Journal of Theoretical and Applied Information Technology
15th July 2022. Vol.100. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IMPROVED DEEP LEARNING APPROACHES FOR COVID-19 RECOGNITION IN CT IMAGES

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ABSTRACT

Since the increasing risk of COVID-19, a set of actions have been achieved to develop tools to handle the spreading of the COVID-19 disease. Though testing kits were being used to diagnose the COVID-19 infection, the process requires time and the test kits suffer from being lack. In COVID-19 management,the computed tomography (CT) is considered an important diagnostic method. Taking into account largenumber of exams performed in high case-load situations, an automated method may help to encourage and save time for diagnosing and identifying the disease. Several deep learning tools have recently beendeveloped for COVID-19 scanning in CT scans as a technique for COVID-19 automation and diagnosticassistance. This article aims to explore the rapid recognition of COVID-19 and proposes an advanced deep learning technique, derived from improving the ResNet architecture as a transfer learning model. The architecture design of the proposed model is based on alleviating the connections between the blocks of the ResNet-50 model. This reduces the training time for scale-ability and handles the problem of vanishing gradient with relevant features for recognizing COVID-19 from CT images. The proposed model is evaluated using two well-known datasets of COVID-19 CT examined with a patient-based split. The proposed model attains a total back-bone accuracy of 98.1% with 97%, and 98.6% specificity and sensitivity, respectively.
Keywords: *COVID-19; CT Images; SARS-Cov-2; Deep Learning; Transfer Learning Model.*

1. . INTRODUCTION

Hardly ever has the threat of disease such coronavirus disease (COVID-19) occupied an extensive portion of our attention. COVID-19 virus was initially detected in December 2019 in Wuhan Province, China, and so far, the COVID-19 virus has indeed been reported contact-transmitted conducts with on-going pandemic affects nearly all countries with a wide-ranging global health, economic, and individualeffect. Since the COVID-19 pandemic; several procedures have been introduced globally to control the COVID-19 pandemic. Quick and precise diagnosis of infected patients, early quarantine, and follow-upare crucial factors to control and containment the COVID-19 spreading. Up to date the significant test for COVID-19 disease identification is a reverse transcriptase-polymerase chain reaction (RT-PCR). TheRT-PCR tests are time-consuming and laborious with complex manual processes [1]. More- over, the lack and accessibility restriction of RT-PCR test kits are considered risky to containment the

COVID-19 disease. Therefore, the chest imaging tool is a reliable alternative tool for COVID-19 diagnosis. Computer tomography (CT) diagnosis of COVID-19 has remarkable sensitivity potential, limited misdiagnosis level, and considerable commercial potential. However, the accuracy of the diagnosis of COVID-19 by chest scans strongly depends on experts. Often, other conditions including pulmonary infections and pneumonia can be misdiagnosed with COVID-19 by a radiologist or doctors. Therefore,artificial intelligence with the application of deep learning approach has been successfully launched, leading to faster and more accurate diagnosis of COVID-19 and are effective as an alternative to RT-PCRtesting tool [2,3,4].

The CT scans generate accurate images of organs, bones, soft tissues, and blood vessels. Internal structures can be identified using CT images, which show their form, scale, texture, and structure. The CT scans, unlike traditional X-rays, produce a series of slices of a specific area of the body without superimposing the various body components. As a result, CT scans provide a much more accurate image of the medical situation than traditional X-Rays. This specific information can be used to assess whethera medical condition exists, as well as the nature and precise location of the issue. For these reasons, several deep learning-based methodologies for COVID-19 screening in CT scans have recently been demonstrated [5,6,7,8,9,10].

Convolutional neural networks significantly improved machine and deep learning models. The convolutional layers' emergence several models such as ResNet, Xception, contrastive learning and VGG were implemented and revealed reliable outcomes [11,12,13,14,15,16]. Numerous studies in the literature have been published that depend on deep learning and convolutional neural networks modelsto identify and recognize COVID-19 with CT images.

Soares et al., developed a convolutional neural network model for COVID-19 recognition based on CT scans of 120 people (2482 CT scans) were acquired, half of whom (60 people) had COVID-19, and they were identified by several networks, the most accurate of which was close to 97.38% [17].

[6] examined 287 patients CT images, which covered three classes of COVID-19, or viral pneumonia, and healthy, and thereafter applied a novel model to detect COVID-19, they classifiedthe data with 91.6% accuracy q [6]. Lin et al., introduced the ConvNet deep learning architecture to retrieve visual features from lung CT scans for COVID-19 identification. They have implemented visual features to differentiate between infected and other not infected lung diseases [7].

However, ConvNet is unable to classify the seriousness of this disease. [5] designed a deep learning model for COVID-19 identifying and quantifying. The method automatically retrieved slices of CT chest scans opacities. The developed system achieved 98.2% sensitivity and 92.2% specificity [5].

Ling et al., introduced a deep learning tool to predict and differentiate COVID-19 from another viral pneumonia. For COVID-19 prediction, the CNN algorithm was implemented. The prediction model's maximum accuracy was 86.7% [9]. Wang et al., analysed CT scans of infected patients with radiographic modifications. They developed a deep learning-based prediction model that utilizes the modified inception transfer learning technique and the authors achieved a test accuracy of 89.5% [18].

In healthcare systems, the diagnostic process of a specific disease is essential to early obviate the severity of the disease and providing appropriate treatment. Thus, the demand for developing an effective automatic recognition model is required which is also the motivation of this study. There are variousreasons for achieving such a goal, including: (1) as a result of the pandemic outbreak, the lack of numerous highly qualified radiologists increases the need for chest x-ray interpretation, (2) increasing number of cases with various progeny and mutations of the disease that require automated tools for recognition, (3) the heavy training of the effective convolution deep learning models makes the task is not scale-ableto many images, and (4) on the CT images, the previous studies provide low performance in detecting the symptoms of the disease.

Our contribution is, therefore, to provide an advance deep learning technique for the early identification of COVID-19- infected patients from their lung CT scans images. The proposed model is based onthe effective transfer learning model called ResNet-50. The architecture design of the proposed model is based on alleviating the connections between the blocks of the ResNet-50 model. This reduces the training time for scale-ability and handles the problem of vanishing gradient with relevant features on CT images. Furthermore, it provides an effective model of high performance. The proposed model is evaluated using a combination of two publicly available CT images datasets (Soares *et al.*, 2020; Zhao*et al.*, 2020).

The rest of this study is structured accordingly. Information of COVID-CT (Zhao *et al.*, 2020) and SARS-CoV-2 CT-scan datasets (Soares *et al.*,

Journal of Theoretical and Applied Information Technology
15th July 2022. Vol.100. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2020) are given in Section 2. Section 3 describes the methods, and Section 4 presents the experiments and the promising findings. Eventually, Section 5 introduces the work's conclusion.

2 . COVID APPROACHES AND KEY PROTOCOLS FOR COVID IMAGE RECOGNITION

This section describes the improved approaches for covid image recognition by identifying and classify ing the covid image and recognizing each covid and non-covid image based on the input image; hence considered a challenging task to the difference in colors, sizes and features of the covid images. The pro-posed approach is improved by combining the ResNet architecture and FC to obtain better covid imagerecognition. The proposed algorithm shows the presented model's covid image recognition. The overallloss function of the covid image recognition for each image is represented by the loss function of the image recognition identified using the binary cross-entropy. As a result, the loss function can be foundin the input image.

In this work, the proposed approach for covid image recognition aims to recognize covid within an image to produce high-quality recognition. This approach is accomplished by improving ResNet architecture to extract more features that are high and low of a covid image; enhancing FC by addition new FC layers for enhanced recognition of covid image with improved ResNet architecture.

2.1 The architecture improvement of proposed ResNet model

This study proposes an adaptive architectural design of ResNet to boost the training process at eachlayer. As a result, it improves the ResNet backbone's capacity. The following section defines a shortcutor bypass link. Even so, there seem to be a number of issues in ResNet, including a) identifying layers that have not received sufficient training; and b) identifying layers that have received excessive training, as shown in Figure 1. The suggested backbone is discussed in the following subsections.

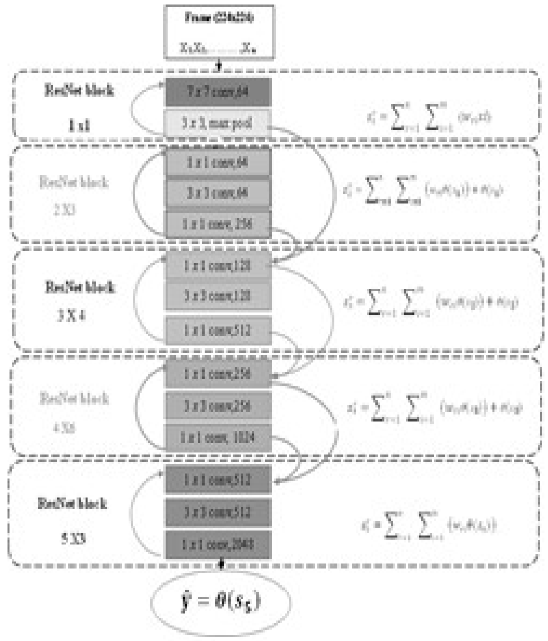

*Figure **1.** The ResNet backbone*

2.1.1 our proposed adaptive resnet architecture

ResNet is a deep learning network that comprises a sequence of blocks to handle the gradient vanishing issue for enhancing the residual neural network's performance. To
address the gradient diminishingproblem,

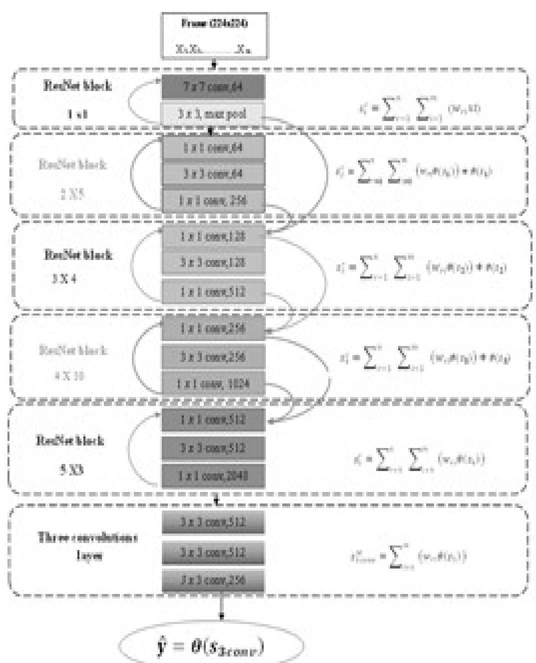

*Figure **2.** The Proposed ResNet backbone*

each ResNet block that requires further training is trained next based on the output of the previous ResNet block. This process is known as skip-connection that concatenates the feature maps of the previous ResNet block output to the next feature maps of the successor ResNet block. However, what characterises our approach is the process of adding ResNet block consecutively to the overall model ensuring at each step a high-accurate accuracy. In particular, we generate the model architecture based on how much accuracy is accomplished by attaching the ResNet blocks to the model. The proposed architecture model depends on repeating the ResNet blocks to achieve a promising accuracy value, and thenthe iteration is terminated. Adopting such a technique helps in reducing the size of the network in whichthe training time is affirmingly decreased. In addition to the feature engineering design, the proposed adaptive ResNet model has three convolution layers for extracting feature maps from shallow layers as shown in Figure 2. Hence the proposed model maintains a few ResNet blocks with high accuracy to the validation set, further dense layers in the classification part.
The FC is enhanced by extending the ResNet architecture for the classification of the covid and non-covid of different sizes in each image. The improved ResNet increases the degree of classification. The proposed enhanced FC is described in the following sub-sections.

2.1.2 Enhancing Fc Using Batch Normalization Layer:

The proposed enhanced FC is achieved by incorporating dropout to control overfitting and batch normalization to speed up optimization, as shown in Figure 4. The batch normalization makes our modelmore accurate and learns faster, where normalizing for each batch permits our model to avoid internal covariate shift. Furthermore, the dropout prevents neurons from settling into their context. This leads another neuron to discover patterns that are needed for obtaining high accuracy where a group of neurons is responsible for distinguishing a specific feature, and they are the only neurons that can distinguish that feature. It makes our model very precarious in this case, thus, we must adopt dropout to solve this problem.
The FC is used to determine the presence of the covid image or non-covid in the input image. The enhanced FC is used to manage multi-scale feature maps and produce the feature map for the image, as illustrated in Figure 4. Enhancing FC is accomplished by repeating batch normalization and dropout for images to obtain feature maps and achieve better accuracy. Figure 3 shows the existing FC layer.

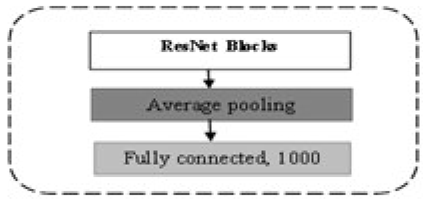

Figure 3. The existing FC layer

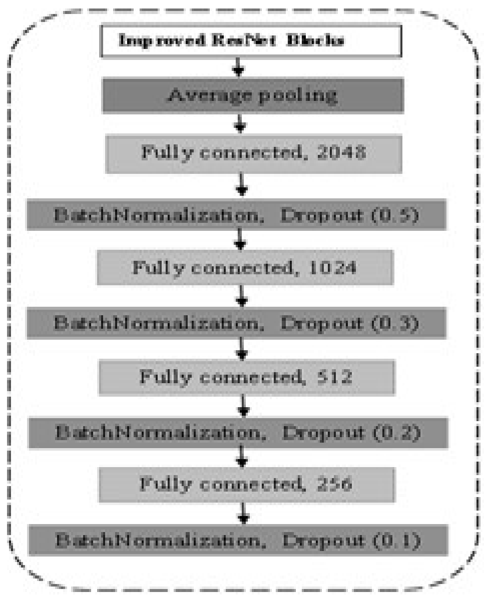

Figure 4. Enhancing of FC

2.2 Transfer learning for CT-based COVID-19 diagnosis

Transfer learning is an efficient representational method where networks trained on a large number of images are applied to initiate networks for tasks with limited data. This study used limited images for training, primarily from the covid dataset [17]. As a result, transfer learning is essential. Transfer learning from pre-trained networks can be applied in two ways in the context of deep learning:feature extraction and fine-tuning. This study recommends fine-tuning as a more successful approach that outperforms feature extraction and produces improved results in this paper, since whole weights areadapted for the current study.

3. EXPERIMENTS, RESULTS AND DISCUSSION

This section describes our experimental design as well as detailed tests to demonstrate the efficacy of our fine-tuned networks. First, we'll go over the experimental parameters. Second, we address datasets.Third, we address performance assessment metrics. Finally, we discuss the outcomes of our model on each dataset.

3.1 Experimental Settings

The proposed approach utilises stratified K-fold cross-validation with K = 5 to test the effectiveness of models, keeping the distribution of the two groups constant inside each fold. The final model valueswere calculated by merging the collected data from the five platforms on their effectiveness varied folds.The experiment was run on an Intel (R) Core (TM) i7-16 GB OF GPU with 13 GB of RAM, as well as the TensorFlow and Keras systems. The optimization method utilised in this design is Adam optimizer. Over 50 epochs for the SARS-CoV-2 CT Scan dataset [17] and 100 epochs for the COVID19-CT dataset [19], the weight decay was 0.0001, the learning momentum was 0.9, and the learning rate was 0.001.

3.2 Evaluation Metrics

In this study, five performance evaluation metrics are used for evaluating models: Accuracy, precision, sensitivity, F1- score (F1) and specificity. where TP denotes the Covid images that have been correctly classified as Covid. The non-Covid images that are successfully categorized as no-Covid are represented by TN. FP refers to the images that are wrongly labeled as Covid despite not being Covid. FN refers to the images that are wrongly labeled as non-Covid despite being Covid.

3.3 Datasets

This section proposes two datasets used in this study. To the state of the art, those are the two largest public datasets available to the public.

3.3.1 Sars-cov-2 ct-scan dataset:

The SARS-CoV-2 CT-scan dataset (Soares *et al.*, 2020) includes 2482 CT images among 120 patients, with 1252 CT imaging from 60 SARS-CoV-2 infected patients[1]. Herein, 1230 CT images of 60 non-infected patients by SARS-CoV-2 from males (32) and females (28), and 1230 CT images of 60 non-infected patients by SARS-CoV-2 from males (30) and females (30), but posing pneumonia dis- eases. Data were gathered from hospitals in Sao Paulo, Brazil. The images in this dataset are digital scans of printed CT assessments, and there is no norm for image size (the dimensionsof the smallest image in the dataset are 104 153, while the largest images are 484 416). The protocol discussed in Ref. [17] suggests arbitrarily dividing the dataset into training (80%) and test (20%) partitions for process assessment.

3.3.2 Covid-ct dataset:

To establish the COVID-CT dataset [19], CT images of COVID-19 infected patients were collected from research papers (pre-prints) published in the medRxiv and biRxiv repositories be- tween January 19 to March 25, and some CT images were provided by hospitals[2].To achieve high quality, CT images were derived from the manuscripts using the PyMuPDF tool. Patient age, gender, location, medical history, scan time, COVID-19 seriousness, and medical report were systematically derived and attributed among each image. A total of 349 CT images from 216 patients were obtained. The authors gathered CT images of non-covid patients through two additional datasets (MedPix and LUNA), the Ra- diopaedia website, and other articles and texts accessible at PubMed Central (PMC). A total of 463 CTimages from 55 patients were acquired. The COVID-CT dataset, such as the former one, has established standards for aspect ratio and contrast. A protocol for creating instruction, validation, and test sets is developed. The validation and test sets were established using COVID-19 im-ages donated by hospitals and derived directly from medical equipment (LUNA and Radiopaedia). The remainder - derived from research articles - is set aside to form the training set. The dataset is availableat https://github.com/UCSD-AI4H/covid-ct.

3.4 Result and discussion

In this section, we present discuss and the results for recognition COVID-19 on SARS-CoV-2 CT- scan [17] and COVID-CT dataset [19] datasets. Herein, the COVID-19 CT image classifications are analysed and discussed by using proposed fine-tuned deep networks. The quantitative results are recorded.

Table 4 shows the mean measurement value for each CT image dataset through various methods. All values are in percentages and the best results are boldly written. In general, there have been some output variations between the SARS-CoV-2 CT findings and the COVID19-CT

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

datasets. In comparison with similar techniques in the recent work, we noticed the effectiveness of our method. Our study provides an advance deep learning technique for the early identification of COVID-19- infected patients from their lung CT scans images. The proposed model is based on the effective transfer learning model called ResNet-50. The architecture design of the proposed model is based on alleviating the connections between the blocks of the ResNet-50 model.

This reduces the training time for scale-ability and handles the problem of vanishing gradient with relevant features on CT images. Furthermore, it provides an effective model of high performance. The proposed model provides an accuracy of 98.1% on CoV-2 CT Scan dataset and 90.6% on COVID19-CT Compared to other models, our model shows state-of-the-art performance, across all metrics we have described.

The performance was improved by choosing an appropriate number of convolution layers and optimizing FC to handle multi-scale feature maps and extracting the features of an input image. More-over, by collecting many local and extracting function maps from shallow layers, the convolution layer boosts the performance of the selection process. In comparison to other backbones, the features are given into other layers, resulting in high performance in accuracy and parameters.

Table 4. Performance Of Various Backbone Networks And Our Proposed Backbone On SARS- Cov-2 CT Scan Dataset

Dataset	Approach	Accuracy	Precision	Specificity	Sensitivity	F1-Score
CoV-2 CT Scan	[17]	97.38	99.16	-	95.53	97.31
	[6]	91.66	-	94	87.5	-
	[18]	90.8	95.7	-	85.8	90.8
	Proposed Model	98.1	96.7	97	98.3	97.48
COVID19-CT	[21]	86	-	79	94	-
	[22]	87.6	84.3	85.2	91.5	87.1
	[23]	83	81.73	81	85	-
	[24]	87.6	-	-	-	86.19
	Proposed Model	90.6	88	86.6	94	91.4

4. CONCLUSION

This study has proposed a COVID-19 rapid recognition approach from CT images. This paper proposes a new model design of of COVID-19 from CT images. Herein, the two biggest datasets of COVID-19 CT examination were used with a split patient-based.

Testing results show that an accuracy score of 98.1% was accomplished, together with a specificity scoreof 97 %, a sensitivity score of 98. 3%. These results demonstrate that the proposed COVID-19 recognition model is more successful than earlier studies carried out for the recognition of COVID-19 using CT scans. This model could be used on systems with low computing capacities, such as smartphones and tablets, or it could even be used to promote integration with radiology systems. Advanced progress will be developed in the future to correlate CT scans systemic features to other factors features for instance epidemiological, genomic, and medical facts to enhanced diagnostics for multi-modelling testing.

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