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A Review on Computer Vision and Radiology for COVID-19 Detection

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***Abstract*- COVID-19 is a virus that is quickly spreading over the world. COVID-19 claimed the lives of 128,000 people as of April 14, 2020, with 1.99 million cases documented in 210 nations and territories, totaling 219.747 cases. Because the virus is spreading so quickly, medical testing kits are in short supply all around the world. Because the respiratory system is the region of the human body that is most impacted by the virus, X-rays of the chest may prove to be a more effective method than thermal screening. We are attempting to establish a method for detecting the novel coronavirus using radiography, i.e. X-rays, in this work. We also offer a dataset for the research along with the paper Various medical research hospital facilities treating COVID-19 patients were used to gather information about the community and future development.**

Keywords- COVID-19, Computer Vision, Radiology

I. INTRODUCTION

In December 2019, a cluster of strange pneumonia cases was discovered in the Chinese province of Wuhan, which subsequently spread to the rest of the world [2 - 5]. Initially, only a few instances were reported in the European Union, primarily in France and Germany, but the number of cases quickly grew alarmingly. As countries throughout the world impose travel restrictions to stop the spread of disease, the outbreak has extended to numerous cruise ships, prompting cruise companies to cancel or change their itinerary [1]. COVID-19 claimed the lives of 128,000 people as of April 14, 2020, with 1.99 million cases reported in 210 countries. In 219.747 occurrences, territories were mentioned. The statistics on confirmed cases around the world are depicted in Figure 1. Figure 2 depicts death numbers from around the world..

COVID 19 is an infectious disease caused by a newly discovered coronavirus virus. It was not recognised until December 2019, after an epidemic in Wuhan, China [6]. Fever, fatigue, and a dry cough are the most common symptoms of COVID-19. The majority of people (about 80%) are recovering from the ailment without the need for additional therapy. COVID-19 affects about one out of every six persons, causing major illness and breathing problems. Senior folks and people with chronic medical conditions such high blood pressure, heart disease, or diabetes are more likely to develop severe illnesses [7]. To date, evidence suggests that the virus that causes COVID-19 is disseminated mostly through contact with respiratory droplets rather than through the air..

Pneumonia is a lung illness that is caused by an acute respiratory infection [8–10]. When a healthy individual breathes, the lungs are made up of tiny pockets called alveoli that are packed with oxygen. When someone gets pneumonia, their alveoli become clogged with pus and blood, making breathing difficult and increasing oxygen uptake. Fever, difficulty breathing, and exhaustion are all symptoms of pneumonia. Pneumonia can be transmitted in a number of ways [11, 12].

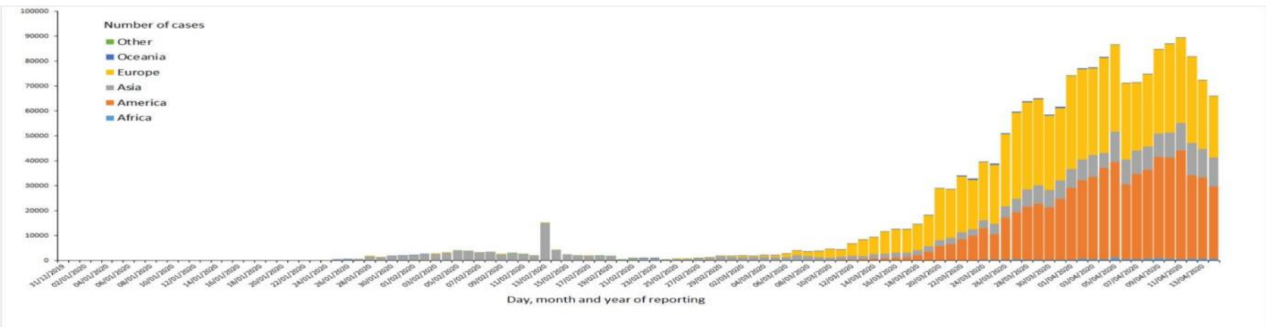

Fig. 1. Image representing the number of cases of COVID-19 across the world [31].

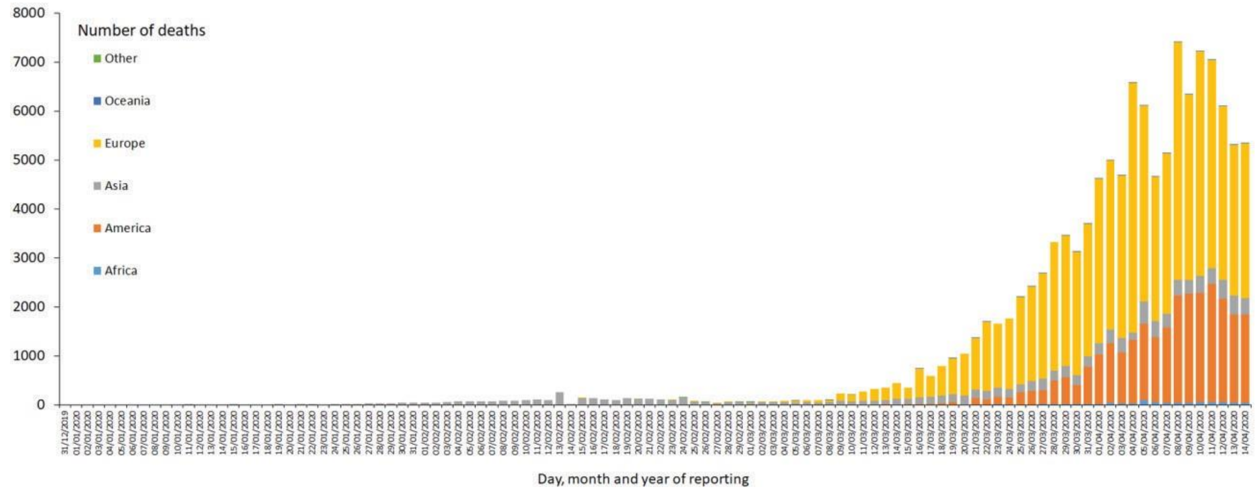

Fig. 2. Image representing the number of deaths due to COVID-19 across the world [31].

Because the respiratory system is the region of the human body that is most impacted by the virus, X-rays of the chest may prove to be a more effective method than thermal screening. Due to breakthroughs in algorithms, the availability of massive datasets, and powerful GPUs that allow deep architecture training, image recognition jobs have progressed in recent years. For applications like picture identification and classification, Convolution Neural Networks (CNNs), Residual Networks, and training approaches like transfer learning have provided state-of-the-art performance. Under-developed antibody tests were adopted on April 4, 2020. As of April 15, 2020, the mass control screening protocol focuses on thermal imaging and large-scale testing with nRT-PCR test kits to identify possible COVID-19 viral patients. The usual testing technique can take anything from a few hours to two days to provide findings. As a result, new technology for screening future COVID-19 patients are critical. In section 5, we used an X-Ray image-based technique to categorise COVID-19 positive patients. Because the symptoms of pneumonia and COVID-19 are similar, and the respiratory system is the most afflicted part of the human body, X-ray screening of the respiratory system would be a safer option.

RELATED WORK

One of the most important articles in Computer Vision was the research of single neuron receptive fields, which described the central reaction qualities of visual cortical neurons as well as how a cat's sensory experience influences its cortical architecture. In 1963, Lawrence Roberts presented a method for extracting 3D data from 2D photographs for solid objects. In essence, the outside world has been reduced to flat geometric outlines. In 1982, it was determined that the eyesight was hierarchical [15]. The visual system's principal role is to produce 3D world models that humans can interact with. Low-level algorithms that could detect lines, curves, and corners were employed as stepping stones to a high-level understanding of visual input in a perception system. Simultaneously, a self-organizing artificial network of simple and complicated cells was built [16], which could recognise patterns and was unaffected by location changes. Several convolutional layers with different receptive fields were used. Filters, which were weight vectors, were used. The goal of these filters was to slide across 2D picture pixel arrays and generate activation events that would be used as inputs for later layers of the network after correct calculations. Applications for text recognition and commercial zip code decoding have been launched [17]. In reality, as a result of this, the MNIST data collection with handwritten digits was created.

A group of academics focused their efforts on recognising artefacts based on attributes about 1999 [18]. Local features that are invariant in terms of rotation, location, and, to some extent, changes in illumination have been established as part of a visual identification system. Soon later, in 2001, the first real-world facial recognition programme was launched [19]. While the system isn't focused on deep learning, it has learned which features can aid in facial recognition. When the field of computer vision began to grow, the group saw a pressing need for an uniform picture dataset and a set of common assessment metrics to evaluate the models' success.

In 2010, ImageNet established the Large Scale Visual Recognition Competition (ILSVRC). This is an annual competition in which the most inventive entries are judged. The ImageNet database, which contains over one million photos, has established a standard for identifying and defining objects across a wide spectrum of object designs. In the years 2010 and 2011, the ILSVRC error rate in picture description was around 26%. The University of Toronto built a convolutional neural network in 2012[20] that has a 16.4% error rate for image identification tests. CNN has reached a watershed moment in its history.

With the localization tasks of its Residual Network or ResNet, Microsoft Research Paper [21] has achieved top results for object recognition and object identification. On the ImageNet test combination, the combination of these residual nets results in a 3.57 percent inaccuracy. In the 2015 ILSVRC classification competition, this result took first position.

Despite the fact that a lot of research is being done on COVID-19 to develop speedy detection methods and develop a cure for it using Artificial Intelligence (AI), to the author's knowledge, no substantial methods exist that exceed medical kit testing for COVID-19 viral identification in the.

II. 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

III. 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 learningrate.

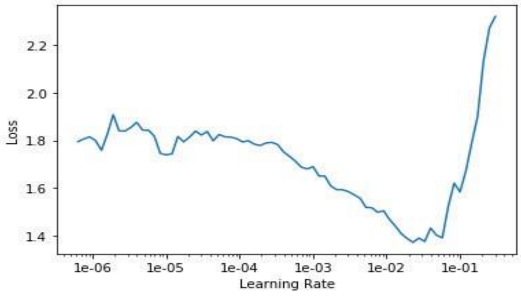

Fig. 3. Loss v/s Learning Rate

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.

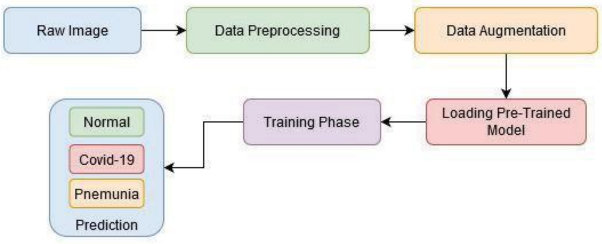

Fig. 4. Schematic representation of the experimental setup established for COVID-19 detection

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.

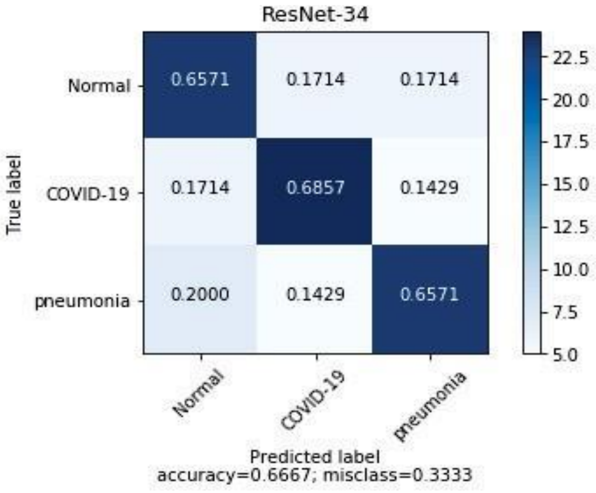

Fig. 5. Normalized Confusion Matix for ResNet - 34 architecture

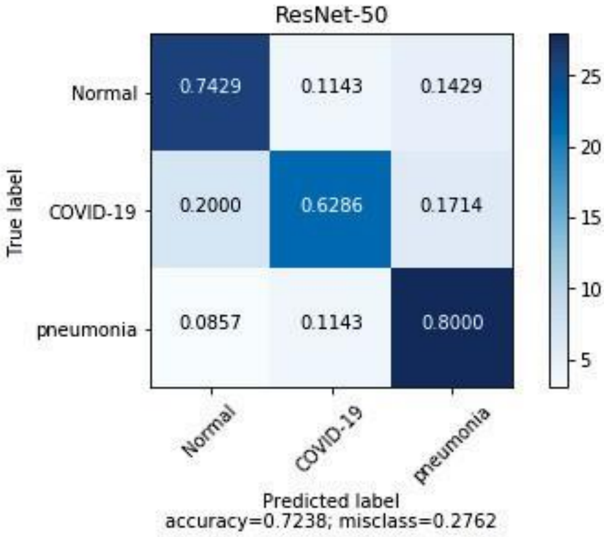

Fig. 6. Normalized Confusion Matix for ResNet - 50 architecture

IV. 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.

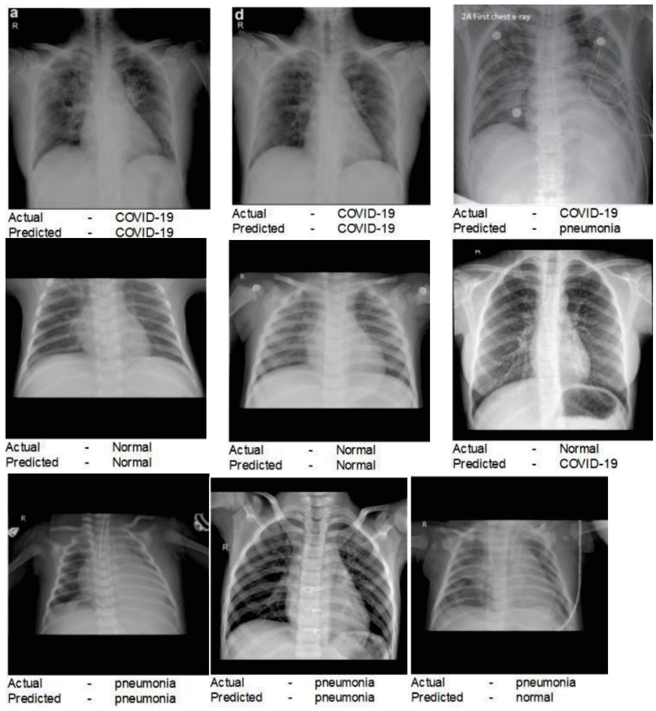

Fig. 7. Random samples chosen from test set, with Actual and predicted labels

V. CONCLUSION & LIMITATION

We used X-Ray pictures to build a new approach for detecting the COVID-19 virus in this paper. The applied methodology also distinguishes between pneumonia and COVID-19 patients, as both have similar symptoms and patients sometimes confuse the two. COVID-19 may be detected with X-Ray at a fraction of the cost of a medical COVID-19 test kit and in the same amount of time as the current thermal imaging technique. As a result, it can be utilised for first screening at airports, hotels, and retail malls. The lack of data quality is one of our research's major flaws. The data collection currently available is insufficient to achieve state-of-the-art performance and to replace the thermal imaging technique. Our present project is in the pilot stage, and we're looking for and testing novel detection methods. COVID-19. We hope that by publishing our paper, other researchers will be inspired to develop innovative approaches for detecting probable COVID-19 infected patients without the use of medical COVID-19 test kits.

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