COVID-19 Classification from X-Ray Images using 2D CNN

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Abstract—**The coronavirus (COVID-19) detection has been a crucial task for researchers, scientists, health experts all across the world and everyone is trying together to find a solution to it. The X-rays images of lungs have become one of the most prevalent and effective procedures used by researchers to monitor COVID-19. Unfortunately, inspecting each case involves multiple radiology experts and time, which is one of the critical tasks in such an outbreak. In this paper, a deep learning approach, 2D convolutional neural networks (CNN) has been used to classify healthy and COVID-19 chest X-ray images. "Curated Dataset for COVID-19 Posterior-Anterior Chest Radiography Images (X-Rays)" dataset has been used in this study. The major indicator of this study is the accuracy of the proposed model. The classification model, 2D CNN has achieved accuracy and f1-score of 0.96 and 0.95 respectively.**

Index Terms—**2D CNN, X-RAY, Images, Deep Learning, Coronavirus, Classification**

I. INTRODUCTION

Respiratory difficulties associated with coronavirus disease 2019 are usually diagnosed as pneumonia with severe acute syndrome and this disease is highly transmissible. COVID-19 was first brought to the attention of the Chinese government in Wuhan in December of 2019, and it has affected more than 147 million individuals in the whole world. Coronavirus poses a threat to all people and technology in the world. A pandemic was declared by the World Health Organization (WHO) in March 2020 [1]. An effective path to control and prevent the spread of this virus is to keep the infected patients isolated by immediate screening. Now, the only method used for COVID-19 detection is (RT-PCR) real-time reverse transcription-polymerase chain reaction [2]. The drawback of RT-PCR has its difficulty and complex issues related to specificity, sensitivity and reproducibility [3]. Furthermore, test kits are not that much accessible to perceive early results in many countries. As a result, an automatic computer-aided diagnostic method and trustworthy screening is needed immediately.

Plain radiography (chest X-ray) provides an overall picture of this disease. The pros of chest X-ray is that it allows performing instant screening and can be done in an isolated room for being portable. However, it is not suitable for patients with mild syndromes. Chest X-ray image is a significant factor, if this shows normal results, then the patient can return home without waiting for the RT-PCR test report. This is the main scope of work in this project. Automatic detection has achieved quality recently by using machine learning for this research.

To identify COVID-19, suggested deep learning model requires pictures of chest x-rays. The model is trained for a few times with chest x-ray images during the training phase. As the COVID-19 samples are imbalanced, 2D CNN was used for classification. Convolutional neural networks (CNN) [4] are powerful feed forward neural networks used in machine learning because of its great precision, CNNs are applied for image classification and prediction.

II. RELATED WORKS

Many researchers applied machine learning techniques to detect various diseases from X-Ray images.

To categorize COVID-19 and healthy chest X-ray pictures Ismael and Sengur [5] used deep-learning-based methodologies, such as deep feature extraction, fine-tuning of pretrained convolutional neural networks (CNN), and end-to-end training of a created CNN model. Deep CNN models were used to extract deep features, and support vector machines (SVM) classifiers with different kernel modules, such as Linear, Gaussian, Cubic, and Quadratic were used to classify the deep features. The aforementioned pre-trained deep CNN models were used for fine tuning procedures. The accuracy of classification was utilized to assess the study's performance. According to the experimental results, extracted features from the SVM classifier and ResNet50 model with the linear kernel function had a 94.7 percent prediction accuracy, the fine-tuned ResNet50 model had a 92.6 percent result, and end-to-end training of the developed CNN model had a 91.6 percent result. Different SVM classifications and local texture descriptor, as well as alternative deep techniques, were employed to compare performance. The findings show that deep techniques are more effective than local texture descriptors in detecting COVID-19 in chest X-ray visuals.

Support vector machine (SVM) and deep feature were used to detect coronavirus infected individuals using X-ray pictures in a study by Sethy and Behera [6]. SVM is used for classification. The methodology consists of three categories of X Ray images, i.e., COVID-19, pneumonia and normal or healthy and it is beneficial for medical practitioners to classify among the COVID-19 patient, pneumonia patient and healthy normal people. For detection of COVID-19 SVM is evaluated using the deep features of different 13 CNN models. The highest accuracy obtained by ResNet50 and SVM is 98.66% where In traditional image classification method, LBP and SVM achieved 93.4% of accuracy.

Panwar et al. [7] used a deep learning neural network-based method called nCOVnet, which is a highly quick screening method for detecting COVID-19 by evaluating patient X-rays and screening for visual markers identified in COVID-19 patient's chest radiography imaging.

A deep convolutional neural network (DCNN) frameworks [8] for automatic binary classification of pneumonia image detection on fine-tuned models of (VGG16, VGG19, DenseNet201, Inception ResNetV2, Inception ResNetV3, Resnet50, MobileNetV2, and Xception) were tested using CT datasets and chest X-Ray containing both pneumonia and normal data and it has been shown that the fine-tuned versions of Resnet50, MobileNetV2 and Inception ResnetV2 have high performance with rate of increase in training and validation accuracy which is more than 96% of accuracy.

Santoso and Purnomo used customized deep neural networks based on the suggested Xception model in their experiment [9].The model is used to detect COVID-19 based on chest X-ray scans.The proposed model employs two stacks of two dense layers as well as batch normalization, and its performance is compared to Resnet50, InceptionV3, and Xception. Despite consuming high computational time, from the experimental result it shows that it has better performance.

The work of Boddu et al. [10] utilizes cutting-edge technologies to improve cancer patient diagnosis, therapy, and care using improvements in artificial intelligence (AI) and machine learning algorithms (ML).

AI and machine learning are being utilized to aid in the epidemiology, medical diagnosis, molecular research, and the development and treatment of COVID-19 medications. AI-based algorithms can detect COVID-19-related pneumonia [11] in CT scans with high specificity and accuracy, as well as differentiate non-COVID related pneumonia.

From the study of the related works, it is observed that there exists multiple machine learning approaches (specifically deep learning techniques) for detecting various diseases like COVID-19, pneumonia, lung cancer from X-Ray and CT scan images. And also used different deep learning and neural network [12] based methods for example :- nCOVnet , to make the scanning faster for detecting COVID-19.

III. PROPOSED MODEL

The proposed model is designed to perform Covid-19 detection in six steps which are performed sequentially as demonstrated in fig. 1 below. Chest X-Ray images of both normal patient and COVID infected people are taken as input in this approach. After completing the pre-processing of raw images, the proposed algorithm is implemented to perform the COVID detection task. In this section, the algorithm implementation is briefly described along with the training and testing of the model.

A. 2D CNN in X-Ray Image Processing

Convolutional neural network (CNN) is widely used by current researchers in medical research in various organ systems including chest, brain and breast. In addition to other disease identification, COVID-19 identification is well known and noticeably used because of the need to introduce

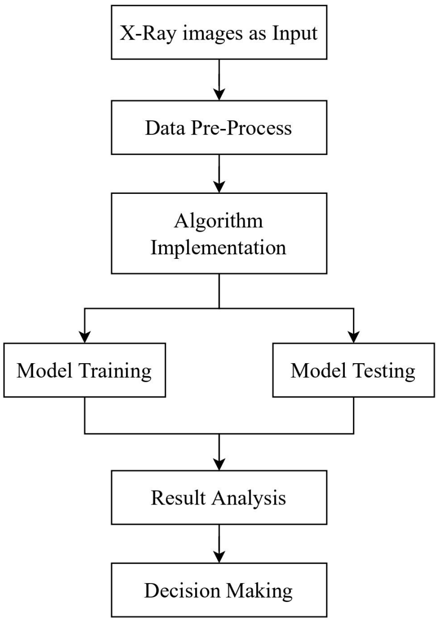


Fig. 1. Proposed workflow for Covid - 19 detection from X-Ray

alternatives to identify the case as soon as possible. Dependencies on testing kits can be reduced significantly if a patients' COVID infection is determinable from images of lung X-Ray. Keeping that in mind, 2D CNN was proposed for processing the images and forming a dependable outcome.

Convolutional neural networks (CNNs) can be expressed as a subsection of artificial neural networks where both take images as input. From this possession, some of the properties of artificial neural networks are used in the CNN architecture. A hierarchic image feature presentation based on numbers of layers is the core of this algorithm. Differentiable functions are iterated through various activities in different layers of the images. Convolutional layer, the nonlinearity layer, the pooling layer besides fully connected layers are mainly combined to form the CNN architecture which enables the scope to work with image data.

B. Workflow

As represented in fig. 1, initially X-Ray images of covid patient and normal people were collected from the used dataset. Since, two different types of data were already separated in the used dataset, so there is no need to classify them further. However, to increase the number of data, various augmentation techniques were used in data preprocessing. Once there was enough data to work with, separation was done to perform training the model and testing it. The dataset used for testing was kept completely unknown in the model until the test stage. Once test results were generated, further analysis were performed to confirm the accuracy of the model and finally making a decision on whether a given patient is covid infected or not.

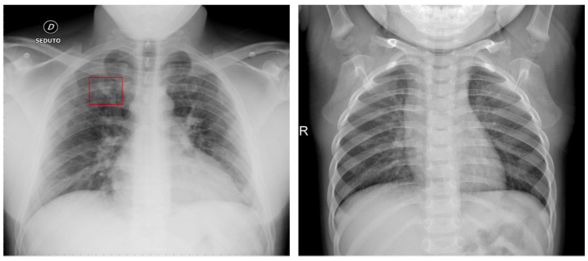


Fig. 2. Covid - 19 and Normal patience chest X-Ray

IV. DATASET DESCRIPTION

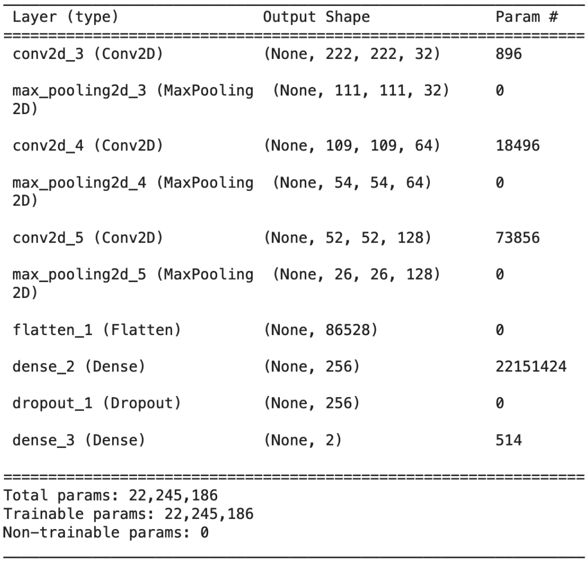
In this section, the collected dataset will be briefly described, the source and authenticity of it. Preprocessing the dataset along with how the uniqueness among the data is identified is demonstrated here. At the end, the way of data shaping was discussed.

A. Dataset Collection

A well organized dataset [13] containing 4558 X-Ray images from mendeley data has been used in this project. Identification of COVID-19 patience from chest X-Ray images are more efficient and so we have used 2 classes among 4 to differentiate the COVID-19 and normal X-Rays. Here,out of 4558 images, 3270 were healthy chest X-Ray results and 1656 items were collected from COVID-19 affected people. The dataset is available for all. The images are already proven as authentic and labeled with the X-ray observations. This annotated dataset is a combination of an already existing two more separated dataset; COVID-19 chest X-Ray, collected from Covid patiences and chest X-Ray dataset containing normal people's chest X-Ray images. Posterior Anterior, Anterior Posterior Supine and Anterior Posterior views of lungs are demonstrated in the collaborated images. However, in this approach, Posterior Anterior view has been considered to train the model and test the accuracy eventually.

B. Dataset Processing

Preprocessing the dataset was needed because of not having united dataset. In two parts the work is performed where identification of unique data is the first part and resizing them according to the need is the last part.



```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 222, 222, 32)      896

max_pooling2d_3 (MaxPooling  (None, 111, 111, 32)      0
2D)

conv2d_4 (Conv2D)            (None, 109, 109, 64)      18496

max_pooling2d_4 (MaxPooling  (None, 54, 54, 64)        0
2D)

conv2d_5 (Conv2D)            (None, 52, 52, 128)       73856

max_pooling2d_5 (MaxPooling  (None, 26, 26, 128)       0
2D)

flatten_1 (Flatten)          (None, 86528)             0

dense_2 (Dense)              (None, 256)               22151424

dropout_1 (Dropout)          (None, 256)               0

dense_3 (Dense)              (None, 2)                 514

=================================================================
Total params: 22,245,186
Trainable params: 22,245,186
Non-trainable params: 0
_________________________________________________________________
```

Fig. 3. Model Summary

1) Unique Data Identification: Since there is a huge number of images to work with, it was easier to identify the uniqueness among them. After leveling the images with the help of convolutional neural network (CNN), the dataset was divided into train_set, val_set for validation and test_set into a 70%, 20% and 10% ratio respectively. However, this data was not good enough to have an efficient model. Thus, shapes were given and reforming techniques were applied to increase the number of dataset images.

2) Shaping Data: Since the chosen data was not in the same size and color, the data was resized. the images were resized into 224 x 224 pixels size. RGB reordering is used to have the sizes. The data augmentation technique was used to increase the amount of data with smaller modifications of unique features by vertical and horizontal flipping and also applied to have enough images to work with. Finally, a significant amount data was added to the number of images for training_dataset and testing_dataset. These additional works gave the dataset more diversity and would make this model efficient.

V. EXPERIMENTAL SETUP

A. *Training Model*

Model summary [14] fig. 3, the "Output Shape" column indicates the output of each layer. The number of parameters that are taught for each layer is displayed in the "Param #" column. All Max_Pooling2D layers have zero parameters, indicating that they do not learn anything. By identifying the maximum values for each 2 × 2 pool, it is used to minimize the model's complexity and extract local characteristics. The first conv2d layer provides a output of (222, 222, 32) and max_pooling2d gives an output of (111, 111, 32) form. The second conv2d layer outputs a shape of (109,109,64) for the max_pooling2d layer input. Each filter with a shape is subjected to max_pooling (54, 54). The pool size in the model for the max_pooling_2d layer is 2 x 2, hence the form of the data will be (54, 54), which is (109 / 2, 109 / 2). Similarly, the input form for the second Max_Pooling_2D layer (max pooling2d 1) is (52, 52, 128). The resulting output shape after performing a 2 x 2 pooling is (26, 26, 128), as displayed in the "Output Shape" column. there are two Con2D layers in the model, and the first Conv2D layer value is 896, while the third Conv2D layer parameter is 18496. The Flatten layer learns nothing because the number of parameters is 0, hence the number of parameters is 0. However, it is intriguing to learn how the output is calculated. As you can see, the flatten layer's input has a shape of (None, 86528). In training model, there are two Dense layers. The input channel for the first dense layer is 86528, while the output channel is 256. The formula for calculating the dense layer's parameter number is:

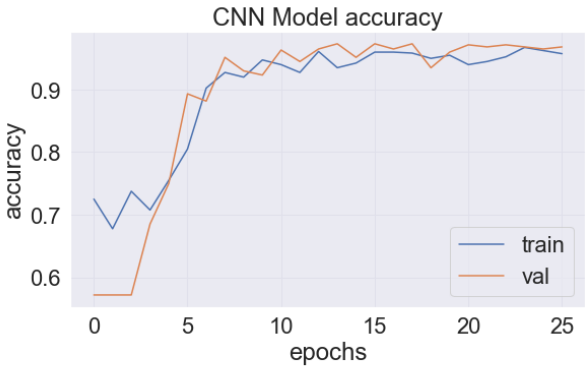


Fig. 4. Model Accuracy

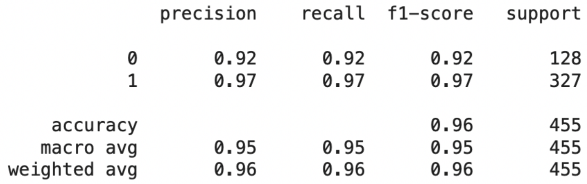
$$PN = OCN * (OCN + 1) \tag{1}$$

Where PN = Parameter_Number, OCN = Output_Channel_Number

The number of parameters in dense layer is 256 * (86528+1) = 22151424.

VI. RESULT ANALYSIS

We have trained our custom 2D CNN model, while training the model it has been achieved stability at 25 epochs without over-fitting. On the basics accuracy



```
              precision    recall  f1-score   support

           0       0.92      0.92      0.92       128
           1       0.97      0.97      0.97       327

    accuracy                           0.96       455
   macro avg       0.95      0.95      0.95       455
weighted avg       0.96      0.96      0.96       455
```

Fig. 5. Classification Report

[15], precision, recall and f1 score we have evaluated model's performance. The validation and training accuracy has intersected at 4th epoch with a accuracy of 0.78. After that, the accuracy has been increased till 25th epoch and reached at it's peak point fig. 4.

A Classification report is made use of for evaluation purpose. The classification report fig. 5 is generalized to find out the quality of the prediction from the 2D CNN classification method. Precision and recall are two most important models of evaluation metrics.

Precision value refers to the relevance percentage of the predicted value. Healthy or normal people have a precision value of 0.97 and it is predicted correctly compared to the other one. Even though the predicting covid patient has a precision score of as low as 0.92, this classification did not distinguish these two classes equally.

Recall Validates the percentage of total relevant accurate results classified by the model. The recall value for Healthy sample detection is 0.97 which means it was predicted correctly most of the time but covid positive sample was predicted right almost half of the times with a recall score of 0.92.

Normal people have an f1-score of 0.97 which makes the prediction almost accurate. Whereas, 0.92 is the f1-score of covid people which is less accurate than the other one. By analyzing the score of f1-score, not both classes were equally predicted accurately with this model.

The confusion matrix of fig. 6 shows that among 417 test samples for the normal patients, 317 of them were predicted accurately and among 128 for covid patients, 118 samples were classified accurately.

From the result, 97% of normal patients were detected successfully whereas 92% of the time covid patients were detected accurately. The accuracy, macro avg, and weighted avg for this model were also calculated. The model has accuracy of 0.96, macro average and weighted average of 0.95 and 0.96 respectively. The weighted average shows that the dataset is quite balanced.

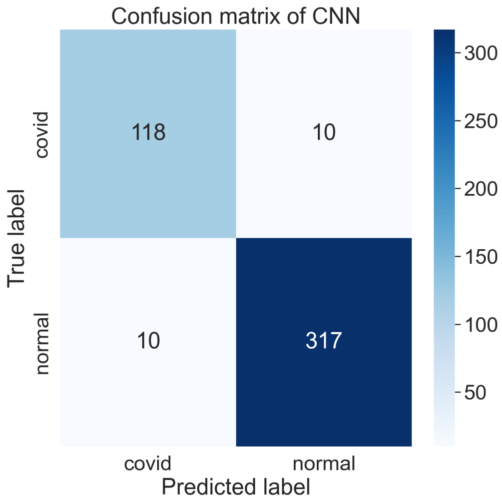


Fig. 6. Confusion Matrix

TABLE I
ACCURACY COMPARISON ON TEST SET

Model	**Accuracy**	**Precession**	**Recall**	**F1**
CNN	95.60%	95%	95 %	95%
MobileNetV2	92.75%	95%	87%	90%

We have used a pre-trained model MobileNetV2 to compare with our model. The table I shows that accuracy and f1-score are 92.75% and 90% for MobileNetV2, whereas our model has obtained 95.60% accuracy and almost 5% higher f1-score from MobileNetV2.

VII. CONCLUSION AND FUTURE WORK

Covid has wide spread all over the world in recent years. It is very important to detect covid as early as we can. A scan of the lungs can show signs of covid. This model helps to detect covid using 2D CNN from X-ray images. Also, this model can detect lung infection just by taking an xray of the lungs of any person. It can give almost 96% accuracy. We have a plan to increase the accuracy in future by giving the model more data and training it for longer hours. The scope our proposed model is huge. Now, It was used to detect covid only but it can be used to detect almost any form of disease using medical imaging. Detection of Cancer, Tooth decay, Tumor or anything that can be diagnosed from X-Rays is possible using this method. With higher accuracy it can also be used in real world medical diagnosis. Anomalies which were even harder for doctors to find will be easy with this model.

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