COVID-19 DETECTION USING TRANSFER LEARNING APPROACH FROM COMPUTED TEMOGRAPHY IMAGES

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Abstract — Our main goal in this study is to propose a transfer learning based method for COVID-19 detection from Computed Tomography (CT) images. The transfer learning model used for the task is a pretrained Xception model. Both model architecture and pre-trained weights on ImageNet were used. The resulting modified model was trained with 128 batch size and 224x224, 3 channeled input images, converted from original 512x512, grayscale images. The dataset is the COV19-CT-DB. Labels for COVID-19 detection. Firstly, a accuracy and loss on the validation partition of the dataset as well as precision recall and macro F1 score were used to measure the performance of the proposed method. The resulting Macro F1 score on the validation set exceeded the baseline model.

Keywords — Transfer Learning, Xception, CT Images, COVID-19 Detection, Macro F1 Score

I. INTRODUCTION

Machine learning has been evolving continuously in different fields. Applications of machine learning include fields such as image and speech recognition, product recommendation, prediction models of different sorts. These various applications are used in economics, politics, healthcare, and engineering systems, and in a plethora of other areas in real life [1].

In healthcare, recently COVID-19 has been classified as a new pandemic. COVID-19 is a virus that first appeared in 2019 in the city of Wuhan, China. COVID-19 was caused by the SARS-CoV-2 virus. Since its first appearance, as of February 2022, 396.5 million people have been infected with this virus. At the same time, 5.7 million people all over the world lost their lives due to the virus or the secondary diseases it causes. Early diagnosis is vital for the effective treatment of the virus and the diseases it causes [2].

The Polymerase Chain Reaction (PCR) test has some disadvantages. These are supply costs, machinery fees, training expenses and also PCR tests sometimes may not give accurate results. [3] Due to these problems and the preventable results brought by these problems, it has become a necessity to bring alternative methods to the PCR test. Our proposed and compared solutions to the aforementioned problem was to design various prediction algorithms using image processing techniques, machine learning tools and to compare their performances.

Our main contributions in this paper are listed below:

- We propose a transfer learning feature extractors modified in the output for COVID-19 detection.
- We help to make data-driven decisions on a challenge and bigger dataset for COVID-19 detection.

II. RELATED STUDIES

Different imaging modalities are used to determine the diagnosis of COVID-19 such as Computed Tomography (CT) and X-ray. X-ray modality is preferred for reasons such as the fact that the images are quick to be produced and low in cost. For this reason, many researchers have included X-ray in their studies. What is more, transfer learning model architectures have been essential parts of much of the medical domain [4].

In a study conducted in 2020, a limited number of (a total of 1000) X-ray images of patients infected with COVID-19 and a number of other collective data of none-infected patients were collected and used. Although a small data set was employed, a 95% accuracy rate was obtained using VGG16 transfer learning model [5].

In a recent study, COVID-19 diagnosis was achieved using a data set consisting of 4-class X-ray images. The model used was called COVID-ResNet. In the data set, there were a total of 5941 X-ray images from 2839 patients. COVID-ResNet model, reached an accuracy of 96% [6].

Yet in another study conducted in early 2021, a novel method was designed for the diagnosis of COVID-19. The method tested the design of Self-Supervised Pretraining using Momentum Contrast Learning algorithm, help from radiologists was taken and the answers of radiologists in the diagnosis of images were compared with the results of the final model’s results. The work shows that Self-Supervised Pretraining using Momentum Contrast Learning algorithm has a much better accuracy rate than human radiologists. This Self-Supervised Pretraining using Momentum Contrast Learning algorithm, which was designed because radiologists can recognize tissues and differences that they do not see, has been clinically tested and forms a basis that can be used in the diagnosis of different diseases [7].

Finally, in another study which used a dataset from the kaggle website named “COVID-19 Radiology Dataset”, performances of different pre-trained deep learning networks are compared to identify the best deep learning technique in terms of extracting the various COVID-19 manifestations [8].
The results also showed the superiority of VGG16, MobileNet, DenseNet169, and InceptionV3 in identifying COVID-19 CXR images with a high sensitivity and accuracy. However, excellence in high performance remained besides VGG16 with high precision.

Our work uses partially the same dataset mentioned in the last study [8] and combines it with other public data for a sufficient size of training data, aiming at comparing transfer learning approaches for COVID-19 diagnosis.

III. THE DATASET

The dataset used in this paper is an extension of the COV19-CT-DB database. The COVID-19-CT database includes annotated CT scan for COVID19 detection. It includes 1,650 COVID annotated cases and 6,100 Non-COVID annotated cases. The dataset corresponds to more that 1150 patients. The number of COVID slices is 724,273 and the number of Non-COVID slices is 1,775,727. The annotation was performed by experts of more than 20 years (4 of them). Each CT scan includes between 50 to 700 slices. In here we use training and test sets (partitions) of it. The dataset is provided via “ECCV 2022: 2nd COV19D Competition” [9] [10] [11] [12] [13] [14].

The training set contains, in total, 1992 3-D CT scans and the validation set consists of 494 3-D CT scans. The number of COVID-19 and of Non-COVID-19 cases in each set are shown in Table I.

| Annotation    | Training Data | Validation Data |
|---------------|---------------|-----------------|
| COVID-19 cases| 882           | 215             |
| Non-COVID cases| 1110         | 289             |

IV. METHODOLOGY

The Xception architecture has 36 convolutional layers. These layers are used for forming the feature extraction base of the network. The model was borrowed through “keras.applications.xception”. The Xception transfer learning approach was followed by a modified output architecture. The input images were all 224x224, 3-channeled. The original images were grayscale of size 215x512.

The model output architecture includes in sequence: a global average pooling, dense layer with 128 filter and a Rectified Linear Units (ReLU) activation, batch normalization, 0.2 dropout, and a dense layer with “sigmoid” activation function and (output unit = 1). Summary of the full Model (method) is shown in table II:

| Layer (Type)             | Output Shape   |
|--------------------------|----------------|
| xception                 | (None, 7, 7, 2048) |
| global_average_pooling_2d| (None, 2048)   |
| Dense_2 (dense)          | (None, 128)    |
| batch_normalization_13   | (None, 128)    |
| Dropout_1 (Dropout)      | (None, 128)    |
| Dense_3 (Dense)          | (None, 1)      |

Total number of parameters is 21,124,393, trainable parameters number is 262,657.

The Xception model was used with 3 channeled input, leveraging the pretrained weights on image net model. In other words, the model’s weights were made non-trainable during the training of our work. On the other hand, call backs were used during the training to reduce the value of the learning rate given undesirable conditions. “ReduceLROnPlateau” call back was used with (monitor=‘val_loss’, factor=0.5, patience=2). The model was compiled on keras with Adam optimizer (learning rate = 0.001) and the loss function was “binary cross entropy”. Finally, the number of epochs was chosen to be 13. The number of epochs is a result of trials and is manually set.

Training the CNN model using a batch size of 128 over 13 epochs took about 7 days over a workstation using GNU/Linux operating system on 62GiB System memory with Intel(R) Xeon(R) W-2223 CPU @ 3.60GHz processor.

V. RESULTS

The task presented for all the three approaches is a binary classification task from CT images aiming at COVID-19 detection. Our results show that the modified Xception model yields an average validation accuracy of 0.74751.

Fig. 1 shows the evolution of train and validation accuracy, and Fig. 2 shows the evolution of train and test precision and recall for the same model.
Table III further shows other performance from the model training.

| The measuring matrix          | The result |
|-------------------------------|------------|
| Average Training Accuracy     | 0.97337    |
| Average Recall                | 0.78862    |
| Average Precision             | 0.77613    |
| Macro F1 score                | 0.78232    |

The Macro F1 score was calculated as in Equation 1:

\[
\text{macro F1} = \frac{2 \times \text{average precision} \times \text{average recall}}{\text{average precision} + \text{average recall}}
\]

*Equation 1*

The Macro F1 score came at 0.78232 exceeding the baseline score of 0.77[14].

Furthermore, in an attempt to report the confidence intervals of the results obtained, the Binomial proportion confidence intervals for macro F1 score are used. The confidence intervals were calculated from the following formulation:

The residuals of the interval can be calculated as in Equation 2 [16].

\[
\text{radius of interval} = z \times \sqrt{\frac{\text{macro F1} \times (1 - \text{macro F1})}{n}}
\]

*Equation 2*

In the above formulation, \(z\) is the number of standard deviations from the Gaussian distribution, which is taken as \(z=1.96\) for a significance level of 95%. By that we can calculate the confidence interval for the macro F1 score (approximately 0.78) as in Equation 3:

\[
\text{interval} = 1.96 \times \sqrt{\frac{0.78(1 - 0.78)}{106378}} \approx 0.00024
\]

*Equation 3*

The number of samples (slices) in the validation set is 106,378. The result from the last equation shows sufficient confidence in the resulting macro F1 score, i.e. the macro F1 score can be said to be 0.78232 ± 0.00024.

VI. CONCLUSION AND FURTHER WORK

In our paper, we used a transfer learning model for COVID-19 detection via CT images. Based on the experiments and the results we obtained, we concluded that the Xception pretrained model with modified output is effective model for our task. The method was verified on COV19-CT-DB database. The macro F1 score on the validation set exceeded the baseline method.

The methodology in this paper and the results were presented at the slice level. In order to make predictions at patient level, CT scan volume level, different class probability threshold can be tested against the output of the model to decide whether a slice is a COVID or NonCOVID. Next majority voting per CT scan can be used to take final diagnosis at patient’s level.

Further work includes trying other dataset to validate the model performance. One possible aspect is trying the same models on a different dataset. Different image modalities can be compared to help obtaining better results. Another aspect to be tried is hyperparameter tuning, such as choosing a higher number of training epochs. In light of these directions, the proposed methods can be improved to be made suitable for clinical use.
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