2021 Fourth International Conference on Computational Intelligence and Communication Technologies (CCICT) | 978-1-6654-2392-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/CCICT53244.2021.00030

Convolutional Neural Network for Covid-19 detection from X-ray images

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***Abstract*– Covid-19 pandemic has crumbled the health systems of the nation's world over. In such a scenario, quick and accurate detection of coronavirus infection plays an important role in timely referral of physicians and control transmission of the disease. RT-PCR is the most widely used method for identification of coronavirus disease 19 patients, but it is time consuming and takes two to three days to deliver the report. Researchers around the world are looking for alternative machine learning techniques including deep learning to assist the medical experts for early Covid-19 disease diagnosis from medical pictures such as X-ray films and CT scans. Since the facility for chest X-rays is available even in smaller towns and is relatively less expensive, it would be useful to design machine learning methods for proving initial Covid-19 detection from chest X-rays to contain this pandemic. Thus, in this work, we propose a Convolutional Neural Network (CNN or ConvNet) for the finding of presence and absence of Covid-19 disease. We compare the CNN model with traditional and transfer learning-based machine learning algorithms. The proposed CNN is accurate compared to the traditional machine learning algorithms (KNN, SVM, DT etc.). The suggested CNN model is almost as accurate as the classifiers based on transfer learning (such as InceptionV3, VGG16 and ResNet50) despite being simple in terms of number of parameters learnt. The CNN model takes less training time.**

Keywords— Covid-19 disease diagnosis, Transfer Learning, Deep Learning, Convolutional Neural Network, Chest X-ray image, Pneumonia

I. INTRODUCTION

A new coronavirus, initially originated from Wuhan city in China, turned into a pandemic almost around the globe. Due to the unavailability of vaccines against the new disease Covid-19, early diagnosis was of extreme importance. This was needed to immediately isolate the suspected persons for preventing the further spread of infection. The current only method of medical checkup for Covid-19 is reverse transcription polymerase chain reaction (RT-PCR) [1]. However, the accuracy of RT-PCR on swabs deep in the nasal cavity, the front of the nose or the throat has been reported to be only 30% to 60%, which is very dangerous [2]. The commonly used tool for pneumonia diagnosis is X-ray photograph or computer-assisted tomography (CT) scans. Both tools have high sensitivity for diagnosing Covid-19 induced pneumonia [3]. X-rays show visual indices that correlate with Covid-19 and capture inflammation in the lungs. Medical practitioners initially prefer Chest X-ray pictures more than CT-scan for pneumonia diagnosis since it is easily available, cheaper, faster and exposes the patient to less radiation[4] [5] [6]. Because there is an enormous shortage of trained radiologists, computerized methods can increase the speed of timely detection of Covid-19 disease.

Machine learning provides efficient tools for solving disease diagnosis problems. Predicting Covid-19 pneumonia severity from chest film using expert system machine intelligence may be an option. Traditionally a two-step procedure is followed for medical image classification, namely features extraction and classification. The end-to-end deep learning structure can predict Covid-19 directly from the original image without extracting features. CNN-based models based on deep learning are superior to traditional artificial intelligence techniques in several areas such as computer vision, facial recognition and medical image analysis. CNN-based models have been used for a varied problem such as classification, regression, segmentation and image optimization [7].

In the situation of the Covid-19 pandemic, we seek to improve the prognostic forecasts to manage the patient care. In this research, we attempt to apply Convolutional neural networks (CNN's) for diagnosing Covid-19 by X-ray films. We compare the performance of CNN with some popular pre-trained ImageNet models for Covid-19 diagnosis from X-rays. The pre-trained models, which come under the domain of transfer learning, are considered accurate. However, the pre-trained models are complex as compared to simple CNN models. The contribution of this research is to compare the performance of ConvNet with pre-trained models in the context of diagnosing coronavirus disease 19 from chest X-ray films.

The organization of the rest of this article is as follows: Section 2 describes essentials of CNN and transfer learning. Section 3 provides literature review of CNN and transfer learning-based machine learning algorithms for Covid-19 disease diagnosis. Next section presents the materials and methods used for this study. Section 5 provides the experimental studies and observations, and finally the paper is concluded in the last section.

II. BACKGROUND DETAILS

Since CNN has shown promising results for classification tasks, we have used CNN for Covid-19 disease diagnosis and compared its performance with state-of-the art deep transfer learning models in this paper. Description of CNN and transfer learning is as follows:

A) CNN or ConvNet: Convolutional neural networks are a specialized type of multi-layer neural network mainly used in image processing and computer vision domain for feature enrichment. These are designed to detect visual patterns directly from pixel images with minimal preprocessing. They can extract topological properties from an image. In CNN, there is no need to extract the features by using other signal processing techniques. Due to its multilayer structure, CNN has the ability to extract low, medium and high-level features. High-level features are a combination of lower and middle-level features. CNN uses a series of filters to process the raw pixel data of the image to extract and learn advanced features that the model can use for classification. CNN mainly consists of four types of layers: convolutional layers, pooling layers, fully connected layers and output layers. A typical CNN architecture is shown in Figure 1. The convolutional layer is made up of a

DOI 10.1109/CCICT53244.2021.00030

convolutional kernel that works by dividing the image into smaller pieces, usually called receptive fields. This layer uses a matrix filter and performs convolution operations to find patterns in the image. Pooling layer regularly follows the convolution layer. It combines a set of values into a single value, resulting in a reduction in the size of the function map. It converts the representation of the common feature into valuable information, retains useful information, and eliminates irrelevant information. Fully connected layer connects each neuron in one layer to each neuron in another layer. In principle, it is the same as the traditional multi-layer perceptron neural network (MLP). It takes the output of the previous layers, "flattened" it, and then converts it into a single vector, which can be used as the input for the next step. The output layer might produce likelihoods of an image belonging to a particular class. This layer uses the sigmoid function as the more generalized nonlinear activation function for binary classification. The first two layers are used for feature maps while the last two layers, which are fully connected, are used for classification.

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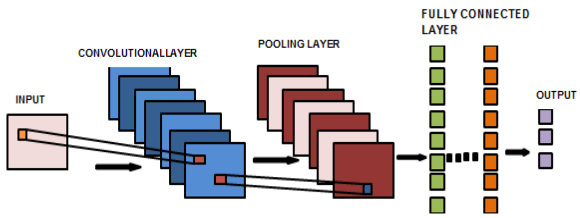


Fig. 1. A Typical CNN Architecture

B) Transfer Learning Approach

In transfer learning, a model learns from one type of problem and then the learning is applied to solve a different but related problem. For example image classification models trained on the ImageNet database with stored weights can detect Covid-19 on the data set used in this paper. Transfer learning is primarily suited to issues where less training data can be used early on to train the model, such as medical image classification. The lower layers of the network have already been trained, the network has learned the general features such as shape and edge of the image etc. and only the higher layers of the network need training. The main advantages of integrating transfer learning with CNN are saving training time and better performance of neural networks even with small amounts of data.

In our study, such pre-constructed models are used as feature extractors. Only the last layer of CNN is tuned according to the number of categories in which the dataset should differ. We have evaluated the performance of three popular pre-trained models on ImageNet database such as InceptionV3, VGG16 and ResNet50.

III. LITERATURE REVIEW

The 2019 new coronavirus (Covid-19) shows many exceptional features as it is very dynamic and continues to evolve [8] [3]. Although the diagnosis can be confirmed by RT-PCR, CT scan and chest X-ray films of patients with pneumonia have also been widely used to detect and examine suspected or confirmed cases of Covid-19. These images show a pattern that is sometimes undetectable for the human eye [9].

Diagnosing Covid-19 on chest radiographs using CNN is one of the most commonly used methods. In [10], authors suggested 121 layers of convolutional neural networks based on chest X-ray dataset and the results were superior in comparison to four practicing academic radiologists. Authors in [11] have proven the useful application of deep training models based on the tailored COVIDX-Net system for Covid-19 X-ray films classification and reported an accuracy of 90%. Wang et al. [12] introduced Covid-Net, a deep ConvNet design to detect coronavirus disease 19 from X-ray pictures and compared the results with VGG 19 and ResNet-50 transfer learning models. At the end of the study, 93.3% normal accuracy was reported. In [13], Covid-ResNet was used as a classifier for Covid-19 disease detection and three other types of infections. The authors reported superior performance compared to Covid-Net with an accuracy of 96.23% and sensitivity 100% for Covid-19 classification. Deep CNN models were used to abstract features from Covid-19 X-ray films [14]. The extracted features from these deep models were classified by SVM. The proposed hybrid model, ResNet 50 and SVM, statistically outperformed other CNN models with accuracy of 95.38%. Abbas et al. [15] proposed a deep CNN called DeTraC for the same. It could detect any irregularity in the image dataset by the class decomposition mechanism. The results of the experiment showed an accuracy of 93% by DeTraC in detecting X-ray films of Covid-19 of healthy and infected cases.

In addition to chest X-rays films, studies were also performed for the detection of coronavirus disease 19 using CT scan. In [16] [17], authors developed a novel weakly supervised deep structured learning model to diagnose Covid-19 disease using upper body CT scans without the need for lesion interpretation for training. The proposed model achieved an average of 88.55% accuracy and 93% sensitivity features respectively, thus providing a quick way to detect Covid-19 patients. However, the main disadvantages of using computed tomography are high radiation, high dose to the patient, and the cost of the examination [18]. In contrast, conventional X-ray machines are capable of producing two-dimensional (2D) projection images of a patient's lungs in all hospitals and clinics. In general, X-ray modulation is the choice of radiologist for the diagnosis of diseases and is used to detect Covid-19 in an average number of patients [9] [19]. Thus, this work focuses only on the usage of X-rays in potential patients with Covid-19.

Another popular CNN architecture learning strategy is to transfer the knowledge learned from a task-driven network to a new task [20] [21]. Pre-trained CNN models such as VGG19 and MobileNetV2 have achieved quite high classification accuracy (97.82) in detecting Covid-19 from X-ray pictures [22]. Similarly, [23] proposed an alternative fast screening method nCOVnet using VGG16 top layers as a bottom model and adding five custom layers as top model showed an overall accuracy of 88.10% in disease diagnosis by X-ray imaging.

Upon review of the related work, it is clear that pre-trained CNN models, although fast and easy to use, achieve higher accuracy at the expense of computational and architectural complexity. Thus, in this study we use CNN architecture which is trained from scratch but has low architectural complexity. The CNN model is less complex, fast in speed and easy to deploy. In the study, a total of 539 chest X-ray pictures were examined for binary classification (Covid-19 and non-Covid-19). All the images have been preprocessed to be given as input to CNN.

IV. MATERIALS AND METHODS

A. The Dataset

The dataset used in this study is the coronavirus disease 19 chest X-ray dataset from two online open-source communities –Cohen [24] and Kaggle [25]. Upper body X-rays of patients with Covid-19 were obtained from a GitHub repository shared by Dr. Joseph Cohen. This repository contains 305 chest X-ray pictures of Covid-19 infected people. X-rays of the chest of healthy individuals were obtained from the Kaggle repository. It contains 234 chest radiographs of healthy individuals. All the images were examined by a board of certified doctors. The dataset is split into three parts namely train (70%),test (15%) and validation (15%) dataset.

B. The Proposed Network Architecture

Unlike the complex architecture of pre-trained models, here we have proposed a simple architecture of CNN and trained it from scratch. The proposed method is based on enhanced CNN learning architecture for classification of chest X-ray films into images with or without Covid-19. All the images have been resized to 240 x 240. The images are first preprocessed to remove noise like blur, high contrast etc. Pre-processing involves several operations on images such as gray scale conversion, image segmentation and morphological operations to remove the unnecessary part of X-ray pictures.

The projected CNN model consists of several convolutional layers, which provide efficient feature maps as input to the primary layer. The model has three convolutional layers, then three pooling layers and two fully connected layers, a flattening function and a sigmoid layer as shown in Figure 2. The model uses the RELU activation function as it reduces the likelihood of vanishing gradient sparsity.

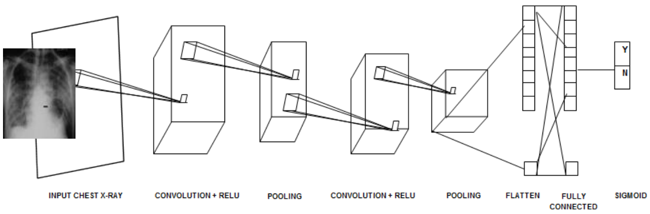


Fig. 2. The Proposed CNN Architecture

C. Performance Metrics

The performance of the deep learning model is evaluated on test data by measuring accuracy, precision, recall and area under ROC.

D. Tools

All the computational experiments are conducted in Python 3 Google Compute Engine Backend (GPU). GPU facilitates faster training of the deep learning and transfer learning models as compared to CPU. Each model is subtly tuned for 24 epochs. The model is trained with a batch size of 32 and ADAM optimizer with step size parameter of 0.0001 which is used to optimize the loss function.

V. RESULTS AND DISCUSSION

Here, we contrast the deep learning model for Covid-19 diagnosis with some of the popular transfer learning models such as InceptionV3, VGG16 and ResNet50. Behavior of models is analyzed with respect to loss/accuracy on training and validation dataset. Figure 3 shows the loss and accuracy plots of all the four models trained for 24 epochs.

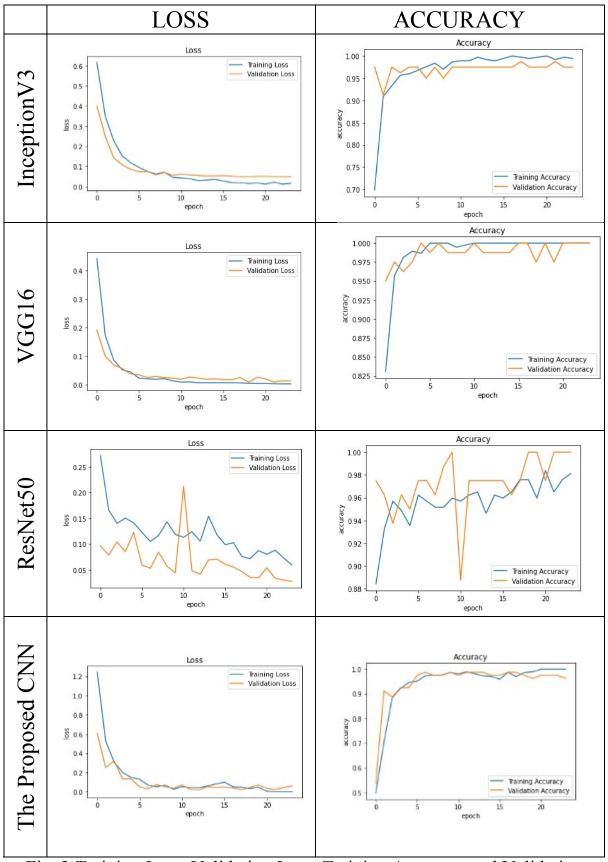


Fig. 3 Training Loss, Validation Loss, Training Accuracy and Validation Accuracy of Learning Models across the epochs.

Figure 3 shows that the ResNet50 model faces the problem of overfitting as train loss continues to decrease with experience and validation loss decreases first and then increases again. Large gap between the two shows that the model does not perform well on the unknown Covid-19 dataset. The proposed CNN model learning curve shows good fit with a small gap between the training loss and validation loss. CNN's performance is comparable to that of the InceptionV3 and VGG16 models. To know the exact number of correctly and incorrectly diagnosed cases, confusion matrix and accuracy of transfer and deep structured learning architectures for the Covid-19 disease diagnosis on the test images are shown in Figure 4.

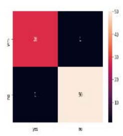
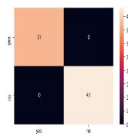
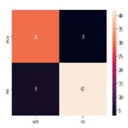
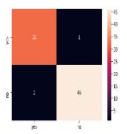
	InceptionV3	VGG16	ResNet50	Proposed CNN
Confusion Matrix				
Accuracy	0.97	1.0	0.94	0.97

Fig. 4 Confusion Matrix and Accuracy of transfer and deep learning architecture for the Coronavirus disease 19 classification

In addition to accuracy, other metrics such as precision, recall and ROC must also be reported for evaluating the performance of a classifier in medical diagnosis. Receiver Operating Characteristics (ROC) curve is used to give overall model performance as the curve is composed of false positive rate and true positive rate. Higher the area under the curve better is the performance of the model on unseen data. The ROC curve for all pre-trained models is shown in Figure 5.

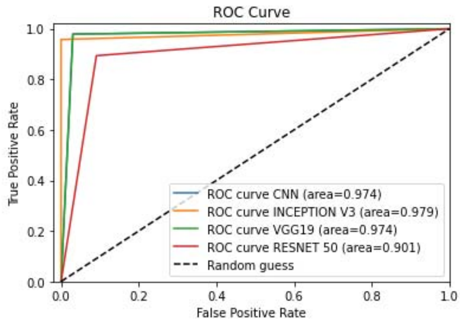


Fig.5 Four CNN ROC Curve for test set

All CNN architectures give higher AUC as compared to the Resnet model. Further, we give a Precision-recall curve to provide the true positive rate as a function of positive predictive rate. Precision-recall curves for all four models are shown in Fig. 6.

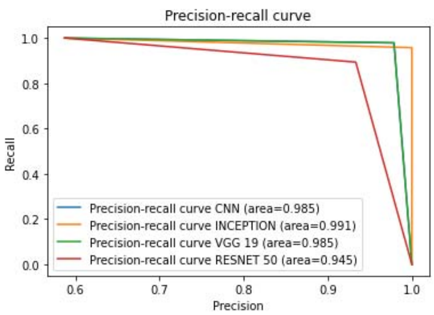
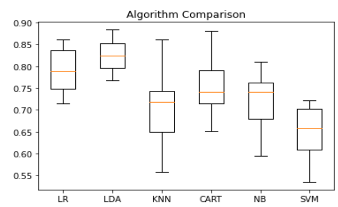


Fig.6 Four CNN Precision-recall Curve for test set

We have also compared the proposed CNN to other traditional machine learning algorithms. Fig. 7 gives the accuracy and standard deviation (in bracket) of several other traditional machine learning algorithms (Linear Regression (LR), Linear Discriminant Algorithm (LDA), K-Nearest Neighbour (KNN), Decision Tree (DT), Naïve Bayesian (NB) and Support Vector Machine (SVM)) on Covid-19 dataset for disease detection. The proposed CNN and the pre-trained models perform better than these machine learning algorithms given in Fig. 7.



LR: 0.792913 (0.049228)
LDA: 0.825914 (0.037965)
KNN: 0.701274 (0.087002)
DT: 0.757918 (0.068225)
NB: 0.720155 (0.061294)
SVM: 0.647342 (0.062027)

Fig. 7 The performance of some other popular machine learning algorithms

Further, the CNN model is more generalized than transfer learning models (Table 1). It is neither overfit nor underfit. The transfer learning models use excessive resources and complexity. These models use a large number of parameters which results in more training time for the model as shown in Table 1. There is no significant difference between the accuracy of CNN and transfer learning models, but the size of the transfer learning modes is usually big, and this makes these models difficult to deploy. The CNN model is trained from scratch; as a result, it uses a smaller number of parameters and takes significantly less training time except VGG16.

TABLE 1 TOTAL PARAMETERS AND TOTAL TIME TAKEN BY LEARNING MODELS

	InceptionV3	**VGG16**	**Resnet50**	**CNN**
Total Parameters	22,098,337	23,269,057	40,398,337	5,959,617
Elapsed Time	14min 42sec	01min 51sec	9min 54sec	1min 40sec

VI. CONCLUSION

This research proposes a ConvNet to diagnose Covid-19 disease from chest X-ray films. The CNN model has shown a useful and robust response to cases of Covid-19. Multiple convolutional layers of CNN make it effective to extract features of Covid-19 from chest X-ray pictures. We have compared CNN with three popular already trained CNN models. The ConvNet model noticeably outperforms the traditional machine learning algorithms for novel coronavirus disease diagnosis. The model is reliable, its accuracy is competitive, gives outcome quickly and requires reduced computational effort to determine the presence of Covid-19 induced pneumonia. The results show that CNN model is a promising option to assist the radiologists to rapidly decide on X-ray films in diagnosing Covid-19. Machine learning algorithms such as CNN can significantly lessen the workload of medical practitioners and increase their efficiency in diagnosing coronavirus disease 19 pneumonia from chest X-rays which are less expensive and are easily available in smaller towns. More experimentation is required to further validate the finding of this research on the performance of CNN and pre-trained models on large repositories of X-ray films and CT scan pictures.

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