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Deep Learning Based Pipeline for COVID-19 Classification

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ABSTRACT: The detrimental and contagious novel coronavirus disease (COVID-19) has severely impacted millions of individuals at a global level. The detection and diagnosis of COVID-19 at an early stage is of utmost importance. The use of advanced and state-of-the-art technologies such as Artificial Intelligence and Deep Learning to efficiently detect the presence of the disease is extensively being researched upon. In this paper, we propose a deep learning based pipeline for automatic medical diagnosis of COVID-19 based on Chest X-Ray (CXR) images. We make use of the COVID-19 Radiography Database consisting of approximately 21,000 CXR images with 4 different classes namely 'COVID', 'Lung Opacity', 'Normal', and 'Viral Pneumonia'. We implement a Convolutional Neural Network architecture for medical image diagnosis. Furthermore, we make use of the pre-trained VGG16 transfer learning model and fine-tuning to improve the performance and decrease the training time. Our model achieved an accuracy of 91.94% on multi-class classification using transfer learning. The presented approach can be effectively used in medical services for detecting COVID-19 in an individual using Chest X-Rays with high efficiency and less time.

KEYWORDS: Deep Learning, COVID-19, Transfer Learning, Convolutional Neural Network, VGG16.

I. INTRODUCTION

The COVID-19 pandemic caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is spreading all over the world at a rapid rate. The disease initially appeared in late 2019 in Wuhan, which is a city belonging to the Hubei province, China. The method for detecting COVID-19 which causes respiratory problems differs from that of other coronavirus diseases. The primary approach for detecting the virus is by undertaking Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests which are time-consuming and require high accuracy. Even today, some countries are facing a dearth of laboratory and testing kits at a large scale. Thus, to detect the virus in a more simple and rapid manner, many doctors are nowadays relying on medical imaging due to its ability to help identify the diseases effectively through radiological examination which includes computed tomography (CT) scans and Chest X-Rays (CXRs). Although the use of CT scans has been effective for detecting coronavirus, they consume a lot of resources and time. A more feasible approach is to use CXRs for the detection of COVID-19 over a period of time [1].

With the proliferation of the disease all over the globe, the domain of Artificial Intelligence is becoming popular for developing automated and intelligent systems to efficiently detect the virus. The application of deep learning for medical image processing and analysis has been widely used by many researchers due to its high computing performance and powerful algorithms. Moreover, Convolutional Neural Networks (CNNs) are proved to be effective for feature extraction. By building a multi-layered machine learning model with a large sample set of data, deep learning learns more accurate features. This can ultimately improve the accuracy of classification and prediction. The task of distinguishing between COVID-19 and other lung diseases is challenging due to the presence of similar radiographic features.

This paper proposes a deep learning pipeline for detecting COVID-19 and classifying the CXRs into 4 classes namely 'COVID', 'Lung Opacity', 'Normal', and 'Viral Pneumonia'. We make use of the COVID-19 Radiography Database which consists of around 21,000 chest X-Ray images. We perform essential data pre-processing steps to reduce the noise and retain relevant information. Moreover, we apply image augmentation to make our model more robust. After the pre-processing, we train a popular VGG16 CNN model also known as OxfordNet, and transfer



learning on the dataset which helps to employ pre-trained weights from ImageNet which is a large dataset. This assists in decreasing the training time of our model. Lastly, we apply fine-tuning for decreasing the training time and increasing the overall model accuracy and other performance metrics.

The rest of the paper is structured as follows: section II talks about the related work. Section III provides a description of the dataset and methodology used in this paper. Section IV describes the experimentation and obtained results. The conclusions of the paper are drawn in section V.

II. RELATED WORK

In the domain of medical detection and diagnosis, a variety of deep learning algorithms have been implemented for analysis [2, 3]. There are various works that use transfer learning along with CNN architecture for identifying, classifying, and detecting COVID-19 patterns. Extensive research has been done upon these algorithms to increase their performance and reduce their overall complexity.

Some of the works are based on Deep Convolutional Neural Network architectures that have high computational complexity. [4] presents two novel Deep CNN models namely CovidResNet and CovidDenseNet that diagnose COVID-19 based on CT scans. These models have achieved an accuracy of 93.87% for binary classification and 83.89% for multi-class classification. [5] implements an end-to-end diagnostic system that combines the use of machine learning classification and deep learning feature extraction. Moreover, it presents an analytical comparison between 5 different pre-trained CNN models. [6] presents a comprehensive overview of the latest CNN architectures such as VGG19, Xception, MobileNet v2, Inception, and Inception-ResNet-v2 trained upon X-Ray dataset. [7] proposed a Resnet-101 based architecture for classifying between COVID-19 and pneumonia that achieved an accuracy of 97.78%. [8] makes use of the ResNet 50 architecture for extraction of features and then SVM classifier for classification. The proposed model obtained an accuracy of 94.70%. [9] obtained an accuracy of 98% with the help of Inception v3 and transfer learning. [10] employed DenseNet-161 architecture for segregation of COVID-19 and normal pneumonia and achieved an overall accuracy of 98.90%. A novel architecture comprising of GoogleNet and DenseNet for feature extraction was presented by [11]. XGB, RF, and SVM classifiers were further used for the classification of the extracted features that obtained an accuracy of 91.70%. [12] performed binary, 3-class, and 4-class classification upon chest X-Ray images using a 22-layer CNN architecture. [13] employed various techniques such as Texture, Wavelet, GLCM, and GLDM and achieved an accuracy of 94% upon 3 class classification (Normal, pneumonia, and COVID-19). [14] proposed a ResNet 101 based architecture for airspace opacity and achieved an accuracy of 71.90%.

Fine-tuning has been performed in several other research works for reducing the training time and increasing the model performance. [15] performed a 3-class classification using various other models out of which VGG16 architecture produced the best performance with an accuracy of 95.88%. A novel method known as DeTrac was presented by [16] that adds a class decomposition layer to the pre-trained deep learning model. An accuracy of 93.1% was obtained by combining VGG19 along with DeTrac. [17] proposed a novel model known as DarkCovidNet that obtained an accuracy of 98.08% for binary classification and 87.02% for multi-class classification. [18] made use of DenseNet201, Resnet50V2, and InceptionV3 along with the weighted average ensembling method and compared the models. An accuracy of 95.7% was reported for binary classification. [19] presents an exhaustive comparison between fine-tuned ResNet18, ResNey50, SqueezeNet, and DenseNet-121 models. [20] proposed a novel MH-COVIDNet algorithm that achieved an accuracy of 99.38%. This model implemented VGG19 for feature extraction and the MH algorithm for feature selection. An integrated stacked deep CNN named InstaCovNet-19 was proposed by [21] that employed InceptionV3, Xception, NASNet, MobileNetV2, and ResNet101. InstaCovNet-19 achieved an accuracy of 99.53% for binary classification and 99.08% for multi-class classification.

III. MATERIALS AND METHODS

This section presents a description of the dataset and also elaborates upon the data pre-processing and data augmentation processes. We then present an overview of the transfer learning architecture and explain the implemented pre-trained model. Lastly, we discuss the performance metrics used for evaluating our model. The block diagram for our proposed model is shown below:

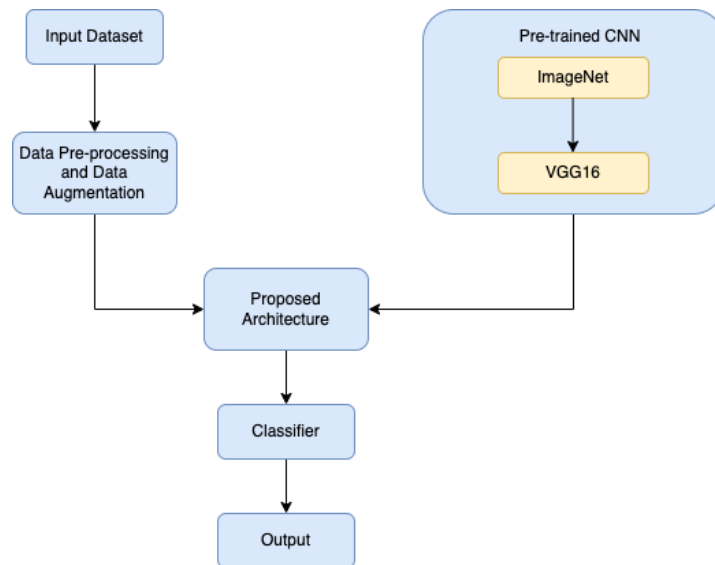


Fig. 1 Block diagram of the proposed model

Dataset Description

We have made use of the COVID-19 Radiography Database [22, 23] which consists of around 21,000 chest X-Ray images consisting of COVID, Lung Opacity, Normal, and Viral Pneumonia. Since there are a large number of Non-COVID-19 chest X-Ray images as compared to COVID-positive images, we perform undersampling and reduce the count for Normal and Lung Opacity classes for better detection and classification of COVID positive images. The types of images along with their count is presented below:

Classes	Number of images before undersampling	Number of images after undersampling
Normal	10192	4316
Lung Opacity	6012	4316
Viral Pneumonia	1345	1345
COVID	3616	3616

Table. 1 Count of class labels

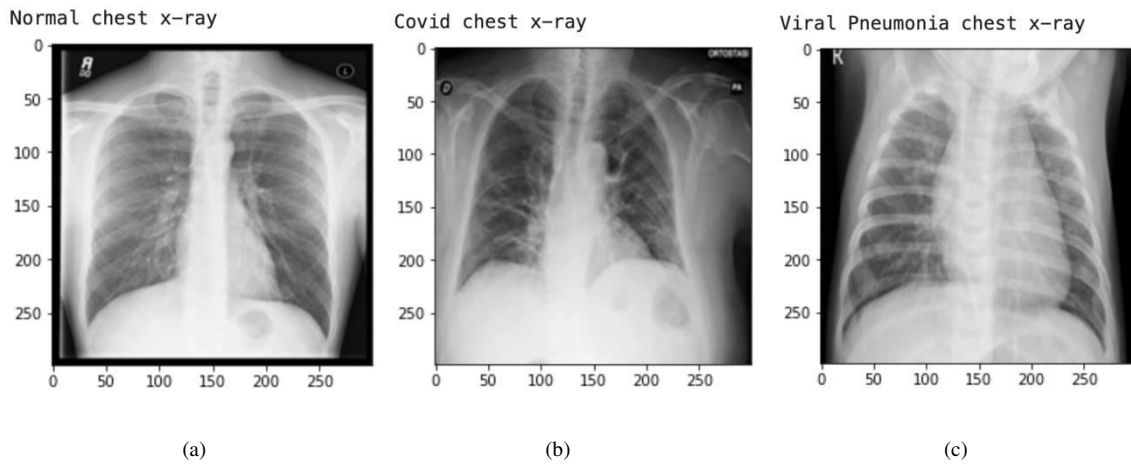


Fig. 2(a) Normal Chest X-Ray image (b) COVID Chest X-Ray image (c) Viral Pneumonia Chest X-Ray image

Data Pre-processing and Data Augmentation

We make use of the Image Data Generator provided by Keras for data augmentation. We use rotation, width shift, and height shift techniques for image augmentation. We set the rotation range to 40 degrees and then distort the image. We set the batch size as 20, color mode to RGB, and resize the images to 224 x 224 for further processing. We divide the dataset into 4 classes namely COVID, Lung Opacity, Normal, and Viral Pneumonia, and assign them labels of 0, 1, 2, and 3 respectively. We split the dataset into training, testing, and validation sets.

Pre-trained Deep Learning Models

We employ VGG16 as a classifier for our deep learning model which is available in Keras and Tensorflow libraries. VGG16 also known as OxfordNet architecture was developed in 2014 by Karen Simonyan and Andrew Zisserman from the University of Oxford. It is used in many image classification problems and is relatively easy to implement as compared to other pre-trained models. The input to VGG16 is a fixed RGB image with size configurations 224 x 224. It consists of convolutional layers having a 3x3 filter with stride 1 and a max pool layer of a 2x2 filter with stride 2. Moreover, it has 2 fully connected layers and softmax as an output. It employs 16 layers as its weights and consists of approximately 138 million parameters.

The following figure gives an overview of the Convolutional Neural Network architecture.

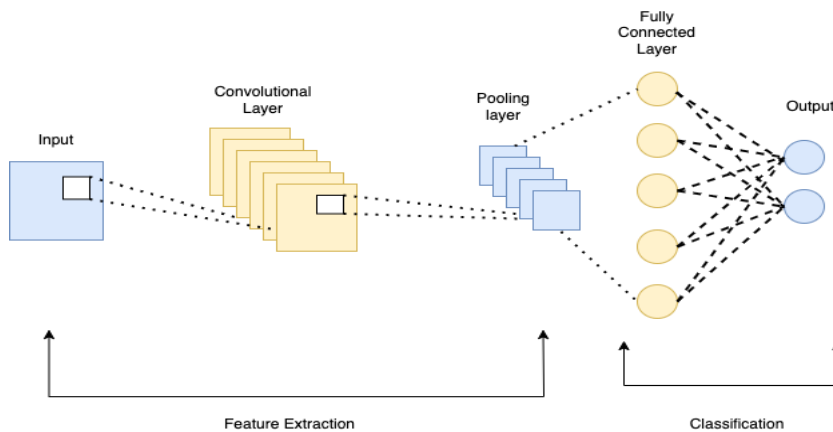


Fig. 3 Block diagram of Convolutional Neural Network

The figure below shows the architecture of VGG16 model [24] used for classification of COVID-19.

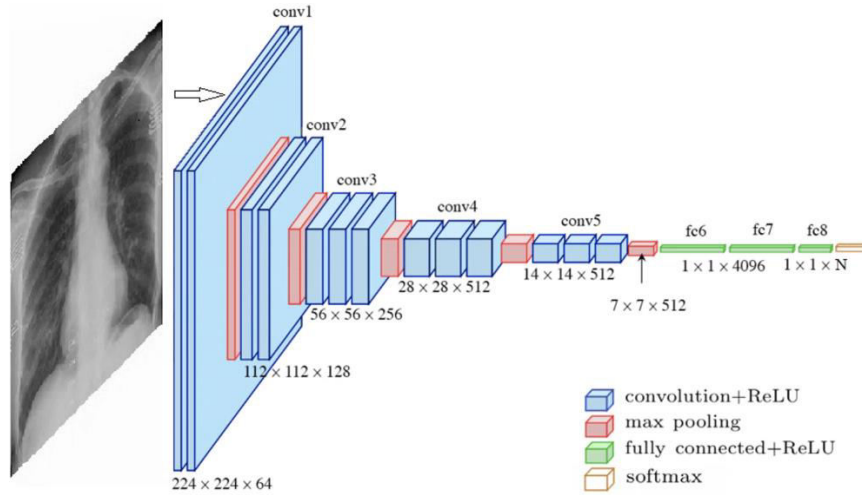


Fig. 4 Block diagram of VGG16 architecture

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
Total params: 14,714,688		
Trainable params: 0		
Non-trainable params: 14,714,688		

Fig. 5VGG16 layers

Transfer Learning

Transfer Learning is a popular technique in deep learning that applies the knowledge of one task to another related task. It gains information about the pre-trained models and uses that information to train our model thereby aiding in training smaller datasets in less time. Using transfer learning, training deep learning models is much easier and efficient. Transfer Learning makes use of an already pre-trained model on a different problem. Training of a CNN is performed using a large dataset and the model is then used on smaller datasets. As per the number of training classes, the fully connected layer is then modified respectively. The key advantages of using transfer learning are the time saved during training, working with insufficient data, and better performance. It also provides the added benefit of faster fine-tuning. The weights can be adjusted by fine-tuning all layers with the option of freezing some front layers or fine-tuning back



layers. To fit the new classification problem, we discard the pre-trained network’s final layers and replace them with new layers thereby fitting with the new classes.

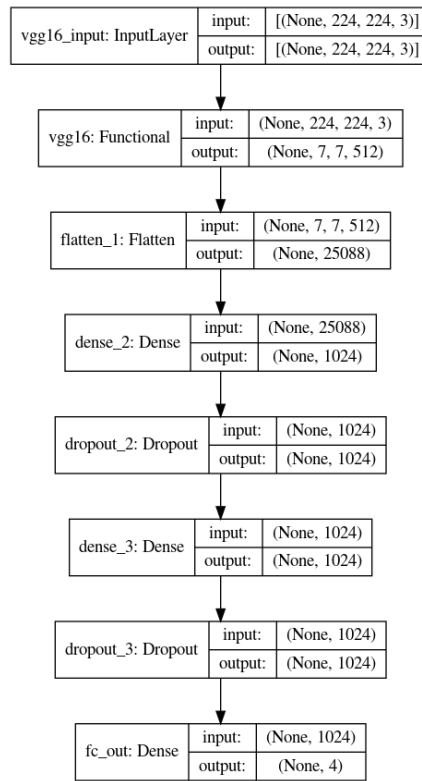


Fig. 6 Model Visualization.

Performance Metrics

This subsection evaluates the performance of the VGG16 model used for multi-label classification. The performance metrics that we used were accuracy, precision, recall, f1-score and support.

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Metric	Formula
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
Precision	$TP / (TP + FP)$
Recall	$TP / (TP + FN)$
F1-Score	$2 * (Precision * Recall) / (Precision + Recall)$

Table 2. Performance Metrics



IV. RESULTS

Experimental Setup

In this paper, the experiment was performed using Python programming language and Google Collaboratory notebook. We make use of Python, NumPy, Pandas, Sklearn, Matplotlib, TensorFlow, Keras, and Open CV libraries. We train our VGG16 model with 50 epochs. We used an Intel i7 core machine with a 3.6 GHz processor and 16GB RAM. We built and trained the experiments for multi-class classifications to evaluate the performance. We used 80% of the data for training, 10% for testing, and the remaining 10% for validation.

Performance and testing of multi-class classification.

We train the VGG16 transfer learning model on the train and validation data using multi-class classification with class 0 for COVID, class 1 for lung opacity, class 2 for Normal, and class 3 for Viral Pneumonia. Figure 7 shows the plot of the accuracy and loss function on the train data for the VGG16 model versus the number of epochs. The accuracy of the training data is 91.87%, and the loss is 0.283. The validation data accuracy is 93.92%, and the loss is 0.1795.

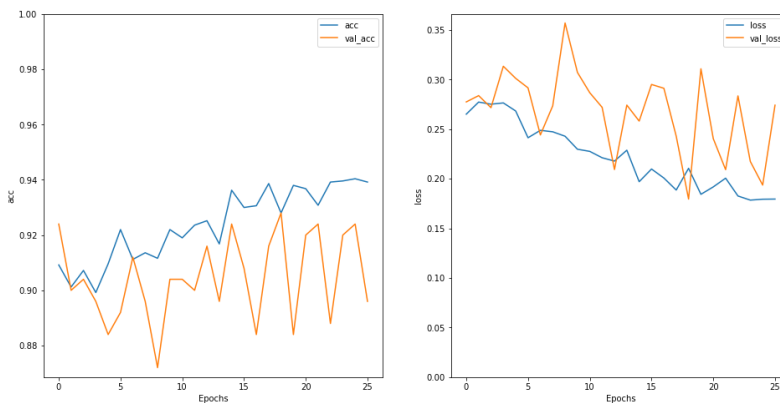


Fig. 7 Graph comparison between accuracy and loss

We successfully evaluate the model on the test set and demonstrate the results for the multi-class classification in Table 3. The performance metrics of the VGG16 model for COVID class are: 97% for precision, recall with 94%, and F1-score with 96%. We report an accuracy of 91.94%. The confusion matrix is shown in Figure 8.

Label	Precision	Recall	F1-Score
COVID	97%	94%	96%
Lung Opacity	91%	88%	89%
Normal	87%	93%	90%
Viral Pneumonia	98%	97%	97%

Table 3. Metric Values for all classes

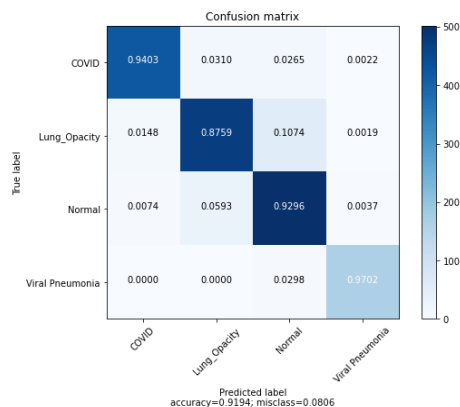


Fig. 8 Confusion Matrix

V. CONCLUSION

In this paper, we successfully performed multi-class classification on the COVID-19 Radiography database with the help of deep learning. We employed a Convolutional Neural Network architecture for image processing and analysis of chest X-Ray images. We classified the images into 4 classes namely COVID, Lung Opacity, Normal and Viral Pneumonia. Furthermore, we used VGG16 along with transfer learning and used pre-trained weights of a larger ImageNet dataset. The results showed that VGG16 is highly effective in classifying COVID-19 CXR images with high accuracy and recall. We reported the classification accuracy, precision, recall and f1-score of 91.94%, 97%, 94%, and 96%, respectively. The use of deep learning architecture for the classification of X-Ray images might prove to be extremely efficient and beneficial for medical practitioners and healthcare providers.

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