Transfer Learning Based Covid Diseases Detection Using ResNet50

A Report for Mini Project

Submitted by

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1. INTRODUCTION

A coronavirus (SARS-CoV-2) outbreak began on December 31, 2019, in Wuhan, the capital of Hubei Province in central China. The World Health Organization (WHO) announced a global health emergency on January 30, 2020, and the World Health Organization (WHO) declared a pandemic on March 11, 2020, after some hesitation. By 14 April 2020, there have been a total of 1,985,135 confirmed cases and 125,344 deaths. The United States has taken on a new role as a global hotspot of 605,354 cases and 25,394 deaths have been registered as of April 14, 2020. COVID-19 pathogenesis is being studied by researchers from several disciplines, as well as public health professionals, and develop measures for control. Imaging patterns on chest radiography and computed tomography (CT) for individuals diagnosed with COVID-19 have recently been discovered. Infected patients in Wuhan had bilateral lung opacities on 40 out of 41 (98 %) chest CTs, with lobular and subsegmental regions of consolidation being the most common findings. Other researchers discovered significant rates of ground-glass opacities and consolidation, with a rounded shape and peripheral lung distribution in some cases. Patients suspected of COVID-19 infection generally require a thoracic radiology examination. Early detection and diagnosis of the condition are critical in ensuring prompt treatment.

Convolutional Neural Network

The Convolutional Neural Network is one of the most widely used deep neural networks (CNN). Convolution is a mathematical linear action between matrices that gives it its name. The convolutional layer, non-linearity layer, pooling layer, and fully-connected layer are some of the layers of CNN. Pooling and non-linearity layers do not have parameters, whereas convolutional and fully-connected layers have. In machine learning issues, CNN performs admirably. Particularly impressive were the applications that deal with picture data, such as the world's largest image classification data collection (Image Net), computer vision, and natural language processing (NLP), with the results obtained.

Due to the availability of large-scale annotated datasets and deep convolutional neural networks, significant progress has been made in picture recognition (CNNs). From a significant amount of training data, CNNs may learn data-driven, highly representative, hierarchical image characteristics. In the medical imaging area, however, acquiring datasets with as much detail as ImageNet is a difficulty. There are currently three basic strategies for successfully using CNNs for medical image classification: training the CNN from scratch, using pre-trained CNN features off the shelf, and undertaking unsupervised CNN pre-training with supervised fine-tuning. Transfer learning, or fine-tuning CNN models trained on natural image datasets for medical imaging tasks, is another effective strategy.

Residual network (ResNet)

In transfer learning, AlexNet, AlexNetOWTBn, GooLeNet, Overfeat, and VGG models are more frequent. Many convolutional layers were stacked. Deep CNN networks have several challenges, including network optimization, the vanishing gradient problem, and degradation issues. The residual network (ResNet) is useful for solving difficult problems and improving detection accuracy. ResNet aims to address the challenges of deep CNN training, like saturation and accuracy loss. Because it is relatively easy to improve and provides higher accuracy, ResNet is a superior deep learning architecture. There's also the issue of declining gradient, which can be avoided by using the network's skip connections. The network's temporal complexity increases as the number of layers in the deep network architecture increases. A bottleneck design can help to simplify things. As a result, we decided to build our framework using the ResNet50 pre-trained model rather than other pre-trained networks with additional layers. Further down, the architecture is fully defined.

2. RELATED WORK:

On a publicly available collection of calls from 46 different bird species, Sankupellay and Konovalov [1] employ ResNet-50 for automated bird call recognition.
Outcome: ResNet-50 was trained using spectrograms (visual characteristics) derived from bird cries and was able to achieve 60 percent to 72 percent accuracy in birdcall recognition.

Wen et al. [2], proposed a novel TCNN(ResNet-50) with 51 convolutional layers of depth for fault diagnosis. CNN(ResNet-50) uses ResNet-50 trained on ImageNet as a feature extractor for defect diagnostics, combining it with transfer learning. A signal-to-image method is created to convert time-domain fault signals to RGB images for use as the ResNet-50 input datatype. Then, a novel TCNN(ResNet-50) structure is presented. Finally, the proposed TCNN(ResNet-50) was tested on three datasets: the bearing damage dataset from the KAT datacenter, the motor bearing dataset from Case Western Reserve University (CWRU), and the self-priming centrifugal pump dataset.

Outcome: TCNN(ResNet-50) has model accuracy of 98.95 % ±0.0074, 99.99 %, and 99.20 % 0 exhibiting that it surpasses other deep learning models and traditional approaches.

Using pre-trained deep learning CNN architectures as a core, Elpeltagy and Sallam [3], constructed an automated technique for detecting and diagnosing COVID 19 in chest X-Ray and Computerized Tomography pictures. They introduced three layers, 'Conv', 'Batch_Normaliz' and 'Activation_Relu' into ResNet50 architecture for precise feature extraction and discrimination.
Outcome: Comprehensive experiments are conducted to evaluate the suggested model's performance. The proposed improvement, injected layers, elevates diagnosis accuracy to 97.7% for the Computerized Tomography dataset and 97.1 % for the X-Ray dataset, which is superior to existing approaches, according to experimental results.

Yuan et al. [4], explore the protection of the privacy of medical images while using ResNet50 as the core network framework for the efficient classification of parotid CT images.
Outcome: When the model is iterated 1000 times, the accuracy of the test set corresponds to 90%, indicating the model has practical relevance and significance for the auxiliary diagnosis of parotid gland tumors and other head and neck tumors.

Ko et al. [5], developed FCONet, an artificial intelligence algorithm to diagnose COVID-19 pneumonia from a single chest CT image and distinguish it from non–COVID-19 pneumonia and non-pneumonia conditions. It was constructed by using transfer learning using one of the pertained deep learning models, VGG16, ResNet-50, Inception-v3, or Xception as a framework.
Outcome: ResNet-50 outperformed the other three FCONet pertained models in the testing data set, indicating better diagnostic performance with a sensitivity of 99.58 %, specificity of 100.00 %, and accuracy of 99.87 %. It had the highest detection accuracy of 96.97% in the additional external testing data set using low-quality CT images, followed by Xception (90.71 %), Inception-v3 (89.38 %), and VGG16 (87.12 %).

Al-Haija and Adebanjo [6], categorized the BreakHis dataset as benign or cancerous using a transfer learning strategy based on the powerful ResNet-50 CNN pre-trained on ImageNet.
Outcome: The simulation results indicate that the proposed model outperforms other comparison models trained on the same dataset with a classification accuracy of 99 %.
Loey et al. [7], annotate and locate medical face mask objects in images using two components, the ResNet-50 deep transfer learning model for feature extraction and YOLO v2 to detect medical face masks.
Outcome: According to the data, the adam optimizer as a detector was found to have the highest average precision percentage of 81%.
Walvekar and Shinde [8], use the ResNet50 model to pre-train and fine-tune CT scans before they are further trained and tested. COVID-19 patients can be recognized for pneumonia and other diseases using this approach.
Outcome: Early detection and a low fatality rate can be achieved by implementing this model.

3. NETWORK ARCHITECTURE AND PRINCIPAL STRUCTURE:

For the classification of covid-19 illness, a residual neural network with 50 layers termed ResNet50 is used. Resnet50 captures the most important aspects of an image and can be applied to similar and smaller datasets. This reusability feature of a pre-trained model not only saves time but also saves money when the training dataset is limited. All photos in the dataset are rescaled to use iteratively in various stages of the ResNet50 model. Mean and standard deviation approaches are used to standardize the images in the ImageNet collection.

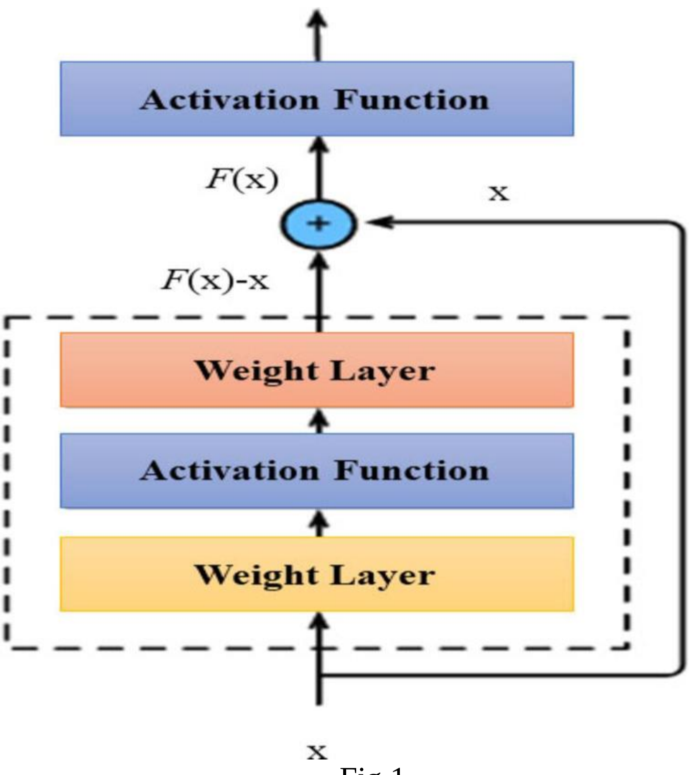
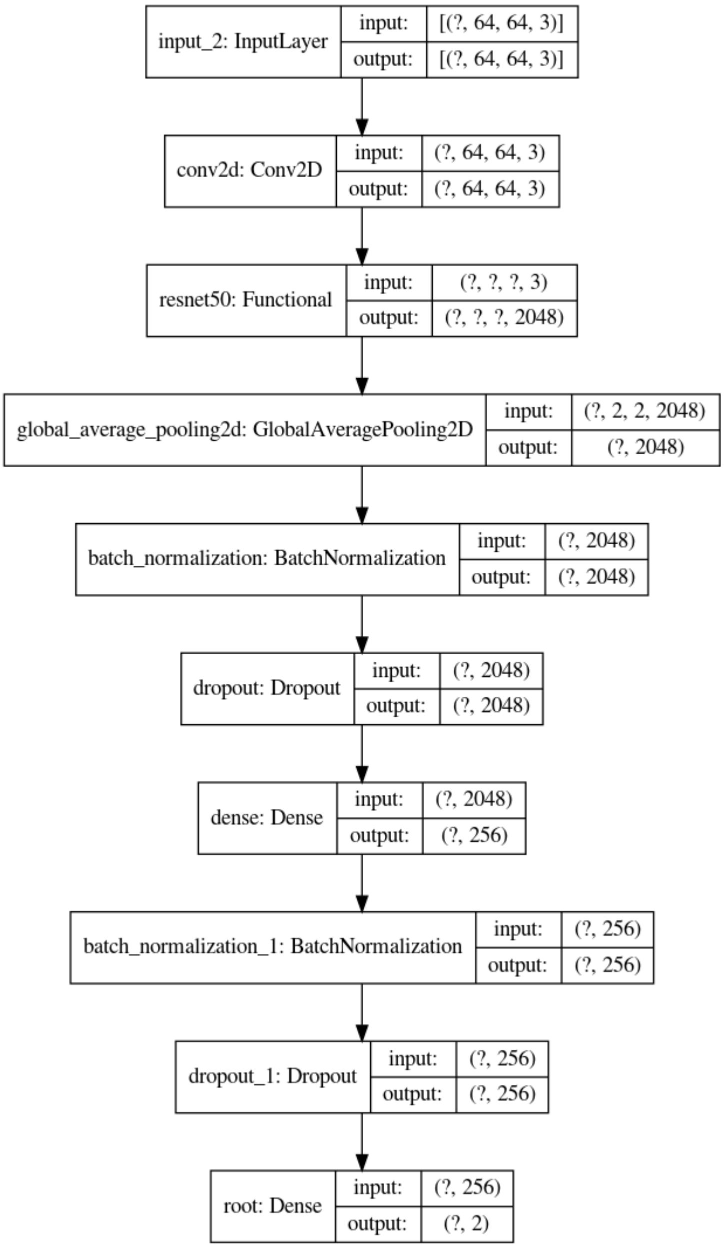


Fig 1

Figure 1 shows a neural network, such as a ResNet50 design, with x as the input. We explored fundamental mapping, which we hoped to accomplish by F learning (x). ResNet50 activation function is at the very top. Before the activation function, we considered mapping. Consider F(x) for mapping and F(x)-x for residual mapping.



The main components of ResNet50 are convolutional layers, Activation unit, pooling, and batch normalization.

a) Convolution layer: Convolution layers in neural networks are responsible for extracting specific information from the input images. Filters are used in a sequential order to accomplish this convolution. From the input photos, this layer generates feature maps.

b) Activation function: A transformation is applied to the output of each convolution layer in a convolution neural network. This is so that nonlinearity can be incorporated into the framework. The ReLU function is a prominent activation function. This ReLU has a low computing cost and good gradient convergence compared to other activation functions. If the input is negative, the output of ReLU is zero, but if the input is positive, the output equals the input.

c) Pooling Layer: The feature maps obtained from convolution operations are summarised using a pooling layer. This layer decreases the number of parameters taken into account during the training procedure. This also assures that the computation time is reduced. This layer also aids in the regulation of the over-fitting process. In the case of max-pooling, the output is the input element's maximum value. The output of average pooling, on the other hand, is the mean value of the input element.

d) Batch normalization layer: The goal of the batch normalization test is to increase convergence quality throughout the training period. The output of the previous layer is regularized in this layer. This layer has the benefit of allowing for a faster learning rate.

4. METHOD AND RESULT:

The SARS-CoV-2 CT scan dataset includes 1252 CT scans that are positive for SARS-CoV-2 infection (COVID-19) and 1230 CT scans for patients who are not infected with SARS-CoV-2, for a total of 2482 CT scans (Fig. 2 and Fig. 3). The information was gathered from genuine patients in hospitals in Sao Paulo, Brazil. The data is better understood from its frequency histogram for species as seen in Fig 4. Sklearn, NumPy, Tensorflow, and Matplotlib were implemented as libraries in the experiment.

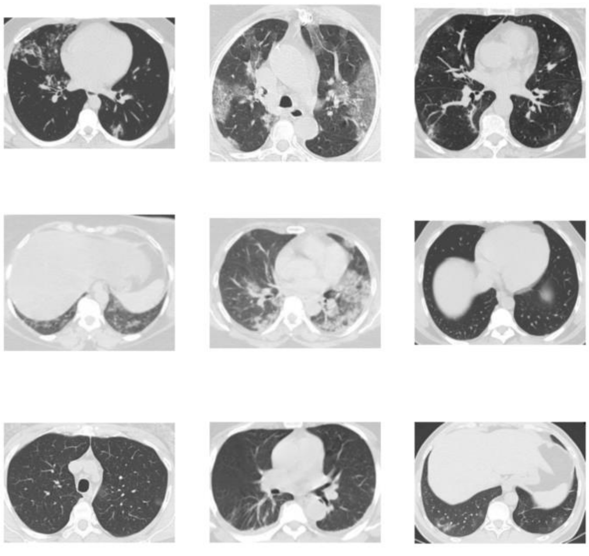


Fig 2. CT scans that are positive for SARS-CoV-2 infection (COVID-19)

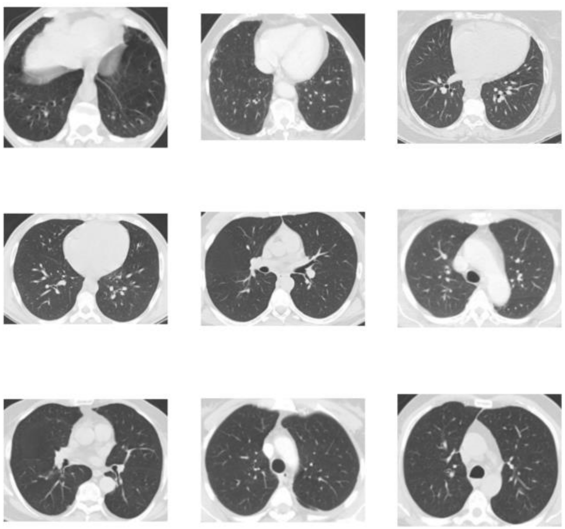


Fig 3. CT scans that are negative for SARS-CoV-2 infection (COVID-19)

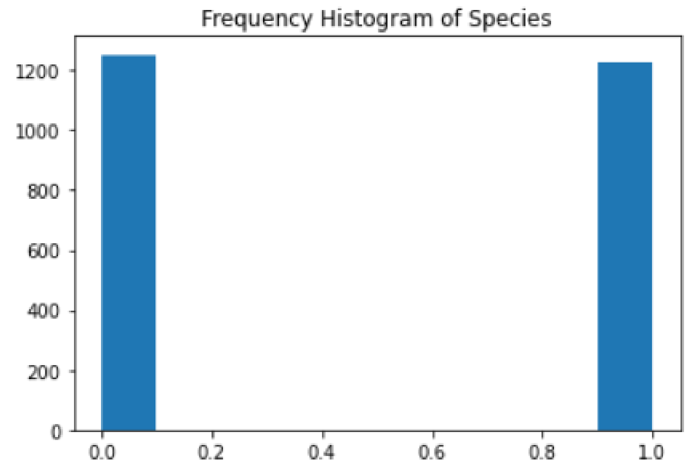


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Fig.4

Data preprocessing: This preprocessing enhances the visual capability of the training operation. A range of variables can help you enhance your visual capacity. Increased contrast, removal of high/low spatial frequency components, and decrease of the noise component in images are included. As part of the preprocessing, the images were reduced to 64 by 64 pixels and the intensity of the images was normalized. The intensity of image pixels is normalized from their original 0–255 values to a normal distribution using the 'min-max normalization' technique. The bias element is thereby removed, resulting in uniform distribution.

Data Augmentation: For training a model, data augmentation is used, resulting in the diversity of the images. Some of the augmentation methods used in this paper are horizontal flipping, vertical flipping, random zoom, and horizontal and vertical shifts.

ResNet50: We have split the total dataset into 80% for training purposes and 20% for testing purposes. ResNet aids in the execution of complicated tasks and improves detection accuracy. ResNet aims to address the challenges of deep CNN training, saturation, and accuracy loss. We used the ResNet50 architecture in this case. ResNet50 had 50 layers of residual networks. For epochs 50 and size 64, ResNet50 is built. An optimizer known as Adam was considered for the case of a learning rate of 0.003. The training of the model was performed using a dynamic learning method. The learning rate was reduced when the improvement phase stops. This is done using ReduceLROnPlateau.

Prediction and Evaluation: The model is then used to predict and the heat map for its actual prediction (Fig. 5) is obtained to analyze the model. It gives a final loss of 0.245 and final accuracy of 0.895. The training set and testing set is compared using an accuracy plot and model loss. The accuracy plot (Fig. 6) shows the test data perform comparatively bad for the initial epoch and then increases in accuracy after 20 epochs reaching and at times surpassing the training set. On the other hand, the test set shows major loss initially when compared to the training set, and then decreases to the level of the train set after approximately 35epoch, in the model loss graph (Fig. 7).

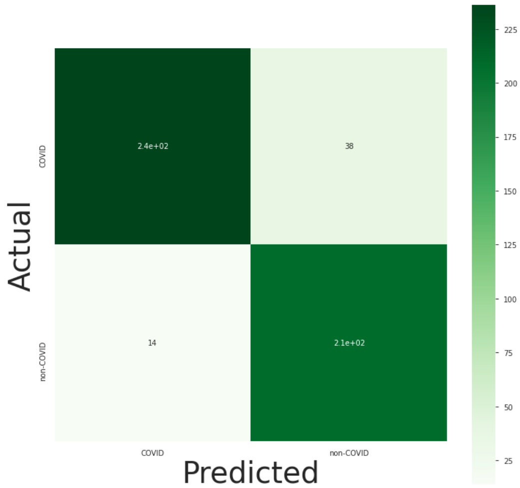

Fig. 5, Actual – Predicted heatmap

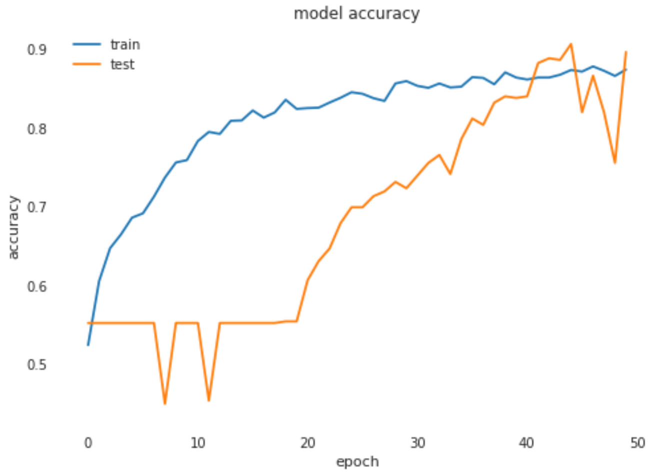

Fig. 6, Model Accuracy

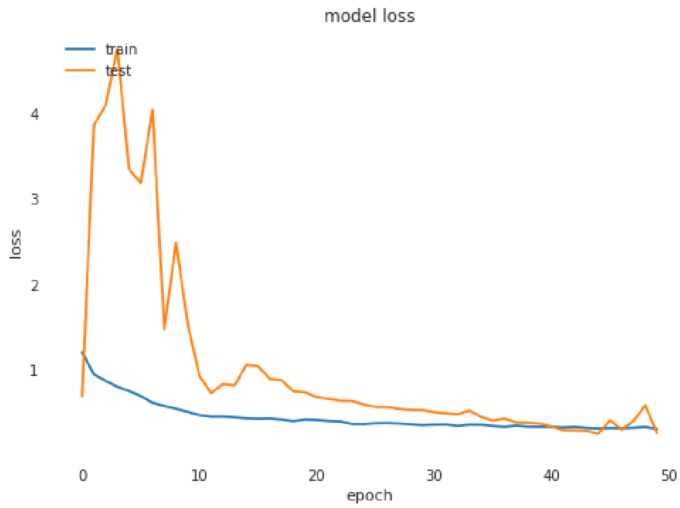

Fig. 7, Model Loss

5. CONCLUSION:

A Convolutional Neural Network was built to automatically identify covid and non-covid CT scan images. More image data is necessary for the best generalization of the CNN model as its depth increases. As a result, after preprocessing the data, we used the augmentation procedure to expand the dataset. Finally, Transfer Learning was performed using the pre-trained model, ResNet50. It gives a final loss of 0.245 and final accuracy of 0.845. The proposed model's overall accuracy was 84.80 %.

6. REFERENCES:

[1] M. Sankupellay and D. Konovalov, “Bird Call Recognition using Deep Convolutional Neural Network, ResNet50,” *Hear to Listen,* pp. 1-8, 2018.

[2] L. L. X. &. G. L. A. Wen, “A transfer convolutional neural network for fault diagnosis based on ResNet-50,” *Neural Comput & Applic 32,* pp. 6111-6124, 2020.

[3] M. Elpeltagy and H. Sallam, “Automatic prediction of COVID− 19 from chest images using modified ResNet50,” *Multimed Tools Appl 80,* pp. 26351-26463, 2021.

[4] J. Yuan, Y. Fan, X. Lv, C. Chen, D. Li, Y. Hong and Y. Wang, “Research on the Practical Classification and Privacy Protection of CT Images of Parotid Tumors based on ResNet50 Model,” *Journal of Physics: Conference Series,* 2020.

[5] H. Ko, H. Chung, W. Kang, K. Kim, Y. Shin, S. Kang, J. Lee, Y. Kim, N. Kim, H. Jung, and J. Lee, “COVID-19 Pneumonia Diagnosis Using a Simple 2D Deep Learning Framework With a Single Chest CT Image: Model Development and Validation,” *J Med Internet Res,* 2020.

[6] Q. Al-Haija and A. Adebanjo, “Breast Cancer Diagnosis in Histopathological Images Using ResNet-50 Convolutional Neural Network,” 2020.

[7] G. M. M. H. N. T. N. E. M. K. Mohamed Loey, “Fighting against COVID-19: A novel deep learning model based on YOLO-v2 with ResNet-50 for medical face mask detection,” *Sustainable Cities and Society,* 2021.

[8] S. Walvekar and S. Shinde, “Detection of COVID-19 from CT Images Using resnet50,” 2020.