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Identification of COVID-19 on chest radiographs: A new approach to early diagnosis

Ali Hussein Ali

Al-Qadisiyah Education Directorate

Email: alihusseinalialjanabi@gmail.com

Khalid Murad Abdullah

Al-Qadisiyah Education Directorate

Email: Khalid.m.alzubaidi@gmail.com

Abstract---Millions of people have died worldwide as a result of the Covid-19 epidemic, which began in December 2019. We design a method of precisely and quickly diagnosing a patient to lessen the severity. We begin by collecting the chest X-ray dataset, after which we develop the various models utilizing Machine Learning (ML) and Deep Learning (DL) approaches, primarily Convolutional Neural Networks (CNN). The algorithms in question include K-nearest neighbor (K-NN), Random Forest (RF), VGG19, ResNet, DenseNet121, InceptionV3, and Xception, to name a few. We can recognize Covid-19 in the photographs and use these photographs to compare the accuracy of the various models. The best model, according to the results, is VGG19 with fine-tuning, which has a 94.34 percent accuracy.

Keywords---Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks, Transfer Learning and Classification, COVID-19, and CT diagnosis.

Introduction

In addition to the economy, life, and politics, Covid-19 has a significant impact on the world. A rapid method of diagnosing this disease is essential due to its high contagiousness and lethality. Even so, we still take a few days or longer to determine if someone has Covid-19. A chest X-ray image could save us time and help us stop the future spread of Covid-19, thus we plan to employ this method. A chest x-ray, according to some research, can't tell the difference between COVID-19 and other kinds of infections of the lung. We expect to discover not only Covid-19 but also chest-related disorders using ML and derived CNN models. To assess the diagnostic performance of various X-ray images, we compile data

and create numerous models. In addition to standard machine learning, we use CNN models to achieve this goal because of their high performance in classifying images and the short time it takes to forecast the outcome. As part of the approach, we use chest X-ray pictures as input and feed the predictions into these derivative CNN models.

Related Work

The COVID-19 pandemic has been going on for over a year now. Covid-19 has been detected using deep learning approaches in numerous investigations. According to our research, CNN models perform best in identifying chest X-ray pictures, and all of them incorporate transfer learning. A shortage of data and transfer learning necessitated the use of data augmentation, translation, and rotation in Muhammad E. H. Chowdhury's study. According to his findings[1], data augmentation increases accuracy by 0.2% and DenseNet201 is the best CNN model. VGG16 was shown to be the most successful at transfer learning when it was tested on a variety of CNN models by Antonio Makris [2]. They also evaluated a variety of CNN models, including rotation and zooming, and found that ResNet-50 had the best diagnostic performance [3]. Covid-19 and other respiratory diseases can't be differentiated from one another using only three of their models, according to a study. As a result, we plan to expand our categorization options throughout our project.

Dataset and feature

The dataset we'll be using for this job was created by others on Kaggle and is being updated regularly. Covid-19, Lung Opacity, and Viral Pneumonia are all included in this dataset, as illustrated in Figure 1. Every class will have the same number of samples to ensure that our model is balanced. So, we have 4000 photos, and each class has 1000 of them. For training, we divided the photos into 80% (training), 10% (validation), and 10% (testing) (testing). 299*299*3 is the resolution of the original color photographs, which means that (length, width) = 299*299*3. (299, 299). Our deep learning algorithms require images with dimensions of 224*224*3. Each image is reduced to a single dimension before being fed into a machine learning model. Using this information, we could do a variety of prediction tasks. A chest X-ray image might be encoded so that it can be detected and decoded, or it could be predicted based on chest X-ray images, for example. Because our primary objective is to accurately detect various types of lung ailments, we opt to make educated guesses as to what illness the subjects may be suffering from.

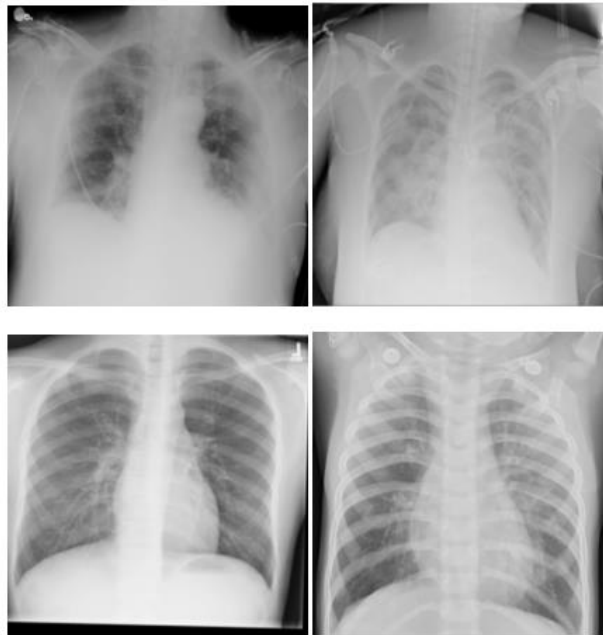


Fig. 1. Different types of data are available (Top-Left) It's called Covid-19, and it was released in (Top-Right) Opacity of the Lungs (Down-Left) Typical (Down-Right) Infectious Pneumonia.

Method

Machine learning and deep learning allow us to compare the performance of several models. Random Forest (RF) and K-nearest neighbor (K-NN) ML algorithms are used to generate models. We employ CNN models in deep learning because they are so good at the classification of images. As a result, we only use 5 derivative models: VGG19, ResNet, DenseNet, InsightV3, and Xception. These models will be introduced briefly in the sections that follow.

K-Nearest Neighbor (K-NN)

Nonparametric classification methods, such as K-nearest neighbor, are used to sort data. It is employed in statistical pattern recognition and relies on a set of pattern vectors dispersed across the system's many categories as training data. While the input of an unknown vector is being processed, the K closest neighbors of the unknown vector are being located among the pattern vectors, and the Class label is determined by a majority vote [4][5]. Our image dataset is reduced to a single dimension in this investigation, with the value of K fixed to 8.

Random Forest (RF)

A classifier based on trees called a "random forest" is used in this application. For this method to work, we put an image through each tree in turn, average their posterior distributions for each feature, and then use the arg max as the classification threshold [6].

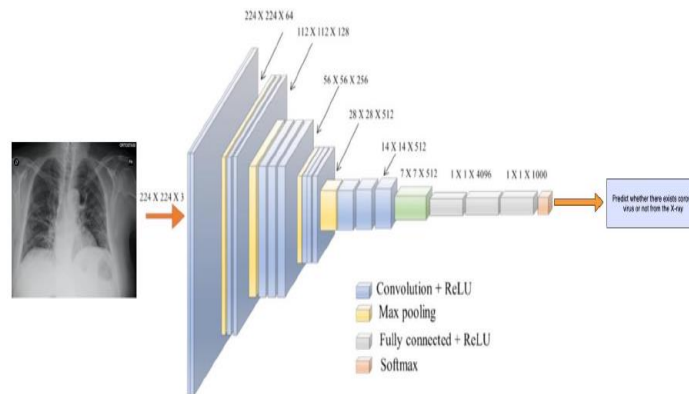


Fig. 2. The structure of VGG19.

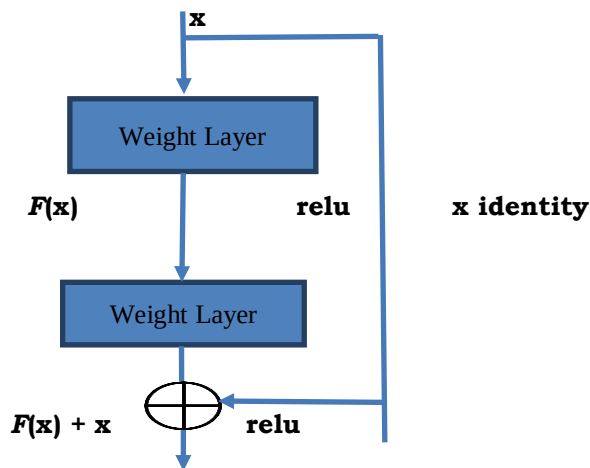


Fig. 3. The structure of ResNet

We begin by reducing the size of our image dataset from three dimensions to one dimension, and then we preserve 20% of the data for testing purposes.

VGG19

Nineteen layers are found in VGG19. Five convolutional layer blocks make up this model, and it also includes pooling and fully connected layers at the front and the end. Convolutional layers are depicted in Figure 2[7] rather than employing 11*11 or 7*7, or even only 5*5 convolutional layers. The receptive field is maintained by stacking additional convolutional networks. In addition, this strategy minimizes the number of parameters in the model and lessens the memory load.

ResNet

At the end of ResNet, there is only one completely connected layer of convolutional layers. As demonstrated in Figure 3[8], the residual of the network is learned using a convolutional layer at a time. The residual mapping is fitted using network layers rather than the desired underlying mapping being fitted directly. To avoid gradient vanishing during training, this structure allows the gradient to update the weights in upper layers more quickly.

DenseNet121

Since all the previous layers are interconnected through DenseNet, each layer receives the cumulative knowledge of the ones before it. As a result, the last layer might receive information directly from the first layer. Since it can solve the problem of vanishing gradient, which appears regularly in high-level neural networks, it may be able to help improve the diminishing accuracy of neural networks. DenseNet121[9][10] is the most basic DenseNet version, and it contains fewer layers than the most modern DenseNet versions (DenseNet169, DeSENNET201, and DeSENNET264).

InceptionV3

Google's Inception CNN's third iteration, InceptionV3, is the latest. An automated 299*299 resizing of the image occurs. Instead of average pooling as in the AlexNet, this approach significantly cuts the number of network parameters and asymmetric convolution kernels while ensuring that the network is as diverse as possible[11]. As the number of layers is increased, overfitting is avoided and the nonlinear expression of the network is amplified. Additional advantages include a reduction in the number of input channels by a single 1*1 convolution before the 3x3 and 5x5 recursive convolutions, respectively.

Xception

A CNN based on separable convolution layers, Xception is one of these networks. Feature mappings are dissociated from cross-channel correlation mapping in this architecture. Convolutional layers of 36 are used. Only the first and last modules [12] [13] have no linear residual connections between them. An Inception module with a maximum number of towers can be seen as a result of this design. Even more advantageous is that the high-level library may be simply defined or adjusted; for example, it can only be used in 30 to 40 lines of code.

Experiment and Results

Table 1. Learning approach results from several models

Model (w/o)	Fine-Tuning	With Fine-Tuning
VGG19	85.30%	94.34%
ResNet50	70.61%	92.82%
DenseNet121	49.83%	92.42%

InceptionV3	52.12%	90.64%
Xception	64.16%	90.71%

Table 2. Results on machine learning methods

Model	Accuracy
K-NN	74.48%
RF	83%

We used seven alternative models, including two machine learning approaches and five deep learning methods, for the classification. As part of a machine learning process, the visual information is reduced to one dimension using TensorFlow. In the K-nearest Neighbor algorithm, every point is given the same weighting. The Random Forest contains 100 trees. When a minimal sample of split samples is reached, or all leaves are pure, the nodes continue to grow and expand. The amount of features multiplied by their square equals the maximum feature. Because we build trees, we use the same weights for all of the samples in our bootstrap analyses.

Deep learning algorithms are tested in two separate contexts to acquire experiment findings. Another approach is to take the ImageNet dataset's pretrained direct weights and then train our softmax-based fully connected layer on top of those, allowing us to achieve the required classification accuracy for all four classes. The only difference between this model and the previous one is the addition of a fine-tuning stage. It's necessary to unfreeze all of the convolution layers' pre-trained weights to use them again once we train the fully connected layer with them. The weights pre-trained by the ImageNet dataset might then be used to better fit the current Covid-19 dataset as a result of this. In the fine-tuning stage, we also set the learning rate to a very low value to allow the weights to slightly shift the cross-entropy loss is our loss function for all models, and Adam is our optimization technique. The image form and number of classes are all based on the batch size, which is set to 32.

Table 1 displays the outcomes of many models, both fine-tuned and unfine-tuned. VGG is the most accurate approach, with a precision rate of 94.34 percent, followed by a rate of 92.82 percent. ResNet50 made this. Random Forest is the most accurate machine learning method, with an 83 percent success rate. Table 2 shows the results.

Discussion

In VGG19, the accuracy and loss are plotted against epochs in Figure 4. We can see that the validation is saturated after just 20 epochs. When the fine-tuning process begins, Figure 5 demonstrates how the loss and accuracy vary. It appears that adding 5 to 10 extra epochs will suffice to increase performance. Compared to the same work done in ECE228 last year, our results were around 10% better. We believe this is because the dataset has grown in size. We train and evaluate the model with 4000 photos, which is a significant increase over last year. In

addition, we apply fine-tuning procedures to improve our outcomes, and you can perceive the difference between the two. To fine-tune the models, we remove the initial weight of VGG from Imagenet and add our own completely linked layer. The good news is that our efforts paid off in the end.

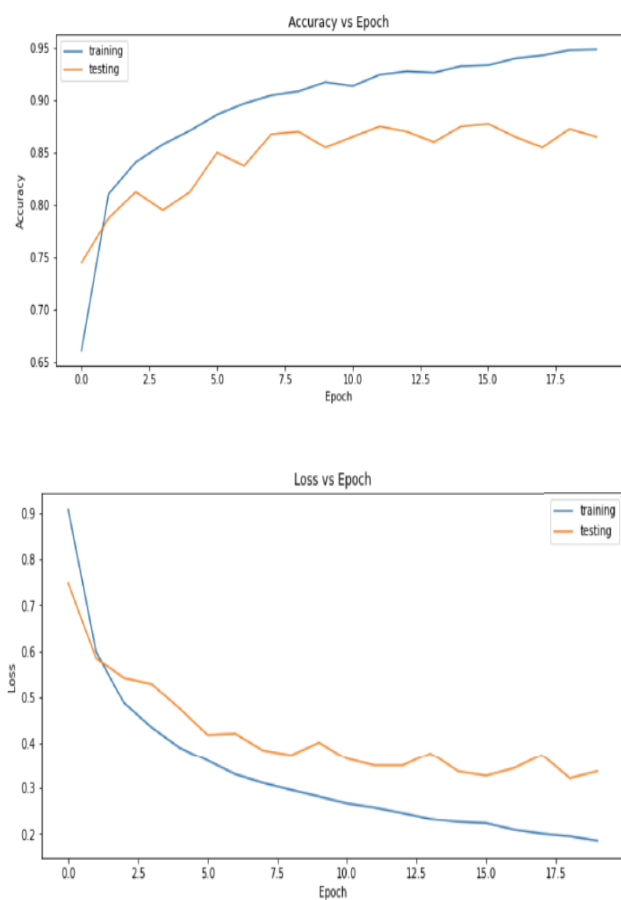
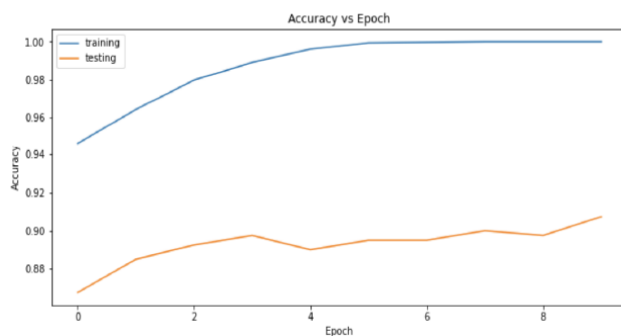


Fig. 4. Pre-tuned VGG19 model accuracy and loss in 15 epochs.



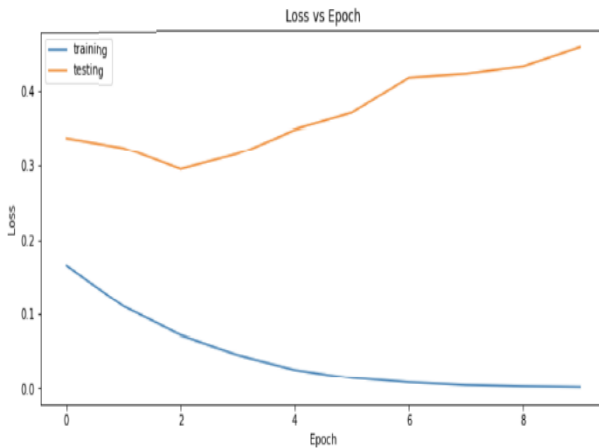


Fig. 5. Gains and losses in fine-tuning the VGG19 pre-trained model

Conclusion

The performance of seven alternative classification models on the Covid-19 pictures from the dataset is evaluated here. First, we compare deep learning models with and without fine-tuning to deep learning models only. As a result of the results, fine-tuning the models enhances their accuracy by 8 to 42 percent, implying that fine-tuning improves the model's performance. Deep learning applications may benefit from fine-tuning, according to one study. To top it all off, we find that the VGG19 fine-tuned is the most accurate model evaluated, coming in at an impressive 94.34% correct.

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