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Detection of COVID-19 Using Deep Learning

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Abstract

The world health organization states that the coronavirus epidemic has created a daily threat to the global healthcare system. After numerous deaths around the world, the pandemic unlocked a new threat making people ready for something which is similar and unpredictable. There were many challenges including the shortage of medical staff, beds, diagnosis centres, and intensive care units. Correct detection of disease is also crucial in surviving the pandemic. So, with a growing need for accurate and rapid diagnosis, there are many alternatives that are derived to identify the disease with the help of Radiology and Computed Tomography (CT) scans. This paper proposes a deep-learning-based approach for the detection of COVID-19 from X-ray and CT-scan images and is based on Predefined CNN architectures such as DenseNet201 and ResNet152, which are fine-tuned to classify images as COVID-19 positive or negative. The results obtained demonstrate that the proposed methods achieve high accuracy in detecting COVID-19 cases from X-ray and CT scan images. Hence, this project can be used as a valuable tool for frontline healthcare workers and public health officials to fight against the COVID-19 pandemic.

Keywords: COVID-19, CT scans, Deep Learning, DenseNet201, ResNet152,X-rays.

1. Introduction

Coronavirus is a subtle but effective disease. It was first discovered in China, in December 2019. In March 2020, the World Health Organization identified COVID-19 as a pandemic [1]. Early detection and accurate diagnosis of COVID-19 are important to control the spread of the disease and the situation. Generally, the reverse transcriptase polymerase chain reaction (RT-PCR) is used to detect the disease. But it lacks fast and effective results in certain suspicious cases. Over the past few decades, technology has improved significantly, and deep learning-based techniques started to show good results in the detection of COVID-19. This works effectively in analysing image datasets such as chest X-rays and CT scans. Deep learning methods can identify certain patterns and extract relevant features from the image. These techniques can quickly and accurately identify COVID-19 cases.

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In this study, we opted for a deep learning-based approach for COVID-19 diagnosis where we used CT-scan and X-ray images as our datasets as they provide a detailed view of the lungs.

So, after a consideration of many CNN models, ResNet152 and DenseNet201 architectures stood out compared to other models. This approach that we proposed aims to improve the accuracy and performance of COVID-19 diagnosis. When DenseNet201 was implemented on X-ray and CT-scan datasets, we obtained accuracies of 92.96% and 97.52%, respectively. Similarly, when ResNet152 is implemented on X-ray and CT-scan datasets, the results are 98.83% and 99.08%, respectively. Through our study, we hope to aid the continuing efforts to develop effective diagnostic tools for COVID-19.

2. Literature Survey

As per studies, the analysis of the presence of viruses in the lungs can be improved by using chest X-ray (CXR) images and computed tomography (CT) scans. To detect covid-19 from medical photos, deep learning-based algorithms [2] have been developed in various articles. In a work [3], some Machine Learning techniques with different classifiers such as Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes are used to identify Covid-19. The accuracies achieved were 76% for RF, 88% for SVM, and 85% for Naive Bayes. Additionally, they want to analyse the dataset using Deep Learning methods like CNN [9] Model.

Some of the Researchers made a review about choosing the most effective DL models to identify the lung segment and predict COVID-19 patients. This review paper [4] used DL networks to do a thorough analysis of the completed studies of COVID-19 diagnosis. In one paper [5], they proposed solutions of using Chest radiographs with different deep learning CNN architectures for the goal of feature extraction. Then those images were used as the input to multiple machine learning classifiers with an accuracy of 88.8%.

Researchers have done various studies in the area of Covid-19 patient detection. In one such work [6] as part of the transfer learning approach they fine-tune two pre-trained models, DenseNet and InceptionV3. Here using X-ray and CT chest scans objectively show the efficiency of DenseNet and InceptionV3. Another work [7] examined the outcomes of a few deep learning techniques on the chest x-ray dataset, including CNN, VGG16, VGG19, and InceptionV3. The outcomes of this paper show the significance of unique deep learning models. A technique [8] has utilized the transfer learning approach to compare various convolutional neural network pre-trained models such as 2-D CNN [11], ResNet50, Inception, ResNetV2, InceptionV3, DenseNet201 and MobileNet V2 on X-ray images and

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also in a work [10], by applying ResNet-34 and ResNet50 to detect Covid-19 on X-ray images ResNet-50 yielded the best performance closely followed by DenseNet201.

As observed, the majority of studies focused on Covid19 detection on X-ray or CT-scan pictures. But in our work, we are trying to implement deep learning models like ResNet152 and DenseNet201 on both X-ray and CT-scan images datasets. We have chosen these models, because as per our study these yielded better performances compared to other models and also, we have taken the maximum number of layers presented in both the models to differ from other research. [17-26]

3. Problem Identification

Generally, medical professionals or doctors identify the condition just by looking at and analysing a radiological image. This requires experts with relevant qualifications. Otherwise, incorrect results can lead to disastrous consequences. As coronavirus spreads fast within no time, we must use methods that can diagnose quickly and reliably. We observed CT-scan and X-ray images are used as they provide a detailed view of the lungs. Later, machine learning and deep-learning techniques were used, among which deep-learning techniquesperformed better. This research paper aims to improve the accuracy and efficiency of COVID-19 diagnosis using deep learning architectures like ResNet152 and DenseNet201.

4. Methodology

4.1 Dataset:

The dataset used in this study was obtained from Kaggle i.e.; from [12-14] was created by a few researchers. As per study we observed that CT scans and X-rays are both effective in detecting COVID-19. Hence, we used both types of image scans to evaluate our proposed architectures. The X-ray dataset consists of 10816 images among those 3616 X-rays of COVID-19 collected from 130 patients and 7200 X-rays of Non-COVID-19 which are collected from 240 patients. The CT Scan dataset consists of 14482 images among those 12231 CT scans of COVID-19 collected from 165 patients and 2251 CT scans of Non-COVID-19 which are collected from 28 patients.

4.2 Data Preparation:

Several sizes and resolutions of X-Ray images can be found in the dataset, since the images were gathered from several local medical centres using different radiology equipment, which often results in non-uniform image characteristics. So, we resized all the images with a fixed size of 224x224 pixels and it is converted to a single gray channel space (grayscale), to ensure uniformity across all datasets.

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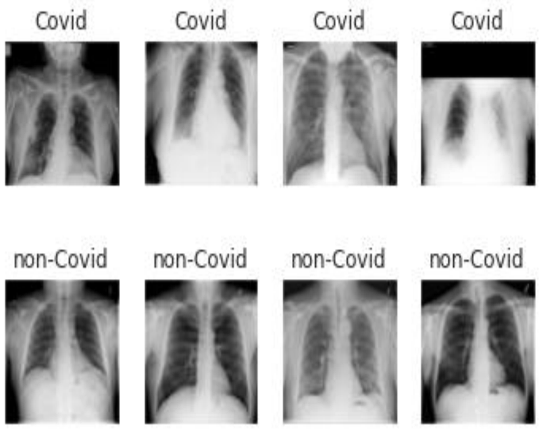

Figure 1: Random images from Xray dataset

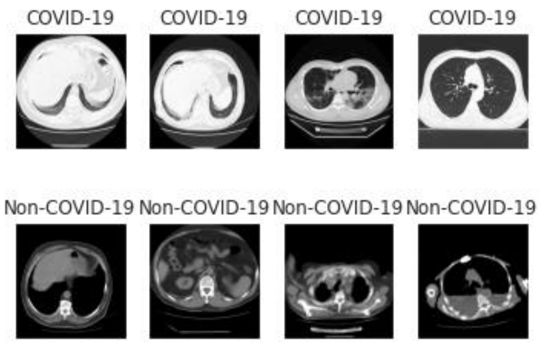

Figure 2: Random images from CT scan dataset

4.3 Data Pre-processing:

Normalization is one of the most essential pre-processing tasks, which is crucial for both enhancing training speed and image convergence speed. For this purpose, we convert the images by rescaling the values in between 0-1 by using the formula 1./255 because the original RGB coefficient range in images is too high for our model to handle.

4.4 Data Augmentation:

CNN based networks are data-driven, as data volume grows, effectiveness rises as a result of the maximal feature area being covered. At the Augmentation stage, data were added to the train dataset using the parameters shown in Table1. This augmentation was carried out in order to provide images that are both the most similar to the original images and do not behave as model noise. All the dataset's images were shuffled before being fed to models.

S.no	Parameters	Selected Values
1	Horizontal flip	True
2	Vertical flip	True

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3	Rotation range	30

Table 1. Parameters of data augmentation

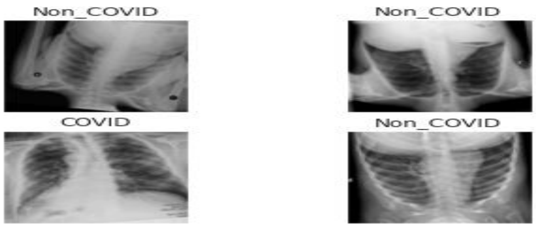

Figure 3: Random Augmented Xray images

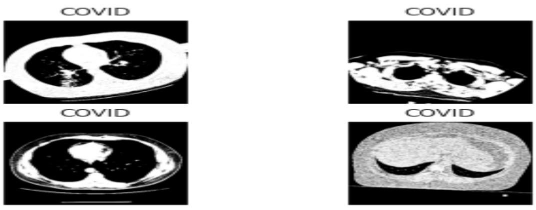

Figure 4: Random Augmented CT scan images

4.5 Transfer Learning:

Constructing deep learning models from scratch is a time consuming, complex process that needs a lot of data. which can easily avoidable via transfer learning. The goal of transfer learning is to transfer information from a big dataset known as the source domain to a more condensed dataset known as the target domain. We fine-tuned two pre-trained models DenseNet201 and ResNet152 that had been trained on a very large dataset called ImageNet. Since the weights of both models were frozen after training, we downloaded them and used them to fine-tune them for our image classification tasks as part of the transfer learning approach.

4.6 Pretrained models:

Here, two pre-trained architectures DenseNet201 and ResNet152 are used in this study for the detection of COVID-19 i.e.; explained below clearly.

4.6.1 DenseNet201

A DenseNet [15] variant called DenseNet201 contains 201 layers as shown in Figure5. Feature extraction can be made through passing input to layer by layer. Better feature reuse is made possible by this model because it is made up of a number of dense blocks where output of each dense block is passed as input to further dense blocks, each of which has a number of convolutional layers with batch normalization and ReLU activation functions as well as pooling and transition layers which performs the feature maps spatial dimensions. Then a global average pooling layer, a fully connected layer, and a softmax activation function is used for classification.

Preprocessed Input
|
Convolutional layer
|
Max pooling layer
|
Dense Block1 x6
|
Transition layer1
|
Dense Block2 x12
|
Transition layer2
|
Dense Block3 x48
|
Transition layer3
|
Dense Block4 x32
|
Global Average Pooling layer
|
Fully Connected layer
|
Softmax activation
|
Output

Figure 5: DenseNet201 architecture

4.6.2 ResNet152

Microsoft Research developed ResNet152. It is a subset of the ResNet (Residual Network) model family, which was created to address the issue of vanishing gradients in deep neural networks. Compared to ResNet50 and ResNet101, the ResNet152[16] architecture has 152 layers and is far more complex. ResNet designs main innovation known as skip connections, which enable a direct information flow from earlier layers to subsequent layers. Vanishing gradients problem is solved by offering a shortcut for the gradients to travel through the network and reach the earlier layers. ResNet152 architecture will look as shown in Figure 6.

Preprocessed Input
|
Convolutional layer
|
Batch Normalization
|
ReLU
|

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Residual Block1 x3
|
Residual Block2 x8
|
Residual Block3 x36
|
Global Average Pooling layer
|
Fully Connected layer
|
Softmax activation
|
Output

Figure 6: ResNet152 architecture

5. Implementation

We are using the Python language which contains several modules and libraries that can be helpful for our work. Since the weights for these models i.eDenseNet201 and ResNet152 are provided by the Tensorflow library [17] in python, it is simple to create and learn deep learning models with it i.e.; clearly shown in below pseudo code. Here after applying data preprocessing steps, then we applied pretrained models on both X-ray and CT-scan datasets to evaluate their performances.

Pseudo Code:

Input: Input image (From both X-ray and CT-scan datasets)

Output: Output image (Detecting whether it is COVID-19 or Non- COVID19)

```
Begin
    Performed Data Preprocessing
    Performed Data augmentation      i.e.; (Horizontal Flip, Vertical Flip,    Rotating)
    Apply pre-trained models    i.e.;    (DenseNet201, ResNet152)
            Pre-trained model = training      ((Input images, Labels))
    Pre-trained model = testing (Input    images)
    Performance=Confusion_matrix      (Predicted, Actual)
End
```

6. Results & Conclusion

Model	X-ray dataset Accuracies	CT-scan dataset Accuracies
DenseNet201	92.96	97.52
ResNet152	98.83	99.08

Table 2. Comparison of models

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After applying DenseNet201 and ResNet152 models on both X-ray and CT-scan datasets. Obtained results are shown below Table2. We noticed that ResNet152 performed more accurately on both datasets by observing the above differences, which are given in Table 2. On the basis of this, ResNet152 can be preferred for detecting COVID-19 disease.

Figure 7 & 8 represents the Confusion matrices on applying DenseNet201 & ResNet152 models on X-ray test dataset.

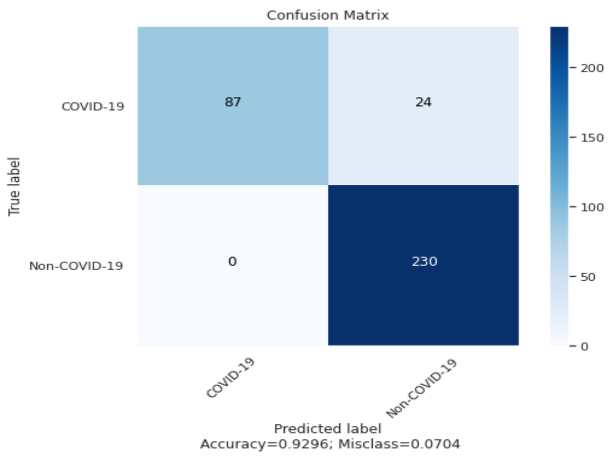

Figure 7: Confusion matrix for DenseNet201 on X-ray dataset.

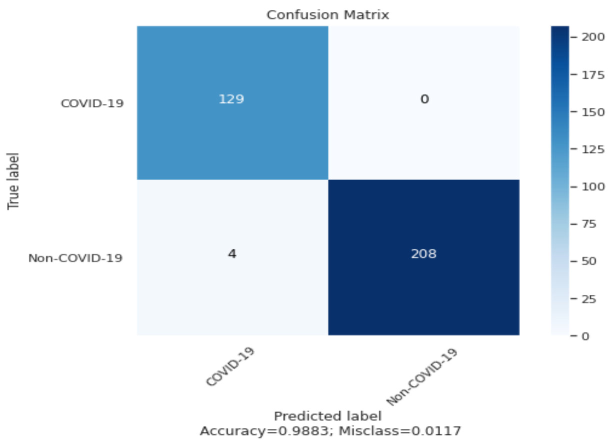

Figure 8: Confusion matrix for ResNet152 on X-ray dataset.

Figure 9 & 10 represents the Confusion matrices on applying DenseNet201 & ResNet152 models on CT-scan test dataset where splitting ratio of the datasetis 80% for training and 20% for testing.

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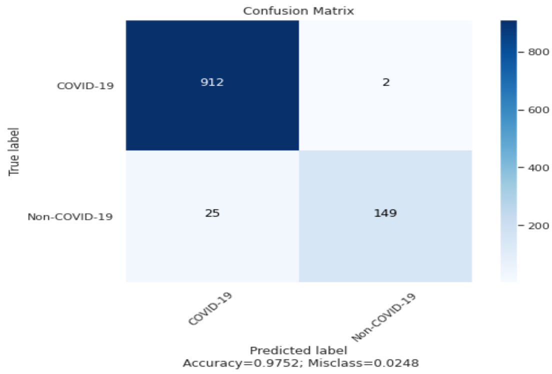

Figure 9: Confusion matrix for DenseNet201 on CT-scan dataset.

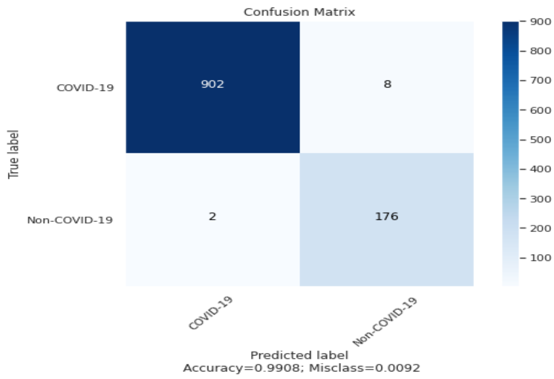

Figure 10: Confusion matrix for ResNet152 on CT-scan dataset.

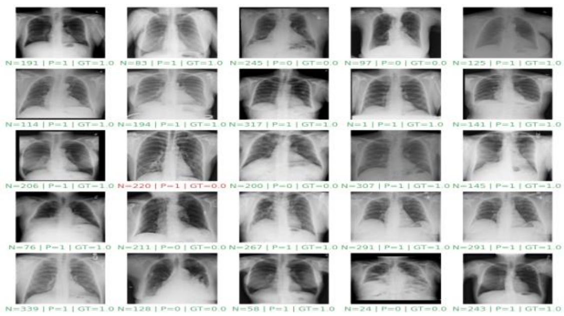

Figure 11: Randomly detecting COVID-19 on X-ray images

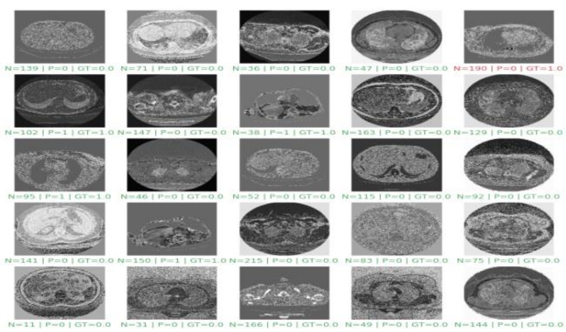

Figure 12: Randomly detecting COVID-19 on CT-scan images

Figures 11 & 12show the process of randomly detecting whether or not a person has Covid by feeding CT and X-ray images into two different models. Here, P stands for predicted value, which means that if it is 0 the person has covid, and if it is 1 then the person does not have covid. The GT value stands for actual value, can be used to decide whether the detected value correct or not.

7. Limitations & Future Scope

This approach is meant to make it easier for radiologists to examine patient lung pictures and lessen their diagnostic workload. According to research, a deep learning-based Covid-19 detection system can perform better when medical images are included, and the idea underlying this framework can be applied to a number of medical imaging models. some possible enhancements are pruning of the created Covid-19 detection model to improve memory and computational efficiency and enable it to function on devices with lower computing strength, such as mobile devices.

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