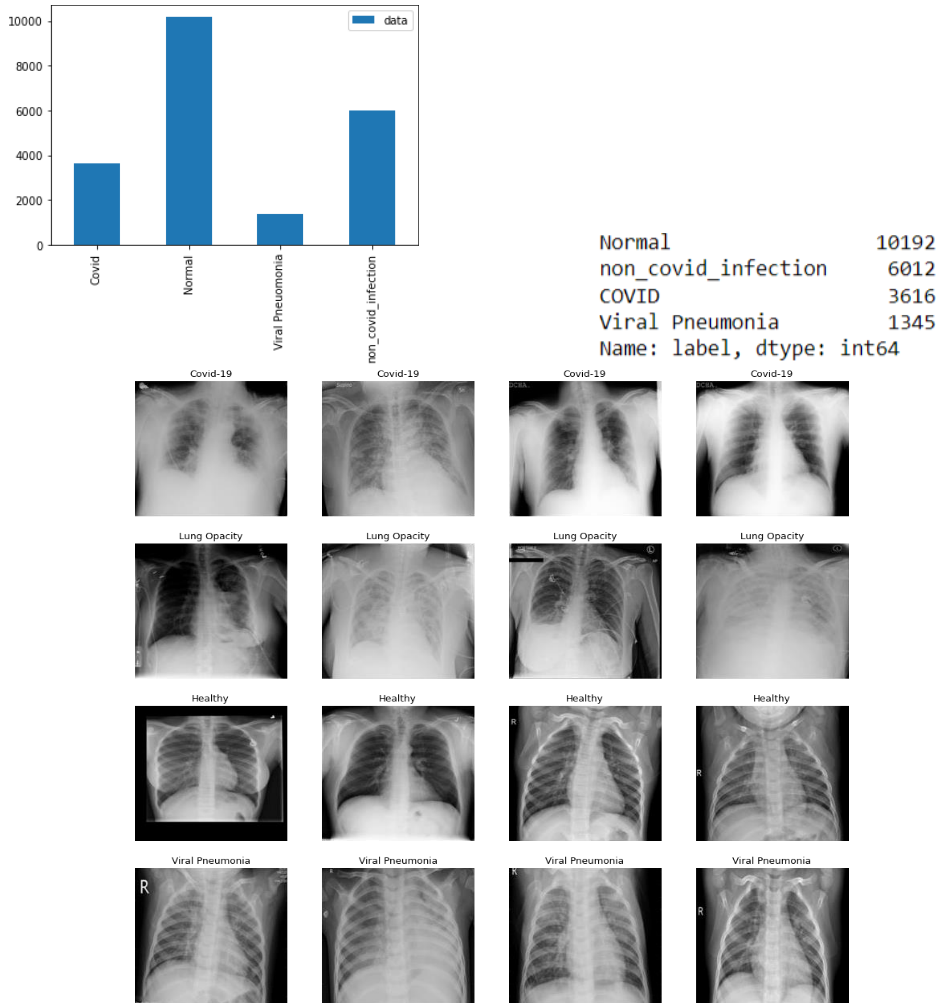

Fig 3. data description and data count along with labels

4.3 Data preparation

Data has been preprocessed according to model requirement and to acquire reasonable accuracy of model, images have been set to pixel size of 299 * 299, color mode as "rgb" with batch size of 64 has been maintained for all data labels, train dataset of size .9 (90 %) has been utilized for training and validation, and test size of .10(10%) has been utilized for various classification. Additionally, a second common test data of around 723 covid images have been utilized to assess the different models ability to classify the lung images infected with Covid-19.

5 Implementation specification

The original data consist of around 20,000 images made of 4 different classes, the research project aimed to find best way of categorizing the images infected by covid, for the purpose the model was utilized in four different ways by categorizations.

Case 1: In this scenario the transfer learning algorithm such as VGG-16 and ResNet-50 were utilized to differentiate four classes namely Covid, Pneumonia, Non-covid infection (lung opacity) and Normal healthy lung images.

Case 2: In this experiment transfer learning algorithms were applied to classify three classes Covid, Pneumonia and normal. Dataset utilized to train model consist of Covid, pneumonia and normal.

Case 3: For this experiment, Anomaly dataset was created to train transfer learning algorithms, Anomaly dataset consist of normal images and anomaly set, anomaly set consist of images from Covid, pneumonia, and non-Covid infection. transfer learning algorithms were applied to differentiate between classes of normal and anomaly(infected), dataset consist of approx. 10,000 images of normal and anomaly images.

5.1 Model evaluation:

When it comes to performance, one of the most important variables to consider is accuracy. However, because the classification problem is in the medical field, the model's dependability is defined not only by accuracy, but also by precision and recall. The ideal model successfully distinguishes true positive and true negative. The accuracy and prediction power of the CNN model are tested, and the loss function evaluates the error score, which is produced using the loss function and captures inconsistencies between expected and actual data. The confusion matrix can also be used to assess the performance of a classification model. Below is a list of the parameters required to calculate the classification model's efficiency(saha p , et al, 2020).

True positive (TP): Patient is accurately predicted

False Positive (FP): Healthy patient scan is inaccurately predicted

True Negative (TN): healthy patient scan is correctly predicted

False Negative (FN): Patient is inaccurately predicted

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP/ (TP+ FP)

Recall = TP/ (TP + FP)

5.2 System specification:

Research was implemented on local desktop with specification of 64 bit Windows 10 operating machine with 8 GB ram, python programming language was utilized as primary language, Integrated Development environment like Anaconda framework along with necessary packages were utilized in data storage and implementation of project in Jupyter framework apart from necessary resources, tools like panda, NumPy, matplotlib ,tensor flow and other relevant packages were employed to achieve results.

5.3 Models Building:

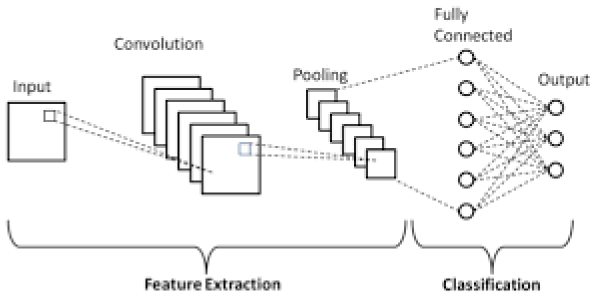

Figure 4. basic CNN architecture (source-net)

Convolutional Neural Networks (CNN) are quite popular when it comes to classification of images. Convolution Neural Networks hidden layers are able to recognize numerous aspects of input pictures, which uniquely identifies an image. In this case, image of lung scans, different forms and patterns contained in an image are recorded by CNN hidden layers, which helps to categorise an image. Different CNN models will be used and their accuracy will be compared. Figure 4. depicts the CNN model's basic architecture for image categorization. CNN is made up of three layers that aid with picture preprocessing: a convolutional layer, a pooling layer, and a fully connected layer.

5.3.1 VGG-16

In their publication "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman from the University of Oxford proposed the VGG16 convolutional neural network model. In ImageNet, a dataset of over 14 million images belonging to 1000 classes, the model achieves 92.7 percent top-5 test accuracy. It was a well-known model that was submitted to the ILSVRC-2014. It outperforms AlexNet by sequentially replacing big kernel-size filters with numerous 33 kernel-size filters. VGG16 had been training for weeks on NVIDIA graphics.
The most distinguishing feature of VGG16 is that instead of having a huge number of hyper-parameters, they concentrated on having convolution layers of 3x3 filter with stride 1 and always utilized the same padding and maxpool layer of 2x2 filter with stride 2. This layout of convolution and max pool layers is maintained throughout the design. Finally, it has two completely connected layers followed by a softmax for output. The number 16 in VGG16 alludes to the fact that it contains 16 weighted layers. This network is rather large, with around 138 million parameters.

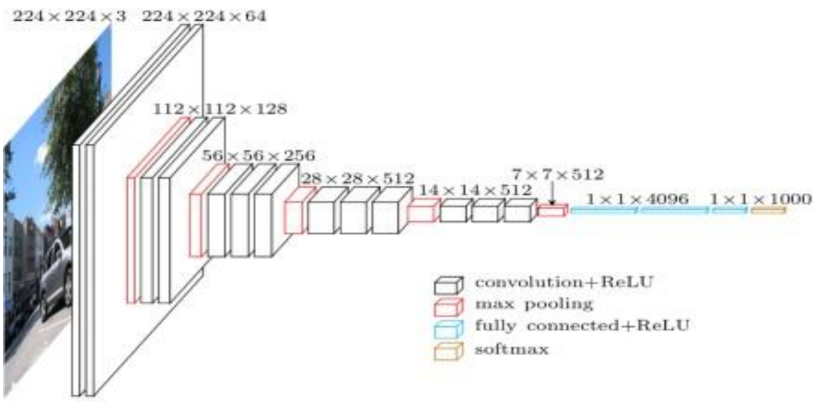

Figure.5. VGG-16 architecture(source-net)

5.3.2 RESNET-50

ResNet is an abbreviation for Residual Network. The term Resnet50 refers to a variation that can function with 50 neural network layers. In their 2015 computer vision research article titled 'Deep Residual Learning for Image Recognition,' Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun proposed a revolutionary neural network. This model was quite successful, as evidenced by the fact that its ensemble took first place in the ILSVRC 2015 classification competition with a 3.57 percent error rate. It also won first place in the ILSVRC and COCO contests in 2015 for ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

While the number of stacked layers can enhance the model's features, a deeper network can reveal the degradation issue. To put it another way, as the number of layers in a neural network grows, the accuracy levels may become saturated and gradually degrade. As a result, the model's performance degrades on both training and testing data. Overfitting is not the cause of this degeneration. It might be caused by the network's setup, optimization algorithm, or, more crucially, the issue of disappearing or exploding gradients. ResNet was built specifically to address this issue. Residual blocks are used in deep residual nets to increase model accuracy.

Figure.6. ResNet-50 architecture(soure-net)

6 Results and Evaluation:

6.1 Case 1:

This involves models' ability to classify four different labels that are, covid, pneumonia, non-covid_ infection and normal images. for this around 15,000 images belonging to 4 classes were utilized to train model, with input shape of 299 *299 pixel, rgb as color mode. Both VGG-16 and ReNet-50 utilized accuracy as metrics with Adam optimizer, resulting accuracy of 89 percentage for VGG-16 and 83.20 onResNet-50 for validation set, Figure 7. below describes the classification matrix of both the model and it can be inferred that ability of models to classify covid is low.

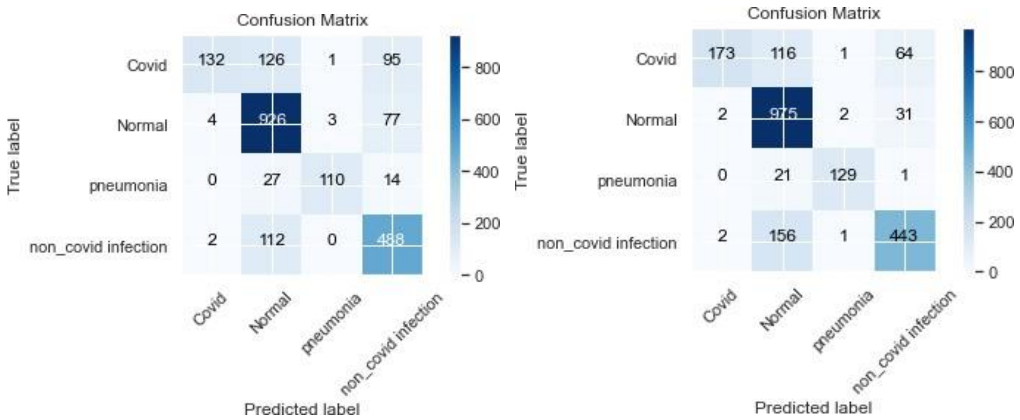

Figure 7. VGG-16 (left)and ResNet-50 (right) classification model of 4 labels

6.2 Case 2 Three label dataset:

In this experiment the models were trained on three labels dataset, that were covid, pneumonia and normal lung images, for the purpose of training approx. 13,000 images belonging to three classes were utilized to train the model, image were set to size of 299*299 dimensions, color mode was set to "rgb", images were processed with brightness range of .8 to 1.2, and zoom range of .75 to 1.

6.2.1 VGG-16

model gave an accuracy of .88 and was run for epoch of 10, Vgg-16 model had a precision of .96 and recall of .52, model did classify 184 images of covid but misclassified 164 images of covid as normal.

Figure 8. accuracy vs epoch (right) for VGG-16, loss vs Epoch(left)

	precision	recall	f1-score	support
Covid	0.96	0.52	0.68	352
Normal	0.84	0.99	0.91	1024
pneumonia	0.99	0.77	0.87	140
accuracy			0.86	1516
macro avg	0.93	0.76	0.82	1516
weighted avg	0.88	0.86	0.85	1516

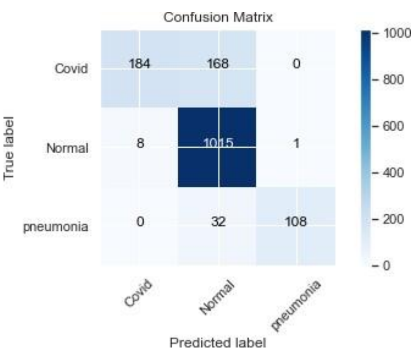

Figure 9. classification report of VGG-16 (left) and confusion matrix-VGG-16(left)

6.2.2 ResNet-50

Transfer learning model was applied to three class classification, images were set to height and width of 299*299 pixel , color mode was set to rgb , model was set to epoch of 15 and all parameter were set identical to VGG-16 model specification. ResNet model had an accuracy of .90 with .97 precision and .63 recall for covid class, Resnet model did perform well comparing to VGG-16 in three class classification, confusion matrix does indicate that model misclassifies 129 covid images as normal.

Figure 10. accuracy vs epoch (right) for ResNet-50, loss vs Epoch(left)

	precision	recall	f1-score	support
Covid	0.97	0.63	0.76	352
Normal	0.87	0.99	0.93	1024
pneumonia	0.98	0.82	0.89	140
accuracy			0.89	1516
macro avg	0.94	0.81	0.86	1516
weighted avg	0.90	0.89	0.89	1516

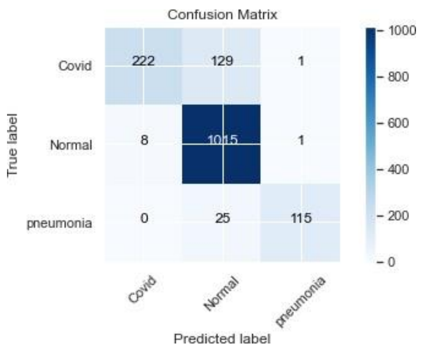

Figure 11. classification report of ResNet-50(left) and confusion matrix_ ResNet-50 (left)

6.3 Case 3 Anomaly dataset:

In this case study VGG-16 and ResNet-50 were applied on two binary class datasets, dataset was separately created from rest of other models, anomaly dataset was utilized to train model, anomaly dataset consisted of two classes normal and anomaly, anomaly class consisted of covid, pneumonia and non-covid infection. Dataset included approx. 10,000 normal and infected (anomaly) images.

For both model fitting, the image size was set to 299*299, color mode set to ‘rgb’, batch size of 64, and brightness range of .8 to 1.2 , along zoom range .75 to 1.0 was set inspired by Kaggle classification of pneumonia detection. Consisting of 20,000 images the model was trained using 15000 images approx. models were validated and tested using 3000 and 2000 images respectively.

6.3.1 VGG_16

VGG-16 model has an accuracy of 85 percent with precision of .78 and recall of .92 for covid label, Confusion matrix predict that model was able to classify 935 images as covid with 80 images being misclassified as normal, epoch for model was set to 12 for minimum loss.

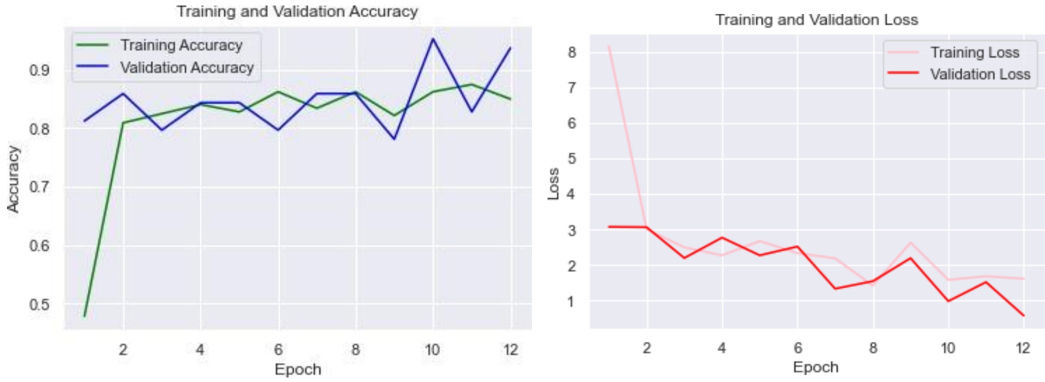

Figure 11. accuracy vs epoch (left) for VGG_16, loss vs Epoch(right) for VGG-16

	precision	recall	f1-score	support
Covid	0.78	0.92	0.84	1015
Normal	0.91	0.76	0.83	1102
accuracy			0.84	2117
macro avg	0.84	0.84	0.84	2117
weighted avg	0.85	0.84	0.83	2117

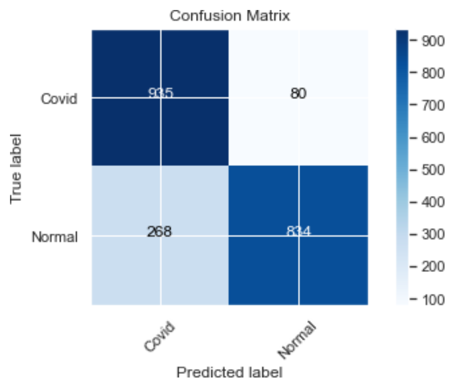

Figure 11. classification report of VGG-16(left) and confusion matric_ VGG-16 (right)

6.3.2 ResNet-50

ResNet-50 model had an accuracy of 85 percent with precision of .80 and recall of .91 for anomaly label, model set tot epoch of 15 for minimum loss, confusion matrix does showcases model classified 927 images as anomaly with 88 images misclassified as normal.

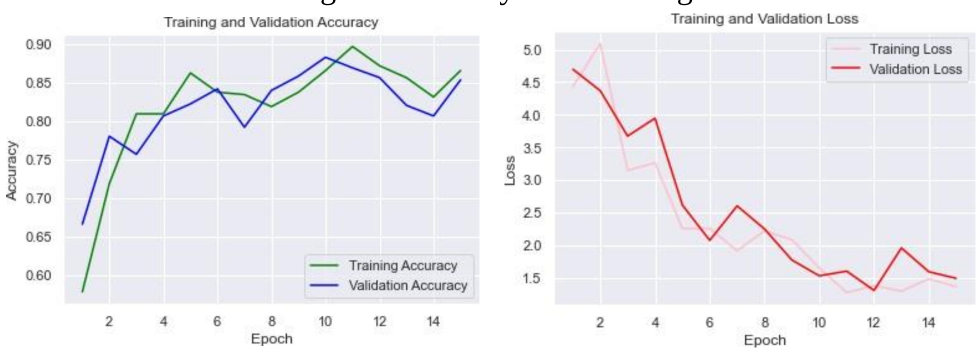

Figure 12. accuracy vs epoch (left) for ResNet-50, loss vs Epoch(right) for ResNet-50

	precision	recall	f1-score	support
anamoly	0.80	0.91	0.85	1015
Normal	0.91	0.79	0.85	1102
accuracy			0.85	2117
macro avg	0.85	0.85	0.85	2117
weighted avg	0.86	0.85	0.85	2117

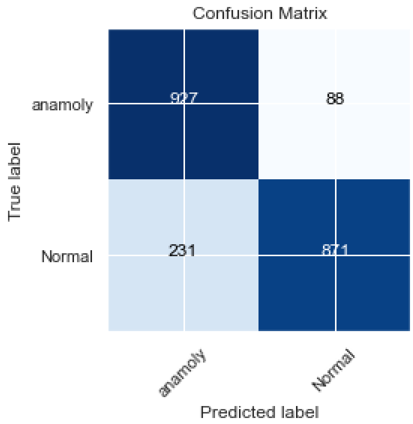

Figure 13. classification report of ResNet-50(left) and confusion matrix_ ResNet-50 (right)

7 Discussion:

As Research is based on medical domain it is important for the model not only to have accuracy but also good precision and recall value, model performance could be detrimental in case if patient with covid is diagnosed as normal than other way round. Model performance and tunning was done keeping this parameter as also a critical factor, apart from above mentioned experiments many more case was involved, and primary finding were notified.

Deep learning algorithm performed well on given set of data, to evaluate on ground basis *common test data* was created consisting of **723 covid images**. Common test data was utilized to assess the model's performance and the results are shown in table below.

Table 1:test performance on common test data, model trained on anomaly dataset (two class).

model	Accuracy	Precision	Recall	true predictions	false prediction
VGG-16	.84	.77	.91	570	153
ResNet-50	.86	.80	.81	535	188

Table 2: test performance on common test data, model trained on three class datasets

Model	Accuracy	Precision	Recall	true predictions	false prediction
Vgg-16	.88	.96	.52	357	366
ResNet-50	.90	.97	.63	259	464

Table 3: test performance on common test data, model trained on two class imbalanced dataset(normal/covid)

Model	Accuracy	Precision	Recall	true predictions	false predictions
ResNet-50	.93	.98	.61	87	628

Table 4: test performance on common test data, model trained on four class imbalanced dataset.

Model	Accuracy	Precision	Recall	test data/ true predictions	test data/ false predictions
Vgg-16	.81	.83	.56	134	589
ResNet-50	.84	.77	.72	110	613

Table 1, Table 2, Table 3 and table 4 showcases the result of model, when tested against common test data consisting of single covid class of 723 images. VGG-16 and ResNet-50 performed comparatively similar and better on test, that were trained using anomaly dataset. Recall value is on higher side for model trained using anomaly dataset.

As neural network are inspired by brain cell and complex neural algorithm mimics the functioning of the brain , it can be assumed that that brain works best when it performs single task at a time.

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