Detection of COVID-19 from CT images using Deep Convolutional Neural Network Design

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ABSTRACT

COVID-19 continues to have a significant impact on patients and healthcare systems worldwide.For effective screening of the infected patient, CT scan became a key screening method used as a complement to RT-PCR testing.CT based screening reported abnormalities in the chest CT images.In order to help medical field in analyzing these abnormalities faster , we designed a deep convolutional neural network architecture that detects Covid19 cases from chest CT images using DenseNet-161 architecture that classifies the given data into three categories: 'Normal', 'Pneumonia' and 'COVID-19'.

I. INTRODUCTION

COVID-19, named the deadliest virus of the twenty-first century, has killed millions of people across the world in the last two years. As we are facing a severe challenge in tackling the deadly virus, our motive was to help the medical field by analyzing the reports faster and taking necessary action immediately.

To diagnose whether a patient has COVID, the most effective way is to check whether the CT scan shows any positive signs of covid, hence a quick CT scan of the chest is helpful for diagnosis.

In the past, Convolutional Neural Networks (CNNs) proved to be quite successful in the classification of medical images. Previous research on CT-based screening have reported abnormalities in chest CT images which are characteristic of COVID-19 infection, but these abnormalities may be difficult to distinguish from abnormalities caused by other lung conditions. Motivated by this, in this work we construct a deep convolutional neural network architecture that is tailored for detection of COVID-19 cases from chest CT images using the densenet161 architecture. Chest computed tomography (CT) imaging has been considered as an alternative screening tool for COVID-19 infection due to its high sensitivity, and is also particularly effective when used as a complement to RT-PCR testing .

II. DATASET

The COVIDx-CT is a dataset of 104,009 chest CT slices across 1,489 patient cases, which we refer to as COVIDx-CT. Notably, this CT imaging data is not novel, as it is derived from CT imaging data collected by the CNCB. The CNCB data is composed of chest CT examinations from different hospital cohorts across China as part of the China Consortium of Chest CT Image Investigation (CC-CCII). More specifically, the CT imaging data consists of chest CT volumes across three different infection types: novel coronavirus pneumonia due to SARS-CoV-2 viral infection (NCP), common pneumonia due to non-COVID-19 infections (CP), and normal controls as you can see in **Figure 1**.The dataset consists of three splits: 82286 for Training, 35996 for Validation, and 25496 for Testing. The CT scans are classified into three categories:

- Normal
- Pneumonia
- COVID-19

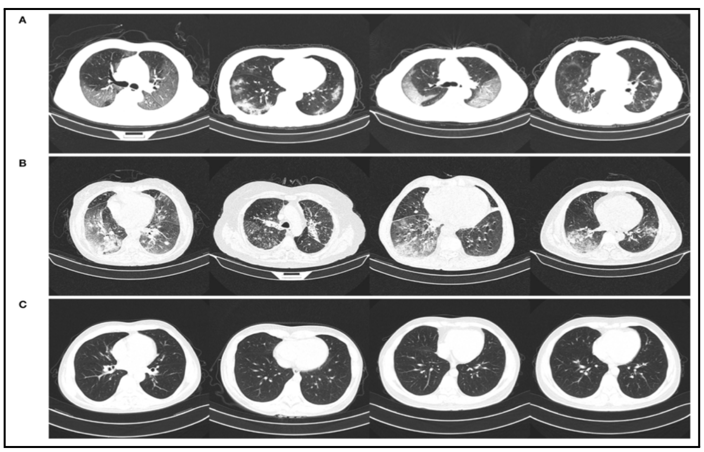

Figure 1: Example Chest CT images from the COVIDx-CT dataset illustrating (A) COVID-19 pneumonia cases, (B) Non COVID-19 pneumonia cases and (C) Normal Control Case.

III. DATA PREPARATION

The images of CT scans were processed and ready to be used for training and testing, after some standard normalization, grayscaling, and resizing. The most crucial part for a Deep learning neural network model is the 'dataset'.The pixel values in the input images must be scaled properly before the building of the neural network model. Deep learning algorithms often perform better with more data. For improving the generalization of models, the training dataset was augmented with random rotation and random horizontal and vertical flipping. The samples were not uniformly distributed in the three label categories so the dataset needed to be resampled and balanced.

IV. MODEL ARCHITECTURE

DenseNet is a type of convolutional neural network that utilizes dense connections between layers, through Dense Blocks, where we connect all layers with matching feature-map sizes directly with each other.

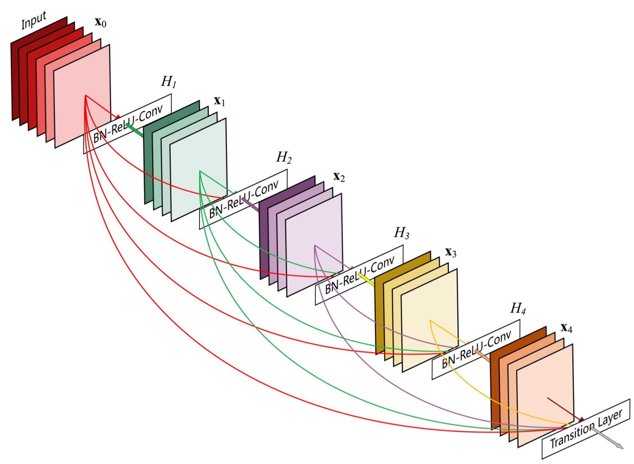

Figure 2: Dense Convolution Network (DenseNet) Architecture

To preserve the feed-forward nature, each layer obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers. Model architecture can be seen in **Figure 2**. Dense Convolutional Network (DenseNet), connects each layer to every other layer in a feed-forward fashion. Whereas traditional convolutional networks with L layers have L connections - one between each layer and its subsequent layer. DenseNet has L(L+1)/2 direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers.

DenseNets have several compelling advantages:

- They alleviate the vanishing-gradient problem.
- Strengthen feature propagation
- Encourage feature reuse
- Substantially reduce the number of parameters

V. PROPOSED ARCHITECTURE

CT scan images are given as the input and preprocessing is performed. In order to train and create predictions on the data, the image must fit the input size as the samples were not uniformly distributed in the three label categories, so the dataset needed to be resampled and balanced. Any mismatch could generate inaccurate predictions, resulting in a patient not receiving the critical care they need so it is resized.CNN Architectures like Vgg16, Vgg19, Resnet101, Resnet152, Densenet 161, Densenet201 are compared to detect the Covid-19 and the Densenet 161 generates the highest accuracy and is classified into 3 categories which are Normal, Pneumonia, Covid-19.

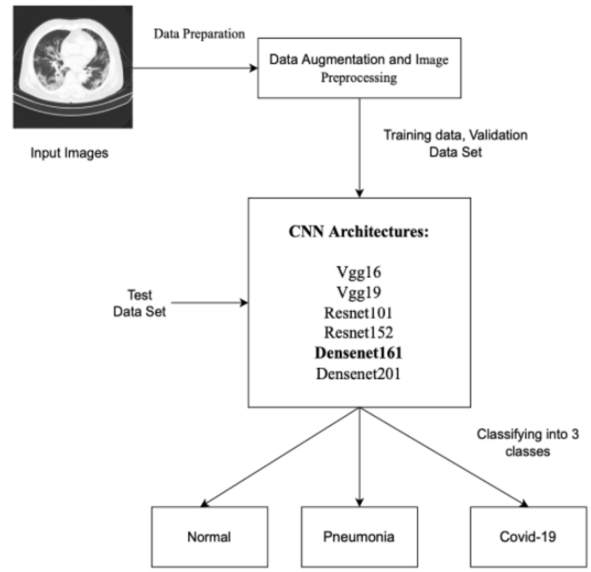

Figure 3 : Architecture diagram

VI. IMPLEMENTATION DETAILS

Hyper-parameters -

- growth_rate = 32
- block_config = (6, 12, 24, 16)
- num_init_features = 64
- epoch=3
- bn_size = 4
- drop_rate = 0
- Optimizer = Adam Optimizer
- Loss Function = Cross Entropy Loss
- Evaluation Metric : Confusion matrix, precision, recall, F1 score.

VII. OPTIMIZATION TECHNIQUES

Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. The method is really efficient when working with large problems involving a lot of data or parameters. It requires less memory and is efficient.Intuitively, it is a combination of the 'gradient descent with momentum' algorithm and the 'RMSP' algorithm.

Advantages-

- It adds to the advantages of Adadelta and RMSprop.
- No need to focus on the learning rate value.
- Good with sparse data.

VIII. ARCHITECTURE COMPARISON

1. Vgg16(Visual geometry group)

	Precision	Recall	F1-score
Normal	91.82	94.14	92.97
Pneumonia	85.29	95.85	90.26
COVID-19	93.66	79.69	86.11

Best Accuracy: 89%

2. Vgg19

	Precision	Recall	F1-score
Normal	86.94	97.73	92.02
Pneumonia	83	95.84	88.96
COVID-19	97.73	70.48	81.9

Best Accuracy: 88%

3. Resnet101(Residual Neural Network)

	Precision	Recall	F1-score
Normal	79.48	86.98	83.06
Pneumonia	74.17	89.81	81.24
COVID-19	91.31	91.31	63.44

Best Accuracy: 80%

4. Resnet152

	Precision	Recall	F1-score
Normal	64.84	90.71	75.62
Pneumonia	71.27	74.89	73.04
COVID-19	86	47.31	61.04

Best Accuracy: 72 %

5. Densenet201

	Precision	Recall	F1-score
Normal	86.94	97.73	92.02
Pneumonia	83	95.84	88.96
COVID-19	97.73	70.48	81.9

Best Accuracy : 91 %

IX. PERFORMANCE MEASURES

There are various methods to evaluate a model's performance. Accuracy, precision, recall, and F1-score are the measures considered to estimate chest CT scan images.

Precision—Precision is the ratio of correctly predicted positive cases, given in the following equation.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}.$$

Recall -The ratio of accurately detected positive cases given in the following equation.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}.$$

F1-Score -The harmonic mean of precision and recall given in the following equation.

$$F1 \text{ score} = 2 \text{ x} \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}}.$$

Accuracy: The percentage of correct predictions among the total number of predictions given in the following equation.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}.$$

Precision, recall, F1-score, and accuracy for all three classes are illustrated below.

X. RESULTS

Confusion Matrix was computed, which summarizes the performance of classification results. From the confusion matrix further metrics like recall, precision and F1 score were computed. The loss function used was cross entropy loss between input and target. It is useful when training a classification problem with C classes.

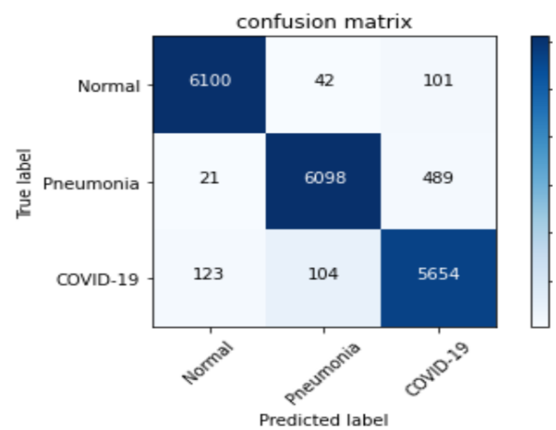

Figure 4: Confusion Matrix

To reduce the nonlinearity in the output of a neuron, certain activation functions are used. The output layer's activation function determines the kind of predictions the model can make. Softmax is used in the last layer, the output layer, to predict a multinomial probability distribution. "Loss" is the network's prediction error, and the cross entropy loss function used to calculate the error. The results were calculated by evaluating the performance measures such as accuracy, precision, recall, and F-score.

	Precision	Recall	F1-score
Normal	97.71	97.69	97.7
Pneumonia	92.28	97.66	94.89
COVID-19	96.14	90.5	93.26

Validation total :

- Loss: 0.1855
- Accuracy : 95.30%
- All prediction accuracy : 95.3%
- MACRO-averaged: prediction= 95.38 %,recall= 95.3 %,f1= 95.34

XI. DISCUSSION

In this study, we have introduced COVIDx-CT dataset using a deep convolutional neural network architecture tailored for detection of COVID-19 cases from chest CT images via densenet architecture. Furthermore, we analyzed the predictions of COVIDx-CT and classified it into 3 categories to better understand the CT image features associated with COVID-19 infection, which may aid clinicians in CT-based screening. We have also compared with the existing modern architectures suited for image predictions.

XII. FUTURE SCOPE

While the proposed model is not yet suitable for clinical use, we aim to increase accuracy, so that it can be used by clinicians.The efficiency of the model can be improved by increasing the amount of data. Also, the disease can be classified gender-based such that we can get information about whether male are affected more or females. More feature engineering can be performed for better results with the same deep learning approach.

XIII. CONCLUSION

Deep learning methods have high accuracy in the differentiation of COVID-19 from non-COVID-19 pneumonia based on chest images. We have also experimented our results with other efficient architectures like Vgg16, Vgg19, Resnet101, Resnet152, Densenet201 and compared their accuracies as well and have concluded that densenet-161 has achieved the highest prediction rate among the other models.

XIV. REFERENCES

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