ANALYZING THE DETECTION OF COVID-19 ON CORONET USING VARIOUS OPTIMIZER

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***Abstract*— This paper aims to analyze the convolutional neural network-CoroNet, that differentiates COVID-19 from heathy, bacterial pneumonia and viral pneumonia , using various optimizers. Covid and other pneumonia disease has similar symptoms, so, it is important to diagnose the covid virus from other cases of pneumonia for proper diagnosis. CoroNet neural network classifies chest X-ray images into four classes : COVID-19 , normal , bacterial pneumonia and viral pneumonia. Just implementing the neural network, by using a single optimizer will not be enough . Optimizers play an indispensable role in diminishing the loss incurred by the network's training process. So, the project implemented four dif ferent optimizers: Adam, Adamax, SGD, and RMS Prop in CoroNet. The CoroNet with Adamax showed higher accuracy, followed by Adam optimizer. Data Augmentation techniques also improved the performance of four class classification. This study also showed that combination of CNN with SVM gave better performance for binary classification. This study examines the pre-existing neural network in order to determine the best way to differentiate covid cases from those with other types of pneumonia. For the purpose of faster diagnosis and automatic COVID-19 identification, a simple learning model that is both accurate and speedy would be of great use to radiologist .**

***Keywords—component, formatting, style, styling, insert** (key words)*

I INTRODUCTION

Covid19 is a needless introduction. Since it first surfaced in China in December of 2019, every one of us has witnessed how severely it had impacted our lives. The laboratory tests or radiological imaging are the diagnosis for the condition. In order to identify COVID19, the RT-PCR (reverse transcription polymerase chain reaction) test is still considered to be the gold standard. Despite the fact that this test substantiates the positive findings, there have been concerns over its level of sensitivity. The time-consuming laboratory test is followed up by radiographic imaging for further confirmation. There is also a home covid test kit that can be purchased these days. This test, which is referred to as a fast antigen test, is a quick method that may be used to validate the result immediately. However, because there have been reports of false negative instances, a second PCR test could be necessary to verify the case. After the PCR test results have been validated, the hospitals will rely on radiological imaging to determine the severity of the lung damage. Imaging techniques such as chest X rays and CT scans are often used in radiology as diagnostic tools. CT scans are expensive, and every health centre would need to have one. However, CT scanning becomes pointless since the disease was rapidly spreading and impacting a significant number of people, despite the fact that CT scans provide precise and reliable data. After diagnosing each of the covid instances, there was also the possibility that the CT scan equipment might become contaminated. When there is a huge population that is afflicted with covid, x-rays can be a diagnostic technique that is easily transportable, affordable, quick, and reliable. Ground glass opacities, bilateral and interstitial abnormalities make up the majority of lung abnormalities that may be noticed on covid x-rays. In this emerging world of Artificial Intelligence, and its application in medical field is promising. Deep learning, a prominent research area has successfully solved medical problems. Deep learning can be defined as the subset of machine learning, which has layered structure of algorithms, called artificial neural network. This is inspired by human brain which can learn and make decisions on its own. In this project., we will be focusing the application of deep learning in analysing covid Xray's. The utilization of deep learning in analysing covid is not only limited to diagnostic image processing, but also for covid positive prediction, disease tracking, and vaccine manufacturing. It had overcome the various obstacles in medical image analysis. However deep learning-based diagnostic tools is still in the early stage and still it needs to be materialized. There are many studies that perform covid detection using convolutional neural net work. Many architectures in the literature have successfully performed two class, three class, and four class classifications. Since the symptoms of covid and other pneumonia cases are similar, it is important to identify covid cases from other pneumonia cases for proper treatment. Their main differences can be easily spotted on chest radiological image. A four-class classification for detection of covid has been studied less. The four classes are covid, normal, bacterial pneumonia and viral pneumonia. This project aims to analyze a convolutional neural network called CoroNet, from the literature, in a four-class classi fication. The network would be analysed using various optimizers like Adam, Adamax, SGD, and RMS Prop. Optimizers are algorithms that are necessary for training the neural network, in order to reduce the losses. A modification of Coronet, by implementing an SVM classifier had also brought significant results in binary classification. A support vec tor machine (SVM) is a type of deep learning algorithm that performs supervised learning for classification or regression of data groups. A simple, accurate, and fast learning model can be helpful to radiologists for faster diagnosis and automated detection of COVID-19.

II. LITERATURE SURVEY

Many research papers have been considered for the survey. There were many proposed neural networks, and optimization methods that showed improved results. Some papers have studied on optimizers as well. This section covers some papers that have studied on four class classification and on different optimizers. The paper by Linda Wang et al proposed CovidNet model that performs two class, three and four class classification [1]. But the accuracy obtained for four four classification was 83.4% only. Another proposed models named Corodet- a 22 layer network showed better performance over other state of art architectures [2]. Though the accuracy obtained was 91.2%, the paper mentions that the accuracy decreased, when the number of layers decreased. So, to train complex features, we need more layers for better results. Darknet53 was used as the training model, for binary and multiclass classification [3]. But the accuracy for four class classification was 73.46% only. Dark Covid Net Model performed only three class and binary class classification and also predicted incorrectly for poor quality x-ray images [4]. Deep learning architectures like AlexNet, DenseNet 201, Inception v3, XceptionNet, Inception, resnet v2, VGG16, VGG19, Google Net, ResNet18, ResNet50, and ResNet101 along with j48 algorithm provided better results with Restnet50 having accuracy of 94.7% [5]. However these paper have not studied on four class classification. Another paper by Chaudhary et. al also mentions that the different pre-processing of data affected the performance [6]. This also says the importance 3 of pre-processing data before training the neural network. The effectiveness of the eight most efficient pre-trained deep CNN models, namely, VGG-16, Inception-V3, ResNet-34, MobileNetV2, AlexNet, Google Net, ResNet-50, and Squeeze Net have been compared with different optimization like SGD, Adadelta, Adam op timizer and RMSProp [7]. The paper by Poonam et al compared two optimizers Adam and RMS Prop optimizers on covid chest xrays for two class classification [8]. Another paper proposed a DenseNet model and the optimizers differentiated include Adamax, Adam, and Stochastic Gradient Descent(SGD) for two class classification of covid X-rays [9]. A com parative analysis of 10 different state-of-the-art gradient descent-based optimizers, namely Adagrad, AdaDelta, SGD, Adam, Cyclic Learning Rate (CLR), Adamax, RMS Prop), Nes terov Adaptive Momentum (Nadam), and Nesterov accelerated gradient (NAG) for CNN was done on MRI images of the brain [10]. Deep feature plus SVM also classified covid cases with better results, but did not compare any optimizers [11]. The studies [13–15] conducted on CNN-SVM, takes SVM as an alternative to softmax function for classification. CoroNet architecture in the literature has performed two, three and four class classifi cation to detect Covid19 [12]. It is computationally less expensive and achieved promising results with the Xception as base model. However, they have not utilized any optimizers to analyze the neural network. The paper also mentions the need of more data for better performance. This project implemented CoroNet and analysed using various optimizers for four class classification. The project also implemented CoroNet with SVM to perform binary classification.

III. CONVOLUTIONAL NEURAL NETWORK - CORONET

A Convolutional Neural Network (CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.The pre-processing required in a CNN is much lower as compared to other classification algorithms.The architecture of a CNN is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. A typical Convolutional Neural Network architecture consists of convolutional layers, pooling layer and fully connected layers. Convolutional Layer-The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the filter entries and the input, producing a 2-dimensional activation map of that filter. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input.

Pooling Layer-Another important concept of CNNs is pooling, which is a form of non linear down-sampling. There are several non-linear functions to implement pooling, where max pooling is the most common. It partitions the input image into a set of rectangles and, for each such sub-region, outputs the maximum. Intuitively, the exact location of a feature is less important than its rough location relative to other features. This is the idea behind the use of pooling in convolutional neural networks. The pooling layer serves to progressively reduce the spatial size of the representation, to reduce the number of parameters, memory footprint and amount of computation in the network, and hence to also control overfitting. This is known as down-sampling. Fully connected Layer-After several convolutional and max pooling layers, the final classification is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular (non-convolutional) artificial neural networks. Their activations can thus be computed as an affine transformation, with matrix multiplication followed by a bias offset (vector addition of a learned or fixed bias term).

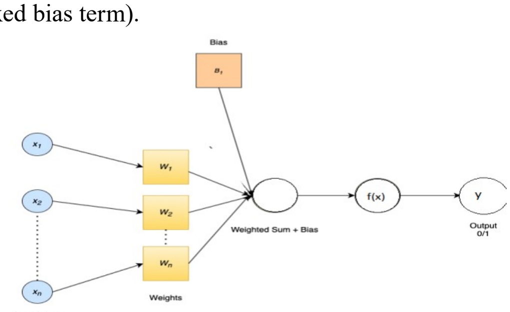


Figure -1 A Neural Network unit

CORONET

CoroNet is a Convolutional Neural Network (CNN) architecture tailored for detection of Covid19 infection from chest X-ray images. It is based on Xception CNN architecture. Xception which stands for Extreme version of Inception (its predecessor model) is 71 lay ers deep. The Xception architecture has thirty six convolutional layers forming the feature extraction base. Xception uses depthwise separable convolution layers with residual con nections instead of classical convolutions. Depthwise convolution is the channel-wise n×n spatial convolution followed by Pointwise convolution.

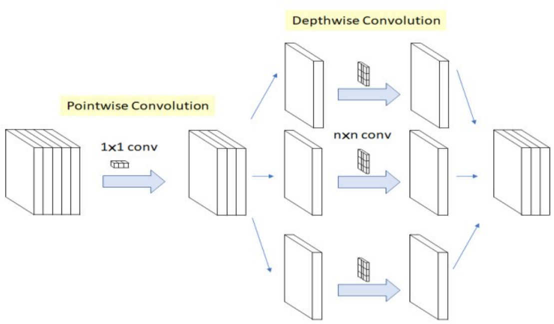


Figure -2 Depthwise Seperable Convolution [17]

CoroNet use Xception as base model with a flatten layer, dropout layer and two fully-connected layers added at the end. CoroNet has 33,969,964 parameters. Flatten layer is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The Dropout layer is a mask that nullifies the contribution of some neurons towards the next layer and leaves unmodified all others. This prevents overfitting. Fully Connected Layers form the last few layers in the network. Dense Layer is simple layer of neurons in which each neuron receives input from all the neurons of previous layer, thus called as dense. The final dense layer classifies the output based on the image input.

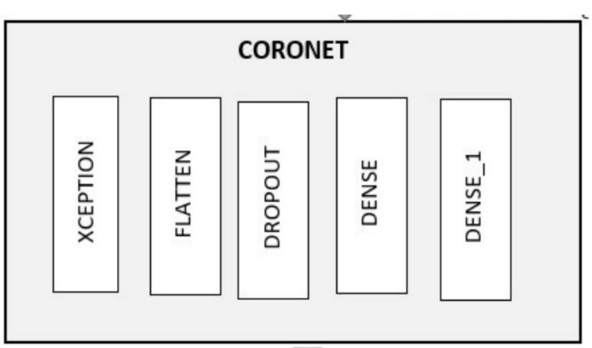


Figure-4 Illustration of layers of CoroNet

IV. IMPLEMENTATION

Deep Learning is all about data which serves as fuel in these learning models. The datasets used are obtained from Kaggle and GitHub repositories. The dataset consist of normal, covid, viral pneumonia, bacterial pneumonia chest Xrays. Different experiments were done using CoroNet neural network in order to measure performance. All the experiment was done on Google Colab in Keras with tensorflow backend. The basic workflow of the exper iment implementation include exploring dataset, data pre-processing and augmentation, building neural network, training and compiling and finally the performance evaluation.

Layer	Output Shape	No.of parameters
Xception	5x5x2048	20861480
Flatten	51200	0
Dropout	51200	0
Dense	256	13107456
Dense	4	1028

Table -1: Details of CoroNet architecture

CoroNet

The CoroNet was implemented with 1119 training images of 4 class, 277 validation images of 4 class and 284 test images. Adam optimizer with an epoch of 80, batch size of 10 and learning rate of 0.001 were utilized. Relu activation with softmax classifier was used in last layers of the network. After the neural network is built, the model is trained using training parameters. The four class classification was done, classifying chest X-rays into covid, normal, bacterial pneumonia and viral pneumonia. And finally the performance measure is found. The same experiment was repeated with an increase of 20% in training data along with data augmentation techniques with 1320 training images of 4 class, 327 validation images of 4 class and 277 test images. This method also improved the overall performance.

Optimizers

The CoroNet was implemented with four different optimizers: Adam, Adamax, SGD, and RMS Prop. The dataset contained 1119 training images of 4 class, 277 validation images of 4 class and 284 test images. In all the cases learning rate of 0.001, epoch of 80 and batch size of 10 were used. The data pre-processing and augmentation was also done. The four class classification was performed, after training the neural network with each optimizer. The class indices are 0,1,2,3 for covid, normal, bacterial pneumonia and viral pneumonia cases respectively. The performance measure was found for all cases.

CoroNet-SVM

The final experiment was implementing CoroNet-SVM. It is done by introducing the SVM classifier in the final layer of CoroNet. This study performed binary classification. This ex periment is done using two dataset. The first dataset was taken from kaggle/khoongweihao containing normal and pneumonia X-rays. This dataset contained 148 training and 40 test 21 ing images. The learning rate of 0.001, epoch of 30 and Adam optimizer was used. While the second dataset was taken from github.com/education454/datasets.git, that contained normal and covid cases. The dataset contained 1811 training set and 484 testing set. The learning rate of 0.001, epoch of 30 and Adam optimizer was used. After training and compiling the model predicts X-rays correctly.

IV RESULTS AND DISCUSSION

The performance evaluation is done by some metrics. The metrics used are accuracy, precision, recall, and F1 score. TP, TN, FP, and FN represent, respectively, numbers of true positive, true negative, false positive, and false negative. True Positive (TP) is an outcome where the model correctly predicts the positive class and true negative (TN) is an outcome where the model correctly predicts the negative class. While false positive (FP) is an outcome where the model incorrectly predicts the positive class and false negative (FN) is an outcome where the model incorrectly predicts the negative class. Some of the performance metric is discussed below.

Accuracy: It is the number of corrected instances over the total number of cases.

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

Precision: It measures the model's accuracy in classifying a sample as positive.

TP/(TP+FP)

Recall: The recall measures the model's ability to detect positive samples.

TP/(TP+FN)

F1 score: Measure of test accuracy and is defined as the weighted average precision and recall. 2(TP)/(2(TP)+FP+FN)

Another way of assessing the performance of a classification model is by confusion metrics. It is a comparison between the ground truth (actual values) and the predicted values emitted by the model for the target variable.

a. *Experiment 1*

The accuracy obtained after implementing CoroNet is 90.85% for four class classifica tion.The other metrics like precision, recall, and F1score is also obtained, which is shown in the Table 8.1. After increasing the training data from 1119 to 1320 images and with data augmentation techniques, the accuracy increased to 93.50%. Adding more data in creases diversity, as more examples are being trained by the model. The class indices are 0,1,2,3 for covid, normal, bacterial pneumonia and viral pneumonia cases respectively. The confusion matrix is also obtained 8.1

Metric	Percentage
Accuracy	90.85
Precision	91
Recall	91
F1 Score	91

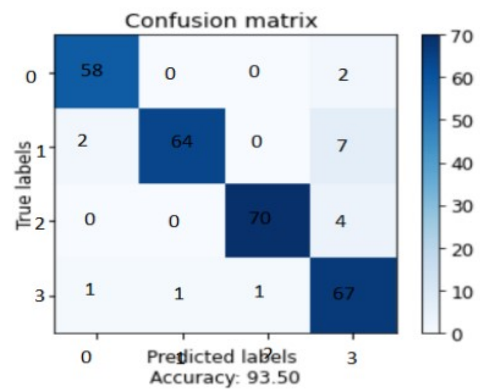
Table -2 : Performance metric obtained after implementing CoroNet

b. *Experiment 2*

The CoroNet was implemented with four different optimizers: Adam, Adamax, SGD, RMS Prop. The accuracy obtained by Adam optimizer was 90.85%. While, the accuracy obtained by Adamax, SGD, and RMS Prop are 96.48%, 83.47%, and 83.1% respectively. The various performance metric obtained is given in Table 8.3. The highest accuracy is obtained by AdaMax optimizers. .While the accuracy obtained by RMS Prop and SGD were almost same. So, CoroNet with Adamax optimizer showed better performance.

Metric	Percentage
Accuracy	93.5
Precision	94
Recall	94
F1 Score	94

Table -3 Performance metric obtained after increasing training data by 18% in CoroNet

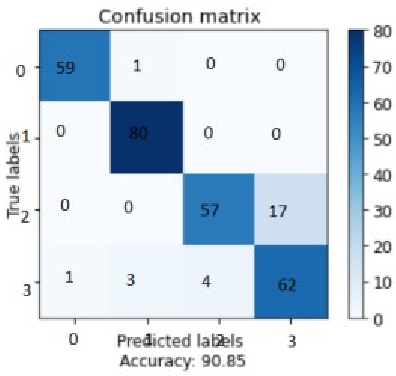


Confusion matrix obtained on implementation of CoroNet with increased training data

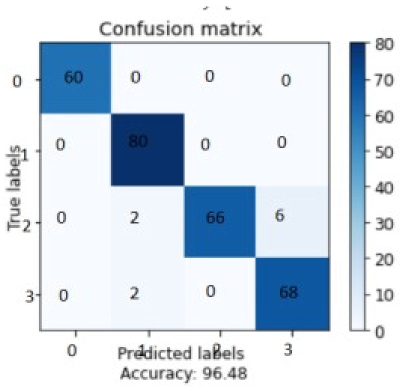
Metric	Adam	Adamax	RMS Prop	SGD
Accuracy	90.85	96.48	83.47	83.1
Precision	91	97	82	86
Recall	91	97	84	83
F1 Score	91	97	83	83

Table - 4 Performance metrics obtained for different optimizer(in percentage)

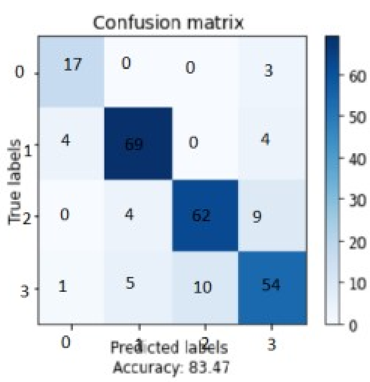
(a)



(b)



(c)



(d)

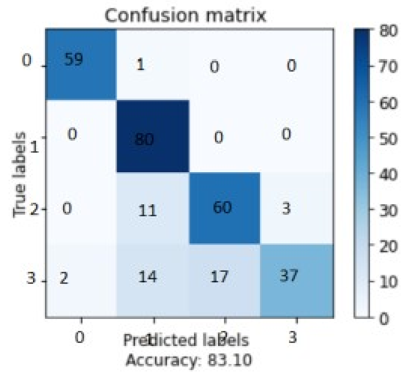


Figure - 5 Confusion Matrix of various optimizers: (a)Adam (b)Adamax (c)RMS Prop (d) SGD

c. Experiment 3

CoroNet with SVM was implemented and predicted the chest Xrays. The accuracy ob tained for the dataset that contained normal, and pneumonia cases (including covid) was 97.5%. And the accuracy obtained for the dataset that contained normal and covid cases was 99.5%. The svm classifier showed significant results for binary classification. The model correctly predicted the chest X-rays. Results are shown in Table 5.

Dataset	Accuracy
Normal and Covid Xrays	99.85
Normal and Pneumonia Xrays(including Covid cases)	97.5

Table -5 Accuracy obtained CoroNet-SVM for different Dataset

V. CONCLUSION

This project have analyzed the convolutional neural network- CoroNet, that differentiated COVID-19 from heathy, bacterial pneumonia and viral pneumonia from X-ray images, us ing various optimizers. Since covid and other pneumonia disease has similar symptoms, it is important to diagnose the covid virus from other cases of pneumonia. Though in the literature, several neural architectures perform classification, four class classification is studied less. CoroNet use Xception as base model with a flatten layer, dropout layer and two fully-connected layers added at the end. The CoroNet network was studied by imple menting four different optimizers: Adam, Adamax, SGD, and RMS Prop. Optimizers play an indispensable role in diminishing the loss incurred by the Network's training process. They are used to solve optimization problems by minimizing the loss function. Loss gives us the measure of mistakes made by the network in predicting the output. The CoroNet with Adamax showed higher accuracy, followed by Adam optimizer. Data Augmentation techniques also improved the performance of four class classification. The studies had shown that combination of CNN with SVM gave better performance. A support vector machine (SVM) is a type of deep learning algorithm that performs supervised learning for classification. So, CoroNet with SVM showed significant results for binary classification. This is performed on two different datasets. This project considered different optimization method and data pre-processing to obtain quality result. The study analyzed CoroNet neural network and was able to differentiate Covid from other pneumonia. This neural network ensures promising results in the future.

Deep learning helps in overcoming challenges in data-driven medical image analysis. Still deep learning assisted tools in medical domain still faces obstacles. Limited data is one such hurdles, that needs to be overcome, for commercialization. This project analyses the existing neural network and its best possibility in differentiating covid from other pneumonia cases. Depthwise convolution applies a single convolutional filter per each input channel a while pointwise convolution is the 1×1 convolution to change the dimension. Residual Connections are a type of skip-connection that learn residual functions with reference to the layer inputs, instead of learning un referenced functions. And hence there is no intermediate ReLU non-linearity. Absence of non-linearity leads to faster convergence and better final performance. Xception architectures are easy to define and modify. Xception model takes just 30 to 40 lines of code to define, compared to other architectures, which are more complex. Xception shows marginally better results than Inception V3 [16]. of the network.

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