PREDICTIVE ASSESSMENT OF POST-COVID-19 IMPACT USING ARTIFICIAL INTELLIGENCE NEURAL NETWORK MODELS

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ABSTRACT

The novel COVID-19 pandemic has spread all over the world. Due to its easy transmission, it is crucial to develop techniques to accurately and efficiently identify the presence of COVID-19 and distinguish it from other forms of flu and pneumonia. Recent research has shown that the chest X-rays of patients suffering from COVID-19 depict specific radiography abnormalities. *This study aims to construct a deep convolutional neural network (CNN) capable of performing feature extraction and binary classification of CT scans of COVID-19 patients from a publicly available dataset sourced from the University of California San Diego and Berkeley (UC San Diego & UC Berkeley). This work presents a 3-step technique to fine-tune pre-trained VGG19, Xception, and Inception V3 architectures to improve model performance and reduce training time. It was achieved by progressively re-sizing input images to 224x224x3 pixels and fine-tuning the network at each stage. Among three selected pre-trained models, the VGG 19 outperformed with 0.99, 0.88, 0.85, 0.86, 0.83, 0.85, 0.85 for Train accuracy, validation accuracy, test accuracy, precision, recall, F1 Score, the area under the curve values, respectively.*

Keywords: SARS-CoV2, Coronavirus, Deep Learning, Transfer Learning, Convolutional Neural Network
DOI: 10.7176/JNSR/14-6-06
Publication date: April 30th 2023

INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious disease that has caused about 386,000 deaths worldwide, among 6.5 million infected cases, as of June 3rd, 2020. One major hurdle in controlling the spreading of this disease is the shortage of tests (Yang et al., 2020). One way of diagnosing COVID-19 patients is through computed tomography (CT). With the aid of a radiologist, CTs can be used to judge whether a patient is infected by viral pneumonia (COVID-19 is a type of viral pneumonia caused by the SARS-CoV-2 virus). Some studies have shown that using imaging technologies such as X-rays or computer tomography (CT scans), characteristic symptoms of the new coronavirus (COVID-19) can be found in these imaging technologies (Xu et al., 2020). Due to privacy issues, publicly available COVID-19 CT datasets are challenging to obtain, which hinders the research and development of AI-powered diagnosis methods of COVID-19 based on CTs. UC San Diego and UC Berkeley have built an open-sourced dataset COVID-CT (Yang et al., 2020), containing 349 COVID-19 CT images from 216 patients and 463 non-COVID-19 CTs. The utility of this dataset is confirmed by a senior radiologist who has been diagnosing and treating COVID-19 patients since the pandemic outbreak. The study aims to perform binary classification using Deep Convolutional Neural Network (CNN) on the given open-sourced datasets (COVID-19 vs. Non-COVID-19) and improve other studies' performance results.

A look into the related literature observed that predictive models trained on laboratory findings could be used to predict COVID-19 infection and can be helpful for medical experts to prioritize the resources correctly. Alakus & Turkoglu (2020) used a medical dataset containing 111 laboratory findings from 5644 patients; these are laboratory findings of the patients seen at the Hospital Israelita Albert Einstein in Sao Paulo, Brazil. Using multiple deep learning models such as CNN, RNN, LSTM, CNNLSTM, and CNNRNN, they obtained an overall accuracy of

86.66%, F1-score of 91.89%, a precision of 86.75%, recall of 99.42%, and AUC of 62.50%. Farooq & Hafeez (2020) used the chest x-rays of patients suffering from COVID-19 and proposed a 3-step technique to fine-tune a pre-trained ResNet-50 architecture to improve model performance and reduce training time; the fine-tuned pre-trained model was called COVID-ResNet. COVID-ResNet was able to achieve this through progressively re-sizing input images to 128x128x3, 224x224x3, and 229x229x3 pixels and fine-tuning the network at each stage. This approach, along with the automatic learning rate selection, enabled them to achieve an accuracy of 96.23% (on all the classes) on the COVIDx dataset with only 41 epochs. Mishra et al. (2020) in their work used several deep CNN-based methods to detect the presence of COVID-19 from chest CT images. A decision fusion method is also proposed, which combines the predictions from multiple separate models to produce the final prediction. Experimental results show that the proposed method based on merging can achieve more than 86% results on all unconsidered performance indicators, and the average AUROC and F1Score are 0.883 and 0.867, respectively. Al-Waisy et al. (2023) explore image processing and deep learning approaches to build an accurate and real-time diagnostic system for the COVID-19 virus in X-ray images. Their proposed system, called COVID-CheXNet, was able to achieve comparable performance with expert radiologists, which could alleviate the pressure on decision-makers caused by the increased number of COVID-19 patients.

Due to its rapid spread, the COVID-19 pandemic has developed into a severe worldwide health emergency. Precise and effective methods are required to recognize and distinguish COVID-19 from other respiratory disorders, such as the flu and pneumonia. Recent research has shown that chest X-rays of COVID-19 patients display specific radiographic abnormalities (Al-Waisy et al., 2023; Hall et al., 2020). The suggested deep learning model can increase detection precision for COVID-19 from CT scans by utilizing transfer learning and fine-tuning techniques, potentially assisting in the disease's diagnosis and treatment. This study's results could contribute to predicting the post-COVID-19 impact by helping medical professionals diagnose and treat COVID-19 patients more accurately and efficiently.

METHODOLOGY

In this study, we utilized an open-source dataset derived from UC San Diego and UC Berkeley COVID-CT, previously used by Yang et al. (2020). The dataset comprises 349 CT images from 216 COVID-19 patients and 463 non-COVID-19 CT images. Notably, one of our approach's critical aspects involved utilizing feature extraction techniques. Feature extraction plays a vital role in classification, clustering, diagnosis, and recognition (Ramesh et al., 2021); at the classification phase, feature extraction is essential to accurately embody images' content. To extract relevant characteristics, the researchers applied many techniques. Recently, transfer learning methods have been used for feature extraction. Transfer Learning is a machine learning technique in which a model trained on one problem is used to develop another related problem. This section deals with a detailed description of the applied methodology.

Pre-processing

The pre-trained CNN models (VGG-19, Xception, and Inception V3) were implemented using Google Colaboratory (Colab) due to its high computational speed and free access to computing resources such as GPUs and TPUs. Google Colab is a web application well-suited for machine learning, data analysis, and educational resources using Python (Bisong & Bisong, 2019). The dataset, containing 348 COVID-19 and 396 non-COVID-19 cases, was obtained by cloning it from the GitHub repository (Yang et al., 2020) and the Python code used for dataset pre-processing.

Pre-trained Model

Transfer learning is a specialized area in artificial intelligence and machine learning that involves the application of knowledge obtained from one task (the source task) to a related but distinct task (the target task). This study used the VGG19, Xception, and Inception V3 models to classify a dataset comprising CT scan images (COVID VS Non-COVID). To achieve this result, transfer learning was employed, which entails utilizing a pre-trained model created by a third party, repurposing it, and fine-tuning it for the specific problem.

VGG-19

VGG19 is a variation of the VGG model, comprising 19 layers, which include 16 convolution layers, three fully connected layers, 5 MaxPool layers, and 1 SoftMax layer. VGG19 has 19.6 billion Floating-Point Operations (FLOPs). The Visual Geometry Group at Oxford University won the ImageNet Challenge 2014, securing the first and second places in the classification and localization tracks using the VGG19 model. The model improves its predecessors, mainly AlexNet, and uses deep convolutional neural layers to enhance accuracy. Using a convolutional neural network in most image classification tasks aims to reduce computational complexity (Simonyan & Zisserman, 2014). The input images were re-sized into 224×224 pixels to reduce computation time, and different techniques were applied to these downsized images. The model comprises convolutional and fully connected layers, enabling efficient feature extraction and Maxpooling, leading to better downsampling and classification using the SoftMax activation function.

Inception V3

The Inception v3 is a neural network designed to support image analysis and object detection, and it was initially introduced as a module for Googlenet. It is the third version of Google's Neural Network, created for the Image Network Recognition Challenge. Inception is used for classifying objects in the field of computer vision. It is based on approximating a convolutional vision network's optimal local sparse structure with available dense components. This architecture of Inception V3 (figure 1) was introduced by (Szegedy et al., 2015).

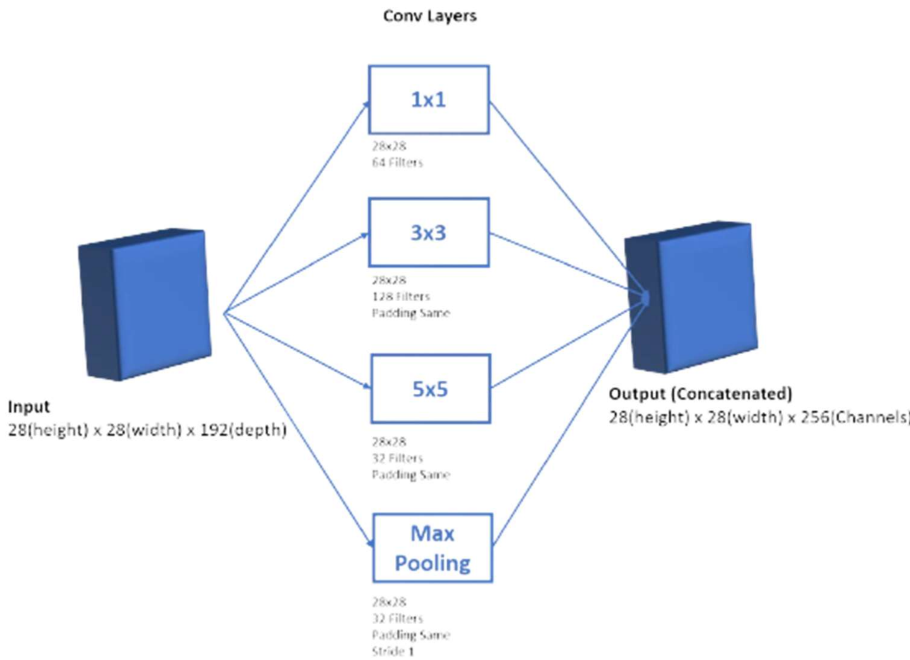

Figure 1: Naive Inception Module (Alake, 2020)

Xception

At Google Inc., Francois Chollet created Xception, short for "Extreme Inception," which surpassed Inception V3's performance on the ImageNet dataset. The model's improved performance is not due to increased capacity but to more efficient use of model parameters. The Xception architecture comprises depthwise separable convolution layers and includes 36 convolutional layers grouped into 14 modules. The first and last modules do not have linear residual connections, but all others do (Chollet, 2017).

Performance Metrics

Standard metrics were used to evaluate the models on validation data to assess the performance of pre-trained models in classifying CT images of COVID-19 vs. non-COVID-19 cases. A graph was plotted to determine whether the model was overfitting or underfitting, and the Keras Dropout regularization technique was applied to prevent overfitting. Evaluation metrics such as validation and training accuracy, precision (negative predictive value), recall (sensitivity), F1-scores, and Area Under the Curve (AUC) were computed during the investigation.

$$Precision = \frac{TP}{TP + FP} \qquad (1)$$

$$Recall = \frac{TP}{TP + FN} \qquad (2)$$

$$F1\,Score = 2\frac{Precision * Recall}{Precision + Recall} \qquad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP\,\_\,FN} \qquad (4)$$

Where:

1. TP = True Positive
2. TN = True Negative
3. FP = False Positive
4. FN = False Negative
5. F1 Score = Harmonic mean of precision and recall

RESULTS AND DISCUSSION

This study used deep learning models (VGG19, Xception, and Inception V3) to predict the COVID-19 outbreak. The investigations were conducted in two phases:

1. **First Phase:** The last layers of the pre-trained models were replaced with a binary classification layer that used sigmoid as the activation function. The "trainable" function of the models was set to false, which prevented them from being trained from scratch, saved computational time, and limited the number of parameters to be trained. The models were compiled using the Adam optimizer with its default learning rate of 0.001. Performance metrics were evaluated, and the best accuracy was recorded.
2. **Second Phase:** This study phase involved fine-tuning all models by incorporating Keras' Flatten, Dropout, and Dense layers. The process followed the same procedures as in phase one.

In Table 1, the pre-trained models are shown to contain a large number of parameters that can be imported from the Keras API library. To classify CT scans as COVID-19 or Non-COVID-19, the last layer of each model was replaced with a binary classification dense layer (Dense = 1) with a sigmoid activation function. All layers except the last one were frozen to avoid compromising the information contained in the models during future training rounds. The fine-tuning of the models involved adding new trainable layers on top of the frozen layers to make predictions on a new dataset. Optimizers, learning rates, and Keras layers were employed to achieve optimal performance results. A dropout layer, which discourages complex or flexible models, was incorporated to prevent overfitting.

Table 1: *Keras Models' sizes and parameters*

Model	**Size**	**Parameters**
VGG 19	549 MB	143,66 ,240
Xception	88 MB	22,910,480
Inception V3	93 MB	23,851,784

Table 2: *Performance value*

Model	**TA**	**VA**	**TeA**	**P**	**R**	**F1**	**AUC**
VGG-19	0.83	0.75	0.75	0.78	0.68	0.73	0.75
FT VGG-19	**0.99**	**0.88**	**0.85**	**0.86**	**0.83**	**0.85**	**0.85**
Xception	**0.97**	0.82	0.80	0.73	**0.93**	0.82	0.80
FT Xception	**0.92**	0.81	0.81	0.77	**0.87**	0.82	0.81
Inception V3	**0.93**	0.75	0.80	0.78	0.83	0.80	0.80

Where:

- TA = Train Accuracy
- VA = Validation Accuracy
- TeA = Test Accuracy
- P = Precision
- R = Recall
- F1 = F1 Score

The original VGG-19 model achieved a TA of 0.83, VA of 0.75, and TeA of 0.75. Its precision was 0.78, recall 0.68, F1-score 0.73, and AUC 0.75. After fine-tuning, the VGG-19 model improved significantly, achieving a TA of 0.99, VA of 0.88, and TeA of 0.85. The model's precision was 0.86, recall 0.83, F1-score 0.85, and AUC 0.85. The original Xception model achieved a TA of 0.97, VA of 0.82, and TeA of 0.80. Its precision was 0.73, recall 0.93, F1-score 0.82, and AUC 0.80. After fine-tuning, the Xception model's TA dropped to 0.92, VA was 0.81, and TeA was 0.81. Its precision was 0.77, recall 0.87, F1-score 0.82, and AUC 0.81. The original Inception V3 model achieved a TA of 0.93, VA of 0.75, and TeA of 0.80. Its precision was 0.78, recall 0.83, F1-score 0.80, and AUC 0.80. There was no significant improvement in the model's performance after fine-tuning.

CONCLUSION

The results of this study suggest that transfer learning is a promising approach to deep learning, particularly for classification problems. Using pre-trained models, specifically VGG19, Xception, and Inception v3, allowed for the accurate binary classification of CT images as Covid or Non-Covid. Fine-tuning these models further improved their performance, with the VGG19 model demonstrating the highest accuracy. These findings suggest that deep learning could be a valuable tool for diagnosing Covid-19 and predicting its post-impact effects. While the results of this study are promising, further research is needed to optimize the models and improve their accuracy. Overall, transfer learning has the potential to revolutionize the field of deep learning and facilitate more accurate predictive assessments of Covid-19 and other diseases.

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