

Detect Covid-19 Patients from X-Ray Images Using Deep Learning

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Abstract—The number of COVID-19 Cases across the globe is still increasing at high-speed, every single day. Two of the most common symptoms of the novel coronavirus include pneumonia or lung infection. In the current times where technology is prevalent, usage of various techniques of artificial intelligence in the field of medical science enables us to get accurate solutions of problems in the field much quicker. The COVID-19 Virus can be detected through a special imaging technique called Computerized Technology (CT). CT Scans, X-Rays, Magnetic Resonance Imaging (MRI), PET/CT, and Lung Ultrasounds are commonly used to detect diseases using AI imaging techniques. In this research, we have demonstrated how to detect the COVID-19 Virus through X-Ray images by using multiple Convolutional Neural Network Models and Transfer Learning.

Index Terms—Covid-19, Computer Tomography, Imaging, Artificial Intelligence

I. INTRODUCTION

The very first detected case of the novel coronavirus can be traced back to December 2019 in the Wuhan Province in China. This was a new variant of a coronavirus that was occurring in humans for the very first time. The little virus soon transformed into an epidemic and before the world even realized, it had turned into a full-fledged pandemic. As of now, over 219 million cases of COVID-19 have been identified across the world, with over 4.55 million deaths from the identified cases. The coronavirus is a large family of homologous viruses that can cause a wide range of serious illnesses – many of the epidemics and pandemics we have seen before fall under this category. This range of serious illnesses start from something as simple as the common cold, and can mutilate into graver diseases such as the Middle East Respiratory Syndrome (MARS) and the Severe Acute Respiratory Syndrome (SARS). However, only 7 to fall seriously ill from the disease – they become prone to lung failure, septic shocks, paralysis, and in worst case scenarios, death [1]. 14th the most prevalent of which are breathing problems. Most of those, around 80 diagnosed with the virus show mild symptoms such as pneumonia symptoms along with fever and coughing. Older people and especially those with existing illnesses such as asthma, diabetes, heart diseases, high blood pressure, etc. are most likely to be most adversely affected by the virus. Recent statistics show that the increasing number of cases each day

could lead up to the world taking at least a few years to get rid of the virus and revive from it. To control the rapid spread of COVID-19 from one person to another, screenings of people who show symptoms to detect the virus is the most important step. Many countries, especially those with a very large population, are facing difficulties in testing people due to a limited number of testing kits. Even the most developed of nations such as USA, UK, and Italy have struggled to deal with the overwhelming number of cases – The increasing demand for Intensive Care Units for those showing the worst of symptoms such as pneumonia, extreme intense respiratory condition, and multi-organ failure have left them clutching at straws to save lives [2]. The most common technique to detect the COVID-19 Virus is the RT-PCR test, which is expensive and a very lengthy process. The main problem with this technique, keeping aside the cost factor, is how much time it takes to get back the results – If the patient does not maintain isolation and other necessary precautions, they are most likely to spread it to other people as well as have their lives in danger. Airspace Opacities, Ground-Glass Opacity (GGO), and later consolidation are few of the primary signs in the lungs which act as the base of detecting COVID-19 primarily in the patients [3]. Due to the limited number of test kits, alternative solutions have been looked deeply into – Several studies have found that CT Scans of Chest X-Ray images can also be effective in early detection of COVID-19 in patients who show symptoms [4] [5]. X-Ray Machines are generally used to identify irritants in a body such as cracks, bone disengagements, lung contamination, pneumonia, and other tumours; CT Scans are modified and advanced versions of X-Ray Machines that magnifies into the more delicate structures of dynamic body parts, and gives us clearer pictures of intricate inward tissues and organs [5]. Given the advancement of CT Scans, X-Rays are comparatively the quicker, simpler, more cost-effective and less critical method [4]. As previously mentioned, pneumonia is one of the most prevalent signs of the presence of COVID-19 in a human body, and the disease opens up holes in a person's lungs much like the SARS disease, giving the lungs a “honeycomb-like” appearance. Chest X-Rays and CT Scans are both used to diagnose pneumonia, and so, they can be seen as the best method for early screening of COVID-19 [4]. Several studies so far have actually gone

on to recommend using X-Rays over RT-PCR tests due to the limited availability of the latter in many countries. As of now, Artificial Intelligence (AI) has become an imminent part of detecting and solving many medical-based issues. The emergence and advancement of Artificial Intelligence (AI) in the medical science field has enabled imaging-based analysis of many diseases, especially COVID-19. Further research in context of the COVID-19 situation has found that deep neural techniques are a better, more accurate and more sensitive method of detecting the virus as opposed to RT-PCR tests. In this study, we have applied multiple convolutional neural network models including VGG16, VGG19, MobileNetV2, Resnet50, Inception V3, and Xception to distinguish between COVID-19, Pneumonia, and normal patients. So, six different models were tested on the X-Ray image datasets, and then the accuracy and precision of the models were analyzed, too.

II. LITERATURE REVIEW

A. Detect Covid-19 Patients from X-Ray Images Using Deep Learning

This chapter is a review of related literature focusing on detecting COVID-19 automatically from X-Ray images, using CNN and transfer learning. Mondhur et al. conducted a study which aims to examine the effectiveness of Transfer learning to detect COVID-19 automatically from Xray images, using convolutional neural networks. They used pre-trained models with some modification in the top of these models. Their dataset used in training is taken from multiple sources of X-rays and Kaggle. The number of images in this dataset involves 274 COVID-19 cases, 380 viral pneumonia cases, and 380 healthy. Before being passed to pre-trained model the images resized to the size of $224 \times 224 \times 3$. After that they divided the dataset into 70 validation set. Transfer learning technique was applied to resolve inadequate data and the time for preparation. The proposed deep transfer learning models were trained separately using the Python Programming Language. All experiments were conducted with Tesla K80 GPU graphics card on Google Collaboratory with Windows 10 operating system. We used tenfold-cross-validation approach to assess the performance of our models. A confusion matrix was also introduced to analyze whether the prediction is consistent with the actual results. They used some different types of models. When they used ResNet50 CNN model along with SVM got 95.38% accuracy. They used COVIDX-Net and got 90.98% of accuracy on the 2-class and 99.57% information at this stage is inadequate as it was mainly based on results obtained from selected regions. Therefore, more detailed and extensive work on more dataset is required to detect COVID-19 automatically from Xray images, using convolutional neural networks. Ankita et al. conducted another study that aims to examine the effectiveness of Transfer learning to detect COVID-19 automatically from Xray images, using CNN models. They used pre-trained models with A total of 2271 chest X-ray images ($895 \times 1024 \times 3$ pixels) were obtained from Clinic Diagnostic Lab, Mumbai India. The image was converted from RGB to gray. The resolution of images was reduced to ($64 \times 64 \times 1$). A total of

1071 images of all three types (i.e., Normal, TB, Pneumonia), split into 70 consisted of 388 normal images, 500 pneumonia images, and 303 TB images. They were doing a 3-way classification. They have used various pre-trained network to get their expected accuracy. At the time of using VGG16 they flatten the output of the Max pooling layer and then have a dense layer with 3 neurons. The learning rate was kept at 0.001 with Adam as the optimizer. They trained the model for 12 epochs and got accuracy of 95.99%. The proposed model will help yield faster and accurate results and will be cost-effective as compared to the conventional RT-PCR method. Sohaib et al. conducted a research to investigate the efficacy of Transfer learning to detect COVID-19 automatically from Xray images using coevolutionary neural networks. They used pre-trained models with some modification at the top of these models. For the training and evaluation of the COVID-19Net they have collected chest radiographic images from 3 open-source databases: 1) GitHub open-source dataset by Chowdhury et al. 2) Dataset from GitHub by Cohen et al. 3) Positive radiographic images (CXR and CT) were carefully chosen from Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE. The network was equipped using their dataset by random weight initialization. The inputs were $64 \times 64 \times 3$ in format. Adam optimization is being used and the hyper-parameters used were a constant learning rate of 0.001, a batch size of 32, steps per epoch 100 and a number of epochs of 20. Further we implemented data augmentation due to shortage of resources to train our model and the types of augmentation used were: rescaling, rotating, zooming, vertical flip, horizontal flip, intensity shift and shear intensity shift (shear angle in counter-clockwise direction). The proposed VOC-19Net model was applied via the Keras platform using the TensorFlow backend. Because they got accuracy of 99.45%. Kiran et al. proposed deep augmented model to solve the problem. Their dataset was of 2 types, X-Ray dataset and CT Scan dataset. X-Ray dataset that contains 536 images of COVID-19 and 536 images non-COVID-19 including augmented images, the CT Scan dataset contains 2760 images of COVID-19 and 2760 images of non-COVID-19 individuals including augmented images. The ratio of train and test samples was 70:30. At first, they accept the colored input images from the data set. Convert the image into grayscale. Then they down sample the images to 50×50 dimension from their original size. In CNN based deep learning model they choose layer sizes = [32; 64; 128], dense layers = [0; 1; 2], and conv-layers = [1; 2; 3]. Convolution with a 3×3 filter size is applied. Activation function RELU is used after convolutional layer. Then 2×2 filter size is applied for Max Pooling. In Step 5 if conv-layers 1; 0 Flatten the matrix. Activation function Sigmoid is used for classification of test image into COVID and non-COVID classes. In training stage, the standard first-order stochastic gradient descent optimizer with a batch size of 32, maximum epochs 30 and binary cross entropy-based loss function are used. The random subsampling method is adopted. Whole dataset is divided into a number of ratios like 90:10, 80:20, 70:30 and 60:40 as training and testing samples.

Various Evaluation Metrics are calculated such as classification accuracy, loss, area under ROC curve (AUC), precision, recall (Sensitivity), Specificity and F1 score. With this approach, the proposed model exhibits higher classification accuracy around 95.38 percent and 98.97 percent for CT scan and X-Ray images respectively. CT scan images with multi-image augmentation achieves sensitivity of 94.78 percent and specificity of 95.98 percent, whereas X-Ray images with multi-image augmentation achieves sensitivity of 99.07 percent and specificity of 98.88 percent. Due to a smaller number of X-Ray or CT Scan images that are used for training the deep learning models, often exhibit the classification accuracies not up to the mark.

III. PROPOSED SOLUTION

The primary purpose of our research is to develop a Deep Learning Technique for the detection of the novel coronavirus which is appropriate for people of all ages and demographics. Our proposed solution is to build a Convolutional Neural Network to detect the existence of the coronavirus in a human body from X-ray Images with maximum accuracy. We will train on different models of Convolutional Neural Network such as VGG16, VGG19, ImageNet, DenseNet, ResNet, etc. on an X-Ray dataset. Then, each model on the dataset will be trained separately to discern the accuracy that each of them bring. After analyzing the accuracy of all six models, we can conclude which model will give us the best results. Our research can help countries where testing kits are limited in numbers and costly. This might even end up motivating people to get tested if they show symptoms as opposed to the RT-PCR tests that are lengthy and expensive, especially for people in countries such as Bangladesh.

A. Methodology

In this section we are going to discuss about methodology of our research. There are also details of some existing platforms, algorithms and techniques related to our research. Then the details of our proposed system are mentioned. There is also a workflow of our research method.

B. Required Knowledge and Skills

- Basics of Machine Learning Algorithms.
- Deep Learning and Imaging techniques.
- Data Cleaning Techniques.
- Technical Terms of Data Science.
- Programming Language (Python)
- Use of Scientific Computing Platforms (Anaconda, Jupyter Notebook)

C. Deep Learning Techniques

- Transfer Learning

Transfer learning is a technique to use a pre-trained model as a starting point or basis for another model. This is a common and famous machine learning technique which is widely used in deep learning. In deep learning we use a lot of hidden layers with hundreds or thousands of nodes in it. It is

too much time consuming and somewhat impossible to train a too much large dataset on this kind of model. We will need a computer or machine with high requirements. Again, to get a better result in deep learning it is needed to input the dataset for number of times for the model to learn. That's why transfer learning technique was introduced. In this technique, a model is trained on a dataset of millions of data and the model is saved with the learned weights. Then we build a model and use that pre-trained model as starting point of the new model. After that, the dataset is trained on the new modified model and this time the model gives better result as the model has already learned on a big dataset.

- Image Augmentation

In order to perform well, deep networks require comprehensive training data. In order to create a powerful image classifier with very little data preparation, an increase in image is normally important to enhance deep networking efficiency. Image enlargement produces training images artificially by various rendering processes or variations such as spontaneous rotation, moves, shear and rotating, etc.

- Algorithms

VGG16: VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR (ImageNet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC (fully connected layers) followed by a SoftMax for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx.) parameters [6].

VGG19: 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. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224 [7].

Xception: Xception is a convolutional neural network that is 71 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. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299 [8].

ResNet50: ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. This model was the winner of ImageNet challenge in 2015. The fundamental breakthrough with ResNet was

it allowed us to train extremely deep neural networks with 150+layers successfully. Prior to ResNet training very deep neural networks was difficult due to the problem of vanishing gradients [9].

MobileNetV2: MobileNetV2, by Google, is briefly reviewed. In the previous version MobileNetV1, Depth wise Separable Convolution is introduced which dramatically reduce the complexity cost and model size of the network, which is suitable to Mobile devices, or any devices with low computational power. In MobileNetV2, a better module is introduced with inverted residual structure. Non-linearities in narrow layers are removed this time. With MobileNetV2 as backbone for feature extraction, state-of-the-art performances are also achieved for object detection and semantic segmentation [10].

Inception V3: In the inception architecture, computational efficiency and fewer parameters are realized. With fewer parameters, 42-layer deep learning network, with similar complexity as VGGNet, can be achieved. With 42 layers, lower error rate is obtained and make it become the 1st Runner Up for image classification in ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2015 [11].

D. Tools

- Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together [12].

- TensorFlow

TensorFlow Federated (TFF) is an open-source framework for machine learning and other computations on decentralized data. TFF has been developed to facilitate open research and experimentation with Federated Learning (FL), an approach to machine learning where a shared global model is trained across many participating clients that keep their training data locally. For example, FL has been used to train prediction models for mobile keyboards without uploading sensitive typing data to servers [13]

- GitHub

GitHub is where over 56 million developers shape the future of software, together. Contribute to the open-source community, manage your Git repositories.

E. Research Implementation Workflow

Research Implementation stage can be divided into some more stages. As we are using deep learning to solve the problem, we need to follow common deep learning implementation stages. The stages are Data Collection, Data Cleaning, Data Analysis, Apply Algorithm, Analyze Result and Modify Algorithm or continue to interpret stage. These stages are further described below:

- Data Collection

In this stage, we need to find a proper dataset to conduct our research. The dataset needs to be from a valid source and be acceptable by researchers. Also, there should be enough data in the dataset to be acceptable. There are a lot of dataset available on the internet that are only for testing purpose. We need to avoid those for research purpose and only select the dataset with enough data. We selected a dataset that is a latest dataset with the most number of data available on this research area. We collected our dataset from- Mendeley Data - Curated Dataset for COVID-19 Posterior- Anterior Chest Radiography Images (X-Rays). This is a combined curated dataset of COVID-19 Chest X-ray images obtained by collating 15 publicly available datasets as listed under the references section. The present dataset contains 1281 COVID-19 X-Rays, 3270 Normal X-Rays, 1656 viral-pneumonia X-Rays, and 3001 bacterial-pneumonia X-Rays. We only used COVID-19 X-Rays, Normal X-Rays and Viral-Pneumonia X-Rays for our research purpose.

- Data Cleaning

The dataset we collect might have raw data or might have invalid or poor data. That's why we need to apply data cleaning techniques before applying algorithm on it. Data cleaning techniques includes removing incomplete data, filling up missing data etc. As we are dealing with image data, we need to clean the images such that unclear images are removed or brightened in such a way that they become clear. We can also use different image cleaning techniques available as python functions and test which technique work better. In our research, we just resized our images to a same size as this is a crucial stage for deep learning techniques. Moreover, our dataset was already preprocessed by the owner of the dataset. According to the source of our dataset, Images with Noise, Pixelated, Compressed, Medical Implants, washed out image, Side View, CT (sliced) image, Aspect Ratio distortion / Cropped / Zoomed, Rotated Images, Images with annotations were detected and removed from the dataset.

- Data Analysis

In this stage, we need to visualize our data and see if the data are okay for the next stage. As we dealing with image data, we visualized X-ray images of different types to see if the images were clearly visible and good enough to apply deep learning algorithms. In our research, we used Image Augmentation technique to create a modified version of tensor images from our dataset. We also split our dataset into training set and validation set. Then we visualized the images to see if they are perfectly stored as tensor images.

- Apply Algorithm

In this stage, we apply our deep learning algorithm on our dataset to classify the images according to the labels we've given below. We can use different algorithms or some techniques like transfer learning in this stage. In our research we used the both techniques. At first step, we created a basic CNN network model to see how our dataset is working. Then we used the pre-trained models on our dataset. In CNN, we used all the 4 classes. In this stage, we used all the classes too.

Our first transfer learning model was VGG16. We resized the images by 150*150*3. We added a convolution base layer after VGG model. We also added a Flatten layer, a Dense layer with relu activation function and another dense layer with softmax activation function. Our optimizer was adam optimizer and we run it for 25 epochs. Then we modified our VGG16 model for 3 classes and changed our batch size to 16 and number of epochs to 20. After that we applied VGG19 model. Our input image size was 224*224*3. We added a flatten layer, a dropout layer and a dense layer after the pre-trained model. Then we used Inception V3 model. Again we added a flatten layer, a dropout layer, a dense layer and an activation function layer to the pre-trained model.

- Analyze Result

In this step, we analyze the result and see if our algorithm model is working fine on the dataset. We used different result analysis techniques like accuracy, precision etc. to analyze our result. Our analysis of the result will be discussed in Results and Discussion section.

- Modify or Continue to Next Stage

We have to modify our algorithm or code as there are thousands of parameters in deep learning algorithms. Also changing the data processing techniques can also change the result of the solution. In our research we had to modify our model several times to find a satisfactory result.

F. Research Summary

Results and Discussion A In this part, we'll discuss the results of the CNN and transfer learning techniques on our dataset. We'll go through the algorithms one by one and then compare it at the last.

- Basic CNN Model:

After running 20 epochs we got training accuracy of 82.5584.09epochs, it was reduced to 0.4092 which is not the best, but a good improvement. We came to the conclusion from this training that our dataset was working and we can do major improvements on it using transfer learning models.

- VGG16 (With 4 Classes):

After running 25 epochs we got training accuracy of 88.07 percent and validation accuracy of 91.98 percent. It was not that much improvement of accuracy from basic CNN model. But there was significant improvement in validation loss. Before it was 0.4092. But in this model, it reduced to 0.2196 which was surely a major improvement. At this time, we researched about the problem a bit and understood that using viral pneumonia and bacteria pneumonia as different classes might be the problem. To make it clear, we modified our model for 3 classes and trained it again.

- VGG16 (With 3 Classes)

Using VGG16 for 3 classes we noticed a major improvement on our result. We got training accuracy of 97.71 percent and validation accuracy of 99.07 percent. We got validation loss of 0.0313. Surely, this gave us a far better result and our assumption was correct.

- VGG19

Using VGG19, the performance did not improve, rather it declined. We got training accuracy of 93.91 percent and a validation accuracy of 97.87 percent. Validation loss also increased from 0.0313 to 0.0987.

- Inception V3

In this case, we got training accuracy of 98.56 percent and validation accuracy of 95.27 percent. Validation loss was 0.6370. The changes of accuracy and loss are shown in the graphs.

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CONCLUSION

As of now, intelligent medical imaging continues to play an imminent role in detecting coronavirus infections across the world, leading to preventing the spread of the virus. In our proposed model, we have elaborately discussed the details of the different methods of deep learning technology, and how each of the models we evaluated worked. We applied those models on the X-Ray dataset, and achieved a wide range of different results for each of the models. After further analysis and comparison of the results we found, we have concluded the best model in terms of COVID-19 detection. Between the models VGG16, VGG19, Xception, MobileNet V2, ResNet50, and Inception, MobileNetV2 has given us the best accuracy (99.74). So it is safe to conclude that a combination of Artificial Intelligence usage and Imaging Techniques can be efficient and effective for overcoming many medical limitations and hence, solving them. In the future, we would like to make the dataset even wider and larger, as a larger set of data will give us more accurate validation when studying the combination of Artificial Intelligence and Imaging Techniques. Furthermore, there are also opportunities to conduct more detailed and in-depth researches on how our model would work on the different strains and variants of the novel coronavirus.

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