Lung disease Multi-Class Classification of COVID-19, Pneumonia, and Healthy Chest X-ray

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Abstract—**As the need for medical treatments grows exponentially, there has been an unprecedented demand for the quick diagnosis of illnesses. This study proposes a computer-aided diagnosis system for automatic disease detection using Chest X-ray images of three classes COVID-19, Pneumonia, and Healthy. The prediction can be done through deep learning algorithms, such as convolutional neural networks (CNNs). The algorithms are trained on a large dataset of X-ray images and can accurately classify the images into different disease categories. In this paper we will use convolutional neural networks. The proposed technique successfully classifies three classes that include COVID-19, pneumonia and normal with an accuracy of 80.38%. At the end for make comparision with our model we add also pre-trained model of Densnet with a test accuracy of 95.76 %**

Index Terms—**Deep learning; Classification; chest X-rays; Convolutional Neural Networks(CNN) ; Pre-trained DenseNet**

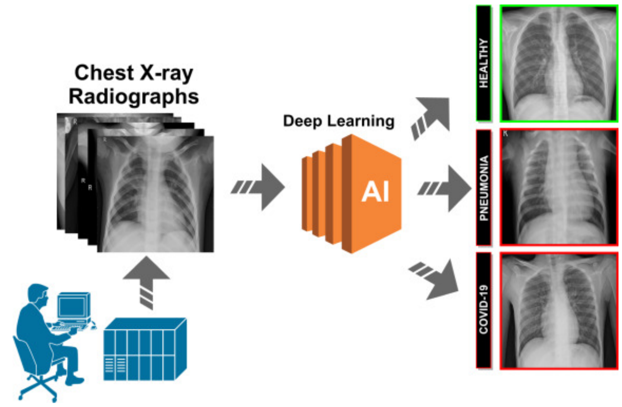

Fig. 1: chest X-ray classification

I. Introduction

The coronavirus (COVID-19) is possibly the biggest human threat of the twenty-first century [1]. It has been causing major lung damage and breathing issues since December 2019. The COVID-19 pandemic continues to have a devastating effect on the health and well-being of the global population, caused by the infection of individuals by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Chest X-rays (CXRs) provide a non- invasive (potentially bedside) tool to monitor the progression of the disease. Recent studies claim to obtain reliable results for the automated detection of the disease from chest X-ray (CXR) scans. [2] Lung disease classification using deep learning involves using artificial neural networks to analyze medical images, such as X-rays or CT scans, and classify different types of lung diseases based on visual patterns in the images. This approach is useful because it can automate the diagnosis process and reduce the need for manual interpretation by radiologists, which can lead to more consistent and accurate diagnoses. Additionally, deep learning algorithms can learn from large amounts of data and improve over time, making them well-suited for medical image analysis. Overall, chest X-ray classification using deep learning is a promising approach for improving the accuracy and efficiency of lung disease diagnosis, and ultimately improving patient outcomes.1

In this study we will use Convolutional Neural Network (CNN) which is a type of deep learning algorithm that is commonly used for image classification tasks. It is inspired by the structure of the human visual cortex and is designed to process image data. A CNN consists of multiple layers, including convolutional layers, activation layers, and pooling layers, that extract and simplify the features in an image, reducing the dimensionality of the data and making it easier to classify. The final layer in a CNN is a fully connected layer that outputs a prediction based on the features extracted by the previous layers (proposed method is Figure 2). CNNs have been successful in a variety of image classification tasks, including medical image analysis, such as chest X-ray classification. This is due to their ability to learn hierarchical representations of image data, which enables them to effectively identify complex patterns in images. During the classification process, an input image is processed through the convolutional and pooling layers in the CNN to extract a set of features that describe the image. These features are then passed to the fully connected layer at the end of the network, which produces a prediction for the class label. In this context, a CNN is trained on a large dataset of labeled images, where the goal is to predict the class label for a new unseen image. After implementing CNN and getting the result we also add the pre-trained network called DenseNet121 which have been utilized for classification and performance comparison purpose. [3]

As a result, Chest X-rays are a quick and accessible way to diagnose lung diseases, and using deep learning algorithms to classify them can improve the accuracy and speed of diagnoses. Moreover, early and accurate diagnosis can lead to earlier treatment and better patient outcomes. Automating the diagnosis process through deep learning algorithms can reduce the workload for radiologists and allow them to focus on more complex cases and leading to increased efficiency in

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Special thanks to Michele Rossi, ICT for Internet and Multimedia Department, University of Padova..

the healthcare system.

II. Related Work

Chest X-ray classification has been a popular area of research in the field of medical imaging. Several studies have been conducted to develop algorithms for classifying chest X-rays into various conditions such as normal, pneumonia, covid-19, and other lung diseases.
Umair et al. [4]presented a technique for the binary classification of COVID-19. A publicly available dataset is used for training and evaluation of the technique, consisting of 7232 chest X-ray images. Over the past decade, many researchers have automatically used deep learning to detect lung infections and diseases from chest X-ray.
For example, CheXNet is a 121-layer CNN-based approach developed by Rajpurkar et al. [5]. This approach was trained using 100,000 chest X-ray images from 14 different diseases. The approach was also applied using 420 chest X-rays, and the results were compared with those of radiologists. Therefore, it was found that the DL-based CNN method outperformed the average performance of radiological pneumonia detection. As a result, Recent related work has focused on developing deep learning models such as Convolutional Neural Networks (CNNs) to improve the accuracy of chest X-ray classification. Some of these studies have used transfer learning techniques to fine-tune pre-trained models on large chest X-ray datasets, while others have trained models from scratch on smaller datasets.
Also,To detect COVID-19, Abraham and Nair et al. [6] built models based on an ensemble of CNNs. The results of this studies showed that pre-trained multi-CNNs outperformed single CNNs in detecting COVID- 19. also, Rousan, L.A. et al. [7]provided above research has been made generally about comparing different methods and has focused on improving the performance of deep learning models for chest X-ray classification. In this paper our aim is to make our own CNN model to predict the labels of different lung decease, atfer that we also show the result of pre-trained model to make the comparison between two part.

III. Processing Pipeline

The proposed methods structure is represented in Tabel 1 and figure2. Convolutional neural network (CNN) has been the preferred deep learning model in image processing applications in recent years. The CNN classifier, in general, consists of a convolution layer, activation functions, a pooling layer, a flatten layer, and fully connected layer components. In this context, Fig.(2) describes the general operation of the CNN classifier. It is possible to examine more detailed information about the functions and operating modes of the layers in the CNN classifier from the studies [8]–[10]. After examining and understanding the data we built a input pipeline by using Keras ImageDataGenerator, the preprocessed and rescaled images in size of (128,128) are fed into the CNN model and at the end make classification. In second model we will use transfer learning to classify images of ('covid', 'normal', 'pneumonia') from a pre-trained network to compare with the CNN. During the training process we would like to emphasize the difference between two ways of customizing a pre-trained model and CNN model. In the pre-trained DenseNet approach we freeze the convolutional base and prevent it to be trained, therefore we only train the additional classifier that we added on top of the base model. Finally, we evaluated the metrics of Accuracy, Loss, Precision, Recall, F1-Score rates and compare the output for both model.

layer	**Shape**	**Model Setting**
Input	128×128	
Conv2D-1 MaxPooling2D-1 Dropout-1	$32 \times 3 \times 3$ 1×2	activation=Relu Kernel-size=(3,3) dropout-rate=0.2
Conv2D-2 MaxPooling2D-2 Dropout-2	$64 \times 3 \times 3$ 1×2	activation=Relu Kernel-size=(3,3) dropout-rate=0.2
Conv2D-3 MaxPooling2D-3 Dropout-3	$128 \times 3 \times 3$ 1×2	activation=Relu Kernel-size=(3,3) dropout-rate=0.2
Flatten Dense-1 Dropout-3	256	activation=Relu dropout-rate=0.1
Output	3	activation=Softmax

TABLE 1: Architecture of Proposed CNN model

IV. Dataset and Features

Many diseases can affect the human lungs, including pneumonia, lung cancer, and, more recently, COVID-19. Chest CT or X-ray pictures are required for the diagnosis of various disorders, as they serve a key and vital role. In this sense, (COVID19, Pneumonia and normal Chest X-ray PA Dataset) which is organized into 3 different folders (covid-19, pneumonia, normal) has been used. The provided X-ray samples of COVID-19 has been retrieved from various sources which can be investigated in detail in the COVID19, Pneumonia and Normal Chest X-ray PA Dataset Paper published by Amanullah Asraf, Zabirul Islam [11]. The dataset consist of 1525 chest x-ray images per each class which sums up to 4575 in total. The dataset satisfies the great expectation of neural networks from the perspective of keeping balance in the dataset among different classes. Then, we applied data augmentation method in order to artificially introduce sample diversity by applying random transformations such as random flip and random rotation.3 Finally, we split the data by reserving 70% for the training, 30% for the test data.

Feature extraction is an important part of the CNN (Convolutional Neural Network) pipeline. In feature extraction, the CNN identifies and extracts relevant features from the input image that can be used for classification. These features are learned through the different layers of the CNN, such as the convolutional layers, pooling layers, and fully connected layers.

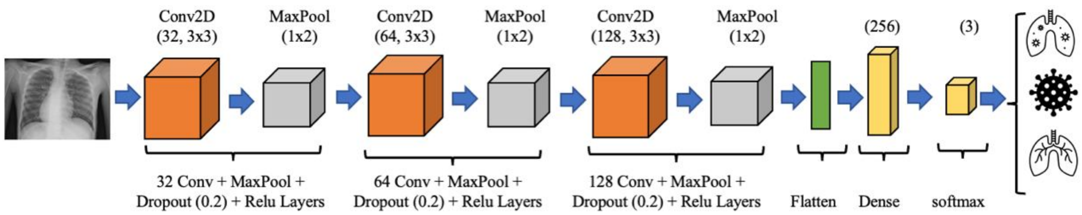

Fig. 2: Proposed Convolutional Neural Network

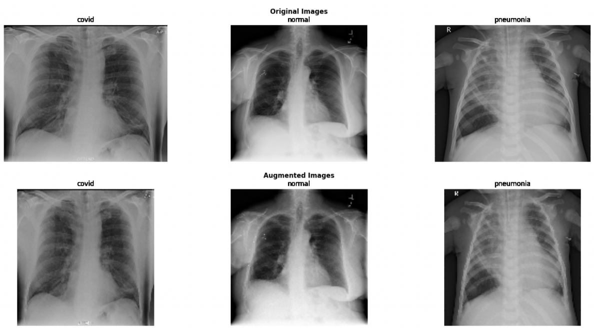

Fig. 3: Visualization of dataset and augmented ones

V. Learning Framework

Proposed Method: A CNN model would take an X-ray chest image as input and then classify the image into different categories, such as "normal" or "covid" and "pneumonia". The CNN would learn the patterns and features in the X-ray images through the convolutional layers, pooling layers, and fully connected layers. The model is trained on a large dataset of labeled X-ray images, and the weights of the network are adjusted to minimize the classification error.

Feature Extraction: In the convolutional layers, the CNN uses filters to scan the input image and extract local features, such as edges and shapes. The pooling layers then reduce the size of the feature map, while retaining the most important information. The fully connected layers, on the other hand, use the extracted features to make a final classification decision.

Classification: In total, 4575 images belong to 3 classes which has been set to have image size as 128 x 128 and batch size as 32 have been used during training. Adam optimizer with the base learning rate 0.0001 and the Categorical Cross Entropy as loss function have been used to compile the model which has been trained with 20 epochs.

Model Evaluation: Precision (1), Recall (2), and F1-score (3) are used to evaluate the classification model performance. A plot line which demonstrate the accuracy and loss performances of the model. Also a confusion matrix which consist of three classes is plotted. The experiments have been carried out on Pycharm tool and the dataset downloaded from the link

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{1}$$

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{2}$$

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{3}$$

VI. Results

In this section we will describe the parameters for our setup, the achieved results, and comparison with benchmark. For implementation of convolutional neural network (proposed method), we used Adam as optimizer with the learning rate of 0.0001 and as a loss function we used Categorical Cross Entropy. In 7^{th} epoch, our model achieved 90.01% and 80.38% train and test accuracy, respectively. As we can see from Figure 4 , by increasing the number of epochs the value of the training and the validation accuracy get better.

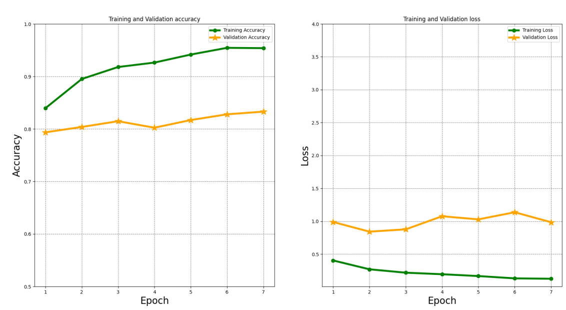

Fig. 4: Training and Validation accuracy of CNN

In figure 5 We calculate the Precision, Recall, and F1-score values, as alternative performance analysing metric. It is obvious that precision for classes 0 and 2 is higher than class 1. More details with regard to results is described in rest of this section.

Also we plot the precision and recall for the three separated class namely in figure 6 : ('covid': 0, 'normal': 1, 'pneumonia': 2) from the information of the fig5.

As demo we plot the figure 9 that includes one sample per each class of images from a batch of test dataset to show the prediction.

	precision	recall	f1-score	support
0	0.96	0.82	0.88	447
1	0.65	0.95	0.77	449
2	0.98	0.62	0.76	448
micro avg	0.81	0.80	0.80	1344
macro avg	0.86	0.80	0.81	1344
weighted avg	0.86	0.80	0.80	1344
samples avg	0.80	0.80	0.80	1344

Fig. 5: Class, Precision, Recall, F1-Score

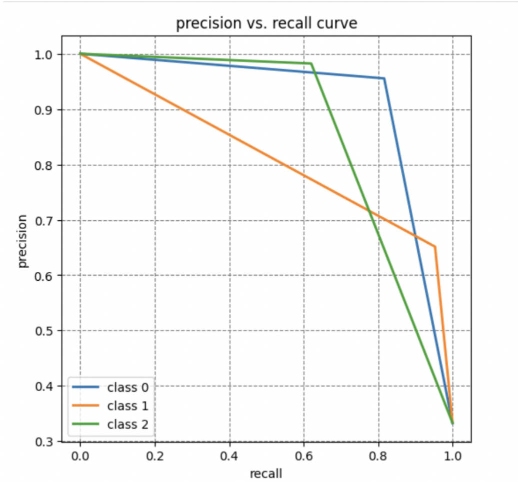

Fig. 6: Precision vs recall for 3 classes

A confusion matrix for the test dataset that is computed by our model can be seen as in the 7. The model is good at detecting COVID- 19 cases and normal but on the other hand, detecting or differentiating Pneumonia cases from other classes is harder according to this confusion matrix.

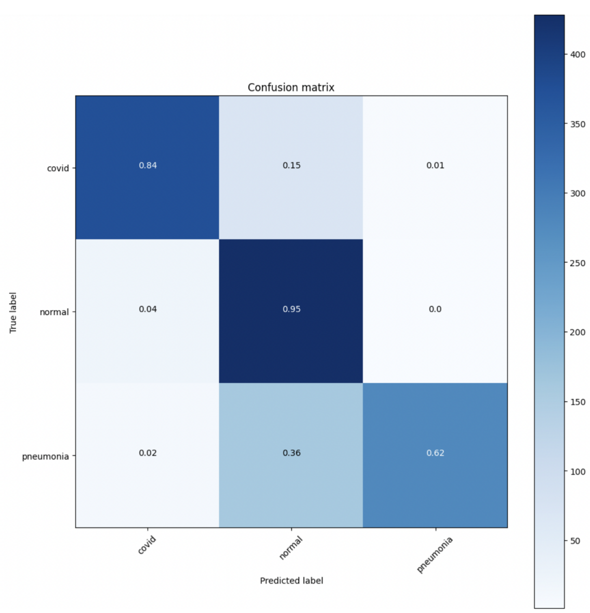

Fig. 7: Confusion matrix

Densenet (benchmark): DenseNet is type of Convolutional Neural Networks (CNNs) used for image classification. However, they differ in their architecture. In a DenseNet, each layer is connected to all previous layers, leading to dense connections and information flow between layers. While both CNNs and DenseNets can be used for image classification, the dense connectivity and skip connections in DenseNets provide improved performance and faster training times. We do Transfer learning which is the process of employing models that have been trained on one problem as a starting point for a new challenge. It is allowing you to employ pre-trained models directly and quickly adapting them to a different situation.
During the implementation of DenseNet after 4 epochs, the model achieved 95.76% test accuracy. 8

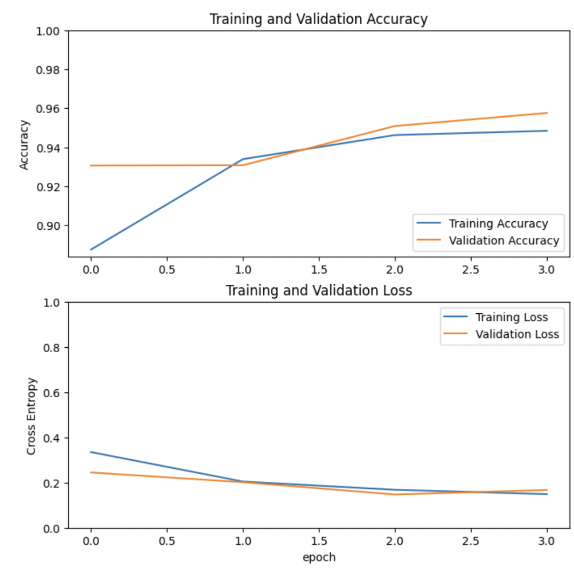

Fig. 8: Training and Validation Accuracy of DenseNet (pre-trained)

VII. Concluding Remarks

The goal of this work was to build a deep learning-based approach for classifying COVID-19, Pneumonia-affected and Healthy chest X-ray pictures utilizing convolutional neural network. In total, 4575 images which are balanced in terms of number of pictures belong to each class have been fed into the feed-forward neural network. We implement the CNN model with using convolutional and pooling layers and adding Dropout in each step between convolutional layer. At the end we compare the output of CNN model with the pre-trained Dendenet. These findings show that deep learning can support human-level effort in image classification tasks, making the diagnostic procedure more pleasant.

References

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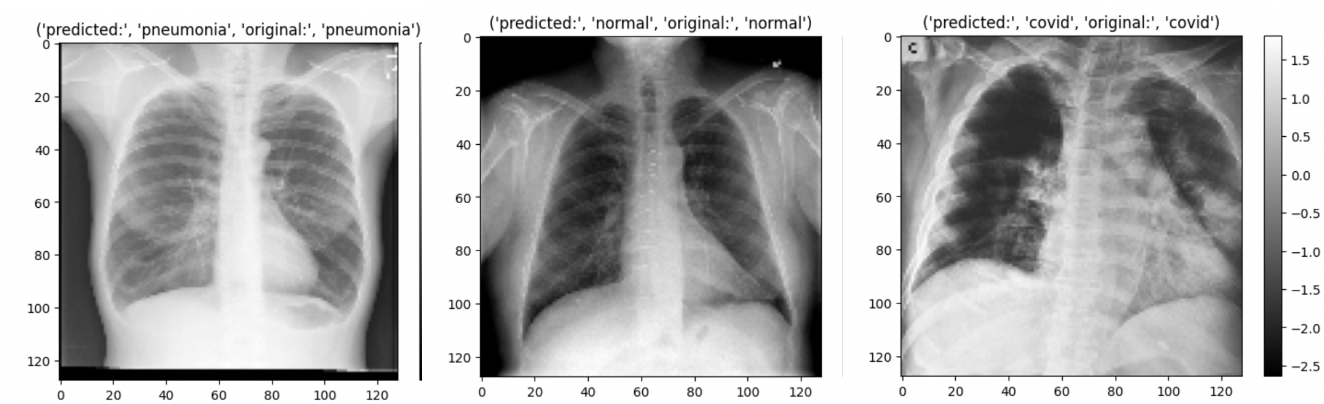

(a) Model performance on Pneunomia

(b) Model performance on Normal

(c) Model performance on Covid

Fig. 9: Model performance of CNN

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