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Fine Tuning CNN for COVID-19 Patterns Detection From Chest Radiographs

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ABSTRACT

The COVID-19 pandemic has crumbled health systems all over the world. 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 test used for identification of COVID-19 patients, but it takes long 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 imaging such as chest films. This study proposes an enhanced convolutional neural network (EConvNet) model for the presence and absence of coronavirus disease from chest radiographs to contain this pandemic. The model is accurate compared to the traditional machine learning algorithms (RF, SVM, etc.). The suggested CNN model is approximately as accurate as the classifiers based on transfer learning (such as InceptionV3, VGG16, and Densenet121). Despite being simple in terms of number of parameters learnt, it takes less training time and demands less memory.

KEYWORDS

Chest Films, Coronavirus, COVID-19 Disease Diagnosis, Deep Convolutional Neural Network, Deep Learning, Pneumonia, Pre-Trained Models, Transfer Learning

INTRODUCTION

A new coronavirus (Covid-19), initially originated from Wuhan city in China, turned into a pandemic almost around the globe. Initially, 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 method of medical checkup for Covid-19 is reverse transcription polymerase chain reaction (RT-PCR) (W. Wang et al., 2020). However, the efficiency 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 (Tahamtan & Ardebili, 2020). The commonly used tool for pneumonia diagnosis is chest radiographs (X-ray) or computer-assisted tomography (CT) scans. Both tools have high sensitivity for coronavirus induced pneumonia (Ai et al., 2020). Chest radiographs show visual indices that correlate with coronavirus disease and capture inflammation in the lungs (Kanne et al., 2020). Medical practitioners initially

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prefer chest radiographs more than CT-scan for pneumonia diagnosis since it is fast, easy, low-cost and exposes the patient to less radiation (Pereira et al., 2020) (Self et al., 2013) (Rubin et al., 2020). 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. Diagnosing 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. Convolutional Neural Network (CNN or ConvNet) deep learning based models 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 (Lee et al., 2017).

In the current situation of the coronavirus pandemic, the study seeks to improve the prognostic forecasts to manage the patient care. The purpose of the study is to apply CNN architectures in solving problems of the pandemic on a preliminary stage. The objective is to introduce and evaluate the performance of a custom-made deep learning architecture enhanced CNN (EConvNet), to classify and detect the chest X-ray films for Covid-19 diagnosis. The researchers attempt to apply Enhanced Convolutional Neural Network (EConvNet) for diagnosing coronavirus disease by chest films. The study also aims to compare the performance of EConvNet with some popular pre-trained ImageNet architectures for novel Covid-19 disease diagnosis from chest radiographs. 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 EConvNet with pre-trained models in the context of diagnosing coronavirus disease from upper body 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 conclusions are presented in the last section.

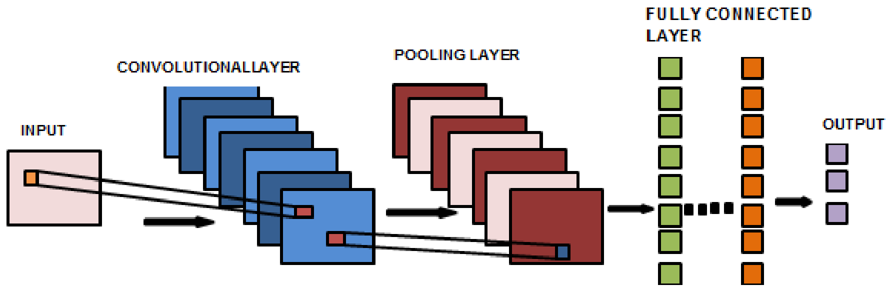
BACKGROUND

Since CNN has shown promising results for classification tasks, the authors 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.

CNN

Convolutional neural networks (ConvNet) are a specific type of multi-layer neural network mainly used in image processing and computer vision domain for feature enrichment. These are specifically designed to process visual patterns directly from pixel images with least 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 number of filters to process the pixel data of the input image to extract and learn feature maps 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 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

Figure 1. A typical CNN architecture



follows the convolution layer. It combines a set of values into a single value and leads to 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. In a fully connected layer a neuron in one layer connects to all neurons in another layer. It is the same as the outdated multi-layer perceptron neural network (MLP). It takes the results of the previous layers, flattens it, and then converts it into a single vector, which can be used as the inputs for the following 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.

Deep Transfer Learning Approach

In deep transfer learning, knowledge acquired from one type of task is applied to solve a different but related task. 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 the study, such pre-constructed models are used as fixed feature extractors for coronavirus dataset. The last layer of CNN is fine-tuned according to the number of classes in which the dataset should differ. The study evaluated the performance of six popular pre-trained models on the ImageNet database such as InceptionV3, VGG16, ResNet50, Densenet121, VGG19 and EfficientNetB1.

LITERATURE REVIEW

The new coronavirus shows many exceptional features as it is very dynamic and continues to evolve (Fang et al., 2020) (Ai et al., 2020). Although the diagnosis can be confirmed by RT-PCR, CT and chest X-ray films of sick persons with pneumonia have also been widely used to detect and examine suspected or confirmed cases of coronavirus disease. These images show a pattern that is sometimes undetectable for the human eye (Ng et al., 2020).

Diagnosing Covid-19 on chest radiographs using CNN is one of the most commonly used methods. Rajpurkar et al. (2017) suggested 121 layers of convolutional neural networks based on a chest film dataset and the results were superior in comparison to four practicing academic radiologists. Hemdan et al. (2020) proved the usefulness of deep training models based on the tailored COVIDX-Net system for Covid-19 X-ray films classification and reported an accuracy of

90%. L. Wang & Wong (2020) 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 models of transfer learning. An accuracy of 93.3% for corona positive was reported. Covid-ResNet was used as a classifier for Covid-19 disease detection and three other types of infections (Farooq & Hafeez, 2020). 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 (Sethy & Behera, 2020). 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. (2021) 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. An automated method where multiresolution analysis is integrated with depth-wise CNN was used for detection of Covid-19 from chest X-ray images (Singh & Singh, 2021). The proposed depth wise separable network utilizes the features generated by multiresolution analysis and achieved accuracy of 96%. Genetic deep learning CNN was used for the prediction of Covid-19 using chest X-ray images and performed better compared to other transfer learning techniques (Babukarthik et al., 2020).

In addition to chest X-rays films, studies were also performed for the detection of coronavirus disease 19 using CT scan. Researchers proposed a novel weakly supervised deep structured learning model to diagnose coronavirus disease using upper body CT films without the need for lesion interpretation for training (Zheng et al., 2020) (Song et al., 2020). The author reported average performance of the model with 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 (Kroft et al., 2019). In contrast, conventional X-ray machines produce two dimensional projection images of a patient's lungs and are commonly available 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 (Ng et al., 2020) (Chen et al., 2020). 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 carry over the knowledge learned from a task-driven network to a new task. Table 1 shows that researchers used several pre-trained CNN models such as VGG16, VGG19, InceptionV3, Resnet50, Resnet101, Densenet121 and EfficientNet for the Covid-19 disease diagnosis. Narin et al. (2021) proposed pre-trained CNN based models such as Resnet50, InceptionV3 and Inception-ResnetV2 for Covid-19 diagnosis using chest films. In the study, binary classification with four classes was carried out using 5-fold cross validation. An average of 97% accuracy was reported with the InceptionV3 model. Gaur et al. (2021) evaluated the pre-trained model InceptionV3 through transfer learning for Covid-19 detection from X-ray images. The performance of the developed classifier was evaluated using metrics such as accuracy, recall, specificity, precision and F1 score. The study showed an average accuracy of 91.32% for the multiclass problem (Covid-19 vs Normal vs Pneumonia). Luz et al. (2021) explored and extended the family of EfficientNet models for Covid-19 detection using chest radiographs. The proposed model produced high-quality and reduced parameters models with an overall accuracy of 93.9% for the classification of Covid-19, normal and viral pneumonia. Jain et al. (2020) designed a two-stage strategy to detect Covid-19 coronavirus with X-ray images. Initially the Resnet50 network model was used to differentiate bacterial pneumonia, viral pneumonia and healthy normal people with the chest X-ray films and achieved an accuracy of 93.01%. Later the Resnet101 network model was used to analyze viral pneumonia chest X-ray images for the diagnosis of Covid-19. In the study the data was validated with both train-validation-testing and 5-fold cross validation. The second stage model achieved an accuracy of 97.22%. With VGG19 architecture, (Apostolopoulos & Mpesiana, 2020) achieved an accuracy of 98.78% in detecting Covid-19 from X-ray films. Similarly, Panwar et al.

Table 1. Recent research papers associated with deep learning techniques for Covid-19 detection

Research Work	Image Type	Models	Classes Used	Accuracy
(Luz et al., 2021)	Chest Films	EfficientNet	Covid-19, Pneumonia, Normal	93.9%
(Narin et al., 2021)	Chest Films	InceptionV3	Covid-19, Normal	97%
(Gaur et al., 2021)	Chest Radiographs	Inception V3	Covid-19, Normal, Viral Pneumonia	91.32%
(Apostolopoulos & Mpesiana, 2020)	Chest Radiographs	VGG19	Covid-19, Bacterial Pneumonia, Normal	98.78%
(Panwar et al., 2020)	Chest X-ray	nCovNet+VGG16	Covid-19, Other	97.9%
(Jain et al., 2020)	Chest X-ray	Resnet101	Covid-19, Other	97.22%
(Minaee et al., 2020)	Chest Films	Resnet50, Densenet121	Covid-19, Non-Covid-19	98%(sensitivity)
(Sethy & Behera, 2020)	Chest Films	Resnet50+SVM	Covid-19+, Covid-19-	95.3%
(Hemdan et al., 2020)	Chest Radiographs	VGG19, Densenet	Negative Covid-19, Positive Covid-19	90%
(Zheng et al., 2020)	Chest CT	DeCovNet	Covid-19 +ve, Covid-19 –ve	90.01%
(Song et al., 2020)	Chest CT	DRENet	Covid-19, Other	94%
(Ozturk et al., 2020)	Chest X-ray	DarkCovidNet	Covid-19, No Findings	98.08%

(2020) suggested an alternate fast screening method nCovNet using VGG16 as a base model and 5 custom layers as head model showed an overall efficiency of 97.9 for the binary class (Covid-19 vs other). Minaee et al. (2020) studied deep neural network framework to diagnose coronavirus patients from chest radiographs by using pre-trained convolutional models such as Resnet50 and DenseNet121. A total of 200 images with binary labels were prepared for the study. The performance metrics used were sensitivity, specificity, ROC curve and precision-recall curve. The proposed models achieved a sensitivity of 98%. In the study of (Ozturk et al., 2020), authors proposed the DarkCovidNet model to predict the disease from chest films. They reported 98.08% and 87.02% accuracies for binary and multiclass classification respectively. However, the application of deep neural network techniques to diagnose coronavirus in chest radiographs is still very limited.

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 authors use CNN architecture (EConvNet) 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 radiographs were examined for binary classification (Covid-19 and non-Covid-19). All the images have been preprocessed to be given as input to CNN.

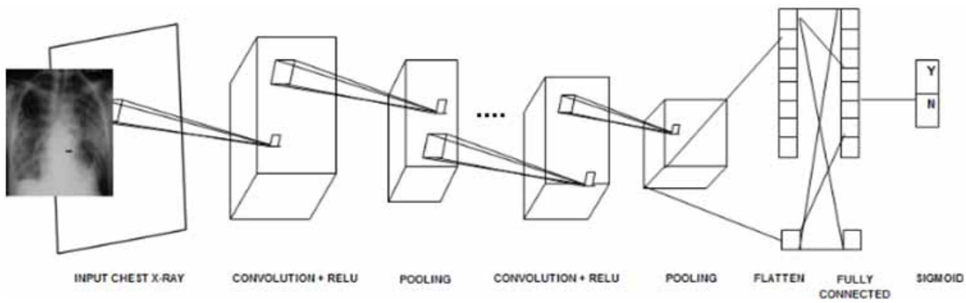
MATERIALS AND METHODS

1. **The Dataset:** The dataset used in the study is the coronavirus disease 19 chest radiographs dataset from two online open-source communities –(Cohen, 2020) and (Chest X-Ray Images (Pneumonia)). Upper body X-rays of persons with Covid-19 were obtained from a GitHub storehouse shared by Dr. Joseph Cohen. This repository contains 305 chest X-ray films of Covid-19

infected people. X-rays of the chest of healthy individuals were taken from the Kaggle storehouse. It contains 234 chest radiographs of non-infected 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. Also the images of Covid-19 are collected from different sources; there is wide variation in the resolution of the images and show different dynamic range from the other ones. So all images have been resized to 240 X 240 and normalized to same distribution to make model less sensitive during the training phase.

2. **Deep Learning Image Classifiers:** This section provides a quick overview of the current advanced deep neural network image classifiers used in the work:
   a. **InceptionV3:** It is one of the versions from the Inception family developed in 2015. It consists of both symmetrical and asymmetrical building blocks, where each block has a number of elements such as convolution layer, average pooling, max-pooling, dropouts and fully connected layers (Szegedy et al., 2015). It is computationally efficient as several components such as auxiliary classifier, factorization of convolution, RMSProp and label smoothing are introduced in it.
   b. **VGG16 and VGG19:** Visual Geometry Group (VGG) network was technologically advanced based on CNN by Oxford Robotics Institutes in 2014 (Simonyan & Zisserman, 2015). VGGNet performed splendidly on the ImageNet database at ILSVRC2014. The key feature of VGG16, the first version of the VGGNet family, architecture is its simplicity and uniformity. It has a few convolutional layers followed by a pooling layer. The number of filters is doubled in every step. Next version VGG19 is deeper and has more ConV3 layers than VGG16. Large number of parameters makes it more expensive to train the network as compared to VGG16.
   c. **Resnet50:** It is a 50 layered deep CNN architecture pre-trained on ImageNet database and was the winner of 2015 ImageNet competition. It makes use of residual modules involving shortcut connections. These identity shortcut connections between layers prevent the distortion that occurs as the network gets deeper and more complex. This solves the vanishing gradient problem in deep neural networks.
   d. **DenseNet-121:** Densely connected Convolutional Network (DenseNet) is another popular CNN architecture already trained on ImageNet database and also the winner of 2017 ImageNet competition. The architecture is computationally and resource efficient as each layer gets feature maps from all previous layers making the network more compact and thinner (Huang et al., 2018). Each layer owns feature maps used as inputs into all successive layers. It has 121 layers with several benefits such as reduced parameters, solves vanishing gradient problem, propagation and feature reuse.
   e. **EfficientNetB1:** It is the first model of the EfficientNet family. It outperforms CNN in terms of accuracy and reducing the parameters and FLOPS. The core idea is introducing the so-called MBConv, a shortcut connection between the beginning and end of a convolutional block (Tan & Le, 2020). It uses a compound coefficient to uniformly scale all dimensions of depth, width and resolution in a correct way. This structure helps in decreasing the number of operations as well as the model size.
3. **The Proposed Network Architecture:** Unlike the complex architecture of pre-trained models, here researchers 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 images into images with or without coronavirus disease. 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. Figure 2 shows the architecture of the proposed EConvNet model. The model has 3 convolutional layers followed

Figure 2. The enhanced CNN architecture



by three pooling layers and double fully connected layers, a flattening function and a sigmoid layer. The model uses the RELU activation function as it reduces the likelihood of vanishing gradient sparsity.

4. **Performance Metrics:** The performance of the deep learning model is evaluated on a test dataset by measuring accuracy, F-measure, precision, recall and area under ROC.
5. **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 using batch size of 32 and Adam solver with step size parameter of 0.001 which is used to optimize the loss function.

RESULTS AND DISCUSSION

Here, the study contrasts the fine tuning learning model for coronavirus 2019 disease diagnosis with some of the popular transfer learning architecture such as InceptionV3, VGG16, ResNet50, DenseNet121, VGG19 and EfficientNetB1. Behavior of models is analyzed with respect to loss/accuracy on training and validation dataset. Figure 3-8 summarizes the learning curves of all the studied and proposed models trained for 24 epochs. Each figure shows both the loss and accuracy plots for the model on both the train dataset (blue) and validation dataset (orange) at the end of each training epoch.

Figure 5 and Figure 7 shows that the ResNet50 model and EfficientNetB1 faces the problem of overfitting as training loss continues to decline 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. Figure 3, 4 and 6 shows the models learned the problem reasonably quickly and well, perhaps converging in about 10 epochs and remaining stable on both datasets (train

Figure 3. Loss and accuracy plots of inception V3 model

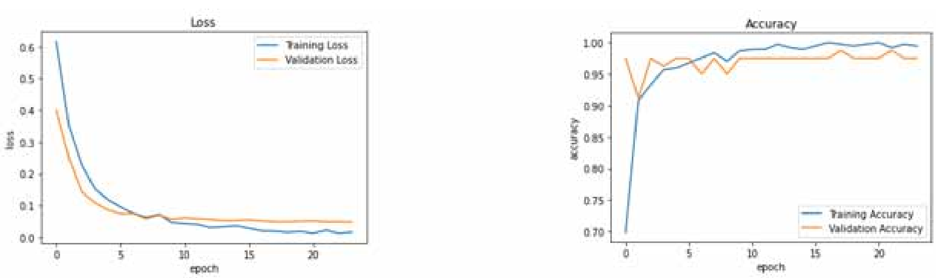


Figure 4. Loss and accuracy plots of VGG16 model

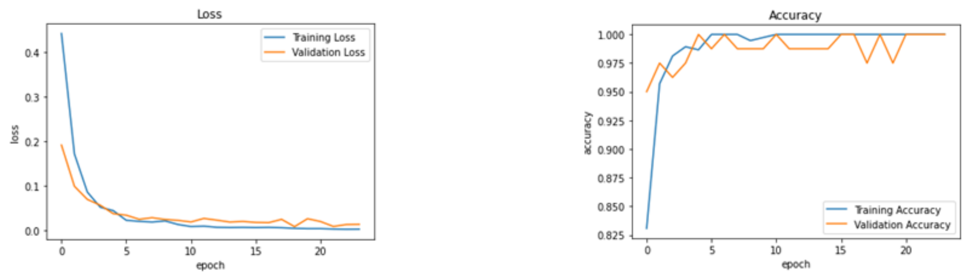


Figure 5. Loss and accuracy plots of ResNet50 model

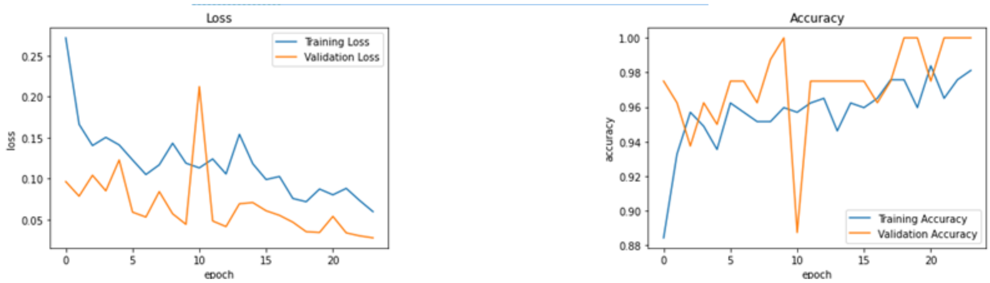


Figure 6. Loss and accuracy plots of DenseNet121 model

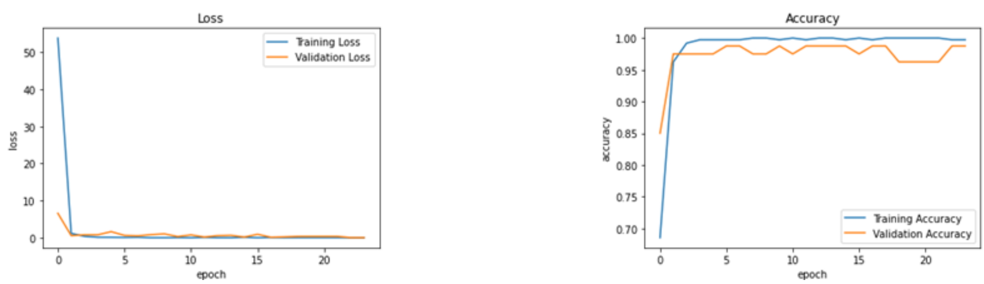


Figure 7. Loss and accuracy plots of EfficientNetB1 model

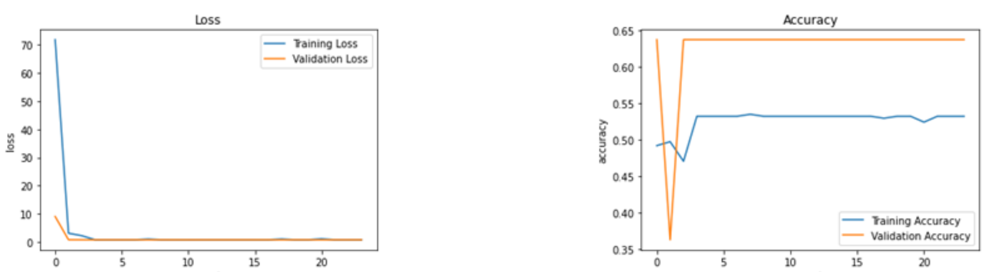
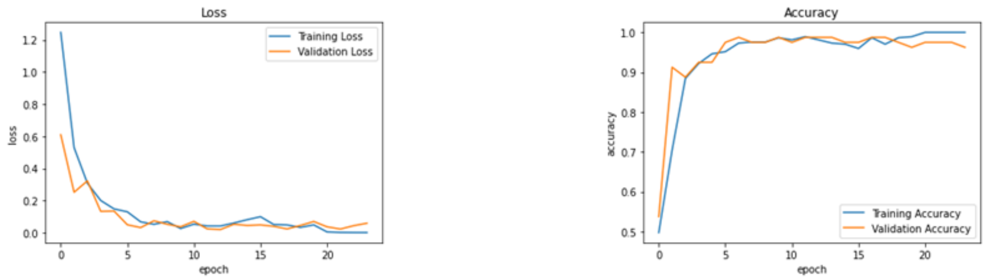


Figure 8. Loss and Accuracy Plots of Enhanced CNN (EConvNet) model



and validate). In these models keeping the hidden layers fixed and using them as a feature extraction scheme resulted in better performance than the other models such as Resnet50 and EfficientNetB1. The proposed EConvNet model (Figure 8) learning curve shows good fit with a trivial gap between the training loss and validation loss. EConvNet performance is comparable to that of the InceptionV3 (Figure 3) and DenseNet121 (Figure 6) models in terms of feature extraction and classification. The performance of the proposed model and deep learning model of the test phase is shown in Figure 9 and Figure 10 in terms of confusion matrix, accuracy and F-measure. The first row and column represent instances in Covid-19 class, while second show normal class. The proposed model, enhanced CNN, classified all the normal instances correctly. However, in the Covid-19 class, among 33 images only 2 were misclassified as normal while rest of the 31 images are correctly classified as Covid-19. F-measure enables the measuring of precision and recall at the same time. High F1-score (97%) of the proposed model shows that the model achieved high value for both recall and precision. EConvNet model shows better results that EfficientNetB1 and Resnet50 with respect to accuracy and F-measure. The results are comparable to that of DenseNet121 and InceptionV3. By analyzing accuracy scores and confusion matrices of all pre-trained models including the proposed one, the study concluded that VGG16 and VGG19 have the best performance among all but at the cost of computational resources.

Along with accuracy, other metrics such as precision, recall and ROC are also 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

Figure 9. Confusion matrices, Accuracy and F-measure of InceptionV3, VGG16, Resnet50 and Enhanced CNN deep learning architecture for the Covid-19 disease classification

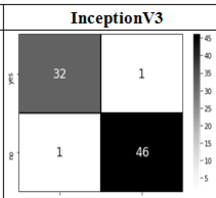
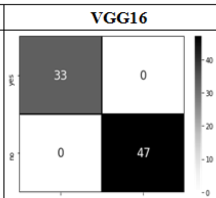
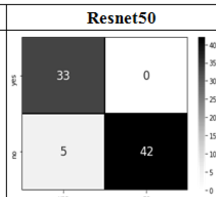
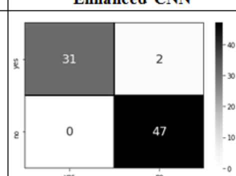
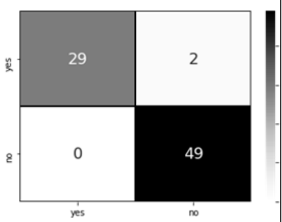
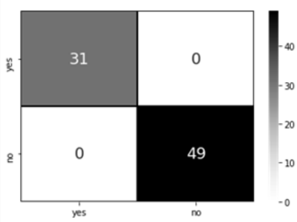
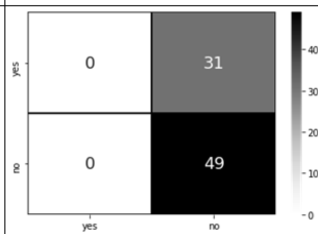
	InceptionV3	VGG16	Resnet50	Enhanced CNN
Confusion Matrix				
Accuracy	97%	100%	94%	97%
F-measure	96%	100%	94%	97%

Figure 10. Confusion matrices, Accuracy and F-measure of DenseNet121, VGG19 and EfficientNetB1 transfer learning architecture for the Covid-19 disease classification

	DenseNet121	VGG19	EfficientNetB1
Confusion Matrix			
Accuracy	97%	100%	68%
F-measure	96%	100%	68%

rate and recall. The area under the curve is the model's performance on unseen data. The ROC curve for all pre-trained architecture and enhanced CNN is shown in Figure 11.

All CNN architectures give higher AUC (>0.95) as compared to the EfficientNetB1and Resnet50 models. The AUC score of the EfficientNetB1 model (diagonal line) shows that it is a no-skill classifier that cannot discriminate between the coronavirus positive cases and coronavirus negative cases and would predict a random or constant class in all cases.

Further, the researchers give a Precision-recall curve to provide the true positive rate as a function of positive predictive rate. Precision-recall curves for all studied models are shown in Figure 12. Figure 12 shows that all models except EfficientNetB1 are good in predicting the positive class (Covid19 positive).

The study compares the proposed CNN to other traditional machine learning algorithms. Figure 13 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), Support Vector Machine (SVM), Random Forest (RF), XGBoost and Random Search on Covid-19 dataset for disease detection. XGBoost displayed

Figure 11. Comparison of ROC curve of enhanced CNN with all transfer learning algorithms

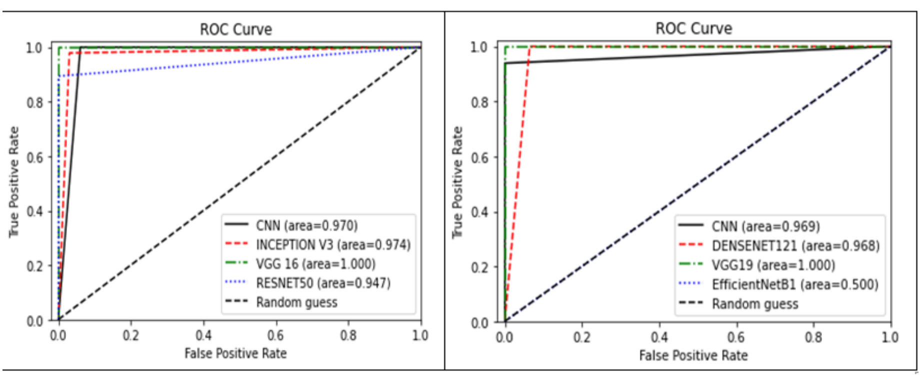


Figure 12. Comparison of precision-recall curve of enhanced CNN with all transfer learning algorithms

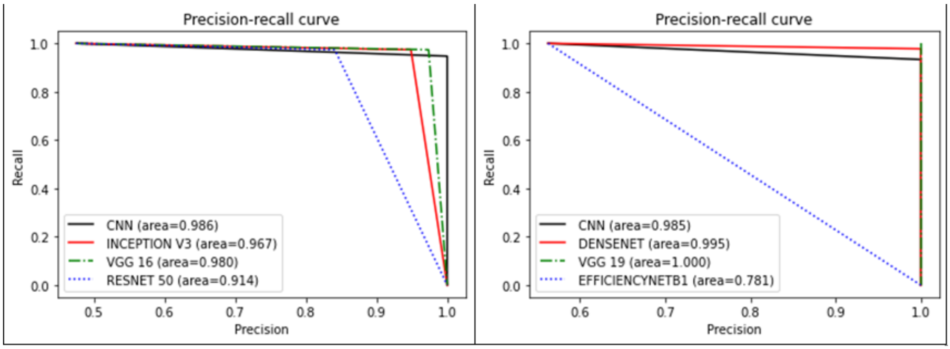
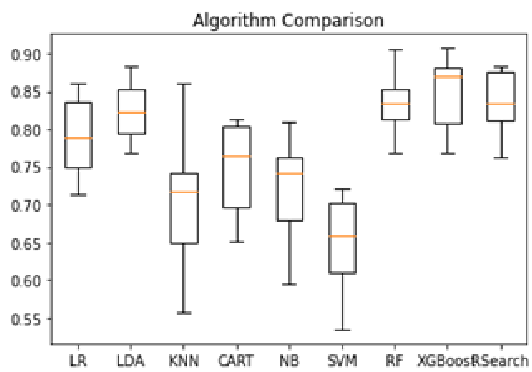


Figure 13. Performance of some other popular machine learning algorithms

```
LR: 0.792913 (0.049228)
LDA: 0.825914 (0.037965)
KNN: 0.701274 (0.087002)
CART: 0.748339 (0.057923)
NB: 0.720155 (0.061294)
SVM: 0.647342 (0.062027)
RF: 0.830731 (0.037031)
XGBoost: 0.849502 (0.046777)
RSearch: 0.832835 (0.042971)
```



high accuracy compared to all algorithms with SVM giving the least value. Clearly the proposed CNN and the pre-trained models perform better than these machine learning algorithms given in Figure 13.

Further, the CNN model is more generalized than transfer learning models (see Table 2). It is neither overfit nor underfit. The transfer learning models use excessive resources and complexity. In terms of parameters, Resnet50 shows the largest value and DenseNet121 shows the smallest value. VGG16 and VGG19 models show 100% accuracy but these are large networks in terms of parameters to be trained for Covid-19 disease diagnosis. All studied shallow models use a multitude of parameters which results in more time for training the model as shown in Table 2. There is no substantial difference between the accuracy of the EConvNet model and transfer learning models, but the size of the transfer learning models is usually big, and this makes these models difficult to deploy. In terms of size, the InceptionV3 model occupies the least memory (86MB) and EfficientNetB1 occupies the highest (138) among all transfer learning models. The CNN model (EConvNet) is trained from scratch; as a result, it uses a smaller number of parameters and takes significantly less training time except VGG16. With

Table 2. Parameters and elapsed time for each deep learning model used in the experiments

Deep Learning Model	#Parameters	Learning rate	MB Size	Elapsed Time (min:sec)
Inception V3	22,098,337	0.001	86	14:42
VGG16	17,959,361	0.001	93	01:51
Resnet50	40,398,337	0.001	120	09:54
DenseNet121	13,493,441	0.001	101	10:20
VGG19	23,269,057	0.001	113	04:21
EfficientNetB1	17,094,408	0.01	136	08:40
Enhanced CNN	5,959,617	0.01	68	01:40

considerably fewer numbers of parameters, the proposed EConvNet model is more computationally efficient, takes less memory (68MB) and also provides better or comparable results. Thus the fine tuning model (EConvNet) is better than shallow (pre-trained) models for Covid-19 disease detection.

CONCLUSION

This research proposes an EConvNet (Enhanced CNN) to diagnose novel coronavirus disease from upper body X-ray films. The CNN model has shown a useful and robust response to cases of deadly coronavirus disease. Multiple convolutional layers of CNN make it effective to extract features of coronavirus 2019 from chest radiographs. The authors have compared CNN with six popular already trained CNN models. The EConvNet model noticeably outperforms the traditional machine learning algorithms for coronavirus disease diagnosis. The model is reliable; its accuracy is competitive, gives outcome quickly and involves reduced computational effort to determine the presence of coronavirus 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 films 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 outcome of EConvNet and transfer learning models on large repositories of chest radiographs and CT scan pictures.

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