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Computer Vision and Radiology for COVID-19 Detection

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***Abstract*- COVID-19 is spreading rapidly throughout the world. As of 14 April 2020, 128,000 people died of COVID-19, while 1.99 million cases in 210 countries and territories were reported in 219.747 cases. As the virus spreads at a very high rate, there is a huge shortage of medical testing kits all over the world. The respiratory system is the part of the human body most affected by the virus, so the use of X-rays of the chest may prove to be a more efficient way than the thermal screening of the human body. In this paper, we are trying to develop a method that uses radiology, i.e. X-rays for detecting the novel coronavirus. Along with the paper, we also release a dataset for the research community and further development extracted from various medical research hospital facilities treating COVID-19 patients.**

Keywords- COVID-19, Computer Vision, Radiology

I. INTRODUCTION

A cluster of mysterious cases of pneumonia were detected in December 2019 in the province of Wuhan, China, which eventually spread to the rest of the world [2 - 5]. Initially, a few cases were reported in the European Union in countries such as France and Germany, which later escalated at an alarming rate. The outbreak has spread to several cruise ships and cruise operators have begun either to cancel or to change their routes as countries around the world have introduced travel restrictions to control the spread of disease [1]. As of 14 April 2020, 128,000 people died of COVID-19, while 1.99 million cases in 210 countries and territories were reported in 219.747 cases. Figure 1 represents the statistics about the confirmed cases across the globe. Figure 2 shows the statistics about the deaths across the globe.

COVID 19 is an infectious illness triggered by the recently identified coronavirus virus. It was not understood until the outbreak in Wuhan, China, started in December 2019 [6]. The most frequent signs of COVID-19 include fever, tiredness, and dry cough. Most individuals (about 80 percent) are healing from the disease without needing extra treatment. Approximately 1 of every 6 people that have COVID-19 are seriously ill and experience trouble breathing. Senior citizens and those with chronic medical issues such as elevated blood pressure, cardiac disorders and diabetes are more prone to experience severe illnesses [7]. Evidence to date has demonstrated that the virus that triggers COVID-19 is mainly spread by interaction with respiratory droplets rather than through the air.

Pneumonia is a type of acute respiratory infection that affects the lungs [8 – 10]. The lungs are made up of little pockets called alveoli, which are packed with oxygen as a stable person breathes. When anyone has pneumonia, these alveoli are packed with pus and blood, rendering ventilation painful and therefore raising the absorption of oxygen. Symptoms of pneumonia can involve fever, trouble breathing, and tiredness. Pneumonia can spread in a variety of ways [11, 12].

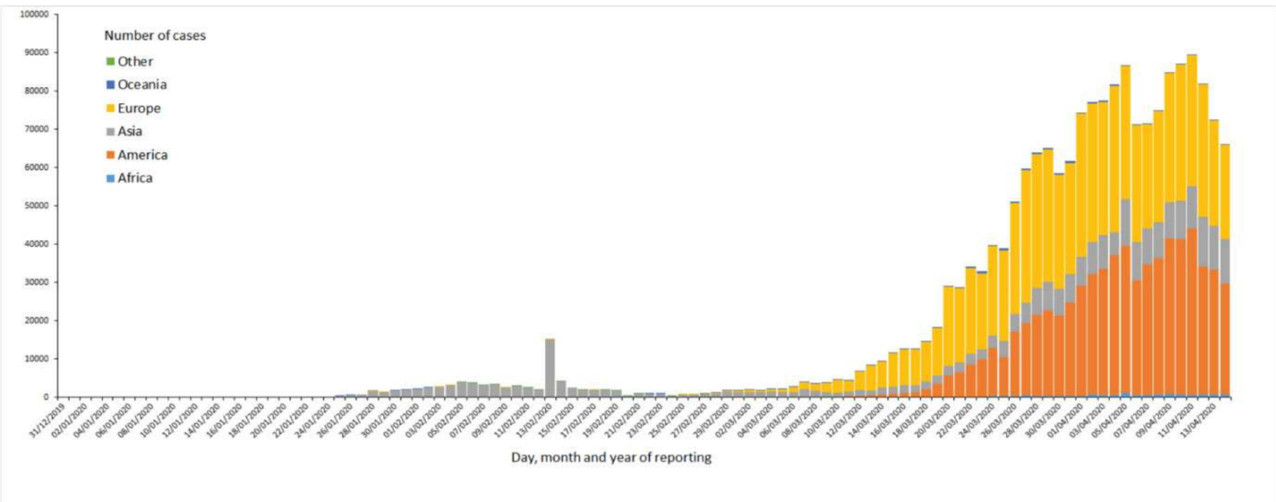

Fig. 1. Image representing the number of cases of COVID-19 across the world [31].

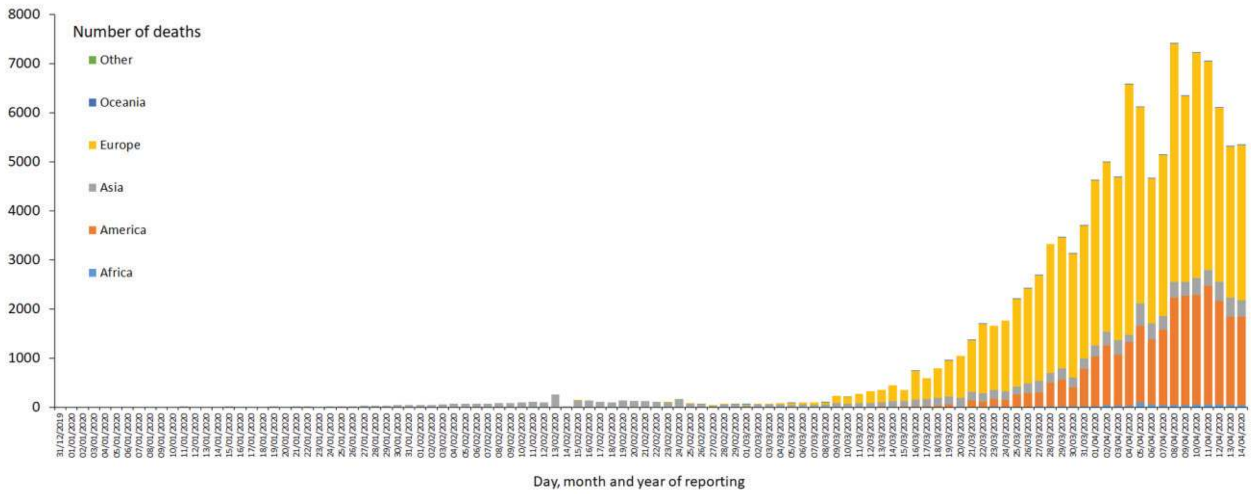

Fig. 2. Image representing the number of deaths due to COVID-19 across the world [31].

The respiratory system is the part of the human body most affected by the virus, so the use of X-rays of the chest may prove to be a more efficient way than the thermal screening of the human body. Image Recognition tasks have progressed in recent years due to advances in algorithms, the availability of large datasets and powerful GPUs that allow deep architecture training. Convolution Neural Networks (CNNs), Residual Networks and training methods such as transfer learning have produced state-of - the-art performance for tasks such as image recognition and classification. As of April 4, 2020, under-developed antibody tests were adopted. As of 15 April 2020, the screening protocol adopted for mass control is focused on thermal imaging and wide scale testing using nRT-PCR test kits to identify potential patients with COVID-19 virus. The standard testing procedure may generate results within a few hours to two days. There is therefore a significant need for advanced technologies to screen future COVID-19 patients. In section 5, we applied an approach to classifying COVID-19 positive patients based on X-Ray Images. The symptoms of pneumonia and COVID-19 are somewhat similar and the respiratory system is the most affected area of the human body, so screening based on the respiratory system using X-Ray would be a safer way.

II. RELATED WORK

The study of single neuron receptive fields that appeared in 1959 was one of the most important papers in Computer Vision [13] describing the central reaction properties of visual cortical neurons as well as how the sensory experience of a cat affects its cortical architecture. Lawrence Roberts [14] described the method used to extract 3D data on solid objects from 2D images in 1963. Essentially, the external world has been distilled into flat geometric shapes. It was established in 1982 that the vision was hierarchical [15]. The primary function of the vision system is to create 3D world models so that we can interact with them. A perception system was developed where low-level algorithms that could detect lines, curves, and corners were used as stepping stones to a high-level understanding of visual information. At the same time, a self-organizing artificial network of simple and complex cells, which could recognise patterns and not be influenced by position changes, was developed [16]. This included several convolutional layers whose receptive fields had weight vectors known as filters. The aim of these filters was to slide through 2D image pixel arrays and, following accurate calculations, to generate activation events that would be used as inputs for subsequent layers of the network. Text recognition and commercial zip code decoding applications have been released [17]. In fact, this culminated in the development of the MNIST data collection with handwritten digits.

About 1999, a number of researchers focused their efforts on the recognition of artifacts based on features [18]. A visual recognition system has been established that uses local features which are invariant in terms of rotation, location and, in part, changes in illumination. Soon thereafter, the first real-world face recognition program was put in operation in 2001 [19]. While not focused on deep learning, the algorithm has learned which features could help to identify faces. When the area of computer vision began to develop, the group felt an urgent need for a standardized picture dataset and common assessment measures to measure the success of their models.

The ImageNet Large Scale Visual Recognition Competition (ILSVRC) launched in 2010. This is presented annually where the most innovative entries are debated. The ImageNet archive consists of more than one million images and has become a benchmark for classifying object categories and defining objects across a wide range of object styles. In 2010 and 2011, the ILSVRC error rate in the image description was roughly 26%. In 2012[20], the University of Toronto developed a convolutional neural network that yielded an error rate of 16.4 per cent for image recognition tasks. It's been a historic moment for CNNs.

Microsoft Research Paper [21] has obtained top results for object recognition and object identification with the localization tasks of its Residual Network or ResNet. The combination of these residual nets results in a 3.57 percent error on the ImageNet test combination. This result won 1st place in the 2015 ILSVRC classification competition.

Although a lot of research is going on COVID-19 to develop fast detection methods and developing a cure for it using Artificial Intelligence (AI), still no significant methods exist in the author’s best knowledge that outperforms medical kit testing for detection of COVID-19 virus in the.

III. DATASET

In the current chaotic situation, it's very hard to find the dataset for outbreaks like the COVID-19 pandemic, especially when most of the world is using thermal imaging instead of X-Rays to detect the infected persons. The X-Ray images of COVID-19 were extracted from online hosted data by Italian research organization [29], European Health Care [28]. The Pneumonia X-Ray Images were collected from the open-source dataset [30]. After removing the noisy images, a dataset with images for three labels COVID-19, PNEUMONIA, and NORMAL with 374 images in each label was extracted.

As the number of collected images is very small, we further applied Data Augmentation steps such as Rotating all images to 45 degrees, zooming images to 30%, and height shifting with a factor of 0.2 were applied to the dataset to create diversity and will improve the quality of prediction. After this, all images were resized to 224x224 and the number of images in each label were made equal to remove the class imbalance issue. This dataset further divided into test, train, and validation set with test and validation provided with 35 images each and train set getting the rest.

The dataset is released publicly with open access for researchers to experiment with methodology and further development at https://github.com/luckykumardev/Covid19-dataset

IV. PROPOSED METHODOLOGY

For the image classification tasks, Residual Network (ResNet) outperformed previous classification networks like CNN, etc [21]. But these deep neural networks need a significant amount of data to train and produce state-of - the-art performance. In addition to the numbers, hyperparameters such as learning rate, drop-out values often play a key role in delivering the best results in a shorter period of time and mitigating the over-fitting problem [23]. Yet picking a random value for the hit hyperparameter and the test procedure can be tricky and inefficient. Value of learning rate plays a significant role, while too low a value is inefficient and time-consuming for the training of the neural networks, on the other hand a value too high can cause divergent behaviour in the loss function [24]. Our methodology is inspired by ADADELTA [25] to select a good learning rate value and avoid hit and trial. A batch of 128 images is trained and loss is computed on defined neural network architecture. A plot is drawn with the Y-axis representing linear value of loss function and X-axis representing the value of learning rate on logarithmic scale. The value of learning rate for which loss function is minimum gets selected as the learning rate. Figure 3 represents the plot of loss function versus learning rate, where 0.05 is selected as the best learning rate.

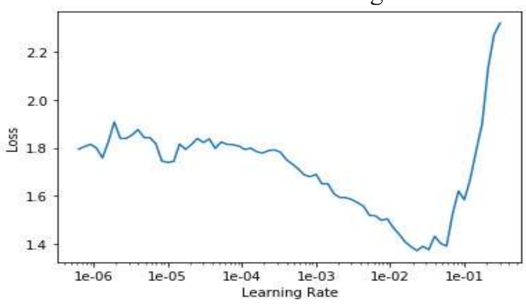

Fig. 3. Loss v/s Learning Rate

A. Transfer Learning

Transfer learning is a type of machine learning, where a method already generated for a task is replicated as a starting point for a specific task [26]. As the dataset for the current study is too small to achieve outstanding results. The procedure includes taking an existing neural network that was previously trained on a larger dataset to produce outstanding output. Therefore, using it as the basis for a new model that utilizes the accuracy of the previous network for a specific task. In recent years this approach has become common to improve the output of a neural net trained on a small dataset. In our work, we selected ResNet-34 and ResNet-50 which were originally trained on the ImageNet data set consisting of 3.2 million images for Image Classification tasks. Both pre-trained architecture models have been re-trained and fine-tuned using transfer learning from the data set obtained [21-22].

The ResNet-34 is one of the most widely used and standard architecture for Residual Network. The complete architecture consists of 5 Stages with convolution and identity Block connected with skip connections in a feed-forward fashion. Each stage consists of 2 convolution layers in itself. Figure 5 represents the normalized confusion matrix when the architecture tested and prediction were made on the test dataset. Some of the key factors for using the Residual Network is the scalability of the training parameters by increasing the complexity of the network by adding additional layers. Like the classic Convolution Neural Network (CNNs), the Residual Network (ResNet) does not face the gradient issue of extinction [27].

The ResNet-50 architecture also consists of 5 stages similar to ResNet - 34. But each convolution block itself consists of 3 convolution layers and the total trainable parameters are 23.52 million. Accuracy and Error rate for both the implemented architecture is discussed in the next section. Figure 6 represents the Normalized Confusion Matrix for ResNet - 50 architecture when predictions were made on the test dataset.

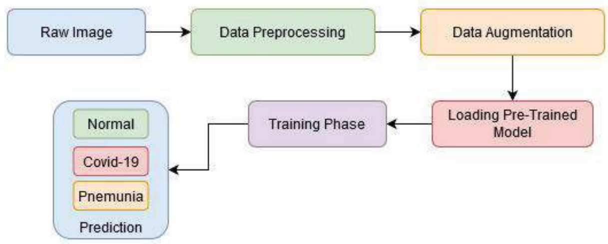

Fig. 4. Schematic representation of the experimental setup established for COVID-19 detection

B. Experimental Setup

Figure 4 represents the schematic overview of the experimental setup. For the basic image preprocessing, augmentation and manipulation OpenCV and python programming language, along with the PyTorch framework, was used [32, 33]. Experimentations were performed on a Linux workstation with Nvidia GPUs. Pre-Trained ResNet-34 and ResNet-50 models were initialized with random weights and further trained with Adam Optimizer [34]. Batch size = 128 with learning rate, as discussed above, were trained for 80 epochs.

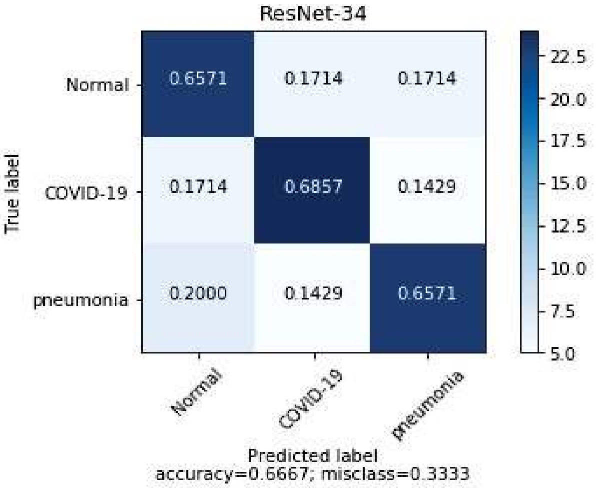

Fig. 5. Normalized Confusion Matix for ResNet - 34 architecture

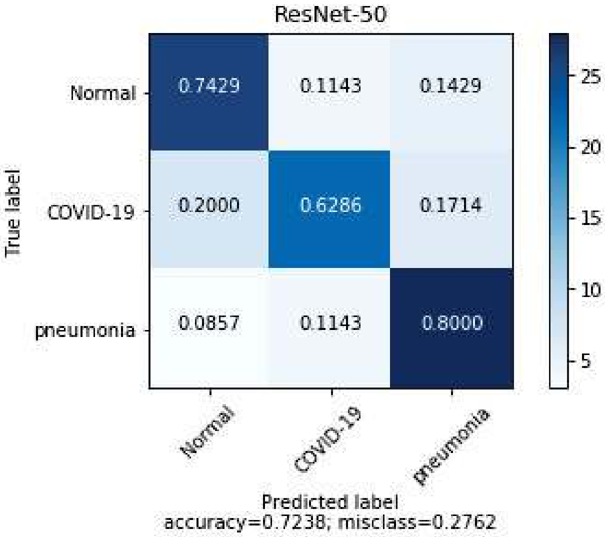

Fig. 6. Normalized Confusion Matix for ResNet - 50 architecture

V. RESULTS AND DISCUSSION

As the current extracted dataset size is too small, so it seems illogical to train the Residual Network from scratch. Hence results reported are only for ResNet-34 and ResNet - 50 trained using transfer learning. The developed models were evaluated on the test set defined in section 4. Table 1 represents the accuracy and error rate of both the models developed. ResNet - 50 architecture performed better, with an accuracy of 72.38%. Adding more layers and increasing the number of parameters in Residual Network architecture definitely helps in improving the accuracy of the overall classification.

TABLE I. SUMMARIZATION OF IMPLEMENTED ARCHITECTURE ALONG WITH THE ACCURACY SCORE AND ERROR RATE.

Model	**Accuracy**	**Error Rate**
ResNet - 34	66.67%	33.33 %
ResNet - 50	72.38 %	27.62%

Figure 7 represents a few random samples of images classified by trained ResNet-50 model from the test set. Each image contains the actual label and predicted label by the model. Such photos were not part of the training collection and were used for the first time.

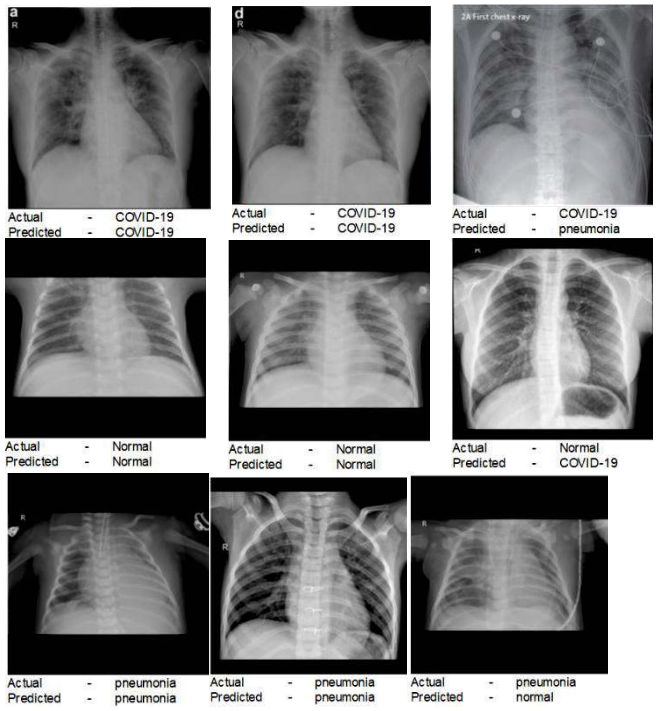

Fig. 7. Random samples chosen from test set, with Actual and predicted labels

VI. CONCLUSION & LIMITATION

In this paper, we implemented a new method to detect the COVID-19 virus using X-Ray images. The implemented methodology also differentiates the patients suffering from pneumonia and COVID-19 as both have the same symptoms and patients usually got confused between the two. Detecting COVID-19 using X-Ray is much cheaper than the medical COVID-19 test kit and as fast as the current thermal imaging technique. Hence, can be used for the first screening at airports, hotels, shopping centres. One of the main drawbacks of our research is the lack of data quality. The presently available data collection is too limited to obtain state-of-the-art performance and to replace the thermal imaging technique. Our current project is in pilot state to search and test new methods to detect COVID-19. We believe that our paper will motivate other researchers to find new methods for detecting potential patients infected with the virus without the explicit use of medical COVID-19 test kits.

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