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Efficient Classification Approach Based on COVID-19 CT Images Analysis with Deep Features

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***Abstract*—Currently, a new coronavirus(COVID-19) has affected millions of people worldwide. For this reason, it's not sufficient that radiologists can slow down the virus spreading manually. Convolutional Neural Networks (CNNs) can be utilized as a tool to aid radiologists in diagnosing COVID-19 images, which consequently can save efforts and time. In this work, a dataset of CT images of confirmed and negative COVID-19 was used for the screening of COVID-19. Some preprocessing operations were applied to enhance the COVID-19 CT images which aim at including only the Area of Interest (AOI). This was accomplished in three stages. First, a conversion of the CT images to the binary scale was performed by applying a global threshold algorithm. Then, the median filter algorithm was applied to remove random noise. Then, we include only the ROI (the lung) and exclude other parts of the images. Finally, we applied VGGNet 19 to extract features from the preprocessed CT images, which is a popular CNN architecture, trained previously on ImageNet. The proposed pipeline showed high performance by achieving 98.31%, 100%, 98.19% and 98.64% of accuracy, recall, precision and f1-score, respectively. To the best of our knowledge, these results are the best published on this dataset when compared to a set of recently published works. Also, the proposed model overcomes several popular CNNs architectures.**

***Index Terms*—COVID-19, Convolutional Neural Networks, VGG 19, Image analysis, Transfer Learning, CT images**

I. Introduction

By the end of 2019, the Coronavirus, COVID-19 started spreading which began in Wuhan in China, then reach most countries by March 2020 which declared to be epidemic by the World Health Organization (WHO) [11]. Currently, every health organization worldwide does its best to control and tackle it by finding a treatment to heal patients as its complications can cause death.

There are no accepted treatments or vaccines for it so far, but several clinical therapeutic tests are performed on a large scale to find a treatment.

Recently, Convolutional neural network (CNN), which considered a deep neural network structure, showed advantages in imaging, especially, image segmentation and classification tasks [15]. VGGNet is one of CNN structures that was founded by Simonyan at the Oxford University in 2014 [18]. VGGNet achieved the highest performance in computer vision tasks in ILSVRC competition in 2014. VGGNet was trained previously on ImageNet dataset which has both diversity (1000 categories of images), massiveness (1.3 million images). VGGNet achieved 92.7% of accuracy in recognition in the tested images in ImageNet. Besides, it showed advantages in several image-based real-world applications.

Image-based medical tests can save much time for COVID-19 detection, which can minimize and consequently control the spreading of the infection. Chest X-ray (CXR) and Computed Tomography (CT) can be considered the main types of images that can play a significant role in beating COVID-19. Unluckily, CT scans are usually private and could not be publicly accessed due to patients' privacy. For this reason, to support the development of computer-aided diagnostic systems, a little number of COVID-19 CT images become available for research purposes by doctors and researchers from different countries. An Image-based screening approach has been applied to diagnose many severe diseases using X-ray or CT images long time ago, however, little number of works have tackled COVID-19, specially using CT images.

In [2], a detection of COVID 19 were performed using patches sized as 16x16, 32x32, 48x48, 64x64 from CT images. The extracted features include Grey Level Co-occurrence Matrix, Local Directional Pattern, Grey Level Run Length Matrix, Grey-Level Size Zone Matrix, and Discrete Wavelet Transform , while the classifier were Support Vector Machines. Several cross validation folds were applied (2, 5, 10 folds), as well as several classification metrices such as accuracy, Sensitivity, specificity, precision, and F-score. The results showed that the best performance was obtained with 10-fold cross-validation on GLSZM features. Also, in In [17], the authors tried to answer the question, can COVID 19 pneumonia (CT scan images) be differentiated from other viral pneumonia? Also, how to distinguish it? The data of lung CT scan from the

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hospitals of Italy, Moscow, China and India were carefully selected. The model was built, trained and tested using prebuilt software environment based on machine learning algorithms of Microsoft azure. The proposed approach achieved 91They suggested that their approach can be used for early detection of COVID 19 because it takes less time (no need for blood sample collection or shipping issues).

Yang et al. [26] proposed a system to test the severity on chest tomography for distinguishing different COVID-19 clinical forms. The performance of the model showed sensitivity and specificity of 83.3% and 94.0%, respectively.

Li et al. [9] used a technique starts with counting acute lung lesions affect each lobe, using overall sensitivity of 82.6% and a specificity of 100.0% using two views (axial, coronal) of lung CT severity index.

Zhou et al. [27] implemented an examination using a semi-quantitative evaluation method of the non-contrast CT Severity Index (CTSI) of 62 COVID-19 patients. The proposed model showed advantage in COVID-19 detection performance in progressive stage than the other stages.

Farooq et al. [7] Used ResNet50 for classifying Chest-X-Ray images to different categories; normal (negative), COVID-19, pneumonia (bacterial) and pneumonia (viral). It was reported that the proposed approach shows advantages compared to COVID-net by achieving 96.23% and 100% of accuracy and sensitivity, respectively.

The main findings of this work can be summarized as follows:

1) Propose an image-based classification pipeline for distinguishing COVID-19 using a CNN along with image analysis and enhancement techniques.
2) Test the proposed technique on a public CT image dataset with both positive COVID-19 as well as negative COVID-19 cases.
3) Validate the proposed technique by comparing it's performance to both, other popular CNN architectures and most recent relevant works on COVID-19 for CT images.

This paper doesn't present a medical tool for COVID-19 diagnosis, but offer a machine-learning based technique for COVID-19 classification purposes based on CNN and image analysis techniques. This work might be considered a computer-aided tool for clinical screening (image-based) in the near future. Remainder sections of this work are organized as follows: Section II presents the material and methods used in this work. The experiments and their results are presented in Section III, while the discussion of the results is presented in Section IV Finally, the conclusion is presented in Section V.

II. Material and Methods

A. Data Preparation and Preprocessing

In this work, We use the dataset of CT images that consists of two classes, COVID-19 positive images and Lung nodules positive images.

In this subsection, we applied some image Preprocessing techniques that aim at improving images by removing unwanted parts while preserving all image details too.

As known that some medical images can be low contrast with lots of variations in terms of scaling, illumination and color scales, so image preprocessing techniques have to be applied carefully to avoid distortion of valuable information inside the images.
To achieve such a target, the following processing techniques have been applied:

1- Image conversion: Each image was converted from gray to the binary scale using the global threshold method as in [21].

2- Noise removal: Median Blur filter technique [24] was applied to restore image pixels distorted by salt and pepper noise , Where the filter smooths image with kernel size.

3- Cropping: To exclude all unneeded areas from the images and keep only the Area of Interest (AOI), a simple technique was applied. First, We found the most top area (row and column) that contains foreground, then we found the most button (row and column) point that is considered as a foreground also. Finally, cut the images based on them, so we preserve only the foreground. The results of applying the image preprocessing techniques are shown in Table I.

B. Convolutional Neural Network (CNN)

We used CNN to extract the features from our images. A pre-trained model called VGG 19 was used, which consists of (3×3) 16 convolution layer, 3 fully connected layers, and 5 max pooling. Used kernels of (3×3) size with a 1-pixel stride size, which enables covering the whole CT image. Spatial padding was added to preserve the spatial resolution of images. Max pooling was also performed over a (2×2) pixel window with a Stride of 2. That was followed by a Rectified linear unit (ReLu) to enable non-linearity, which consequently achieve both; enhance the model performance and minimize computational time. RELU showed advantages over Sigmoid and Tanh functions for many classification problems. Also, there are three fully connected layers, two of them are of size 4096, while the third contains 1000 channels. The final layer is a Softmax.

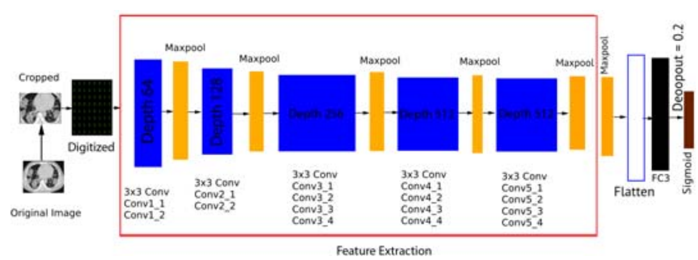

Fig. 1. Model Architecture

When loading a transfer learning model, the fully connected layers should be removed, which are responsible for the classification of ImageNet dataset, then adapt it based on

TABLE I
SAMPLES FROM COVID-19 IMAGES BEFORE AND AFTER APPLYING PREPROCESSING OPERATIONS

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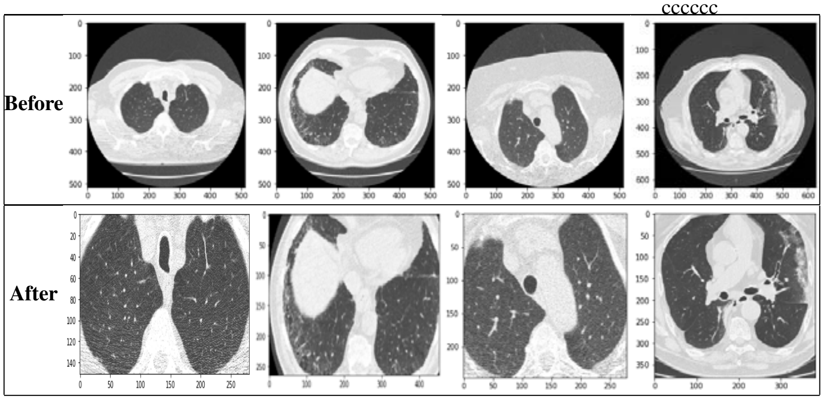

TABLE II
TABLE TYPE STYLES

Feature	value
Max pooling layer	2×2
Convolution stride	1 pixel
Padding stride	2 pixel
Rectification	ReLU
Total layers	21 layers

our problem, which is a binary classification in this paper. Then one max-pooling layer is added with a (2×2) pixel window with a stride of 2, followed by one fully connected layer (FC3) with 294,976 nodes Which is followed by a layer called "dropout" to avoid over-fitting. with $(p = 0.2)$ followed Finally by a Sigmoid classifier to perform the output. We used the RMSprop optimizer for weight updating, cross-entropy as a loss function, and assign 0.001 as a learning rate. The network has a total size of 295,041 trainable parameters.

C. Dataset description

The data used in this work comes from two different publicity available datasets; the Italian Society of Medical Radiology [10] for COVID-19 CT images. The images were collected from patients of age between 20-86 years old from Italy.

While Due to the lack of non-COVID-19 (normal) CT images, we used a CT for Lung nodule disease, which is available from Vision and Image Analysis Group [22]. The images were taken from a single breath-hold with a slice thickness of 1.25 mm.

The whole number of images used in the experiments contains 591 CT images. 206 images for COVID images and 385 lung nodules images.

D. Validation criteria

To validate the proposed approach, we used accuracy, precision, recall, f1-score metrics The formulas of these measures are as follows:

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

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

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

$$F_1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Where "TP" (True Positives) refers to the CT images that are correctly labeled as COVID-19 by the model, while "TN" (True Negatives) is the number of CT images that are correctly classified as Lung Nodule disease by the model. "FP" (False Positives) are the number of CT images that were incorrectly labeled as COVID-19 by the model, while "FN" (False Negatives) is the number of images that were incorrectly classified as Lung Nodule disease.

E. Implementation environment

The proposed technique was implemented using Python 3 on Windows 10 64 bit virtual machine using Core i7 with 24 CPUs and 224 GB RAM. The model was developed using the Keras library [4] with a Tensorflow backend [1].

III. RESULTS

Our experiments have been performed on 70% of the images used for training the proposed approach, while 30% of the images were used for testing (Validation). All results present in this work were performed on the testing data. We use K-fold cross-validation with 10 folds to avoid over-fitting.

A. Performance of the proposed technique

In this subsection, we perform experiments to figure out how the proposed technique performs. This is done by comparing the proposed technique which is mainly based on VGG 19 with the basic VGG 19 model. Table III shows a comparison between the proposed technique and VGG 19.

Table III shows that the proposed technique outperforms the basic VGG 19 in Accuracy, recall, precision and F1- score. For

TABLE III
PERFORMANCE OF PROPOSED APPROACH AND VGG 19

Performance	VGG 19	Proposed approach
Accuracy	96.62%	**98.31%**
Precision	95.61%	**98.19%**
Recall	99.09%	**99.09%**
F1-Score	97.32%	**98.64%**

more analysis of the proposed technique's performance, we show the confusion matrix for both, the proposed technique and the basic VGG 19 model.

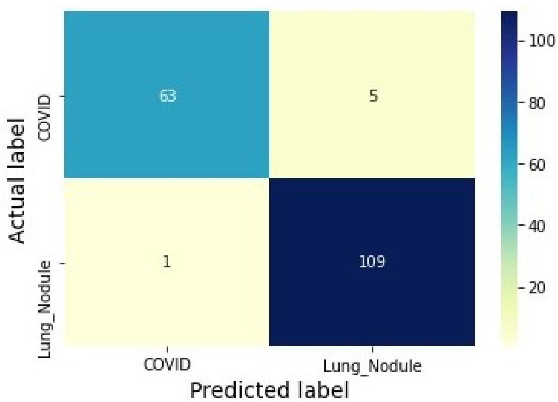

Fig. 2. Before Segmentation

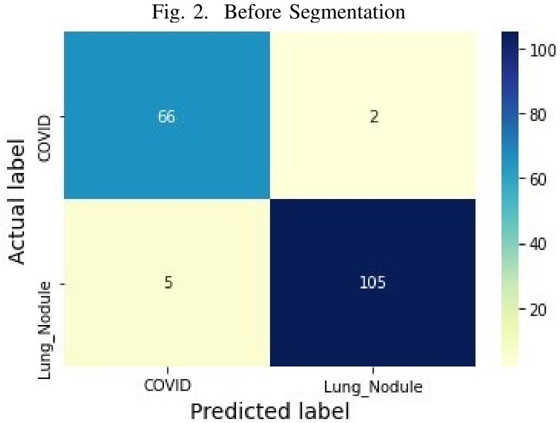

Fig. 3. After Segmentation

Fig. 4. Model Confusion Matrix

Figure 4 shows that the basic VGG 19 model miss-classifies 5 images of COVID-19 and predicts them as Lung Nodule, While the proposed technique miss-classifies only 2 images as Lung Nodule. The total number of truly predicted images for both classes in the basic VGG 19 are 172, while in our technique, it reaches 171.

B. comparison with other CNNs

In this subsection, we compare the performance of the proposed technique to other CNN structures in terms of accuracy, recall, precision and F1-score. Most compared CNNs has more complex architecture than ours in terms of structure and consequently, the feature set produced. For example, MobileNet-V2 [16] which produces 50 K feature vector, while Inception-V3 [20], Xception [3] and ResNet 152 [8] which produce a feature vector size of 51 K, 100 K and 100 k, respectively. While VGG 16, VGG 19 and the proposed technique produce a feature vector size of 25 K features. The comparison is shown in Table IV.

As shown in Table IV, the proposed technique comes first compared to other CNN structures in most classification criteria. However, it's not the best in terms of storage capacity or number of trainable parameters. VGG family (VGG 16 and VGG 19) come second and third in terms of classification performance, respectively. This is aligned with as they came first in the ILSVRC challenge [12] This also matches with [14] who applied efficiently the same CNN structure it in other medical application.

MobileNet V2 is the next version of the MobileNet that shows acceptable results. This family is generated by Google which was built based on the idea of using a depth-wise separable Convolution as efficient building blocks. This aligned with [13], where also MobileNet V2 outperforms other CNNs in other medical application. ResNet 152 and Inception V3 come last in most classification metrics. ResNet 152 is the next version of Residual Network (ResNet) family generation with 152 deep layers.

C. Comparison with other related works

In this section, we make a comparison between our work and the most relevant published works on COVID-19 CT image classification. Table V shows the recent published works on the COVID-19 for CT images. It's noted that no such works have been done on CT images because it's relatively expensive and not available in most places, especially, in underdeveloped countries. Also, there are other published works on COVID-19 classification but using X-ray images such as [5], [6] .

As seen in Table V, the proposed technique showed higher classification accuracy with the least number of CT images compared to the other works. Shuai et al. [23] used a dataset consists of two classes; 325 and 740 CT images of positive COVID-19 and positive viral Pneumonia positive cases, respectively. Their pipeline consists of; Pre-processing of CT images, feature extraction of pre-processed images and training the model, then finally, classification with a fully connected network. Their model used Inception network.

While Song et al. [19] used a dataset with 2 classes: 777 images of confirmed COVID-19 cases and 505 images of bacterial Pneumonia. The proposed CNN technique consists of three main phases. First, feature extraction of the lungs, then filling the blank of lung segmentation with the raw lung image to avoid noise caused by different lung contours. Finally, they applied a CNN structure called Details Relation Extraction Network to extract the main features of the CT images and obtain the image-level predictions.

IV. DISCUSSION

COVID-19 has infected millions of people from 216 countries across the world. Unfortunately, this number still rises

TABLE IV
DEEP LEARNING MODELS' RESULTS

Model	Accuracy	Precision	Recall	F1-Score	Size (MB)	Parameters	Depth (Layer)
VGG 16	97.19%	98.16%	97.27%	97.71%	528	138,357,544	23
VGG 19	96.62%	95.61%	99.09%	97.32%	549	143,667,240	26
MobileNet-V2	96.62%	94.82%	**100%**	97.34%	14	3,538,984	88
Inception-V3	66.85%	65.64%	97.27%	78.38%	92	23,851,784	159
Xception	92.69%	92.92%	92.45%	94.17%	88	22,910,480	126
ResNet 152	61.79%	61.79%	**100%**	76.38%	232	60,380,648	152
Proposed approach	**98.31%**	**98.19%**	99.09%	**98.64%**	549	143,667,240	26

TABLE V
COMPARISON WITH RECENT WORKS ON CT IMAGES

Article	Model	Number of CT images	Accuracy
Shuai et al. [23]	Inception	1065	82.9%
Song et al. [19]	Details Relation Extraction neural network (DRE-Net)	1282	86%
Sharma, S [17]	ResNet on Microsoft azure	100 axial CT images from Italy. 349 CT images from China. About 1000 CT images from Russia. About 100 CT images from India	91%
Xiaowei et al. [25]	ResNet-18	443	86.7%
Proposed approach	VGG19	591	98.3%

significantly. Accordingly, it is necessary to develop deep learning approaches that can be sufficient for detecting Covid-19 automatically which can minimize risks by preventing medical physicists from physically exposed to viral infection.

The proposed technique successfully achieves two important targets, higher performance with the least number of CT images which is efficient in terms of resources including memory usage and storage capacity. Moreover, using a few samples to build a CNN architecture is one of the challenging tasks because CNN needs too many samples to make complex relations, work efficiently and consequently, perform efficiently. This work sheds light on the importance of image pre-processing operations that can improve the entire image classification job as shown in Fig 4. Also, it's not necessarily that going deeper in terms of the model's structure, that the performance improves. As noticed in [17] and [25], both applied ResNet which is a deeper architecture of CNN than ours (VGG 19), 152 depth layers compared to only 26 layers as shown in Table V. However, our results are better (for both their and our datasets). It's obvious that a CNN architecture is based on data and there is no optimum architecture for all data type.

V. CONCLUSION

In this work, a new approach for COVID-19 classification based on CT image analysis is proposed. It's fully automated With no need for hand-crafted feature extraction or selection. The proposed technique shows high performance as it reached, accuracy 98.31%, and F1-Score 98.64%. The comparison with other CNN architectures shows that the proposed approach outperforms them. Also, compared to other related works on CT images, the proposed technique achieves better results compared to them.

We think that these results were affected positively by applying appropriate and simple image processing techniques. Applying precisely image-based algorithms that include only Area of Interest (AOI) and exclude un-needed image parts, can improve the model's performance significantly.

Our future work might include more datasets with different types of images, such as X-ray images for the same purpose, COVID-19 detection.

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