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Deep Transfer Learning Based Approaches for Classification of Chest CT Scans: Normal, COVID-19, and Pneumonia

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***Abstract*—Since the start of 2020, the global community has been shocked by the coronavirus disease(COVID-19). The most popular method for diagnosing COVID-19 is RTPCR testing, which is very time-consuming and requires isolating environment. On the other hand, radiography images has been proven to be beneficiary in automated and early diagnosis of COVID-19, which can reduce the fatal transmission as well as mortality rate. In this research work, transfer learning was employed where InceptionV3, VGG19 and ResNet50 were used as pre-trained models. These three convolutional neural network(CNN) architectures were initially trained on ImageNet dataset and then Large COVID-19 CT scan dataset for training, testing and validation. The dataset went through several pre-processing and augmentation steps like - image resizing and rescaling followed by rotation, brightness adjustment, horizontal and vertical flipping and normalization. Subsequently, feature extraction was performed using the three pre-trained CNN architectures and additional layers were introduced including flattening, dense, batch normalization, and dropout for further refinement. Lastly, the images were classified into three classes - Normal, Covid-19 and CAP(Community Acquired Pneumonia) in the last dense(fully connected) layer with a softmax activation function. Hyperparameter tuning was undertaken to maximize the performance of the models. The comparative analysis of the performance of InceptionV3, VGG19 and ResNet50 was presented, highlighting ResNet50 as the top-performing architecture based on its robust accuracy and F1 score metrics. The experimental result depicts that transfer learning on pretrained ResNet50 architecture outperformed InceptionV3 and VGG19, achieving a test accuracy of 97% and F1 score of 98%.**

***Index Terms*—COVID-19, RTPCR, Chest CT scans, InceptionV3, VGG19, ResNet50, Deep Learning, Transfer Learning, Convolutional Neural Network**

I. Introduction

With the COVID-19 outbreak, the largest pandemic of this century has surfaced. More than 200,000 people have died and over three million individuals have been infected in more than 200 countries thus far [1]. Physicians may diagnose the disease based on clinical symptoms, but early detection of the rapidly spreading illness with data science techniques is essential to combating it.The virus causes a respiratory disease having breathing difficulties, fever, coughing, and sore throat in an infected individual [2]. Most individuals infected with the virus have mild to moderate respiratory sickness, which they recover from without the need for specialized medical attention. However, some of them will get really sick and need medical attention.A major sickness is more likely to strike an older person or someone who already has an underlying medical problem. People of any age can get sick from the COVID-19 virus, and those who do so run the danger of being very sick or possibly dying [3]. This virus is spread by patient droplets that are released when they cough or sneeze. A person becomes infected if they come into indirect or indirect touch with an infected person. Physicians may diagnose the disease based on clinical symptoms, but early detection of the rapidly spreading illness with data science techniques is essential to combating it.

Real-time "reverse transcription polymerase chain reaction (RT-PCR)" is the most popular method for detecting COVID-19. However, RT-PCR kits are expensive, and it takes six to nine hours to confirm the patient's illness [4]. Because RT-PCR has a lower sensitivity, it yields a higher number of false-negative results. To address this issue, COVID-19 is detected and diagnosed using radiological imaging techniques such as computed tomography (CT) and chest X-rays [5].CT scans are recommended in this paper above X-ray images. In the past, 87% of COVID-19 patients with chest CT (69 studies) received a reliable diagnosis. Only 21% of those without COVID-19 had their COVID-19 wrongly diagnosed. In addition, chest X-ray (17 studies) misdiagnosed COVID-19 in 27% of patients who did not have it while correctly diagnosing COVID-19 in 73% of those who did [6]. The diagnosis of COVID-19 is therefore more accurate with CT scans.

Interest in deep learning and some machine learning architectures' potential application to clinical imaging problems has increased due to their rapid advancement. In these problems, the three main stages for assessing the performance of the models are data preprocessing, feature extraction, and classification [7]. These techniques can be applied to train the weights of convolutional neural networks on large datasets as well as fine-tune the hyperparameters of pre-trained networks on small datasets. This paper's goal is to provide an automated deep learning based method for identifying infections in chest CT images.

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II. Related Works

University of Waterloo researchers and Darwin AI, a university-affiliated firm, developed their very unique model for deep learning named "COVIDNet-CT" to recognize COVID-19 out of infected chest CT scans [8]. The China National Center for Bioinformation acquired CT images, which they used to create the "COVIDx-CT" dataset. 104,009 CT image slices from 1,489 patient cases are included in "COVIDx-CT". They assessed the software's performance on distinguishing COVID-19 images from CT scans after achieving impressive outcomes on the labelling of COVID-19 affected images out of chest X-ray images. They have implemented ResNet50 V2, DenseNet121, Inception V3 and Xception. And the performance of the models was measured based on sensitivity and F1 score. Amid of the open-source models, the Xception architecture gave better result than ResNet50, DenseNet121 and Inception. In a related study, they presented an ensemble deep learning model to generate a strong COVID-19 classifier on noisy annotated chest CT scan images using pretrained Residual Attention and DenseNet architectures [9]. The new aspect of this approach is how these two deep networks reinforce one another by putting their attention on global, complementary, and attention-sensitive sets of properties. To deliver the final robust prediction, a meta-learner stacks and processes the features those are extracted by using the two deep networks (base-learners) separately. In order to increase the generalizability of their classifier, they also created a sizable and geographically diversified by selecting publicly available datasets, the COVID-19 CT scan dataset. Another study used large, diverse, and multinational patient cohorts to train upgraded deep neural networks for detection of COVID-19 from chest CT scans. They achieved this by incorporating two entirely new CT benchmark sets, the largest among which comprises a diverse collection of samples of 4,501 patients from a minimum of 16 different countries. To the best of their knowledge, this constitutes the biggest, most varied international cohort for open-access COVID-19 CT scans. They also unveiled COVID-Net CT S, a new lightweight neural network architecture that is faster and smaller than the COVID-Net CT architecture that was previously introduced [10].

III. Dataset Description

The dataset used in our research is "Large COVID-19 CT scan slice dataset" [9]. The dataset was created by selecting data from seven publicly available datasets that have been shown to be effective in deep learning applications and were utilized in the relevant works for COVID-19 diagnosis. As a result, by combining the knowledge from all these sources, the integrated dataset is anticipated to enhance the deep learning techniques for better generalization. There are 17,104 images in total including three categories of images- Normal, COVID-19 and CAP(community-acquired pneumonia).

IV. Methodology

Convolutional neural networks(CNNs) belong to a category of deep neural network those are used in computer vision and

TABLE I
Dataset Description

Normal	COVID-19	CAP	Total
6,893	7,593	2,618	17,104

image analysis [11]. It is also used for feature extraction as well as image classification tasks. In this research, we used pre-trained models (Inception V3, VGG19 and ResNet50) for feature extraction and training. After that we fine tuned the hyper-parameters and added one fully connected layer and several dense layers followed by Flatten, Batch Normalization and Dropout layers for better regularization. Finally, softmax activation function was used in the last fully connected layer of the pre-trained architecture for image classification. The proposed methodology's workflow is illustrated in Figure 2.

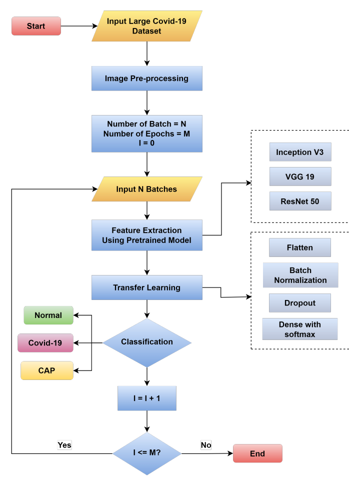

Fig. 1. Proposed methodology.

A. Data Preprocessing

Data preprocessing is a phase in machine learning that converts raw data into a format that computers and machine learning algorithms can comprehend and assess. Unprocessed real-world data, such as text, images, and video, are chaotic. It typically lacks and has an irregular, inconsistent design, in addition to the potential for errors and inconsistencies. In the dataset, there are 6,893 images of normal CT scan, 7,593 images of Covid-19 affected CT scan and 2,618 images of CAP patient.

1) Image Resizing & Rescaling: Images in the dataset were resized into 180×180 pixels from 512×512 pixels and rescaled with a scaling factor 2.84. Through resizing and rescaling dimension of feature was reduced.

2) Data Augmentation: We may have a dataset of images taken in a particular set of conditions in the actual world. However, our picked out set of images could exist in a wide range of unique scenarios, including variations in scale, brightness, orientation and position among them. These conditions can be taken into account by feeding our neural network more artificially manipulated training data. Data Augmentation helps to expand the amount of necessary data in our dataset. In our work, data augmentation was performed on run-time while training the model at every epoch. To augment data, we used horizontal_flip, vertical_flip, brightness_range, rotation(45°) and normalization.

3) Train-Test Splitting: The images in the preprocessed dataset were divided randomly in the proportion of 80:20. To ensure that the training and testing sets were equally representative of the entire dataset, the shuffle parameter was set to true and the random state value was fixed. Therefore, out of 17,104 images, 13,684 and 3420 images were selected for training and testing sets respectively. Moreover, from the 13,684 training set images, 20% (3420 images) were split for validation test.

B. Feature Extraction & Classification

For image classification, CNN models take an image as input, then perform the necessary operations to extract features from it, and then use those features to classify the image as one of the given categories. Each input images were fed through a series of convolutional layers with a defined size of filters, pooling layers, fully connected layers, and an output layer. Pretrained weights were employed from the ImageNet dataset. Lastly, softmax activation function was used to categorize the input with a probabilistic value that ranges between 1 and 0.

1) Inception V3: Inception V3 is one of the most popular pre-trained models and a CNN architecture mostly used in image classification. It is a better version of Inception V1 that was introduced as GoogleNet during the ImageNet Recognition Challenge in 2014. The ImageNet Project is basically a large database of more than 14M images of more than 20K categories. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a yearly software competition where software programs compete to accurately identify and detect objects and sceneries, has been organized by the ImageNet project since 2010 [12]. It is more efficient and optimized version which allows deeper network while preventing the excessive increase in the number of parameters [13]. In InceptionV3 there are 48 layers including kernels of different sizes, max pooling, convolution, batch normalization and label smoothing. Transfer learning was employed to train the model. Afterwards, it was trained over 20 epochs. However, the model doesn't learn after 10 epochs since there was a increase in parameters. Therefore, we trained upto 10 epochs at best. The model was compiled using Adam optimizer with a learning rate 0.001, categorical cross entropy loss function and accuracy as success metric. We incorporated an extra flattening layer into the architecture. And a dense layer was employed with softmax activation function.

2) VGG19: This is a standard deep Convolutional Neural Network (CNN) with multiple layers; VGG stands for Visual Geometry Group. The word "deep" is used in term of it's number of layers for VGG-16 and VGG-19 having 16 and 19 convolutional layers respectively. For a range of tasks and datasets outside of ImageNet, the VGGNet, a deep neural network, performs better than benchmarks. [14]. VGG19 is one of the VGG model modifications that, in essence, comprises 19 levels (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer). VGG11, VGG16, among others, are further versions. First the model was trained over 20 epochs but it is observed that the model starts overfitting after 10 epochs. Hence the model was trained upto 10 epochs at most. The model was compiled using Adam optimizer with a learning rate 0.001, categorical cross entropy loss function and accuracy as success metric. We applied a flttening layer on the pretrained model at first. Then we added a dense layer with softmax activation function.

TABLE II
MODEL SUMMARY WHEN INCEPTIONV3 IS PRETRAINED(BASE) MODEL

Layer	Output shape	Parameters
InceptionV3 (InputLayer)	(None, 180, 180, 3)	0
OutputLayer	(None, 2048)	0
Flatten	(None, 2048)	0
Dense	(None, 3)	6147
Total parameters:		21,808,931
Trainable parameters:		6,147
Non-trainable parameters:		21,802,784

TABLE III
MODEL SUMMARY WHEN VGG19 IS PRETRAINED(BASE) MODEL

Layer	Output shape	Parameters
VGG19 (InputLayer)	(None, 180, 180, 3)	0
Conv2D	(None, 11, 11, 512)	2359808
MaxPooling2D	(None, 5, 5, 512)	0
OutputLayer	(None, 512)	0
Flatten	(None, 512)	0
Dense	(None, 3)	1539
Total parameters:		20,025,923
Trainable parameters:		1,539
Non-trainable parameters:		20,024,384

3) ResNet50: Deep residual networks (ResNets), which include the well-known ResNet-50 model, are another type of convolutional neural network architecture (CNN). 50 layers altogether, comprising a fully connected layer for classification and 49 convolution layers arranged into residualblocks, make up the ResNet50 variant of the ResNet model. [15]. To enable them to disregard the weights supplied by ImageNet, all of the layers in the pretrained ResNet50 architecture have had their trainability turned off. The model found suitable weights for the target dataset by layer freezing. The 180 x 180 x 3 size preprocessed chest CT images were the input to the first convolutional block. The first convolutional block has a kernel (7 x 7, 64), meaning that it is 7 x 7 in size and has 64 distinct kernels, each of which has a stride size of 2, providing us with one layer. The output from this layer is 87 x 87 x 64. Then with a stride size of two, the architecture then exhibits maximum pooling giving us a output dimension of 43 x 43 x 64. There are three different kernels in the second convolutional block: kernels of dimension (1 x 1, 64), (3 x 3, 64) and (1 x 1, 256) respectively. There are 3 total repetitions of these 2 layers, for a total of 9 layers in this

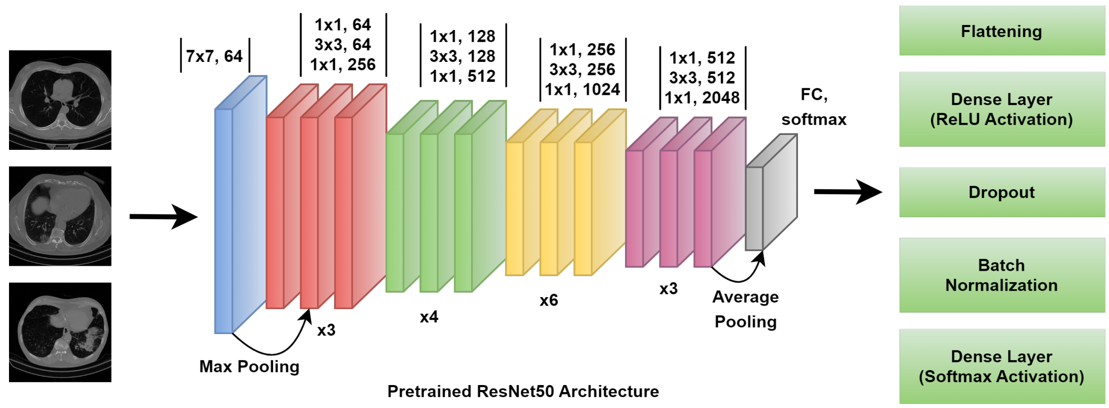

Fig. 2. Architecture of the Proposed Model when ResNet50 had been used as pretrained(base) model.

step. The third block has a kernel of (1 x 1, 128), then one of (3 x 3, 128), and finally one of (1 x 1, 512); this phase was repeated four times, giving us a total of 12 layers in this step. After this step, there is a kernel with the value (1 x 1, 256), followed by two more kernels with the values (3 x 3, 256) and (1 x 1, 1024); this process is then repeated six times, depicting us a total of 18 layers. And next to that, a (1 x 1, 512) kernel, followed by two more with a dimension of (3 x 3, 512) and one with dimension of (1 x 1, 2048); this process was repeated three times, providing us a total of 9 layers. Then an average pooling is performed that has one-dimensional vector with 2048 features per pixel. The process finishes with a fully connected layer that has 1000 units and a softmax function. The last fully connected layer classifies object features into 1000 categories. Table IV demonstrates the overview of parameters of the proposed model.

TABLE IV
MODEL SUMMARY WHEN RESNET50 IS PRETRAINED(BASE) MODEL

Layer	Output shape	Parameters
ResNet50 (Functional)	(None, 7, 7, 2048)	23587712
Flatten	(None, 2048)	0
BatchNormalization	(None, 2048)	8192
Dense	(None, 512)	1049088
BatchNormalization	(None, 512)	2048
Dropout	(None, 512)	0
Dense	(None, 256)	131328
BatchNormalization	(None, 256)	1024
Dropout	(None, 256)	0
Dense	(None, 128)	32896
BatchNormalization	(None, 128)	512
Dropout	(None, 128)	0
Dense	(None, 64)	8256
Dropout	(None, 64)	0
BatchNormalization	(None, 64)	256
Dense	(None, 3)	195
Total parameters: Trainable parameters: Non-trainable parameters:		24,821,507 1,227,779 23,593,728

Trainable layers were added one after the other in the second phase, with the classifier portion skipped. Four dropout layers, one layer for flattening, five batch normalization layers and five dense layers (whose weights were initialized using the default initialization method) were added in total. The first four dense layers had ReLU activation function to introduce non-linearity and the fifth one has softmax activation function to classify the images into Normal, Covid-19 or CAP(community-acquired pneumonia). At first flatten layer was added and then the pretrained model's 50% were dropped out using five dropout layers followed by batch normalization and dense layer. The model was then compiled using Adam optimizer with a learning rate 0.001, categorical cross entropy as loss function and accuracy as success metric. And 20 epochs were used to fit the model.

C. Experimental Setting

Applying a learning rate of 0.001, "Adam" was employed as the optimizer to boost overall performance and efficiency of the model. Since the purpose of this research work was to classify the input images into three categories- Normal, Covid-19 or CAP(community-acquired pneumonia), "Categorical crossentropy" was used as the loss function and "softmax" as the last layer activation function. After the validation split, the training images were divided into 428 batches by setting the hyperparameter batch size as 32. The proposed model was iterated through 20 epochs on these training images to avoid overfitting.

D. Evaluation Metrices

Accuracy, Precision, Recall, F1-score, and the confusion matrix were used to evaluate the performance of our suggested model. The True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) terms should be clarified before we can discuss the evaluation measures [16]. When ground value and outcome are both positive, the output is called TP, while they are both negative for the output called TN. Positive results with regard to negative ground truth are expressed as FP, and negative results with regard to positive ground truth are expressed as FN.

1) Confusion Matrix: The confusion matrix (CM) provides a detailed summary of a classification algorithm's performance by displaying the numerical measure of correct and incorrect predictions generated by the model on a dataset. Fig. 3 represents the confusion matrix generated from the prediction by ResNet50 based proposed architecture.

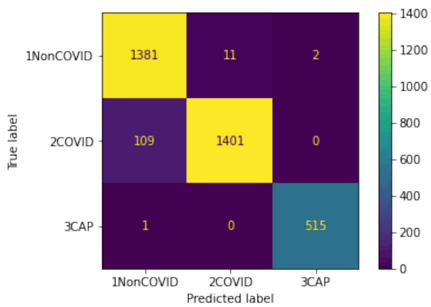

Fig. 3. Confusion Matrix of Proposed ResNet50 Based Model

2) Measuring Matrices: The results for accuracy and f1-score were determined using the following equations [17]-

$$\text{AC} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{PR} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{RC} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 Score} = \frac{2 \times RC \times PR}{RC + PR} \tag{4}$$

The accuracy is calculated by dividing the correctly predicted items by total predicted items, both accurate and inaccurate. And F1 score is calculated from Precision and Recall.

3) Classification Report: Using the above mentioned formulae and the numerical values of true positive, true negative, false positive, and false negative, we calculated the values for precision, recall, f1-score and demonstrated in the table below.

TABLE V
PERFORMANCE EVALUATION OF RESNET50 BASED MODEL

	Precision	**Recall**	**F1 Score**
Normal	0.93	0.99	0.96
COVID-19	0.99	0.93	0.96
CAP	1.00	1.00	1.00

V. RESULTS AND PERFORMANCE ANALYSIS

Three different ImageNet-trained models (InceptionV3, VGG19, ResNet50) were employed for image classification. Inception V3 and VGG19 based models were tarined for both 10 and 20 epochs. For VGG19 model, the accuracy decreased as the epochs increased due to vanishing gradient problem. Accuracy obtained in Inception V3 model is 84% and in VGG19 model is 87%. ResNet50 based model was trained for 20 epochs. Moreover, hyper-parameter tuning and regularization was done in all the three models. The validation accuracy of 97% was achieved for ResNet50.

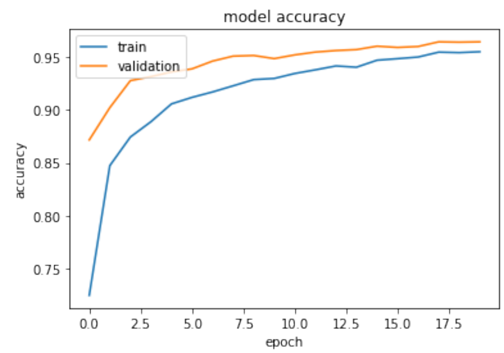

Fig. 4. Accuracy Curve of ResNet50

Data Augmentation, train-validation split, regularization, dropout and early stopping improved the generalization performance and reduced overfitting. Following the calculation of the evaluation metrics, we contrasted our suggested model for multiclass image classification, which was tested on the same dataset [9]. The comparisons are given in the table below

TABLE VI
RESULTS OF THE EVALUATON MATRICES FOR THE PROPOSED MODELS AND THEIR PERFORMANCE COMPARISONS WITH OTHER MODELS.

Model	**AC (%)**	**F1 (%)**
DenseNet-121 [9]	92.57	90.85
Residual Attention-92 [9]	91.76	90.73
Ensemble with FC [9]	95.07	93.89
Ensemble with FC + SVM [9]	95.31	94.23
Inception V3	84	86
VGG19	87	88
Proposed Model (ResNet50)	97	98

Linear models, like SVM, frequently fail to gain knowledge from unprocessed image data. A popular practice under these circumstances is to turn a raw image into a feature vector, which offers a low-dimensional, also noise-resistant approach to represent these images. One popular method of extracting features from a picture is to input it into a traditional, previously trained neural network and use the representation of that image in the intermediary layers of the network. To do this, we used ResNet50 model that have already been trained on the ImageNet dataset to extract representations of provided images. Moreover, SVM underperforms when there are overlapping classes. In our dataset COVID-19 and CAP class was nearly similar. Hence, more accurate results were obtained using ResNet50 model.

VI. CONCLUSION

The whole world had witnessed an outbreak of a viral pneumonia by the end of the year 2019. The World Health Organization entitled the virus as "severe acute respiratory syndrome coronavirus 2 (SARS-CoV2)" [18], and the resulting pneumonia was named as (COVID-19) [19]. More than 800 million confirmed infected cases and 10 million deaths had happened worldwide till date. Therefore, the deep transfer learning model has proven to be extremely helpful in assisting the radiologists with automated and faster diagnosis of COVID-19. Early detection can reduce the death rate upto 63% as well. In this study the size and number of the kernel, the learning rate, the number of neurons used in the dense layers, batch size and the dropout rate were among the critical factors that determined how well the proposed model performed. All of these hyper parameters have undergone meticulous control, and numerous trials were used to determine the best values. In this work, the dataset is smaller in compared to other datasets like- COVIDx CT-3 dataset that contains 431,205 CT slices [20]. There are less number of CAP samples compared to COVID and normal cases in our dataset. So, our model may face difficulty while performing prediction on bigger dataset with larger number of pneumonia samples. On the other hand, the suggested model perform better than many other advanced models those are now accessible. Due to the transfer learnings' various hyperparameters being fine-tuned, performance is improved.

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