Novel Approach in Classification and Prediction of COVID-19 from Radiograph Images using CNN

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***Abstract*—Effective screening and early detection of COVID-19 patients are highly crucial to slow down and stop the disease's rapid spread at this time. Currently, RT-PCR, CT scanning and Chest X-ray (CXR) imaging are the diagnosis mechanisms for COVID-19 detection. In this proposed work radiology examination by using CXR images is used for COVID-19 detection due to dearth of CT Scanners and RT-PCR testing centers. Therefore, researchers have developed various Deep and Machine Learning systems that can predict COVID-19 using CXR images. Out of which, few are exhibited good prediction results. However, Most of the models are suffered with over fitting, high variance, memory and generalization errors which are caused by noise as well as datasets are limited. Therefore, a Convolutional Neural Network (CNN) with the leveraging Efficient Net architecture is proposed for COVID-19 case detection. The proposed methods have an accuracy of 99% which gives the better results than the present available methods. Therefore, the proposed model can be used in real-time covid-19 classification systems.**

***Keywords*—COVID-19; x-ray images; deep learning technique; CNN; efficient net**

I. Introduction

SARS-CoV-2 has never been discovered in people before December 2019, is the virus that causes the unique Coronavirus Disease 2019 (COVID-19), an infectious and lethal disease that has never been seen before in the world [1]. Finding infected individuals through efficient screening is a crucial responsibility in halting the rapid spread of COVID-19 so that they can be separated and given prompt medical attention. The RT-PCR test is now the most widely utilised screening method for COVID-19 case detection [2]. There are still a number of difficulties with RT-PCR testing, despite it being acknowledged as the "gold standard" for identifying infected cases of the disease. Tahamtan et al recent study [3] found that the detection sensitivity is highly varied and can lead to both FN and FP i.e. False-Negative & False-Positive results. The Radiograph imaging and CT Scan are performed and analysed by radiologists to determine whether or not a suspected person was Infected by Covid-19. This alternative effective screening method to RT-PCR is for the quick identification of COVID-19. All three of these tests are typically used to diagnose COVID-19. The RTPCR test, which is used to diagnose viral infection, can identify viral RNA in sputum or nasopharyngeal swabs [4]. Using CT scans, a 3D radiographic image is examined from various perspectives as part of a CT-based examination. The main drawback in the CT scan is that, it requires lots of time and the equipment is not readily available all the time and in all the areas and high radiation. Although CT scans are more sensitive to pulmonary disorders, they have a number of drawbacks that prevent them from being used in COVID-19 case detection on a broader scale. These drawbacks include non-portability, prolonged scanning, and the potential for patient exposure. In compared to CT scans, CXR imaging offers an adequate level of accuracy in the detection of COVID-19 cases while being portable, quicker, and more widely accessible and less expensive. Due to these advantages, CXR image analysis for COVID19 case detection has become the focus of numerous recent investigations [5, 6]. With the pandemic's rapid spread, certain studies, in particular, advise using portable CXR imaging as a reliable tool for finding COVID-19 cases.

Many writers recommended combining the RT-PCR test with additional clinical procedures like the CT & CXR (chest X-ray). A few recent studies provide estimates of the sensitivity of professional radiologists to diagnose COVID-19 using CT scans, RT-PCR, and CXR. A research on 51 individuals who had a chest CT and RT-PCR performed within three days found that the CT had a sensitivity of 98% and the RT-PCR had a sensitivity of 71%. Similarly RT-PCR will require at least 12Hrs of time, which is not ideal as COVID19 +ve patients should be identified and tracked as soon as feasible, and it requires specialised materials and equipment that are not readily available [7][8].

A sensitivity of 69% for CXR was found in a different study on 64 patients. An analysis of 636 ambulatory patients revealed that the majority of patients with confirmed coronavirus who visit urgent care facilities have normal or barely abnormal CXR results. The professional eye accurately diagnoses only 58.3% of these cases. Although CXR imaging is fairly quick, COVID-19 case detection must be done manually by qualified radiologists, which takes professional knowledge and is a laborious process. However, there are many fewer radiologists than there are people who are being monitored. These scenarios will all broaden the application of AI-driven algorithms for detecting COVID-19 from chest radiographs.

II. Previous Work

Thus, a diagnostic system powered by artificial intelligence (AI) is required to help radiologists screen COVID-19 cases in a more quick and reliable manner. Without such a system, it is likely that infected individuals may not be promptly identified, isolated, and treated. Based on the AI[17] aided diagnosis many authors proposed different approaches in diagnosing Covid-19 which are based on CT-scan and radiographs along with the technology end depends on transfer learning and machine learning etc.

CNN based data driven deep learning methods have shown promising performance for the classification challenge of COVID-19 case detection with CXR pictures, which is essentially a machine learning problem. As a result, there are numerous recent research that seek to train new deep learning models for infected case detection with CXR images by reusing or changing existing deep neural networks on top of gathered CXR image datasets. Although several research in their articles indicate considerably higher prediction accuracy for their proposed deep learning models with their own datasets, in practice, noise and restricted training data size may cause a deep learning model to suffer from over fitting, excessive variance, and generalization mistakes.

Deep learning (DL) methods for automated image processing have the potential to significantly improve the role of CXR pictures in the rapid diagnosis of COVID-19[20]. A reliable and accurate DL model could enhance medical decision-making and be used as a triage tool. Recent investigations claim to have achieved outstanding sensitivities > 95%, which is much higher than expert radiologists. Numerous deep learning & Transfer Learning based AI-assisted detection techniques have been proposed to lessen the load of detection from radiography pictures (e.g., CT and CXR images) for radiologists [09][10].

CXR pictures are evolving into a well-liked and often used data source for COVID-19 case detection due to its many advantages over CT images, including mobility, availability, accessibility, and quick testing. When AlexNet, ResNet18, DenseNet201, and SqueezeNet were used to identify two classes (i.e., COVID-19 and Normal) for CXR images, Wynants, L. et al. [11] came to the conclusion that SqueezeNet performed better than the other neural networks. Instead, Narin et al.'s [18] comparison of various CNN models trained on CXR images for COVID-19 case detection, including ResNet-50, Inception V3, and Inception-ResNetV2, revealed that ResNet-50 surpasses the other two models with 98 percent accuracy.

A three class prediction with the help of transfer learning was proposed by E. H. Chowdhury et al. and attained an accuracy of 99% by implementing it in the CNN environment [12]. Farooq et al. [13] provided a COVID-ResNet by fine tuning a pre-trained ResNet-50 architecture with a reported accuracy of 96.23%. A semi-supervised few-shot segmentation for the detection of Covid-19 was proposed by Mohamed Abdel-Basset et al. [14] which is a Deep learning based architecture and the implementation was based on CT scans, the limitation of less data set availability overcomes by this approach. In the similar manner with the DL and TL approaches in the diagnosis of COVID-19 from the X-ray and CT images have been implemented in Halgurd S. Maghdid et al. approach [15]. Linda Wang et al. [16] came up with a huge chest X-ray dataset based approach by a DCNN design and attained good accuracy with the model with this huge dataset system can encounter technical issues [19].

III. Proposed Method

A. Datasets

The dataset of 15000+ of (512x512pixel) images are collected from Kaggle which are used to train and test the model. The dataset consists of properly labeled radiograph images by radiologists. When a lot of patients need to be examined in a short amount of time, a model like this can help medical practitioners diagnose COVID-19 cases considerably faster than a radiologist having to go over each scan one by one. The sample images are shown in Fig. 1.

B. Learning Rate

Learning rate plays an important role in defining the accuracy of the model. In general convergence can be improved by Low Learning rate but the accuracy will be not as expected. Similarly overshooting can be possible with higher learning rate, therefore choosing learning rate properly will improve the performance there by accuracy. In proposed method the model experience with 10e-4 rate which led the model with low error rates on test dataset.

C. Batch Size

With reference to the literature article [22] batch size in association with learning rate plays a vital role in accuracy. Increase in batch size like 256 or 128 or 64 might lead the system into memory issues. Therefore depends on system performance and other factors in proposed method tested with 32. Hence proposed model trained with a batch size of 32 and learning rate of 10e-4.

D. Epochs

The EfficientNet b3 model consists of 12 Million parameters and the images used in the proposed model have chosen for the training instance is around 15k+ images. With the dataset trained model attained accuracy of 99% at 7th epoch. And the system used about 10 epochs with different batch sizes and learning rate combinations.

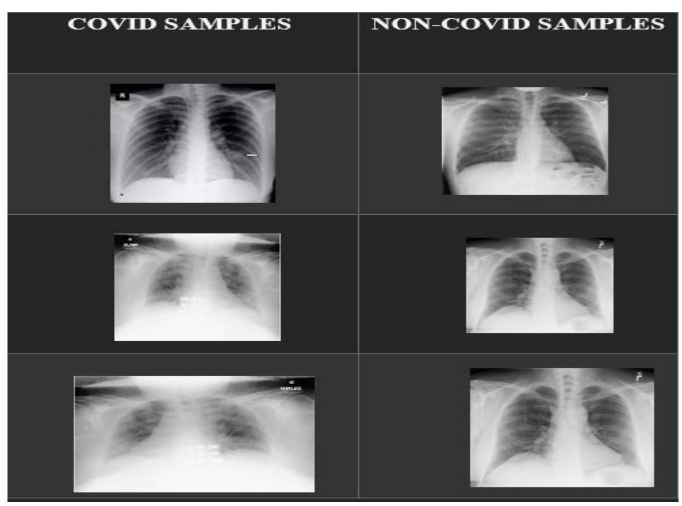

Fig. 1. Images taken as Sample for Covid & Non-Covid.

E. Pre-Trained Model

In the current quickly evolving technology era, applying this technology to the medical diagnosis will leads to better outcome. Computer Vision is one of the fields where we make a use of diagnosing Covid-19. With reference to the Google AI Blog [21] in our proposal we have chosen EfficientNet in which b3 version has chosen to overcome issues in system configuration instead of using VGG16 or Resnet50. In general most of the architectures are too wide, deep or with high resolution therefore while increasing these characteristics will initially help the model but later it leads to saturation and there by become in-efficient, where as in the chosen EfficientNet model these are scaled in a more principled way [23].

Coming to the architecture representation of EfficientNet-B3 will be shown in Fig. 3.

The difference that we can observe between different EfficientNet models will be the number of feature maps i.e. channels, which leads to increase in number of parameters.

The proposed model initially trained on Google Colabs environment which is an effective tool for learning and quickly creating machine learning models in python with pytorch. Later, implemented the same model in the system environment (Fig. 2).

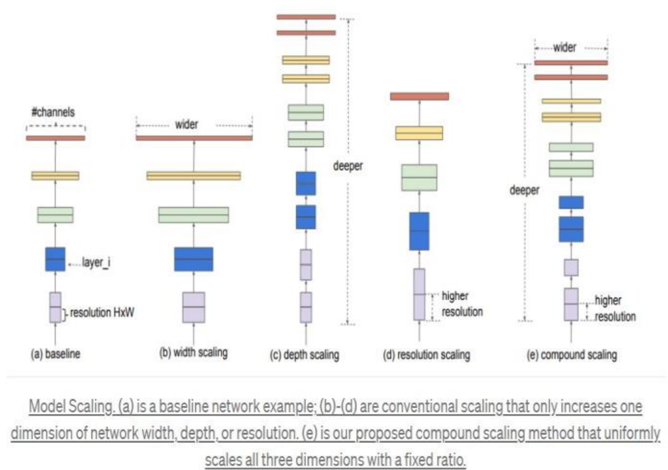

Fig. 2. Model Scaling.

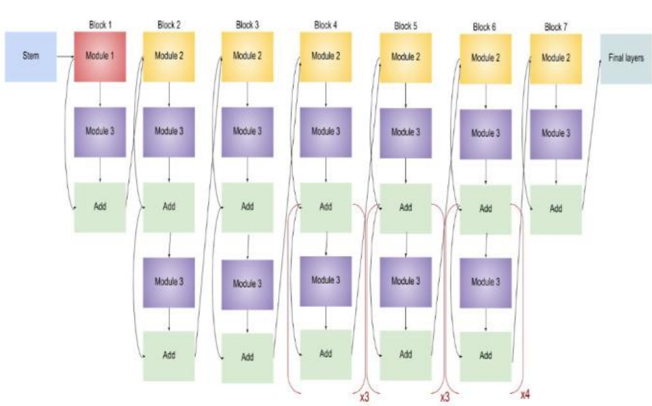

Fig. 3. Architecture for EfficientNet-B3.

Development of the proposed work implemented with the help of PyTorch which will be well suited for the Computer vision applications. When we give radiograph image as input the trained model has to detect the provided image was COVID-19 positive or Negative.

F. Flowchart

The proposed model flow of implementation can be seen in Fig. 4. The existing Dataset consist of the images for training and testing. By applying the transformation method to resize the images and this transformation will be helpful in data augmentation. If more than 90% of the photos in the training dataset belong to the non-Covid class, the training dataset is markedly unbalanced. A naive learning method that just outputs the class of the majority class as the output would achieve high accuracy with severely unbalanced sets, which is a problem. In other words, even though only 10% of people truly have Covid, it will classify everyone as being Covid-free and achieve a "accuracy" of 90%. For the training images with the help of this transform method we can up sample the minority class which is Covid, so that in both the classes we can have same number of images which will be quite helpful improving the accuracy of the model. Now these newly created images can be split into training and validation at a ratio of 80:20. These images are given as input to the system. Across the preprocessing with the help of Data loader Batch size of 32 applied on the training dataset and shuffled them to ensure approximately equal representation of both classes in all the batches. While this process is taking place it's always best practice to save the weights generated at the time of training process to ensure that even though the model got crashed due to any technical reason, instead of starting from the scratch we can call the saved weights and reinitiate the process. Initially while doing the training in the Google colabs the model got crashed because of the number of training images are huge in number and it cannot support these many iterations on the training data as well as testing. Therefore saving the weights will always the best way. And that's why developed model implemented on system environment.

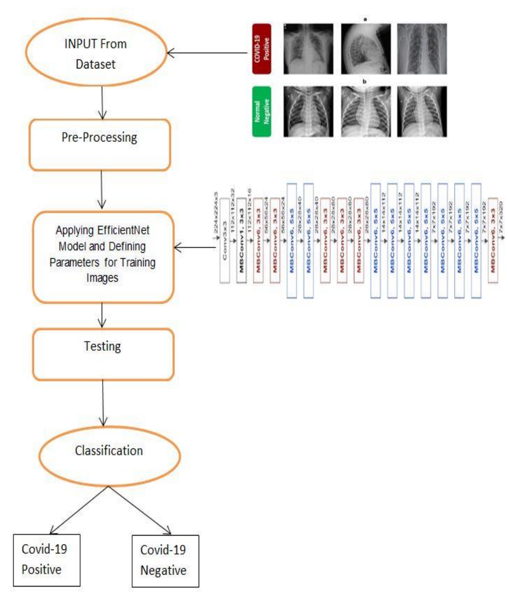

Fig. 4. Flow Chart Representation of Proposed Model.

IV. Evaluation and Result

There are various methods we can apply for the Loss calculation. Here in the proposed method cross-entropy loss is used for the calculation of the losses because of the chosen classification. In the similar manner for the weight update Adam optimizer has chosen which is well suited for deep learning applications. Proposed network trained with above mentioned parameters and the number of epochs is set to 10, out of which the network attained an accuracy of 99%. Training model attained the accuracy for both the classes as 99%-100%.

Fig. 5 shows the Graph between Accuracy and Loss. There is over 7000+ batch iterations taken place and the plot showcases these changes occurring in the values with respect to the batch iterations.

After the training is performed now the trained model has to be applied for the testing samples. Now the transforms are composed and applied to the test dataset to make it conform to the same distribution as the training dataset. Proposed model performed prediction of the test image with an accuracy of 99%. With the proposed model, a medical practitioner can identify Covid accurately in 99 out of 100 people rapidly.

Comparison of the proposed model results with the few of the existing models are shown in Table I.

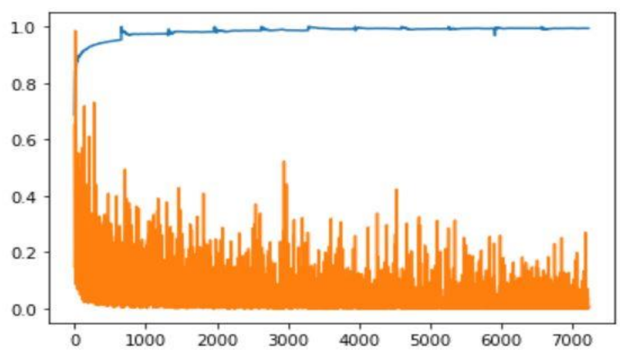

Fig. 5. Plot between Accuracy and Loss.

TABLE I. Comparison of different Model Accuracies

Authors	**Imaging Type**	**Dataset Size (No.of Images)**	**Model Used**	**Accuracy**
Boran Sekeroglu et al.	CXR	6100	CNN	98.5%
Thiyagarajan Padmapriya et al.	CXR & CT	650 349	Multimodal covid network	99.75%
Yu-Huan Wu et al.	CT	3855	JCS	95.9%
Guangyu Jia	CXR & CT	7592	Dynamic CNN	99.3%
Bhawna Nigam	CXR		EfficientNet	93.4%
DandiYang	CT	2481	VGG 16	99%
Proposed Method	CXR	15000+	Efficient b3	99%

V. Conclusion

The most important factor in life is health; therefore early diagnosis of any disease is required. In this current pandemic kind situations early and accurate diagnosis of Covid-19 from radiological examinations like CT scan and Radiograph images is very important for Doctors as well as patients. Proposed model implemented with Deep learning approach based on X-ray images to reduce the financial cost and radiation effect to the patients as well as to diagnose in less time. The proposed model is capable of classifying the radiograph images as Covid positive or negative in less time with an accuracy of 99%. The model trained on huge data samples and attained an accuracy of 100% in training and 99% in testing. This way the proposed approach constructed with CNN architecture on EfficientNet can provide desired assistance in diagnosing Covid-19 for radiologists.

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