DETECTION OF COVID19/RESPIRATORY DISEASES USING DEEP LEARNING ALGORITHM

Project Report submitted to

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(Validity- June 2019-June 2022)

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We here by declare that this submission is our own work and that, to the best of our knowledge and belief, it neither contains materials written by another person nor material accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that the report entitled " **DETECTION OF COVID-19/ RESPIRATORY DISEASES USING DEEP LEARNING ALGORITHMS** ", is a bonafide record of the project work done by **ANNSANA BABY**, **ASHIK POLLY**, **JEFIN PAUL** and **VISHNUDEV S** during the year 2020-2021. This report is submitted to APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the degree of Bachelor of technology in Electronics and Communication Engineering.

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ABSTRACT

Each year, millions of people suffer from lung diseases, doctors uses X-Rays and Computed Tomography to detect these diseases. A highly contagious Novel Coronavirus Disease has been widespread since December 2019 and results in severe acute respiratory diseases and organ failure.

Using X-rays Radiologists can detect many respiratory-related diseases such as pneumonia, emphysema, interstitial lung disease and researches are going on to detect novel COVID-19 virus. When it comes to other lungs diseases like Pneumonia, Infiltration, the human-assisted diagnosis has many limitations. When it comes to other lungs diseases like Pneumonia, Infiltration, the human-assisted diagnosis has many limitations. With the growing number of patients, it is difficult for doctors and nurses to check mild to severe health conditions for every patients

Today machine learning is present everywhere so that without knowing it, one can possibly use it many times a day. CNN uses both the structured and unstructured data of a hospital to do classification. While other machine learning algorithms only work on structured data and time required for computation is high. At the current situation, any missed cases would continue to cause COVID-19 spread. So, it has posed a great challenge to our radiologists with such a tremendous amount of work as well as high diagnostic accuracy required.Thus, developing an artificial intelligence (AI) method for computer-aided COVID-19 has the potential to greatly reduce the health workers suffer on their job.

Hence an automated method is needed to make things easier for doctors through which early-stage detection of these diseases are possible. Our model compares X-Rays and for detecting and classifying the respiratory diseases. The respiratory diseases and COVID-19 are diagnosed using Data Analytics with X-Rays.

CONTENTS

LIST OF ABBREVATIONS

COVID19	Corona Virus Disease 19
VGG16	Visual Geometry Group 16
CNN	Convolutional Nueral Network
DBN	Deep Belief Network
DLA	Deep Learning Algorithm
AI	Artificial Intelligence
IR	Image Recognition

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CHAPTER 1

INTRODUCTION

The novel COVID-19 virus came to light in December 2019 in Wuhan Province, China, where it originated from animals and quickly spread around the world. The easiest way to transmit COVID-19 is through the air and physical contact, such as hand contact with an infected person. Early detection and diagnostics are critical factors to control the spreading of COVID-19. Chest X Rays is one of the cheapest and easiest diagnostics technique used by radiologists to detect and classify lung diseases like pneumonia, emphysema, infiltration and others.Pneumonia is one of the leading causes in children which occur due to the infection caused in air sacs of lungs. Using Chest x-rays graph it is easier to detect pneumonia without the help of radiologists.

1.1 Motivation

With the growing number of patients it is becoming difficult for doctors and nurses to check mild to severe health conditions for every patients, hence an automated system is needed to make things easier for doctors through which even early-stage detection of these diseases are possible.

Our motivation behind the idea is to create such an automated system. We aim to help our society in times of a pandemic crisis by reducing the workload of health workers, providing safer ways for analysis and prediction of disease at very low costs. This way any average person facing such a crisis has better chance for early results and hence appropriate treatment.

1.2 Objectives

The main objective of this project is to design a website/web application that can be used to predict infected patients from normal. Models of Covid-19 and Pneumonia has been selected for analysis and prediction. Transfer Learning models like Inception V3 and VGG-16 was used wherein based on the size of the dataset convolutional and pooling layer is used in a pre-trained network which will identify the shape and edge-based features, then at the end, one or two linear dense layers are added to obtain the desired output.

CHAPTER 2

LITERATURE SURVEY REPORT

2.1 Introduction

2.2 A Novel Deep Learning Architecture for Detection of COVID-19

[1]Ouchicha, C., Ammor, O., Meknassi, M. (2020). CVDNet: A novel deep learning architecture for detection of coronavirus (Covid-19) from chest x-ray images.

Advantage of CNN is that it's not only used for extracting features but they automatically learn from data. In their research, they have used the model CVDNet, a deep CNN to detect the presence of COVID-19 using chest x-ray images.A number of artificial intelligence systems based on deep learning, in particular convolutional neural networks have been proposed and the results have been very promising in terms of accuracy in the detection of patients infected with COVID-19 using chest x-ray images. The reason for this success is that deep convolutional neural networks are not based on extracting features manually, but these algorithms automatically learn features from the data itself.

The dataset contains three classes that are COVID-19, Pneumonia Viral and normal. In chest x-ray images, Groundglass opacities are observed as early features for COVID-19, and they come in different sizes, to capture multi-scale features, two parallel convolutions with large and small filters are used.To minimize the average loss on the training set, formalization is used. 70:10:20 was used for training, testing and validation. The efficiency of the model was evaluated along with recall, precision, f1- score, and had an accuracy of 97.20 percentage.

2.3 Deep Bidirectional Classification Model for COVID-19 Disease Infected Patients

[2] Y. Pathak, P. K. Shukla and K. V. Arya, "Deep bidirectional classification model for COVID-19 disease infected patients," in IEEE/ACM Transactions on Computational Biology and Bioinformatics focusing on the comparison of chest x-ray and CT scan on intensive study of chronic respiratory diseases.
newline

Taking into account the present scenario where the corona virus is spreading at an exponential rate, researches have proved that the imaging techniques such as chest radiography and computed tomography are to be analysed for detecting the severity of the infection that virus has caused. They have also done a comparison between the chest x-rays and CT scans and have concluded that CT scans have proven to be a better criteria for image matching techniques as they show the exact location and a 3-d image of the chest.

The researchers did identify certain methods like Random Forest, Artificial Neural Networks (ANN) , etc. but these methods were ineffective as they required feature selection approaches and pre-processing tools. So they have decided to use Deep Learning approaches which have the ability to extract the features automatically. These Deep Learning approaches can be used to design classification models for COVID-19 disease in patients from the chest-CT images dataset, but then they require large number of features for classification and hence this is still an open research topic.

2.4 Designing Disease Prediction Model Using Machine Learning Approach

[3] D. Dahiwade, G. Patle and E. Meshram, "Designing Disease Prediction Model Using Machine Learning Approach," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)

Studies have shown that people are facing various diseases due to the environmental conditions and living habits. Accurate prediction of diseases based on symptoms were actually becoming difficult for doctors. Under the present condition, correct prediction of diseases is actually becoming a challenge .Thus, in order to tackle this problem data mining has been widely used for disease prediction, i.e. based on the large medical datasets it was actually possible to detect the disease. AI was actually able to make the computer think and predict based on various datasets that were given as input to them. Various machine learning algorithms like K-Nearest Neighbour (KNN) and Conventional Neural Network (CNN) were used to sort large sets of data and for disease prediction.

Studies also showed that CNN uses both the structured and unstructured data of a hospital to do classification. While other machine learning algorithms only work on structured data and time required for computation is high, they are also lazy because they store entire data as a training dataset and use complex methods for calculation. Studies also showed that a wide variety of datasets from hospitals and medical fields were available for disease prediction. In short this paper proposed a general disease prediction model based on a machine learning algorithm using KNN and CNN.

2.5 Very Deep Convolutional Networks For Large-Scale Image Recognition

[4] Karen Simonyan Andrew Zisserman investigates the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. The main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. The findings were the basis of the ImageNet Challenge 2014 submission.

The paper also tries to address another important aspect of ConvNet architecture design – its depth. To this end, the paper fixes other parameters of the architecture, and steadily increase the depth of the network by adding more convolutional layers, which is feasible due to the use of very small (3×3) convolution filters in all layers. As a result, it comes up with significantly more accurate ConvNet architectures, which not only achieve the state-of-the-art accuracy on Imagenet Large-Scale Visual Recognition Challenge classification and localisation tasks, but are also applicable to other image recognition datasets, where they achieve excellent performance even when used as a part of a relatively simple pipelines.

2.6 Image Recognition Method Based on Deep Learning

[5]Xin Jia Tianjin University of Technology, Tianjin.Image recognition method based on deep learning. Deep learning algorithms are a subset of the machine learning algorithms, which aim at discovering multiple levels of distributed representations. Recently, numerous deep learning algorithms have been proposed to solve traditional artificial intelligence problems. This work aims to review the state-of-the-art in deep learning algorithms in computer vision by highlighting the contributions and challenges from recent research papers.

The classification accuracy rate of CNN and DBN on the database is 99.28 percent and 98.1 percent respectively, and on the real-world handwritten character database is 92.91 percent and 91.66 percent respectively. The experiment results show that deep learning does have an excellent feature learning ability. It don't need to extract features manually. Deep learning can learn more nature features of the data.

CHAPTER 3

PROPOSED WORK

3.1 Introduction

Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Because the computer gathers knowledge from experience, there is no need for a human computer operator to formally specify all of the knowledge needed by the computer. The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones; a graph of these hierarchies would be many layers deep. By gathering knowledge from experience, this approach avoids the need for human operators to specify formally all of the knowledge needed by the computer.Deep learning is an AI function that mimics the workings of the human brain in processing data for use in detecting objects, recognizing speech, translating languages, and making decisions. Deep learning AI is able to learn without human supervision, drawing from data that is both unstructured and unlabelled. Deep learning, a subset of machine learning, utilizes a hierarchical level of artificial neural networks to carry out the process of machine learning. Convolutional Neural Network and Transfer Learning is proposed which can detect the type of lung diseases including Pneumonia along with COVID-19. Our model detects COVID-19 and pneumonia more accurately using Data Analytics from lung X Rays

3.2 Convolutional Neural Network

Convolutional Neural Network is coming under neural network. A Convolutional Neural Network or CNN or ConVNet is a Deep Learning algorithm which can take in an input image, and it is commonly applied to analyse visual images. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function.

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and output an activation value. The behavior of each neuron is defined by its weights. When fed with the pixel values, the artificial neurons of a CNN pick out various visual features.

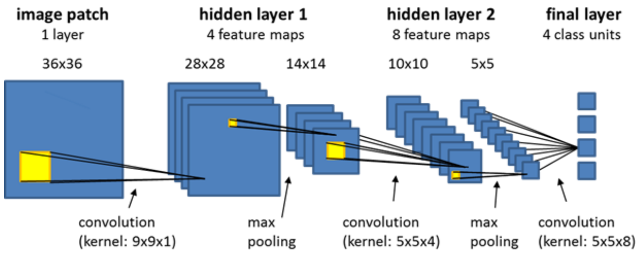

Figure 3.1: Convolutional Nueral Network

CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme. Especially the applications that deal with image data, such as the largest image classification data set (Image Net), computer vision, and in natural language processing (NLP) and the results achieved were very amazing.

Convolutional layers are not only applied to input data, but they can also be applied to the output of other layers. The stacking of convolutional layers allows a hierarchical decomposition of the input. It contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. In other words, the filter is slid across the width and height of the input and the dot products between the input and filter are computed at every spatial position.

When an input image is given into a ConvNet, each of its layers generates several activation maps. Activation maps highlight the relevant features of the image. Each of the neurons takes a patch of pixels as input, multiplies their color values by its weights, sums them up, and runs them through the activation function. The first (or bottom) layer of the CNN usually detects basic features such as horizontal, vertical, and diagonal edges. The output of the first layer is fed as input of the next layer, which extracts more complex features, such as corners and combinations of edges. As you move deeper into the convolutional neural network, the layers start detecting higher-level features such as objects, faces, and more.

3.2.1 Architecture of Convolutional Neural Network

An architecture of CNN consists of various steps which have to be considered while training the model to get the best accuracy. It includes batch normalization, activation layer, pooling layer, padding layer, dropout layer and fully connected layer.

Batch Normalization : We normalize the input layer by adjusting and scaling the activations. For example, when we have features from 0 to 1 and some from 1 to 1000, we should normalize them to speed up learning. If the input layer is benefiting from it, why not do the same thing also for the values in the hidden layers that are changing all the time, and get 10 times or more improvement in the training speed. Batch normalization reduces the amount by which the hidden unit values shift around (covariance shift).batch normalization allows each layer of a network to learn by itself a little bit more independently of other layers. To increase the stability of a neural network, batch normalization normalizes the output of a previous activation layer by subtracting the batch mean and dividing by the batch standard deviation.Consequently, batch normalization adds two trainable parameters to each layer, so the normalized output is multiplied by a "standard deviation" parameter (gamma) and add a "mean" parameter (beta). In other words, batch normalization lets SGD do the denormalization by changing only these two weights for each activation, instead of losing the stability of the network by changing all the weights.

Pooling Layer : The main idea of pooling is down-sampling in order to reduce the complexity for further layers. In the image processing domain, it can be considered as similar to reducing the resolution. Pooling does not affect the number of filters. Max-pooling is one of the most common types of pooling methods. It partitions the image to sub-region rectangles, and it only returns the maximum value of the inside of that sub-region. One of the most common sizes used in max pooling is 2×2. This means that stride 2 is used in pooling. The pooling layer is commonly applied after a convolution layer to reduce the spatial size of the input. It is applied independently to each depth slice of the input volume. Volume depth is always preserved in pooling operations.

Activation function : The activation function is a node that is put at the end of or in between Neural Networks. They help to decide if the neuron would fire or not. The activation function is the non-linear transformation that is done over the input signal. This transformed output is then sent to the next layer of neurons as input. The function is attached to each neuron in the network, and determines whether it should be activated or not, based on whether each neuron's input is relevant for the model's prediction. Activation functions like sigmoid also help normalize the output of each neuron to a range between 1 and 0 or between -1 and 1. An additional aspect of activation functions is that they must be computationally efficient because they are calculated across thousands or even millions of neurons for each data sample. Modern neural networks use a technique called backpropagation to train the model, which places an increased computational strain on the activation function, and its derivative function.

Dropout Layer : Dropout is a technique used to prevent a model from overfitting. Dropout works by randomly setting the outgoing edges of hidden units (neurons that make up hidden layers) to 0 at each update of the training phase. It reduces overfitting of the model. Using dropout, some nodes in the layer are randomly chosen to stay inactive for some instances. In this way, it prevents the model from getting too familiar with the data.

Fully Connected Layer : The fully-connected layer is similar to the way that neurons are arranged in a traditional neural network. Therefore, each node in a fully-connected layer is directly connected to every node in both the previous and in the next layer, each of the nodes in the last frames in the pooling layer are connected as a vector to the first layer from the fully-connected layer. These are the most parameters used with the CNN within these layers, and take a long time in training. Fully connected layers are an essential component of Convolutional Neural Networks (CNNs), which have been proven very successful in recognizing and classifying images for computer vision. The CNN process begins with convolution and pooling, breaking down the image into features, and analyzing them independently. The result of this process feeds into a fully connected neural network structure that drives the final classification decision.

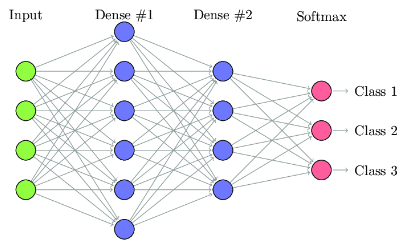

Figure 3.2: Fully Connected Layer

The major drawback of a fully-connected layer is that it includes a lot of parameters that need complex computations in training examples. Therefore, we try to eliminate the number of nodes and connections. The removed nodes and connection can be satisfied by using the dropout technique. For example, LeNet and AlexNet designed a deep and wide network while keeping the computational complex constant. Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multilayer perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images. Flattened matrix from the pooling layer is fed as input to the fully connected layer to classify the lung CT images as COVID-19 positive or COVID-19 negative.

Padding : One of the drawbacks of the convolution step is the loss of information that might exist on the border of the image. Because they are only captured when the filter slides, they never have the chance to be seen. A very simple, yet efficient method to resolve the issue, is to use zeropadding. The other benefit of zero padding is to manage the output size. However, by adding one zero-padding, the output will be 7×7, which is exactly the same as the original input.

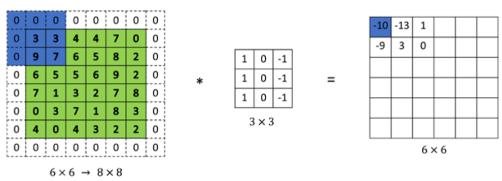

Figure 3.3: Padding Operation

Dense layers : Dense layers add an interesting non-linearity property, thus they can model any mathematical function. However, they are still limited in the sense that for the same input vector we always get the same output vector. A densely connected layer provides learning features from all the combinations of the features of the previous layer, whereas a convolutional layer relies on consistent features with a small repetitive field.

3.2.2 Training of Convolutional Neural Network

One of the great challenges of developing CNNs is adjusting the weights of the individual neurons to extract the right features from images. The process of adjusting these weights is called "training" the neural network. In the beginning, CNN starts off with random weights. During training, the developers provide the neural network with a large dataset of images annotated with their corresponding classes.

The ConvNet processes each image with its random values and then compares its output with the image's correct label. If the network's output does not match the label—which is likely the case at the beginning of the training process—it makes a small adjustment to the weights of its neurons so that the next time it sees the same image, its output will be a bit closer to the correct answer. The corrections are made through a technique called backpropagation (or backprop). Essentially, backpropagation optimizes the tuning process and makes it easier for the network to decide which units to adjust instead of making random corrections.

Every run of the entire training dataset is called an "epoch." The ConvNet goes through several epochs during training, adjusting its weights in small amounts. After each epoch, the neural network becomes a bit better at classifying the training images. As the CNN improves, the adjustments it makes to the weights become smaller and smaller. At some point, the network "converges," which means it essentially becomes as good as it can. After training the CNN, the developers use a test dataset to verify its accuracy. The test dataset is a set of labeled images that were not part of the training process.

Each image is run through the ConvNet, and the output is compared to the actual label of the image. Essentially, the test dataset evaluates how good the neural network has become at classifying images it has not seen before. If a CNN scores good on its training data but scores bad on the test data, it is said to have been "overfitted." This usually happens when there's not enough variety in the training data or when the ConvNet goes through too many epochs on the training dataset.

3.3 Transfer Learning

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in skill that they provide on related problems.. In the transfer learning method, a pre-trained CNN network on ImageNet database with saved weights was loaded and then trained on the dataset used in this work. The advantage of using transfer learning methods to train the CNN is that the initial layers of the network are already trained, which are otherwise very hard to train due to the vanishing gradient problem. The other benefit is that the network already has learned basic features like recognizing shape, edges of the image etc. Thus, the pre-trained model benefits from the knowledge acquired in the form of learning basic features of the images from the existing database. This method of training the network reduces the computational time as only the final layers of the network need to be trained.

3.3.1 Transfer Learning Scenarios

The three major Transfer Learning scenarios:

1.ConvNet as a fixed feature extractor: Take a ConvNet pre-trained on ImageNet, remove the last fully-connected layer (this layer's outputs are the 1000 class scores for a different task like ImageNet), then treat the rest of the ConvNet as a fixed feature extractor for the new dataset. In an AlexNet, this would compute a 4096-D vector for every image that contains the activations of the hidden layer immediately before the classifier. We call these features CNN codes. It is important for performance that these codes are ReLUd (i.e. thresholded at zero) if they were also thresholded during the training of the ConvNet on ImageNet (as is usually the case). All images train a linear classifier (e.g. Linear SVM or Softmax classifier) for the new dataset.

2.Fine-tuning the ConvNet. The second strategy is to not only replace and retrain the classifier on top of the ConvNet on the new dataset, but to also fine-tune the weights of the pre-trained network by continuing the backpropagation. It is possible to fine-tune all the layers of the ConvNet, or it's possible to keep some of the earlier layers fixed (due to overfitting concerns) and only fine-tune some higher-level portion of the network. This is motivated by the observation that the earlier features of a ConvNet contain more generic features (e.g. edge detectors or colour blob detectors) that should be useful to many tasks, but later layers of the ConvNet becomes progressively more specific to the details of the classes contained in the original dataset. In the case of ImageNet for example, which contains many dog breeds, a significant portion of the representational power of the ConvNet may be devoted to features that are specific to differentiating between dog breeds.

3.Pre-trained models. Since modern ConvNets take 2-3 weeks to train across multiple GPUs on ImageNet, it is common to see people release their final ConvNet checkpoints for the benefit of others who can use the networks for fine-tuning. For example, the Caffe library has a Model Zoo where people share their network weights.

3.3.2 Types of Transfer Learning

VGG-16 :

VGG16 is a convolution neural net (CNN) architecture which was used to win imagenet competition in 2014. It is considered to be one of the excellent vision model architectures till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and max-pool layer of 2x2 filter of stride 2.

VGG-19 :

VGG-19 is a convolutional neural network that is 19 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

ResNet :

ResNet first introduced the concept of skip connection. The diagram below illustrates skip connection. The figure on the left is stacking convolution layers together one after the other. On the right we still stack convolution layers as before but we now also add the original input to the output of the convolution block. The ResNet-50 model consists of 5 stages each with a convolution and Identity block. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers.

Inception :

Inception Modules are used in Convolutional Neural Networks to allow for more efficient computation and deeper Networks through dimensionality reduction with stacked 1×1 convolutions. The modules were designed to solve the problem of computational expense, as well as overfitting, among other issues.

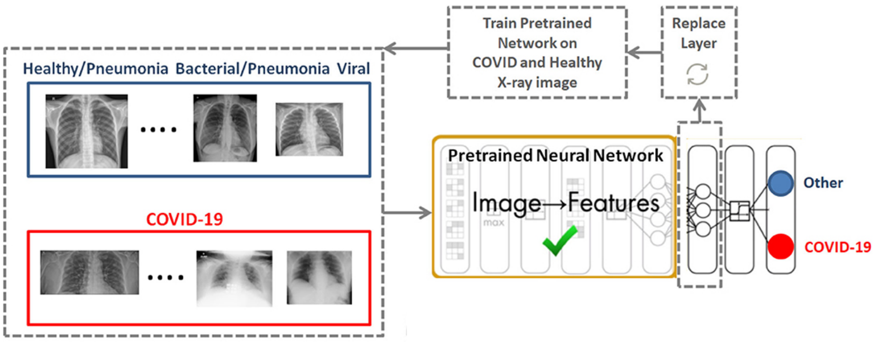

Figure 3.4

VGG-16 was used for the detection of Pneumonia and Inception V3 for COVID-19 detection and ResNet 50 was used based on the size of the dataset for both COVID-19 and Pneumonia detection. A convolutional and pooling layer is used in a pre-trained network which will identify the shape and edge-based features, then at the end, one or two linear dense layers are added to obtain the desired output. Several activation functions were used based on the size of datasets and how similar the datasets were from each other. To reduce overfitting, a dropout layer is used, wherein some input nodes would be active and some would be inactive and finally after extracting features, it is flattened and passed onto a dense layer. The output achieved high accuracy for all models, which was found through a confusion matrix.

3.4 Python Flask

Flask is considered more Pythonic than the Django web framework because in common situations the equivalent Flask web application is more explicit. Flask is an API of Python that allows us to build up web-applications. It has less base code to implement a simple web-Application. flask provides you with tools, libraries and technologies that allow you to build a web application. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions. However, Flask supports extensions that can add application features as if they were implemented in Flask itself.

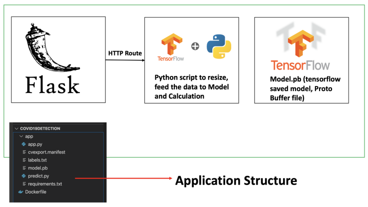

Figure 3.5: Flask:Operational block diagram

CHAPTER 4

MODEL METHODOLOGY

Three models were proposed for Covid-19, Pneumonia and for detecting both Covid-19 and Pneumonia. For Covid-19 detection we use Inception-V3 transfer learning model, meanwhile for Pneumonia detection VGG16 transfer learning model was-ResNet50 transfer learning model was used which can detect both Covid-19 and Pneumonia.

4.1 Deep Learning Model for Pneumonia Detection

4.1.1 Dataset

Chest X-ray images were selected from retrospective cohorts of pediatric patients, For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert. After splitting the test, train and validation images, the number of train images were 5216 and test images were 624.

Table 4.1: Pneumonia data sets

Data Set	Pneumonic	Non-Pneumonic
Training Set	2607	2609
Testing Set	312	312
Validation Set	8	9
Total	2927	2930

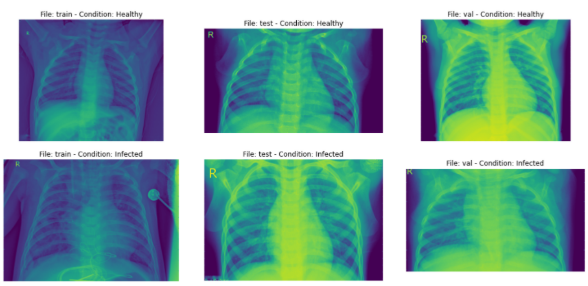

Figure 4.1: Chest X-ray Images

4.1.2 Model Definition

These datasets were first normalized and augmented, these images were then passed as an input to the VGG16 transfer learning model. VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". The Kernel size is 3x3 and the pool size is 2x2 for all the layers. The input to the Vgg 16 model is 224x224x3 pixels images.

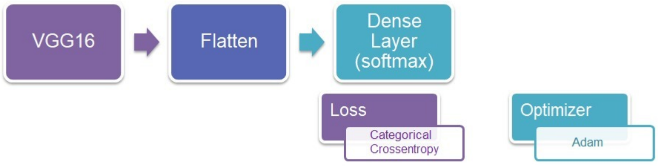

Figure 4.2: VGG16 Function Block Diagram

Then we have two convolution layers with each 224x224x64 size, then we have a pooling layer which reduces the height and width of the image to 112x112x64. Then we have two conv128 layers with each 112x112x128 size after that we have a pooling layer which again reduces the height and width of the image to 56x56x128. Then we have three conv256 layers with each 56x56x256 size, after that again a pooling layer reduces the image size to 28x28x256. Then again we have three conv512 layers with each 14x14x521 layers, after that, we have a pooling layer with 7x7x521 and then we have two dense or fully-connected layers with each of 4090 nodes. and at last, we have a final dense or output layer with 1000 nodes of the size which classify between 1000 classes of image net.

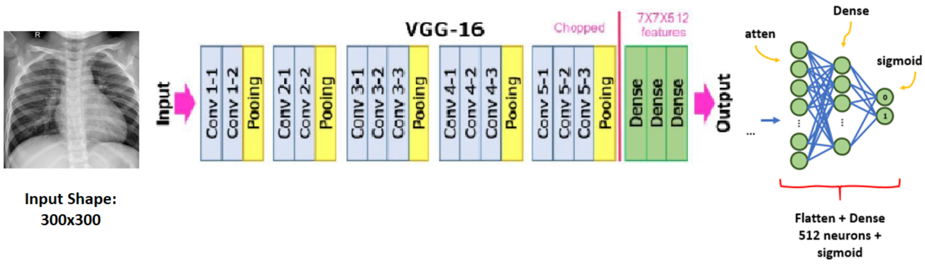

Figure 4.3: VGG16 model diagram

After passing it to the transfer learning model, it was then flattened and was fed into the final dense layer. Softmax function was used as the activation function for the output layer and Adam was used as an optimizer. After training the model, they are visualized based on model accuracy, model loss. These models were trained for 25 epochs for each 25 steps. Categorical cross entropy was used as an optimizer and finally their accuracy was calculated, our model got 95percent accuracy.

4.2 Deep Learning Model for Covid-19 Detection

4.2.1 Datasets

For the detection of Covid-19, the Chest X ray images were used and the datasets were collected from public sources as well as through indirect collection from hospitals and physicians which were uploaded in Github repository. The images contained 513 Covid-19 images and 505 Non-covid images, these images were then splitted into test, train and validation sets. For training 752 images were used. And rest were used for test images.

Table 4.2: Covid-19 datasets

Data Set	Covid-19 Positive	Covid-19 Negative
Training Set	440	434
Testing Set	65	64
Validation Set	8	7
Total	513	505

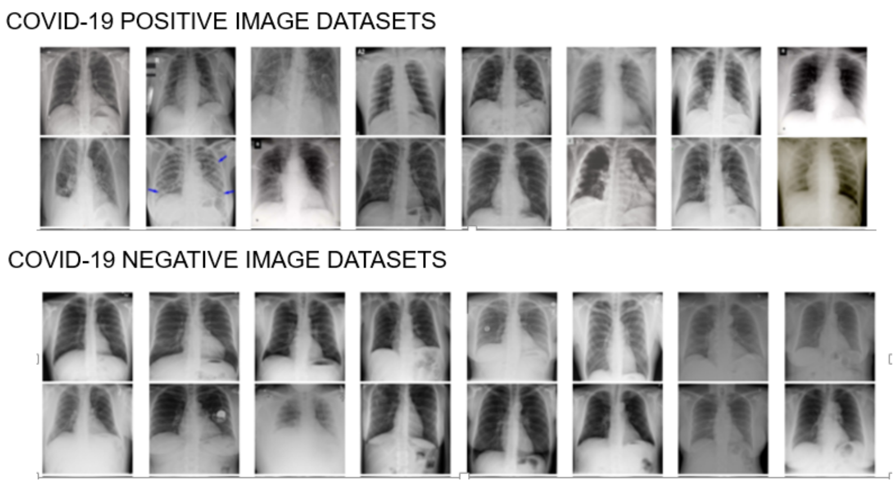

Figure 4.4: Covid-19 Image Datasets

4.2.2 Model Definition

First these datasets were augmented and normalized and then these were passed onto the InceptionV3 transfer learning model. Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1percent accuracy on the ImageNet dataset.

The model is the culmination of many ideas developed by multiple researchers over the years. Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network. The recently introduced architecture,

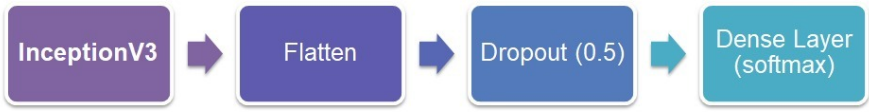

Figure 4.5: Basic Block Diagram

Inception shows promise on improved accuracy as well as optimized use of computational resources. Inception architecture reduces computational resource usage in highly accurate image classification.

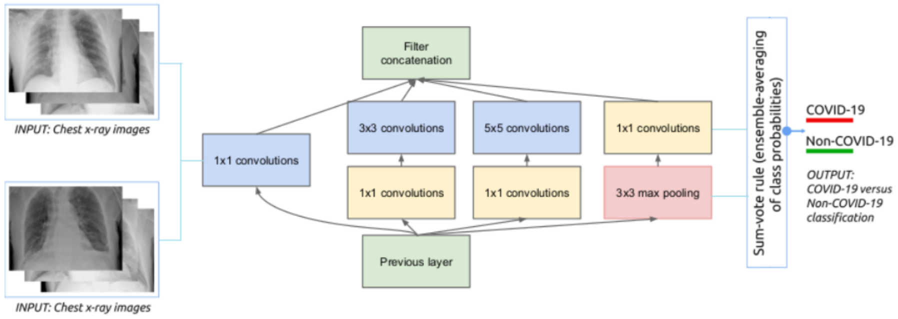

Figure 4.6: Function Diagram

This model was trained for 500 epochs, images after flattening were passed onto the dropout layer with value 0.5, then softmax was used as activation function. Categorical cross entropy was used as the loss and Adam was used as optimizer. After training, this model was tested against the label images and our model finally got an accuracy of approximately 93percent. Their respective classification report and confusion matrix were calculated.

4.3 Deep Learning Model for both Covid-19 and Pneumonia Detection

4.3.1 Dataset

Table 4.3: Dataset Combined Model

Data Set	Covid-19	Pneumoia	Normal
Training Set	1432	1432	1437
Testing Set	463	463	463
Validation Set	413	413	413
Total	2132	2313	2313

A study was conducted and a total of 2313 samples of normal and pneumonia were obtained from Kaggle and were classified into 1437 for training, 463 for testing and 413 for validation. The datasets of patients suspected of COVID-19 were collected from the Radiopedia, the Italian Society of Radiology and the Fig share data repository websites. The total 2313 datasets of COVID-19 and normal were classified into 1437 for training, 463 for testing, and 413 for validation. These total datasets of 6939 samples containing the chest X-Ray images were organized into three folders namely, Covid19, pneumonia and normal which uses 2313 samples for each case.

4.3.2 Model definition

Once the x-ray goes into the supervised training model it will undergo image segmentation from where the image will be partitioned to different segments and after this, the image is dimensionally reduced to a more manageable group for processing the raw image using the feature extraction technique. After reduction, the image is classified based on the contextual information and finally, the image is tested against the trained dataset to predict the output of disease identification. The model was developed from the dataset and was allowed to train. Transfer Learning and Convolutional Neural Network approach was used for training. After Augmenting the Images they were passed onto the following layers.

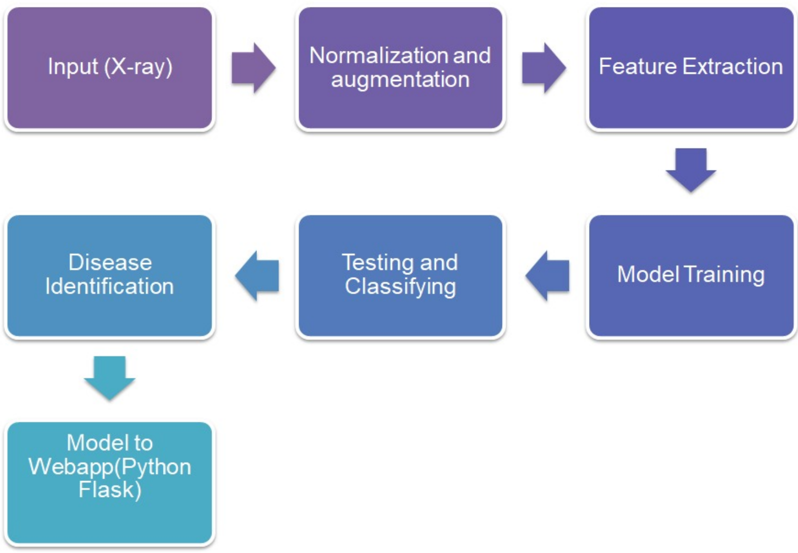

Figure 4.7: Flow Chart of Model

In transfer learning, ResNet50 was used wherein a pre-trained network is applied to the task of our own design, transferring what the model learned from one step to another. Last some layers and filters are removed and a linear layer is added at the end to fulfill the task. ResNet50 stands for Residual Network which delivered a top-5 error rate under 3.6percent using a deep convolutional neural network composed of 152 layers. Skip connections also called shortcut connections is the key to train such a deep network. When we add input x to the output of the network, the network is forced to model h(x) – x where x is the input rather than the target function h(x).
While initializing our neural network, the weights are assigned close to zero so that the network outputs a value that is close to zero. Then while adding the skip connections, the resulting network outputs a copy of its inputs, that is it initially models the identity function. To speed up our training, the target function was made close

to the identity function.

Here the finally connected layer is removed and a new fully connected layer is added since the Imagenet is not similar and datasets are too large, the parameters are also changed along with adding the final layer which depends on the difference of the data from the pre-trained model's data.

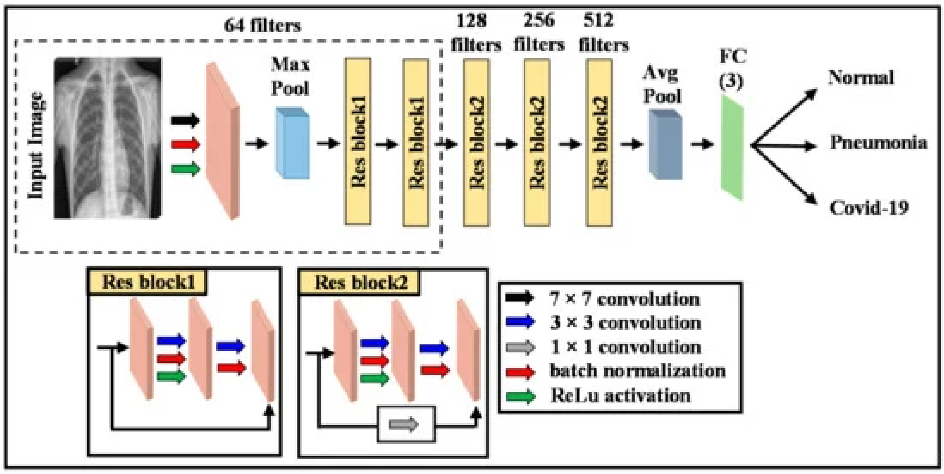

Figure 4.8: ResNet Function Diagram

After passing through the ResNet50 layer, its last layer is flattened and two fully connected layers are used, where first Batch Normalization is done after each fully connected layer to normalize the input given to the respective layer which also improves the model's learning rate.

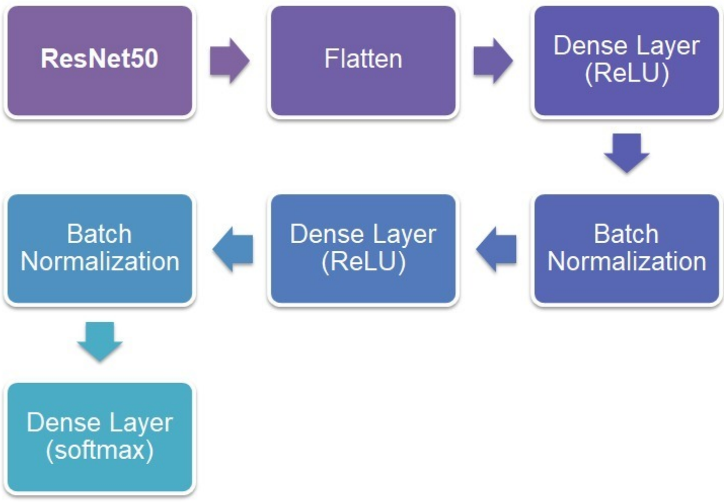

Figure 4.9: ResNet Block Diagram

Activation function was used at the end of each fully connected layer as well as at the output layer. ReLU activation function was used at the end of each fully connected layer whereas for the output layer softmax functions are used. ReLU activation function is used in multi- layer neural networks, it does not activate all the neurons at the same time and it will output the input directly if it is positive otherwise zero is shown as the output. Softmax function has two benefits, first it converts the output in such a way that the sum of all the output will be equal to one and second the output of the softmax function is the probability distribution.

RMSprop was used as the optimizer which converges faster and decreases the step for large gradients to avoid vanishing and exploding gradient problems. As the loss function Categorical-cross entropy was used this includes both softmax as well as cross entropy and output a probability over the class for each image. Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks. Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks.

First, StratifiedKFold shuffles your data, after that splits the data into n-splits parts, it is just like Kfold where the entire data is split for 5 times doing the epoch(1-15), see the output for the next block code, running fold keeps iterating everytime epoch 1-15 is completedKFold is cross validation technique and Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample. ModelCheckpoint callback is used ito connect with training using model.fit() to save a model or weights (in a checkpoint file) at some interval, so the model or weights can be loaded later to continue the training from the state saved, and that is stored in variable called callback.

CHAPTER 5

SOFTWARE IMPLEMENTATION

5.1 GUI

We have decided to use a web app or a website for displaying the output of the deep learning model. The technical diagram given below will show the interaction of users with the website and how the backend will work.

Figure 5.1: Technical Diagram

As you can see from the above image. The user will upload the chest X-ray after registering on the website/web app. Once the image is submitted, the image will go to the Flask server where the supervised training model will be used to predict the output. After this, the response will be sent back to the web app via the server.

The supervised training model is linked to the front end using python's micro web framework flask. The flask server integrates the python code for prediction of pneumonia and covid in the form of a form code. There are two forms, one for covid and another for pneumonia and later we can add as many forms as we want for diagnosing different respiratory diseases using the chest x-rays. Each form will take the x ray to their corresponding model and process it for getting the desired output based on the predictions by comparing the chest x ray with the trained datasets.This can be done in two ways: one either by creating separate python files named train.py and test.py for making the predictions. Second, by integrating the entire test train and the components into a single python file named app.py.We have used the second method for covid-19 and first method for pneumonia detection.

5.2 Website Overview

This website asks the user to upload the chest x-ray separately for covid and pneumonia. If the user submits the x-ray for checking covid-19 , then input x-ray will then go to the corresponding server of covid through the flask. If the user submits the x-ray for checking pneumonia , then the input x-ray will then go to the corresponding server of pneumonia through the flask. In the case of covid this image is tested against the train datasets of covid-19 which are there in our training model

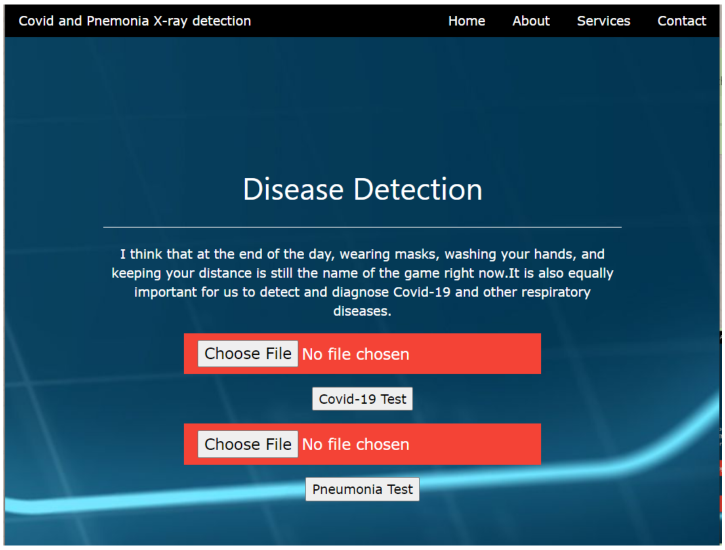

Figure 5.2: Website Frontpage

that detects whether the person is having covid or not and in the case of pneumonia, this image is tested against the trained datasets of pneumonia which are there in our training model that detects whether the person is having pneumonia or not.

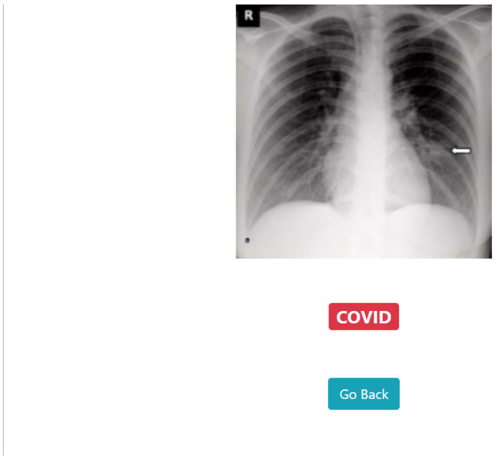

Figure 5.3: X-ray Image of Covid Positive

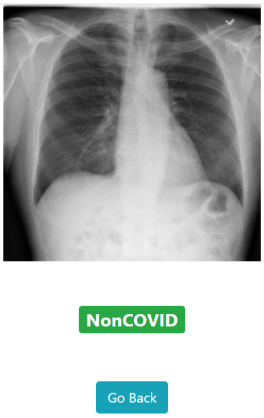

Figure 5.4: X-ray Image of Covid Negative

Figure 5.5: X-ray Image of Pneumonia Positive

Figure 5.6: X-ray Image of Pneumonia Negative

CHAPTER 6

RESULT AND DISCUSSION

6.1 Result for Pneumonia Detection

After training the images for 25 epochs their corresponding results were obtained, their output images were taken differentiating normal patients with pneumonia patients and model loss and model accuracy graphs were plotted.

6.1.1 Model Accuracy

A plot of accuracy on the training and validation datasets over training epochs is shown below:

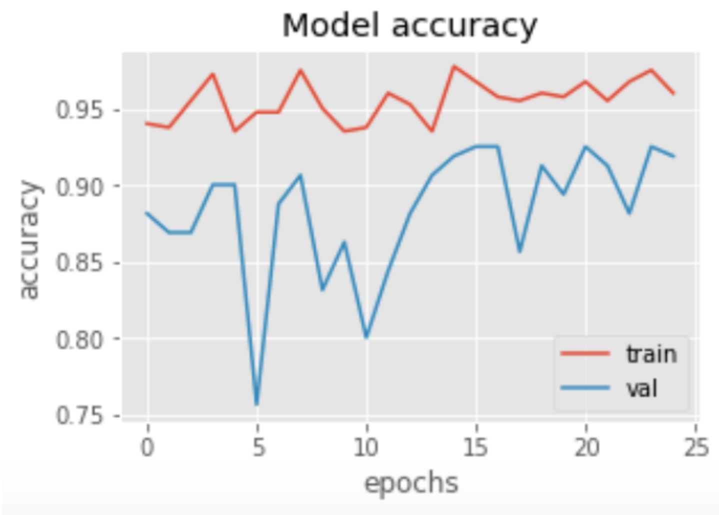

Figure 6.1: Model Accuracy

A most used curve to understand the progress of Neural Networks is an Accuracy curve. Learning curve calculated from the training dataset that gives an idea of how well the model is learning. Learning curve calculated from a hold-out validation dataset that gives an idea of how well the model is generalizing. From the plot of accuracy, we can see that the model was trained well for higher epochs. But we can see that the model could probably be trained a little more as the trend for accuracy on validation datasets is low for the first few epochs. Hence from the graph it is clear that the model performed well on the training set with an accuracy of 95percent and the validation set with an accuracy of approximately 93percent.

6.1.2 Loss Curve

A plot of model loss on the training and validation datasets over training epochs is shown below:

Figure 6.2: Model Loss

From the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labeled test). Hence it is clear that the model performed well with a training loss of 0.137 and validation loss of 0.2913

6.2 Result for Covid-19 Detection

This model was trained for 500 epochs, they were then tested against the label and their corresponding results were obtained, roc curve of the model was obtained in the graph, confusion matrix with normalization and without normalization is also obtained and their respective classification report were calculated, then their model accuracy and model loss graph were plotted for each epoch in the form of graph.

6.2.1 Roc Curve

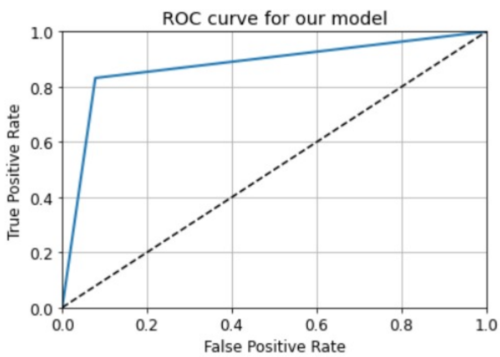

Figure 6.3: ROC Curve

The receiver operating characteristic (ROC) curve is another common tool used with binary classifiers. The ROC curve plots the true positive rate against the false positive rate. In our plot, the dotted line represents the ROC curve of a purely random Classifier. Since the classifier is to the top left corner of the dotted line, our model performed well.

6.2.2 Confusion Matrix

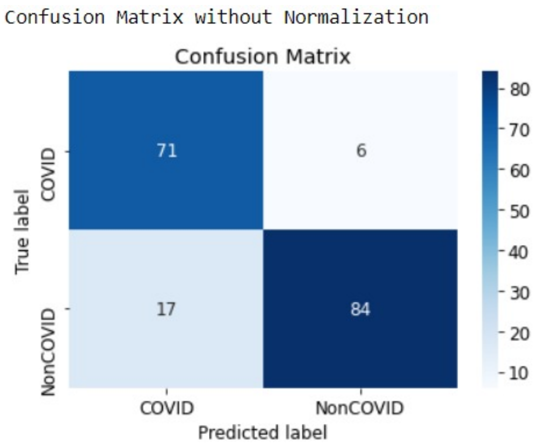

Figure 6.4: Confusion Matrix Without Normalization

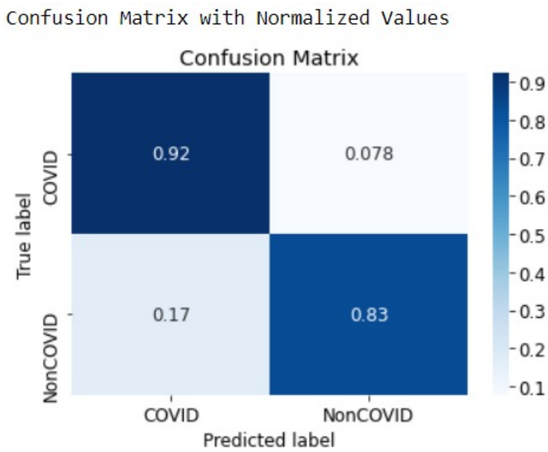

Figure 6.5: Confusion Matrix With Normalization

Confusion matrices with Normalized value were obtained and from the image it is clear that our model got almost 92percent for Covid and 83percent for Non-Covid. From the classification report our model got 93percent accuracy for Covid-19 and 84percent accuracy for Non-Covid patients. 81percent precision for Covid and 93percent precision value for Non Covid.

6.2.3 Model Accuracy

From the plot of accuracy, we can see that the model was trained well for higher epochs. But we can see that the model could probably be trained a little more as the trend for accuracy on validation datasets is low for the first few epochs. Hence

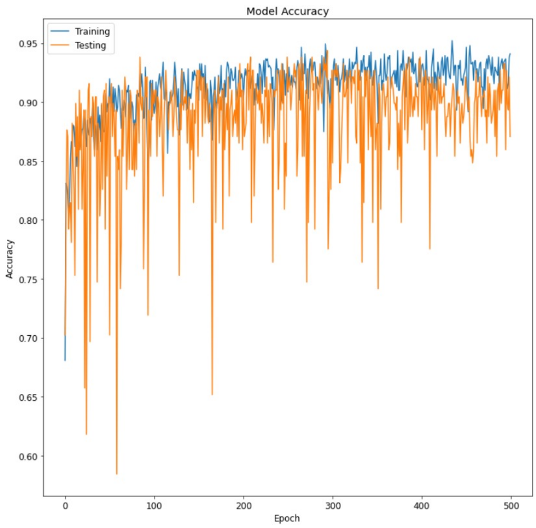

Figure 6.6: Model Accuracy Graph

from the graph it is clear that the model performed well on the training set with an accuracy of 93percent and the validation set with an accuracy of approximately 92percent.

6.2.4 Model Loss

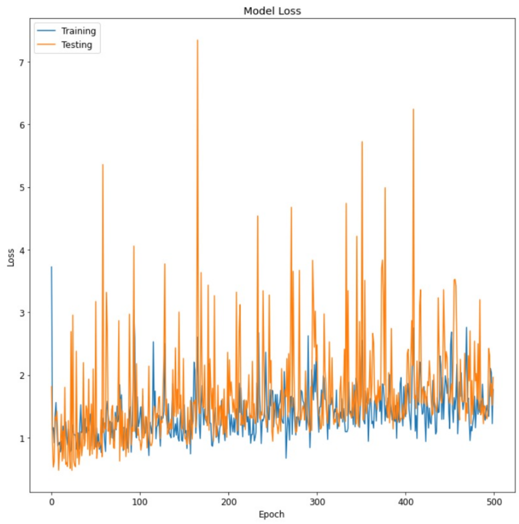

Figure 6.7: Model Loss Graph

From the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labeled test). Hence it is clear that the model performed well with a training loss of 1.770 and validation loss of 0.87.

6.3 Result for both Covid-19 and Pneumonia Detection

After passing the images into the training model, they were tested and their values were obtained and plotted in the graph, here Cross validation was used that is StratifiedKFold with K=5 and for 15 epochs with 345 steps in each epoch. Then their corresponding precision vs recall curve, roc curve, classification report and confusion matrix were obtained.

6.3.1 ROC Curve

It is a performance measurement for the classification problems at various threshold settings. Our model got almost 99.6percent ROC AUC score for the ovo strategy. Ovo strategy means one v/s one strategy where it checks between the one to be detected and the one with which it is checking. Ovo is preferred for the less training set.

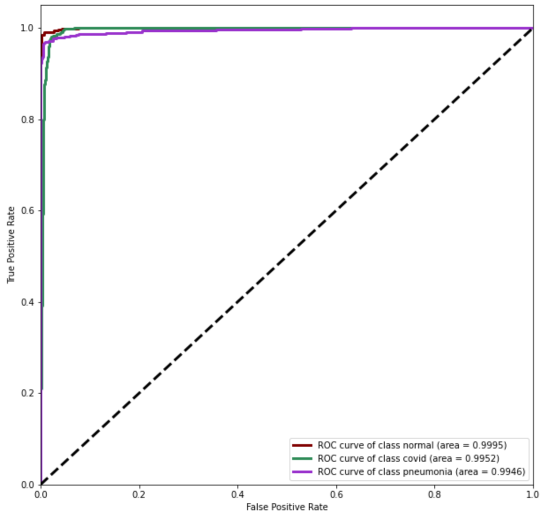

Figure 6.8: ROC Curve Graph

The receiver operating characteristic (ROC) curve is used for binary classification. Here we obtained an ROC curve by plotting the true positive rate versus our false positive rate. In our plot, the dotted line represents the ROC curve of a purely random Classifier. Since the classifier is to the top left corner of the dotted line, our model performed well. We also measured the area under the curve (AUC) in order to compare our classifier for COVID and pneumonia. It was found that the area of class normal was 0.9995, class covid-19 was 0.9952 and that of class pneumonia was 0.9946.The classifier was perfect since the ROC AUC was approximately equal to 1.

6.3.2 Precision Recall Curve

A precision-recall curve helps to select the best threshold for a specific problem and also helps to visualize how the choice of threshold affects the classifier performance.

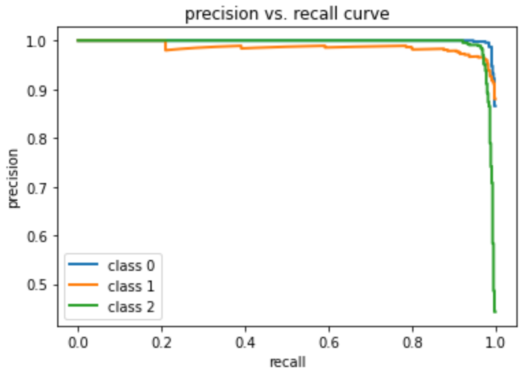

Figure 6.9: Model Loss Graph

When we plot our precision directly against recall, we found that the three curves are completely overlapping. From this precision-recall curve, it is seen that the precision really starts to fall sharply around 95percent recall.

6.3.3 Confusion Matrix

The performance of the classifier was evaluated using the confusion matrix we obtained as shown below.

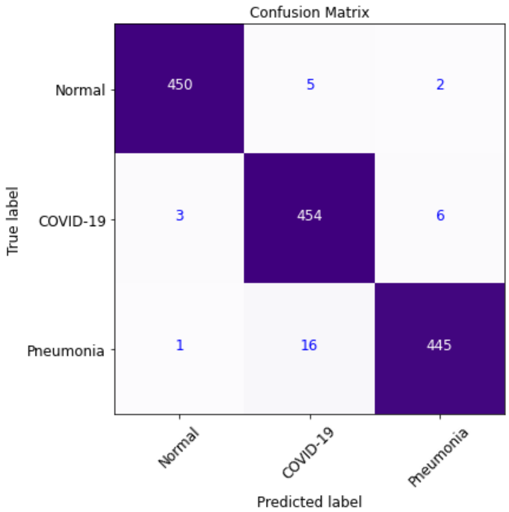

Figure 6.10: Confusion Matrix Label

From the confusion matrix obtained, accuracy was measured to be 0.963 for COVID-19, 0.963 for pneumonia and 0.963 for normal, precision of the classifier was obtained and found to be 0.91 for COVID-19, 0.99 for pneumonia, and 0.99 for normal. The recall obtained was 0.99 for COVID-19, 0.96 for pneumonia, and 0.92 for normal. F1 score which is the harmonic mean of precision and recall was obtained from confusion matrix as 0.95 for COVID-19, 0.98 for pneumonia and 0.95 for normal.

6.3.4 Model Score

Table 6.1: Model Score

Model(ResNet)	Testing Images	Accuracy	Recall	F1-Score	Precision
Covid-19	463	0.963	0.99	0.95	0.91
Pneumonia	457	0.963	0.98	0.98	0.99
Normal	462	0.963	0.95	0.95	0.99
Macro Average	1382	96.3per	96.3per	96.41per	96.41per
Weighted Average	1382	96.3per	96.3per	96.4per	96.63per

Our model got 96.3percent accuracy for Covid-19, Pneumonia and Normal images respectively and 99percent recall value for Covid-19, 96percent recall for Pneumonia and 92percent recall for Normal, As for the F1 score we got 95percent for Covid-19, 98percent for Pneumonia and 95percent for Normal and finally for precision, 91percent was obtained for Covid-19, 99percent for Pneumonia and 99percent for Normal. Their macro average and weighted average value for each are also shown on the table.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

A model which is based on deep learning algorithm was made to diagnose and detect COVID-19 and pneumonia. The proposed model has been made automatic, using CNN and transfer learning. An accurate reconstruction followed by categorical algorithms plays a very important role in developing an application specific medical imaging system to diagnose a disease reliably. The study shows that the use of transfer learning reduces the required observations for detecting pneumonia and COVID-19 with desired accuracy compared to the conventional method. Simulation results shows that the proposed model scheme offers very high prediction accuracy on X-Ray images. The models proposed in this research for the detection of pneumonia and COVID-19 on the frontal chest x-ray images using CNN and Transfer learning approaches have significant results.

Most recently, there have been several researches on the same dataset. However, our models have outperformed the results from previous researches to attain state-of-the art. Neural Networks were used to develop models for efficient extraction of features from an x-ray image and predict the presence or absence of both pneumonia and COVID-19. Also, in this research, the testing data was increased by data augmentation techniques and thus, the models were tested on a greater number of images as compared to a few other approaches.

7.2 Future Scope

The application of the current model can be extended to accommodate more respiratory diseases. The proposed method may be extended as a generalized automatic computerized system to assist medical professionals by localizing the region of interest like brain tumor, cancerous cell etc. The project may include other disease management, promoting this as a daily clinician work tool for handling patients at home in the prevention of complications and acute events.

With advancements of computer applications in the medical sector, respiratory diseases can be effectively detected using chest radiographs with the help of technologies like CNN and deep learning. In this research, methodologies were developed using which pediatric pneumonia can be predicted with higher accuracy. Automated diagnosis in medical field is the key area that will benefit directly from our research.

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APPENDIX A

PUBLICATION

1. Annsana Baby, Ashik Polly, Jefin Paul, Vishnudev S
   Detection of COVID-19/Respiratory diseases using deep learning algorithms
   Conference Name: 2nd International Conference on IoT based Control networks and Intelligent Systems ICICNIS
   Organizer: St. Joseph's college of Engineering and Technology, Kottayam, India
   Status: Accepted for the second round

2. Annsana Baby, Ashik Polly, Jefin Paul, Vishnudev S
   Detection of COVID-19/Respiratory diseases using deep learning algorithms
   Conference Name: 79TH Device Research Conference
   Organizer: Material Research Society (MRS)
   Status: Submitted

APPENDIX B

CONFERENCE PAPER

2nd International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS 2021)

Detection of Covid-19/Respiratory Diseases Using Deep Learning Algorithms

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A B S T R A C T

Each year, millions of people suffer from lung diseases, doctors use X-Rays and Computed Tomography to detect these diseases. A highly contagious Novel Coronavirus Disease has been widespread since December 2019 and results in severe acute respiratory diseases and organ failure. Using X-rays Radiologists can detect many respiratory-related diseases such as pneumonia, emphysema, interstitial lung disease, and researches are going on to detect novel COVID-19 virus. When it comes to other lung diseases like Pneumonia, Infiltration, the human-assisted diagnosis has many limitations. When it comes to other lung diseases like Pneumonia, Infiltration, the human-assisted diagnosis has many limitations. With the growing number of patients, it is difficult for doctors and nurses to check mild to severe health conditions for every patient. Hence an automated method is needed to make things easier for doctors through which early-stage detection of these diseases are possible. Our model compares X-Rays and for detecting and classifying respiratory diseases. The respiratory diseases and COVID-19 are diagnosed using Data Analytics with X-Rays.

1. INTRODUCTION

The novel COVID-19 virus came to light in December 2019 in Wuhan Province of China, where it was originated from animals and quickly spread around the world. The easiest way for transmission of COVID-19 is through the air and physical contact, such as hand contact with an infected person. Early detection and diagnostics are critical factors to control the spreading of COVID-19. Chest X Rays is one of the cheapest and easiest diagnostics techniques used by radiologists to detect and classify lung diseases like pneumonia, emphysema, infiltration and others. Pneumonia is one of the leading causes in children which occur due to the infection caused in air sacs of the lungs. Using the Chest x-rays graph it is easier to detect pneumonia without the help of radiologists. With the growing number of patients, it is becoming difficult for doctors and nurses to check mild to severe health conditions for every patient, hence an automated system is needed to make things easier for doctors through which even early-stage detection of these diseases are possible. Classification of the patient from chest X-Ray is difficult with a large image dataset. Convolutional Neural Network and Transfer Learning the machine is proposed which can detect the type of lung diseases including Pneumonia along with COVID-19. Our model detects COVID-19 and pneumonia more accurately using Data Analytics from lung X Rays.

Many researchers have done investigations to relate machine learning schemes for the prediction of X-ray image diagnostic information. Using CNN and Transfer learning the result is observed and the final output is obtained using a confusion matrix, suppose if the patient has Pneumonia and the result also came out to be true then it is True Positive and if the patient doesn't have Pneumonia and the result predicted is false then it is marked as True negative. Similarly False positive and false negative are determined based on which Precision, Recall, Accuracy and F1 scores are calculated. With the control of computers along with the huge volume of records being unrestricted to the public, this is high time to resolve this complication. This solution will help to decrease medical costs with the enlargement of computer science for health and medical science projects.

ResNet50 was used wherein based on the size of the dataset convolutional and pooling layer is used in a pre-trained network which will identify the shape and edge-based features, then at the end, one or two linear dense layers are added to obtain the desired output. Re-Lu was used for each layer and for the dense layer Sigmoid is used. To reduce overfitting, a dropout layer is used, wherein some input nodes would be active and some would be inactive and finally after extracting features, it is flattened and passed onto a dense layer. The output achieved an accuracy of 97% to 98% for all models, which was found through a confusion matrix.

Figure B.1: Pg:1

2. MAJOR COMPONENTS

2.1 Flask

Flask is a micro web framework that consists of a small core that is direct and straightforward in nature. It is known as a microframework because it does not require specific tools or libraries for its implementation. A database abstraction layer, form validation, or any other components containing third-party libraries that provide common features are not present in the flask. This framework is also considered to be more explicit than other frameworks available in python. Flask is also very easy to learn as a beginner because there is very little boilerplate code or repetitive code for developing a simple responsive app. Flask framework acts as an alternative to Django as it provides more flexibility on deciding how they want to implement things. Flask is also useful for building basic locales with inactive substances, like blogs as it gives the user a great deal of customizing options.

2.2 GUI

We have decided to use a web app or a website for displaying the output of the deep learning model. The technical diagram given below will show the interaction of users with the website and how the backend will work.

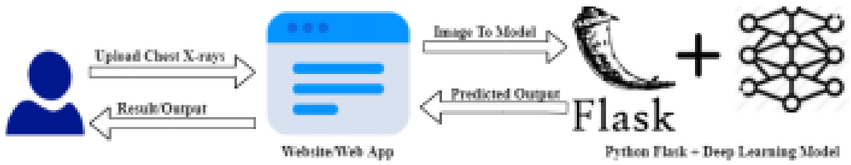

Fig (1): Flow chart of Detection model

As you can see from the above image. The user will upload the chest X-ray after registering on the website/web app. Once the image is submitted, the image will go to the Flask server where the supervised training model will be used to predict the output. After this, the response will be sent back to the web app through the server.

2.3 Website Overview

This website asks the user to upload the chest X-ray from which it will be redirected to a registration form after which the user is allowed to submit their chest X-rays which will then go to the server through the flask. This image is tested against the train datasets which are there in our training model that detects whether the person is covid positive, or whether the person is infected with normal pneumonia.

Fig (2): Website Homepage

If the person is found healthy, then a message will be displayed saying 'healthy' and if the person is infected with covid-19, a message will be displayed saying 'covid-19 positive' and if the person is having normal pneumonia then the message saying 'pneumonic' will be displayed.

Figure B.2: Pg:2

3. MODEL AND IMPLEMENTATION

3.1 Data Distribution

Table (1): Dataset for training, testing and validation

	Covid-19	Pneumonia	Normal
Training Set	1432	1432	1437
Testing set	463	463	463
Validation set	413	413	413
Total	2313	2313	2312

A study was conducted and a total of2313 samples of normal and pneumonia were obtained from Kaggle and were classified into 1437 for training, 463 for testing and 413 for validation. The datasets of patients suspected of COVID-19 were collected from the Radiopedia, the Italian Society of Radiology and the Fig share data repository websites. The total 2313 datasets of COVID-19 and normal were classified into 1437 for training, 463 for testing, and 413 for validation. These total datasets of 6939 samples containing the chest X-Ray images were organized into three folders namely, Covid19, pneumonia and normal which uses 2313 samples for each case.

3.2 Model Data

Table (2): Model Architecture

Layer	Output Shape	Params
In put Layer	(None, 224, 224, 3))	0
ResNet50	…	…
Flatten	(None, 100352)	0
Dense	(None, 4096)	411045888
Batch Normalization	(None, 4096)	16384
Dense	(None, 4096)	16781312
Batch Normalization	(None, 4096)	116384
Dense	(None, 3)	12291
Sigmoid Activation	(None, 100352)	0

The model was developed from the dataset and was allowed to train. Transfer Learning and Convolutional Neural Network approach was used for training. After Augmenting the Images they were passed onto the following layers

Figure B.3: Pg:3

3.2.1 Transfer Learning

In transfer learning pre-trained network is applied to the task of our own design, transferring what the model learned from one step to another. Last some layers and filters are removed and a linear layer is added at the end to fulfill the task.
Here finally connected layer is removed and a new fully connected layer is added since the Imagenet is not similar and datasets are too large, the parameters are also changed along with adding the final layer which depends on the difference of the data from the pre-trained model's data.

3.2.2 Resnet50

ResNet50 which stands for Residual Network which delivered top-5 error rate under 3.6% using deep convolutional neural network that composed of 152 layers. Skip connections also called shortcut connections is the key to train such a deep network. When we add input x to the output of the network, the network was forced to model h(x) – x where x is the input rather than the target function h(x). While initializing our neural network, the weights are assigned close to zero so that the network outputs a value that is close to zero. Then while adding the skip connections, the resulting networks outputs a copy of its inputs that is it initially models the identity function. To speed up our training, the target function was made close to the identity function.

3.2.3 Fully Connected Layer

After passing through the ResNet50 layer, its last layer is flattened and two fully connected layers are used, were first Batch Normalization is done after each fully connected layer to normalize the input given to the respective layer which also improves the model's learning rate.

3.3 Activation

Activation function was used at the end of the each fully connected layer as well as at the output layer. ReLU activation function was used at the end of each fully connected layer whereas for the output layer softmax functions are used. ReLU activation function is used in multi- layer neural network, it does not activate all the neurons at the same time and it will output the input directly if it is positive otherwise zero is shown as the output. Softmax function has two benefits first it converts the output in such a way that sum of all the output will be equal to one and second the output of the softmax function is the probability distribution.

3.4 Optimizer and Loss

RMSprop was used as the optimizer which converges faster and decreases the step for large gradients to avoid vanishing and exploding gradient problems. As the loss function Categorical-crossentropy was used this includes both softmax as well as cross entropy and output a probability over the class for each image.

4. RESULT

Our model was used for 20 epochs for each 5 sets of StratifiedKFold validation. Cross Validation was used which shuffle the dataset randomly and split dataset into KFolds and specific operation is done for each unique group. Also after training when we classify the images, we run image through all classifiers and see which one is the best.

4.1 Precision VS Recall

A precision-recall curve helps to select the best threshold for a specific problem and also helps to visualize how the choice of threshold affects the classifier performance.

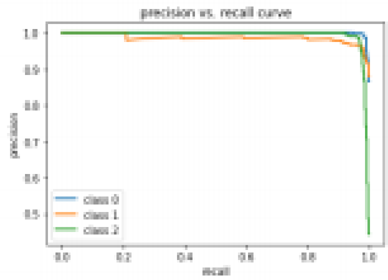

Fig (3): Precision V/S Recall curve

Figure B.4: Pg:4

When we plot our precision directly against recall, we found that the three curves are completely overlapping. From this precision-recall curve, it is seen that the precision really starts to fall sharply around 95% recall.

4.2 ROC-AUC-SCORE

It is a performance measurement for the classification problems at various threshold settings. Our model got almost 99.6% ROC AUC score for the ovo strategy. Ovo strategy means one v/s one strategy where it checks between the one to be detected and the one with which it is checking. Ovo is preferred for the less training set.

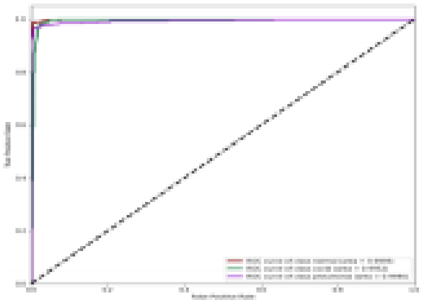

Fig (4): ROC Curve

The receiver operating characteristic (ROC) curve is used for binary classification. Here we obtained an ROC curve by plotting the true positive rate versus our false positive rate. In our plot, the dotted line represents the ROC curve of a purely random Classifier. Since the classifier is to the top left corner of the dotted line, our model performed well. We also measured the area under the curve (AUC) inorder to compare our classifier for COVID and pneumonia. It was found that the area of class normal was 0.9995, class covid-19 was 0.9952 and that of class pneumonia was 0.9946.The classifier was perfect since the ROC AUC was approximately equal to 1.

4.3 Model Score

Table (3) – Accuracy, Recall, F1 score and Precision score

Model (ResNet50)	**Testing Images**	**Accuracy**	**Recall**	**F1-Score**	**Precision**
Covid-19	463	0.963	0.99	0.95	0.91
Pneumonia	457	0.963	0.98	0.98	0.99
Normal	462	0.963	0.95	0.95	0.99
Macro Average	1382	96.3%	96.3%	96.41%	96.41%
Weighted Average	1382	96.3%	96.3%	96.4%	96.63%

Our model got 96.3% accuracy for Covid-19, Pneumonia and Normal images respectively and 99% recall value for Covid-19, 96% recall for Pneumonia and 92% recall for Normal, As for the F1 score we got 95% for Covid-19, 98% for Pneumonia and 95% for Normal and finally for precision, 91% was obtained for Covid-19, 99% for Pneumonia and 99% for Normal. Their macro average and weighted average value for each are also shown on the table.

Figure B.5: Pg:5

4.4 Confusion Matrix

The performance of the classifier was evaluated using the confusion matrix we obtained as shown below.

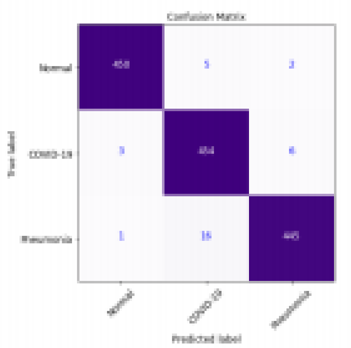

Fig (5): Confusion matrix for Covid-19, Pneumonia and Normal

From the confusion matrix obtained, accuracy was measured to be 0.963 for COVID-19, 0.963 for pneumonia and 0.963 for normal, precision of the classifier was obtained and found to be 0.91 for COVID-19, 0.99 for pneumonia, and 0.99 for normal. The recall obtained was 0.99 for COVID-19, 0.96 for pneumonia, and 0.92 for normal. F1 score which is the harmonic mean of precision and recall was obtained from confusion matrix as 0.95 for COVID-19, 0.98 for pneumonia and 0.95 for normal.

CONCLUSION

A model which based on deep learning algorithm was made to diagnose covid-19 and certain respiratory diseases. The proposed model has been made automatic, using CNN and transfer learning algorithms. Various datasets of CT-scan and X-rays along with data analytics have made this model optimized. The performance analysis on both the benchmark chest-CT d and chest X rays revealed that the proposed model on the chest-CT scan outperformed the competitive models which used chest x-rays in terms of accuracy.

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Appendix A. Dataset for ResNet50-Xray

ResNet50 model is chosen for transfer learning which is stored in base model. Covid19, pneumonia and normal datasets are taken for the training process to differentiate between chronic lung diseases. https://www.kaggle.com/jefinpaul/covid-pneumonia-and-normal-using-resnet50-xray

Appendix B. Sample Detection results

Covid19 detection based on chest X-ray scans using transfer learning algorithm: VGG16, ResNet50, InceptionV3 and Xception. The models were trained for 500 epochs on around 1000 X-rays and around 750 CT Scans on Google Colab GPU. https://github.com/kaushikjadhav01/COVID-19-Detection-Flask-App-based-on-Chest-X-rays-and-CT-Scans

Figure B.6: Pg:6

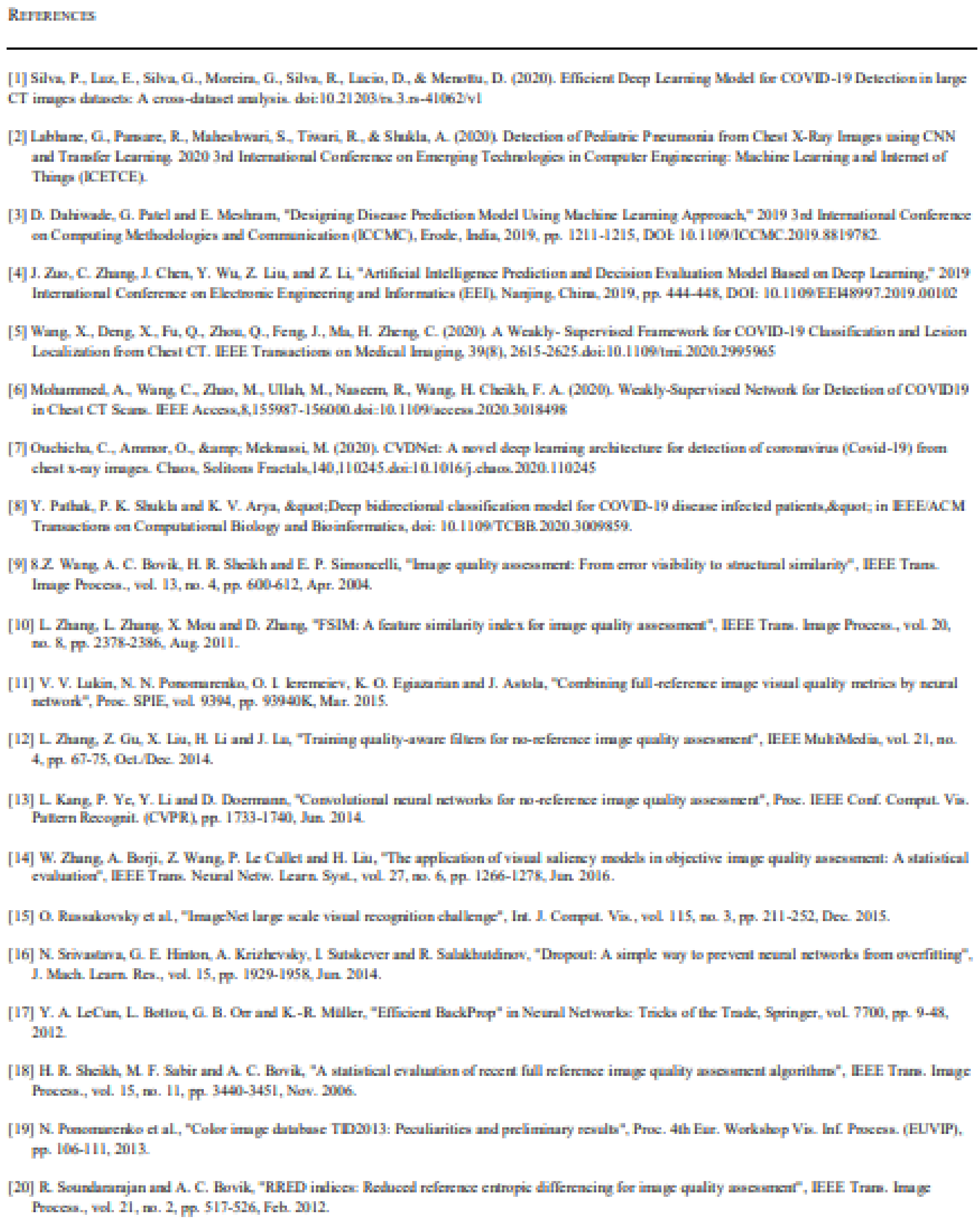
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Figure B.7: Pg:7