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GTA 3D-DLD: Greedy Training Approach for 3D Deep Learning Diagnosis Based COVID-19 CT Scan

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Abstract: A numeral of deep learning models has been suggested for COVID-19 examination in computed tomography (CT) scans as an automation tool to help in diagnosis. Although, deep learning models achieved high accuracy, but training approaches are still inefficient to detect injections due to some deep learning models did not meet the requirement of a generalization term in deep learning. Furthermore, other traditional algorithms achieved low detection for 3D CT. Therefore, is high time to develop a deep learning model to diagnose COVID-19 infections in a regularization mode. In this research, greedy learning approach (GLA) is utilized to design and implement the 3D convolutional neural network (3D CNN) model, greedy learning approach is consistings of two stages; the first stage generates many 3D CNN models based on the randomness in the layers, for providing many movements toward solving one problem which is diagnosing COVID-19.Then, the second stage selects an optimal 3D CNN model based on high accuracy of 3D CNNs obtained in the first stage, optimal 3D CNN model is to be significate solution among them. We evaluate the proposed approach on the 3D Mosmed-1110 and 2D SARS-CoV-2 CT Datasets, the best accuracy scores obtained by the present approach are 1.00% and 98.87% respectively on the said datasets in terms of metrics, such as accuracy, precision, recall, and F1. The proposed system also exhibited good generalization and robustness, when it was trained and tested using a portion of data (80%) and (20%).

Keywords: COVID-19, 3D CNN, Deep learning, Generalization, Ensemble learning.

1. Introduction

The world has been taken aback by emergence of COVID-19, a new coronavirus. As per the World Meters study, the virus has infected more than 500 million individuals worldwide [1]. The rapid diagnosis of an infected person is essential to stopping the coronavirus's spread due to the virus' contagiousness and insufficient treatment [2]. Symptoms suggesting a problem in the patients are the primary source for identifying the infected individual. Headache, diarrhea, sore throat, breathing problems, cough, as well as fever are all symptoms that an infected individual may experience. COVID-19 symptoms, on the other hand, might not occur in all affected individuals [3]. Therefore, detecting an infected individual is extremely challenging. The significant growth in corona-affected males has depleted the health systems of many wealthy countries. Corona testing kits and ventilators are in scarce supply in these nations. As a result, many nations have declared a state of emergency in order to disrupt the coronavirus cycle and preserve their populations. In addition to imposing lockdown, patient screening is essential for isolation and treatment. For identifying coronavirus infection in patients.

The standard method of polymerase chain reaction (PCR) is utilized [4]. Clinical samples from patients are used for the PCR, and results can be obtained in a few hours to two days. Given the limited sensitivity of PCR and scarcity of kits, studies show that PCR is less prone than other testing modalities to produce false negatives [5]. Chest scans may be appropriate for COVID-19 identification, according to past studies [6]. As a result, a computerized tomography (CT) method can be employed to diagnose and identify coronavirus infection in COVID patients. Two well-known radiological procedures are the chest X-ray as well as the chest CT scan. Owing to the simple availability of X-ray machines in hospitals and the low ionising radiation exposure to patients, the chest X-rafavoreasionally favored over the chest CT scan [7]. The radiological specialists must examine chest X-rays in order to identify COVID-19 imaging patterns. The comparison between CT scan and X-ray pictures in COVID-19, CT scan is performed better when utilizing deep learning (DL) models to detect positive instances. The CT scan approach provides superior contrast and produces comprehensive quality images, allowing models to derive exact information about CT for patients from the data [8]. DL techniques provide a powerful and an effective model for diagnosing many illnesses in medical imaging [9]. DL approaches derive characteristics from a provided image eliminating, the need for user participation. The DL approach proposed to diagnose COVID-19 by 2D CNN algorithms [10, 11] and 2D performance models show an acceptable level of accuracy. 3D convolutional neural networks (CNNs) have also been utilized to categorise COVID-19 on CT volumes in the latest research. 3D CNNs offer spatiotemporal modeling of CT volumes, and researchers have developed and taken advantage of the serious development of 3D CNN to classify CT scans into positive and normal states as in [12, 13]. Although the 3D DL relies on 3D CT images with a greater rate of prediction [14], the series of mutations that accompanying in the coronavirus becomes a dangerous and constantly evolving. Recently, different learning approaches are proposed to develop CNN algorithm in different application of deep learning [15, 16]. Sequential learning is used to train DL models, which are then used to extract a new representation of COVID-19 features using ensemble approaches that combine multiple models including efficientNets, 3D-Resnet, and Long short term memory (LSTM) models [17-19]. These approaches lack general solution to find optimal detection or accuracy because deep learning architecture contains huge parameterizations [20]. Researchers have been using meta heuristic approach to avoid local optima issue (general sulotion) but meta-heuristic methods need to have excessive hardware resources for development and training [21]. As result, this research proposes a new approach to train 3D CNN by finding a significat solution for generalization issues through greed or light approach in 3D CNN model. This publication's key contribution are given as follows:

1 This research proposes a new approach (GTA) to implement and select an optimal 3D CNN model.
2 Analysis is presented to interpret the behavior of 3D CNN models in the train and validation steps.
3 According to our result, The 3D model is recommended using GTA for diagnosis of normal or COVID-19 infected cases in 3D CT volume images.

The structure of the publication is divided into the following categories. First, previous studies are reviewed on COVID-19 categorisation utilising CT images in Section 2. Then, the recommended 3D CNN using GRA approach is described in Section 3. Section 4 highlights description of COVID-19 datasets is used in the current experiment along with evaluation metrics are used to measure the performance of proposed model. The observed outcomes with in-depth analysis based on 3D CNNs that have been mentioned in Section 5 and 6. Finaly, Section 7 concludes the overall work with some future directions.

2. CNN models and related work

2.1 CNN models

In comptur vesion, CNN algorithm is able to deal with image as matrics for extracting partial features from gray or color images. CNN algorithm contains two parts, namely feature extraction and classification,The feature extraction technique uses convulotion and pooling operation as feature mapping or filter mapping in addition to finetune layers for classification image according to labels. The loss is minimized by optimizing the weights by using gradient descent based low level of representation layers [22]. We can classifiy the CNN models according to their architectures as shown in Fig. 1 and those models are explained as follows:-

2.1.1. Simple CNN model

pooling and only two classification layers. The convulotion and pooling extracts the simple features from input by executing convolution operations.

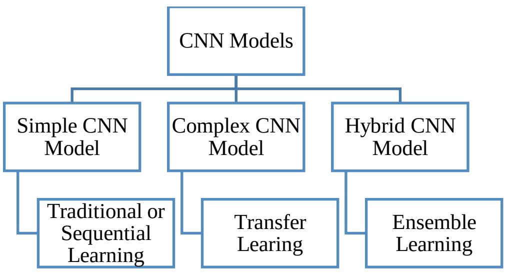

Figure. 1 CNN model types

Each layer is a set of nonlinear functions of weighted sums at different coordinates of spatially nearby subsets of outputs from the prior layer, allowing the weights to be reused []. The feature extraction is performed by convolution and pooling layer. The traditional learning could be learning from scratch by forwarding an input data to convolution layer and followed by pooling layer of CNN algorthim. Simple CNN model uses a traditional learning and simple dataset for classification task. The simple model is reconigized by soft archirecture with few convulation and pooling layers, it is clearly easy implementation with acceptable level accuracy but low classification for complex data as COVID-19 ct sacn images [7].

2.1.2. Complex CNN model

The complex model is consists ofed complicated architectichecture and pre-training approach. This kind of CNNs uses transfer learning to extract important features of ImageNetsnte and fine turning weights and biasais based on classes. The architecture contains for many parameters such as convolution and pooling layers to perform feature extraction operation, and some classification layers. VGG and Resnet are commoenly used tohe developed CNN algorithms in computer vision [23], their architectures are descripted as follows:

2.1.2.1. Visual geometry group model (VGG)

VGG Architecture is consisted of deeper structure of 38 layers are thirteen convolution layers, five pooling layer which are used to extract the important features and three fully connected layer for classifying features based on labels to reduce errors.VGG algorithm, are trained by Nvidia Titan Black GPUs for multiple weeks based on ImageNet around 14 millons image with size 224×224 dimension belong to 1000 labels. Most researches use transfer learning technique to extract the features and then follow by simple train for finding parameters as wieight and bais in full connect layers [24].

2.1.2.2. Residual network model (ResNet)

VGG versions suffer vanishing and exploring problem. Researchers solve this probem by adding Residual Network to VGG algorithm by constructing a new model namely ResNet. Various ResNet versions are proposed for training very large network to enhance detection. The bulk of Resnet models share a similar design with convolutional and pooling layers, although this architecture is built with an uneven number of layers. ResNet's first model contains 34 layers total, including convolution and fully dense layers where 31 are convolution and 3 full dense layers. Resnet50 model is improving its accuracy ; Resnet50 has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. ResNet can be scaled up from ResNet-18 to ResNet-200 by increasing the number of layers [25].

2.1.2.3. EfficientNets model

In general, CNN architecture uses a fixed resource to train and build CNN model, where the performance could be enhanced by increasing the accuracy and reducing loss or error, This work is requires an increase in hardware sources and time to improve accuracy. Researchers proposed an efficient network to enhance the accuracy with limited resources. EfficientNets algorithm has different architecture from VGG and ResNet algorithm. EfficientNets consists of seven block, where each block contains various operations to scale the data. In addition, its size starts with a minimum number where 237 parameters of the EfficientNetB0 are to scale up 813 parameters in EfficientNetB7 model [26].

In general, all kinds of complex CNN models are trained based on ImageNet of Google. Most researchers construct complex structure for CNN model by using pre-trained or transfer learning technique to extract important features, whereas the finetune weight and bias are within the full dense layer to perform classification or recognization task. One of the biggest limitations to transfer learning is negative transfer. Transfer learning only works if the feature and target problems are similar enough for training VGG model. Other drawback is a difficulty to improve or change the kernel of VGG algorithm for finding low-level features [26].

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2.1.3. Ensemble model

This model is trained by using an ensemble learning approach, where two or more complex CNN models fit on the same data and the models' predictions are combined to achieve a better performance as compared to any individual model. This involves both deciding how to create models used in the ensemble and best combine the predictions from the ensemble members [27]. An ensemble learning presents a good low feature representation of data by combining two or more CNN models. The ensemble learning is proposed as a new version of transfer learning. In reality, the researchers are unable to develop the kernal of CNN models using ensemble learning; instead, they create diagnostic models using the same architecture that Google trained on ImageNet.

2.2 Related work

COVID-19 has been identified on 2D CT scans in most prior studies [28]. Al-Waisy *et al*. [29] suggested a sample-efficient convolutional neural network (CNN) to identify COVID-19 on CT images. By incorporating a new transfer learning technique, the authors create an efficient model for diagnosing CT images, where they fine-tune DenseNet-169, DenseNet-121, ResNet-50, ResNet-18, as well as VGG-16 models utilizing ensemble learning approach. A novel CNN is designed with three convolutional layers and one classification layer has also been suggested by the authors. This CNN model is based on a limited number of model parameters and CT scans being developed utilizing transfer learning of ImageNet dataset. In addition, Yujin *et al*. [30] proposed a patch-based simple CNN algorithm with a few samples of the dataset for training the CNN model parameters to build a COVID-19 diagnosis. Furthermore, the approach is motivated by statistical estimation of potential imaging biomarkers by using chest X-ray (CXR) radiograph mini-batch data. AI technologies, including DL, have been shown to be effective in detecting patterns like those observed in damaged tissues. Utilising torso radiographs, the authors develop and evaluate a VGG16-based DL model for the detection of COVID-19 and pneumonia [24]. The researchers [31] proposed modification and transfer learning of AlexNet with its modified AlexNet. Both algorithms of the AlexNet model have been combined to design an ensemble CNN model for classifying CT into the binary diagnostic. The DenseNet121 is optimized by using a gravitational search algorithm (GSA). The GSA is used to choose the optimum DenseNet121 hyperparameters for diagnosing COVID-19 from chest X-ray images s [32].

Although researchers use deep learning with a simple X-ray for diagnosing the injuries of COVID 19, a computed tomography scan is able to send radiation through the body that offers a deep level of details by creating a computerization of 360-degree views of the body's structures. Consequently, CT scans provide a faster and more accurate diagnosis of COVID than X-ray tools [33]. That helps deep learning algorithms more accurate diagnosis COVID-19 in people with early infections. Utilizing both 2D and 3D CT images, a previous review [34] reviewed all artificial intelligence algorithms linked to COVID-19 classification. The 3D deep neural network performs a critical function in prompt quarantine and medical treatment to forecast the probability of COVID-19 infectiousness for more accurate and quick identification of COVID-19 suspected [35]. 3D CNNs were constructed by Wang *et al*. [36] to identify COVID-19 infections on 3D CT scans. Apart from that, the authors employed a U-Net model to separate lungs on CT images before feeding a set of CT images into the recommended 3D CNN. Note that 3D convolution filters, AlexNet, as well as ResNet models are all utilized in the suggested 3D model architecture. For the categorisation of non-pneumonia, common pneumonia, and COVID-19 patients, Han *et al*. [37] suggested attention-based 3D multiple instance models. This technique uses 3D convolution on the 3D CT images to create 3D features. Combining the obtained 3D characteristics with a bag model offers the classification of infections.

Previous works have used simple or complex DL models for solving the COVID-19 diagnosis problem based on gradient descent optimization. We emphasized that training was directed in one manner according to one initial weight and bias as single learning or path in ensemble learning or transfer learning approach. Consequently, most researchers are not able to find an optimal solution for best accuracy. In comparison to existing models, our recommended method involved more generation in the deep structure of 3D CNN by combining different random parameters at every level of CNN architecture that provided many paths to find optimal structure for the best accuracy.

3. Methodology

The purpose of this paper is to introduce a new method for developing a 3D convolutional neural Network model for improving the generalisation capabilities for COVID 19 detection. We suggest

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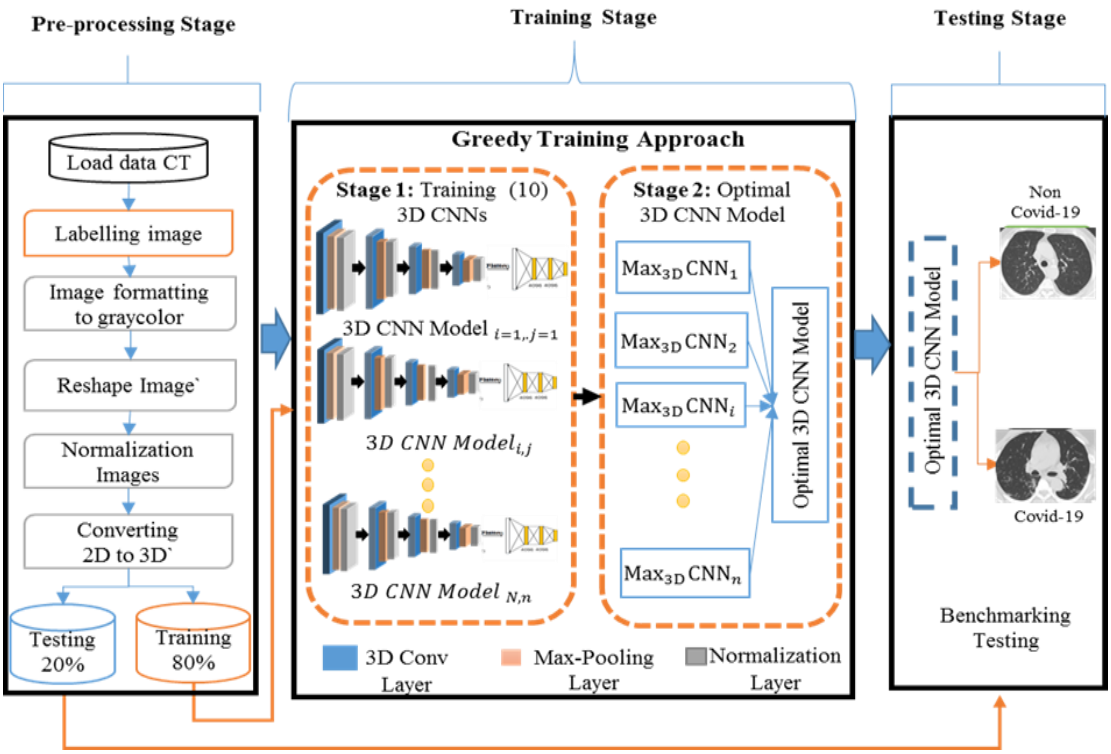

Figure. 2 Proposed 3D deep learning framework using GTA

three stages based on various CNN networks that operate independently. In the pre-processing stage, the input data is processed and transformed into 3D CT images. Ten models are to be trained using the greedy training approach; each 3D CNN model contains four layers of CNNs. Each training contains a checkpoint step to check the accuracy of each epoch in one training, specific epoch offers high accuracy. Which is pointed to the best 3D CNN model using 3D image ct scan. At end of each training, the model is to be selected through a good accuracy. This process continues with whole training of ten 3D CNN model, the ensemble 3D CNN model is selected among the best models in traing stage. While the testing stage is criterial point to measure the ability of our system for diagnous COVID-19 in real scenoria as illustrated in Fig. 2.

3.1 Preprocessing stage

Pre-processing techniques may be effective for reducing undesired noise, accentuating parts of the image that can aid in the identification job, or even aiding in the training phase of deep learning (DL). Throughout the training phase, this pre-processing is required for model convergence [38], a basic pixel intensity normalization between the range of [0, 1] whereas images were between range [0,255]. By converting 3D CT scan images, the input images for convolutional network models are frequently adjusted to preserve compliance with the recommended network models. The 3D CNN model is like other supervised DL models; the errors and weights are optimised based on comparison between the actual and predicted labels of COVID-19, therefore, labelling data is done by adding normal and abnormal of labels to CT image [39]. The COVID-19 data diagnosis lacks a public dataset, and our DL system used 3D architecture, where to resize and reshape input data to 3D CT scan images are crucial. To show a realistic testing, the 3D dataset is split into 80% of train and 20% of valid, and the test is also monitored for interpreting the system behaviour through accuracy and loss criteria over training models.

3.2 Training stage

The CNN architecture has matrix elements in different layers. The elements parameters are generated randomly such as weights and biases. A greedy training approach (GTA) is proposed to obtain the best 3D CNN architecture containing optimal parameters. GTA isincluded group or set of networks (N) of 3D CNN models. Here, set architecture $N = \{3D\ CNN_{i,j} \ldots\ldots 3D\ CNN_{i,n}\}$, Each architecture or network (i) has many parameters are trained by many epoch numbers to generate models as $3D\ CNN_{i,j}$ as shown in Fig. 3.

Where (j) refers to epoch in each training and (n) indicates to total number of epochs in one

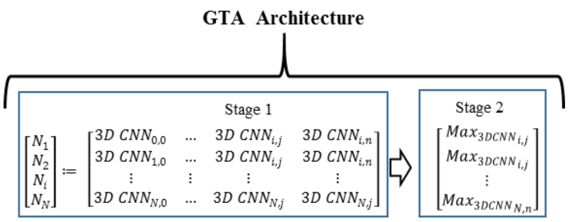

Figure. 3 Greedy training approach

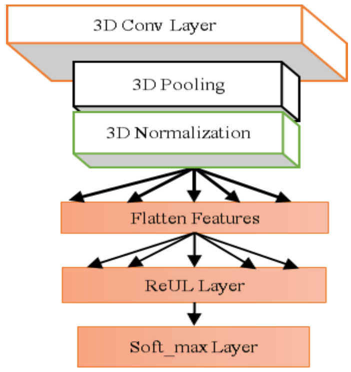

Figure. 4 CNN architecture

training for one architecture (i). GTA approach consists of two stages as shown in Fig. 1, these phases are explained as follows:

3.2.1. Phase 1: training 3D CNNs

In this Phase 1, four CNNs machine is used to every 3D CNN model, each 3D CNN machine architecture is consisted of six layers as shown in Fig. 4. Layers are including conventional architecture with major layers geared for feature extraction, the features of COVID-19 are extracted by Convolution, pooling, and BatchNormalization layers. In contrast, the fully-connected (FC) layers are designed to classify the extracted features based on labels. These layers are explained as follows:

3.2.2. Convolutional layer

The mathematical operation with respect to the convolution is conducted between a filter having $MxMxM$ particular size and the input of an image (x). The dot product between the filter (K) and the input image concerned with the size of the filter $(MxMxM)$ is obtained by sliding the filter over the input image, and the output is referred to as the feature map and this layer, suppose to be bais in terms of (b_i), i^{th} filter (K_i) is defined in Eq. (1).

$$\mathrm{Cov_i} = \mathrm{f}\left(\sum_M \mathrm{x}_M^{l-1} * \mathrm{K}_i^l + \mathrm{b}_i\right) \quad (1)$$

3.2.3. Pooling layer

The major objective of this layer is to minimise computational expenses by reducing the convolved feature map size. Subsequently, this is achieved by minimising the connections between layers and focusing on each feature map individually as defined in Eq. (2). The biggest piece from the feature map is used in Max Pooling. In addition, the components' average in a predetermined-sized Image section is calculated utilising Average Pooling. By dividing the three-dimensional input into cuboidal pooling regions and calculating the maximum of each sector, Max Pooling performs downsampling in 3D CNN Tthe scale of pooling from each axis (xyz) is defined as follows:

$$\mathrm{P_i^l} = \max_{\mathrm{xyz}}\{\mathrm{Cov_i}\} \quad (2)$$

3.2.4. BatchNormalization layer

Batch normalization applies a transformation that maintains the mean output close to 0 and the standard deviation output close to 1. Importantly, batch normalization (B) works differently during training and inference. The layer normalizes its output utilizing the mean and standard deviation of the current batch of inputs. Each channel being normalized by Eq. (3).

$$y = \left(\varepsilon * \left(\mathrm{B} - \mu(\mathrm{batch})\right) / \mathrm{sqrt}\left(\mathrm{var(B)}\right) + \epsilon\right) + \beta) \quad (3)$$

Where the variables could be presented as follows:

- Mean (μ)is average of data layer.
- Epsilon (ϵ) is small constant (configurable as part of the constructor arguments)
- gamma (ε) is a learned scaling factor (initialized as 1), which can be disabled by passing scale=False to the constructor.
- beta $(\beta)$is a learned offset factor (initialized as 0), which can be disabled by passing center=False to the constructor.

3.2.5. Fully-Connected (FC) layer

By integrating the biases and weights with the neurons, this layer links the neurons between two distinct layers as inducated in Eq. (4). A CNN Architecture often places the output layer before the final few layers. Note that this stage involves flattening the input picture from the former layers and supplying it to the FC layer. The mathematical function operations often take place after the flattened vector passes through a few additional FC layers. The categorisation procedure begins at this point.

$$(\mathrm{C_i}) = \left(\mathrm{W^T} + \mathrm{b_i}\right) \quad (4)$$

Thus, a lot of weights and biases are randomly generated for ten 3D CNN models in this stage. Our results may offer unequal and variousy levels because the stochastic nature of greed train algorithm (GTA) by showing the differences in numerical accuracy and loss.

3.2.6. Phase 2: optimal 3D CNN model

Many 3D CNN models ($\mathrm{Model_{N,n}}$) had been trained and validated using 3D COVID-19 dataset in stage 1, where models have different accuracy or validation performance, these variations do not reflect optimal solution for classification task of three-dimension dataset of CT scan technique. To find global solution, stage 2 contains set of models which are generated over whole training. Stage 2 consists numerous of 3D CNN models as $\mathrm{Max_{3D}CNN}_{i,j}$, whcih achevie high accuracy in every training within epoch (j) in stage 1 and 3D CNN model has the acceptable accuracy as shown in Figure 2 . We have formed Eq. (5) for finding out 3D CNN models.

$$\mathrm{Max_{3D}CNN_{i,j}} \coloneqq \sum_{\mathrm{i_0 j_0}}^{\mathrm{N,n}} \mathrm{Model_{i,j}} \geq \mathrm{Max\_acc} \quad (2)$$

These $Max_{3D}CNN_s$ seemed to be good classifiers for recognizing 3D COVID-19 CT scan. Finally, The optimal 3D CNN model is selected from $Max_{3D}CNN_s$ based on the high accuracy achieved over the entire training approach as shown in Eq. (6).

$$\mathrm{Optimal_{3D}CNN} \coloneqq \sum_{\mathrm{S=i,j}}^{\mathrm{N,n}} \mathrm{Max_{3D}CNN_{i,j}} \quad (6)$$

Based on Eqs. (5) and (6), we can offer a novel approach for training the 3D CNN algorithm using the Greedy Training approach. Greedy training approach algorithm reflected a greed approach for training (N) architecture 3D CNN, each network or architecture of (i) has four CNNs machine as indicated in step 5 and 6. At step 8 and 9 start training (i=0), number by epoch number from (j=0) for first 3D CNN, each model ($\mathrm{3D-CNN_{i,j}}$) is trained based on call back function for montoring the behaviour of 3D CNN model over training stage in step 11, whereas step 14 keeps the model ($Max_{model_{i,j}}$) has been performed maximum validation accuracy, this process (step 13) is repearted from (j=0) to (i=N). The phase one is completed over from step 6 to step 15 for training 3D CNNs and generating munerous solutions. The optimal model is selected by best accuracy over steps 16-18.

GREEDY TRAINING APPROACH ALGORITHM	
STEPS	Description of GTA Steps
1.	**Max=** model achieves maximum accuracy**, N**= total number of 3D CNN network**, (i)** = individual 3D CNN architecture, **(j)** = Epoch number**, (n)**=total number of epoch
2.	Pre-processing Dataset
3.	Load COVID-19 dataset
4.	Convert input images to 3D CT scan image
5.	Split dataset to training and validation input data to 3D CNN
	Phase One
6.	(N) = Ten 3D CNN architectures
7.	(i) = individual or one 3D CNN architecture where (i) is to be started $\{\mathrm{i_0} \rightarrow i_N\}$.
8.	For $(i_0 \dots\dots\dots i_N)$
9.	For $\left(epoch_j \dots\dots\dots epoch_n.\right)$ # one 3D CNN architecture
10.	{
11.	Train individual $\mathrm{3D-CNN_{i,j}}$
12.	}
13.	End #step 9
14.	$Max\_model_{i,j}$= $\mathrm{Max\_Model\_acc_{i,j}}$
15.	return Step 8.
	Phase Two
16.	**While (**$\mathrm{Max\_Model\_acc_{i,j}} < 0.99$)
17.	Select maximum accuracy among (N) 3D CNN models
18.	$optimal\_acc_i \leftarrow \mathrm{Max\_Model\_acc_{i,j}}$
19.	End
20.	**Optimal Accuracy (3D CNN)**

3.3 Testing stage

Ten 3D Models were designed and implemented in training stage, three cross-validition had been used to interpret the behavior of 3D CNN models based on 3D COVID-19 images over training stage. Many studies split their test tools into 90% and 10% of training and testing, respectively for evaluating their models. Due to the majority of sample images used to train and test of models, we cannot consider truth testing to prove an ability of system for diagnosing unclear patterns in COVID-19 overfitting issue [40]. Therefore, the input data were divided into data training (80%) and data testing (20%) for achieving significant analysis in a real scenario of testing including measurement or evaluation of the CNN model through images never seen before [41].

4. Experimental setup

In this section, we present evaluation metrics and COVID-19 dataset that are used to train and test the proposed works.

4.1 COVID-19 data set

The two datasets used in this investigation are described in this section. To our knowledge, these are the two largest publicly accessible databases and description as follows:.

4.1.1. Mosmed-1110

In the framework of outpatient computed tomography centres in Moscow, Russia, 1110 CT scans from outpatient clinics were collected. There were five distinct 3D CT volume types in the Mosmed-1110 dataset, namely CT0, CT1, CT2, CT3, as well as CT4. The CT0 incorporated 254 3D CT volumes, all of which were standard scans. The normal level suggested that there was no COVID-19 or pneumonia symptom on the patient's CT scan. CT1 comprised 684 3D CT images that exposed a 25% COVID-19 infection in the lungs. Alternatively, CT2 had 125 3D CT scan with 11% % COVID-19 infection in the lungs. CT3 had 45 3D CT images, which revealed a 50% COVID-19 infection in the lungs. Two 3D CT scans with 75% COVID-19 infected lungs were included in the CT4 category. Subsequently, mild (CT1) and moderate (CT2) levels showed that the patient did not require intensive hospital care and may thus stay at home. Patients in the severe (CT3) and critical stages, on the other hand, must remain in hospital and get intensive care (CT4) [41]. As illustrated in Fig. 5, the suggested Artificial Intelligence (AI) approach was developed and assessed on two sets of MosMed datasets.

4.1.2. SARS-CoV-2 CT

The SARS-CoV-2 CT-scan dataset [42] comprised 2482 CT scans obtained from 120 patients. There were 1252 CT scan images of (60) infected patients from men (32) and females (28), as well as 1230 CT scan images of uninfected patients (60) from males (30) and females (30) with various pulmonary disorders. The information was gathered from hospitals in Sao Paulo, Brazil. The images were digital scans of printed CT tests, in which there was no standard for image size (the smallest image in the collection was 104 × 153 pixels, whereas the biggest image was 484 × 416 pixels), as seen in Fig. 6. The contrast of the images in this collection was likewise unstandardised.

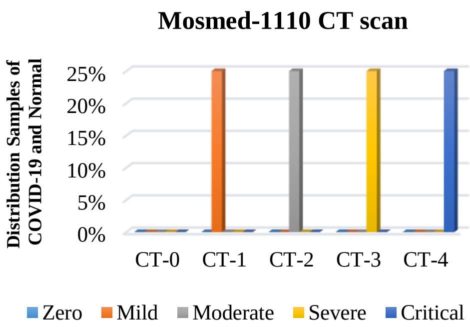

Figure. 5 Mosmed-1110 distribution

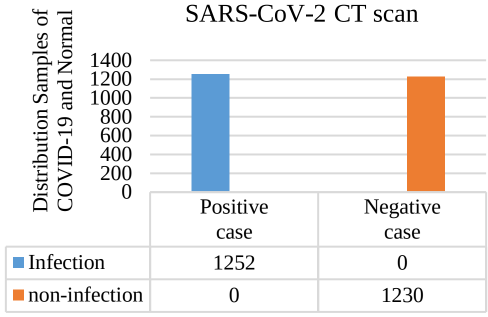

Figure. 6 SARS-CoV distribution

4.2 Evaluation metrics

The suggested models' categorization performance were evaluated by F1-Score (*F*1), Recall (*R*), Precision (*P*), as well as Accuracy (*Acc*) are the confusion-matrix-based quantitative measurements [43].

1. By measuring the accurately predicted labels, (*Acc*) may be described as the model's total performance. (*Acc*) may be mathematically described as follows:

$$\left(\text{Accuracy} = \left(\frac{\text{TP+TN}}{\text{TP+TN+FN+FP}}\right)\right) \tag{7}$$

2. *P* is the proportion of properly detected positives, as witnessed in (9):

$$\left(\text{Precision} = \left(\frac{\text{TP}}{\text{TP+FP}}\right)\right) \tag{8}$$

3. *R* is a metric that counts the number of accurate classifications penalised by the number of missing entries as follows:

$$\left(\text{Recall} = \left(\frac{\text{TP}}{\text{TP+FN}}\right)\right) \tag{9}$$

4. As seen in equation 6, F1-Score establishes a compromise between *P* and *R*:

$$\left(\text{F1} = 2 * \frac{(\text{P+ R})}{(\text{P*R})}\right) \tag{10}$$

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5. Performance analysis

Experiments were conducted on a 25 GB Ram, GPU collab pro, the Tensor Flow/Keras framework for Python, as well as one Titan X Pascal with 166 GB. The trainied models had used the Adam Optimizer and 100 epochs with a learning rate of 0.001 based on the categorical binary-entropy loss. The methodology could design ten three-dimensional convolutional neural networks (3D CNN). Each network had different parameters such as weight and bias. The 20 models were individually trained and validated by accuracies, and loss analysis based on SARS-CoV-2 and Mosmed-1110 for diagnoses of the COVID-19 diseases. The SARS-CoV-2 images were resized with $(16 \times 16 \times 16 \times 1)$ as well as Mosmed-1110 images with (128×128×128×1) dimension. The 3D networks as namely $(3D\ Nets)$ are equal to $\text{3D Net}_1 = \left(\text{Max}_{3\text{D}}\text{CNN}_{1,j}\right)$, $3D\ \text{Net}_2 = \left(\text{Max}_{3\text{D}}\text{CNN}_{2,j}\right)$, $3D\ Net_i ,= \left(\text{Max}_{3\text{D}}\text{CNN}_{i,j}\right)$, $\text{3D Net}_{10} = \left(\text{Max}_{3\text{D}}\text{CNN}_{N,n}\right)$, Which generated and donated the 3D CNNs by phase 1 and phase 2 of proposed framework research. The 20 3D CNNs are implemented, investigated and presented as follows:

5.1 Exp 1: SARS-CoV-2 CT classification

Table 1 reflects a summary of accuracy, and loss achieved from the ten 3D CNN models for the prediction of COVID-19 on the SARS-CoV-2 CT dataset. Each Net_i presented 3D CNN model that achieved acceptable accuracy and loss at sepecfic epoch over one training. In terms of generalized performance, the accuracy of training and validation to 3D CNN $_5$ were 0.99 and 0.98, respectively. It is better than other networks such as Net_1, Net_2, and nets where, from 0.97 (Net_1), 0.97 (Net_5), 0.97 (Net_6) to (Net_{10}). Hence, Net_5 achieved the highest accuracy with low loss validation as presented in Table 1.

The accuracy and loss plot is given for training of Net5 model in Fig. 7 and 8, respectively. 0.05 error or false predictions are observed with a 0.98 true prediction for COVID-19 (+ve), including normal subjects. The model fits well and avoids overfitting,

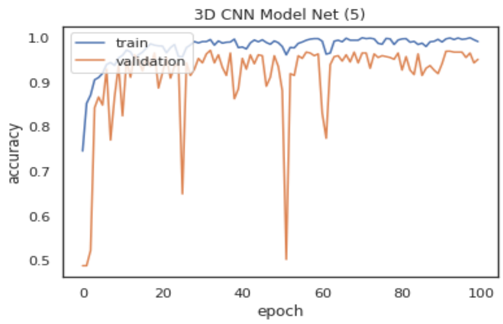

Figure. 7 SARS: train and valid accuracy

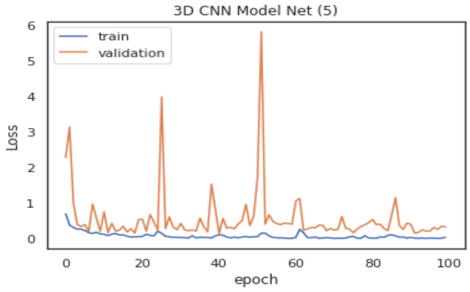

Figure. 8 Train and valid loss

as shown by the minimum (approximately 0) difference between the training and validation error, as presented in the loss plot.

5.2 Exp2: Mosmed-1110 classification

The performance evaluation of the suggested technique for Net_i as shown in Table 2. The dataset is divided into 400 of images for training of network ($\boldsymbol{N_i}$) and validation ($\boldsymbol{v_i}$). Note that the above-mentioned approach appeard to produce equivalent outcomes. The 3D Nets achieved high validation accuracy with low loss, and 3D CNN Net_7 and Net_2 achieved the greatest training accuracy of 1.00, which is more advanced than other networks such as Net_1, Net_2, and other nets were, 0.99 (Net_1), 0.99 (Net_3), 0.99 (Net_4). The optimal behavior of 3D CNN achieved by (Net_7) based on lowest error.

The accuracy and loss plot for the Net_7 model that are shown in Fig. 9 and 10, respectively. 0.00010

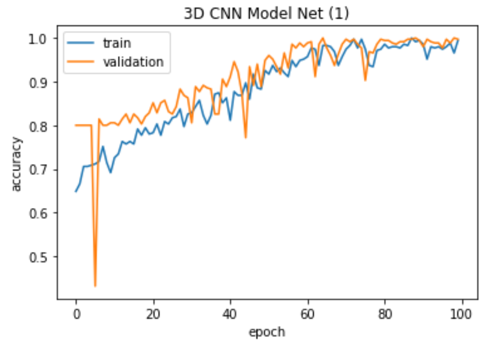

Figure. 9 Mosmed: Train and valid accuracy

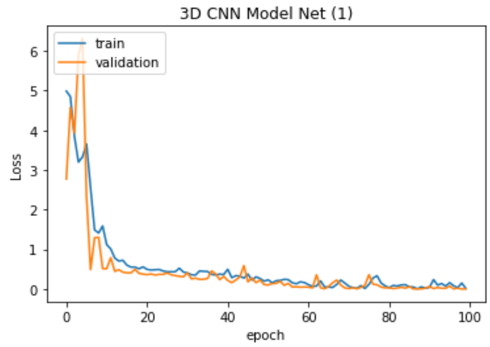

Figure. 10 Mosmed: Train and valid loss

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Table 1. (Ten) 3D Nets based SARS-Cov2 CT

Net_i	Accuracy (T_i)	Loss (T_i)	Accuracy validation	Loss validation
Net_1	0.99731	0.00286	0.97746	0.01529
Net_2	0.99839	0.00243	0.97262	0.02391
Net_3	0.99893	0.00231	0.9799	0.01661
Net_4	1.000	0.00280	0. 97476	0.002047
$\boldsymbol{Net_5}$	**0.99785**	**0.00286**	**0.98229**	**0.02048**
Net_6	0.99946	0.00115	0.97262	0.02203
Net_7	0.99946	0. 00150	0.97262	0. 02164
Net_8	0.99495	0. 00199	0. 97585	0.01949
Net_9	0.99839	0.00156	0.9742	0.02195
Net_{10}	0.99573	0.00532	0.97746	0.02022

Table 2. (Ten) 3D Nets based Mosmed-1110

Net_i	Accuracy $\boldsymbol{N_i}$	Loss $\boldsymbol{N_i}$	Accuracy $\boldsymbol{v_i}$	Loss $\boldsymbol{v_i}$
Net_1	0.999	0.02189	1.00	0.0016
Net_2	1.00	0.00412	1.00	0.0089
Net_3	0.998	0.02095	1.00	0.0020
Net_4	0.997	0.0230	1.00	0.0022
Net_5	1.00	0.00412	1.00	0.0089
Net_6	0.999	0.02189	1.00	0.0016
$\boldsymbol{Net_7}$	**1.00**	**0.00052**	**1.00**	**0.0010**
Net_8	0.998	0.02095	1.00	0.0020
Net_9	0.997	0.0230	1.00	0.0022
Net_{10}	1.00	0.00052	1.00	0.0010

error or false predictions were observed with a 1.00 true prediction for COVID-19, including normal subjects. As can be observed from the loss plot, the model fits high-generation training-based Mosmed-1110 while avoiding overfitting, as evidenced by the lowest (0 error) difference between validation and training error.

6. Realistic testing

To evaluate the performance of model in realistic scenario, we tested the (Net_5) and (Net_7) with 20% samples of 3D COVID-19 dataset that is not seen before over training models. A confusion matrix was obtained for the proposed model (Net_5) using SARS-CoV-2 CT scan in Fig. 11.

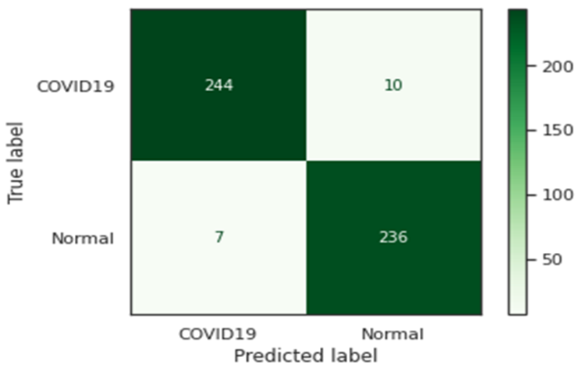


Figure. 11 SARS-CoV-2 CT: confusion metrics

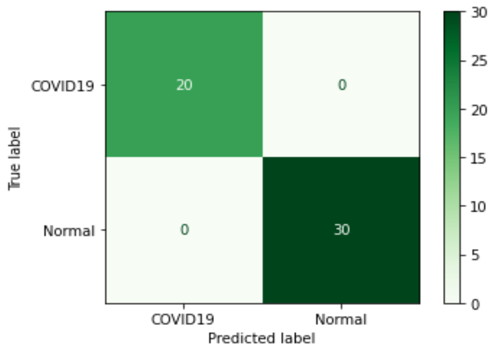


Figure. 12 Mosmed-1110: confusion metrics

In contrast, the normal class was classified by Net_5 with 244 as the true case with ten false negatives of the total normal class. In addtitional, Net_7 classified the COVID-19 with 20 true positive and non-false negative (0) classes. In contrast, the normal class was classified by Net_5 with 20 true positive cases with (0) false negatives of the total normal class as shown in Fig. 12.

7. Comparison result

The results were compared with accuracy, precision, recall, and F1-score, Table 3 includes the suggested binary classification of proposed 3D CNN and state-of-the-art approaches utilizing an 80:20 sample rate for training and testing for two 3D datasets. The researchers [44] and [11] trained and tested their CNN models utilizing 2D dataset (SARS-CoV-2 CT), where P. Silva et al. [44] analysed an EfficientNet-B0 algorithm used The results were compared with accuracy, precision, recall, and F1-score, Table 3 includes the suggested binary classification of proposed 3D CNN and state-of-the-art approaches utilizing an 80:20 sample rate for training and testing for two 3D datasets. The researchers such as [44] and [11] trained and tested their CNN models utilizing 2D dataset (SARS-CoV-2 CT), where P. Silva et al. [44] analyzed an EfficientNet-B0 algorithm used SARS-CoV-2 CT scan based on three evaluation approaches namely “Random”, “Slices”, and “Voting” with 5-fold cross-validation. EfficientNet-B0 model had complex architecture by using transfer learning or pretrain approach with optimized parameters for learning rate of 0.001 and the Adam optimizer over 20 epoch by using the binary cross-entropy. The cross-dataset analysis had shown that the EfficientNet-B0 model was at an acceptable level on the voting evaluation for accuracy, pricesion, recall and F-score of 0.89, 0.80, 0.94, 0.86, respectively.

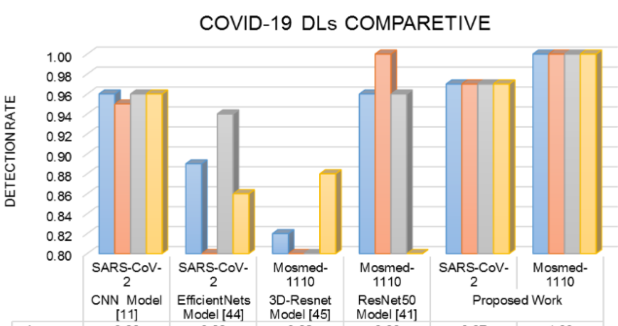
S. Pathan et al. [11] proposed complicated work to diagnose COVID 19 through five complex CNN architectures, Binary Grey Wolf Optimizer, and WOA-BAT algorithm. The five complex namely, ResNet-50, AlexNet, VGG19, Densenet, and Inception V3 , were to construct ensemble CNN model, each model was trained by using transfer learning approach without classification task over 20 epochs and 0.0004 of learning rate, and also Binary Grey Wolf Optimizer was used for selecting important features from extracted features whereas WOA-BAT was to select important parameters to classify images into normal and COVID 19. Although the authors offered to optimize CNN algorthim to enhance COVID 19 detection, inefficient result was gained by accuracy, F1-score, precision and recall of 0.96, 0.96, as well as 0.95 and 0.96 respectively.

Accordingly, Mosmed-1110 CT scan of 3D DL model was proposed to diagnose COVID 19 based on 3D images of chest CT scan [45], the authors used ensemble learning approach for building 3D DL model based ResNet3D101, and DenseNet3D121. The researchers used sample algorithm to drop unwanted 3D image CT, Adam optimizer and 0.001 of learning over 200 epoch. The results were 0.95, 0.96, as well as 0.96 for accuracy, F1-score as well as precision.

Furthermore, S. Serte and H. Demirel [41] designed the ResNet50 COVID model by transfer learning approach based on 3D CT scan COVID-19 with acceptable level diagnose of COVID-19. Few studies [11, 44, 45, 41] acknowledged that transfer learning and ensemble learning are used for building complex CNN models by ResNet algorithms, EfficientNets and CNN. The transfer learning and ensemble learning generated CNN model with accepted accuracy by generating one solution to detect or classify COVID 19 CT scan. In contrast,our model was successful with a high detection with two datasets. Futhermore, our system outperformed other previous works such as [11, 44, 45, 41], the proposed ensemble (3D CNN) has set four CNNs machine for feature extraction and three layer classification based on optimizing parametres of Adam optimizer and Mean Square Error. Our system achieved a high evaluation metrics in terms of accuracy, precision, recall and f-score by utilizing Mosmed-1110 and SARS-CoV-2 data, the 3D CNN achieved high accuracy, precision, with 0.98 and recall, and f-score with 0.97 for SARS-CoV-2 dataset. In addition, the detection was higher for COVID-19 in Mosmed-1110 dataset with 1.00 rate to criteria evaluation. The performance of the proposed model and state-of-the-art methods in [11, 44, 45, 41] are as shown in Fig 13. Furthermore, the proposed model is able to detect COVID-19 with a high diagnosis rate better than CNN [11], EfficientNets [44], 3D-Resnet [45], and ResNet50 [41] models in terms of accuracy, precision, recall, and F-score in both 3D COVID dataset.

The strength of the proposed model is trained and implemented using GTA approach in addition lowest computational time by few layers consisting of four CNNs machine for feature extraction and three layers classification based on optimizing parametrs are adam optimizer, Mean Square Error.

GTA offers multi solutions or paths depending on numerous randomaus architectures, greedy search used to find optimal solution based signaficat accuracy of 3D CNN models. The best ConvNet architecture is able to extract important features from 3D CT scan by convolution, pooling layers and then



	SARS-CoV-2 CNN Model [11]	SARS-CoV-2 EfficientNets Model [44]	Mosmed-1110 3D-Resnet Model [45]	Mosmed-1110 ResNet50 Model [41]	SARS-CoV-2 Proposed Work	Mosmed-1110 Proposed Work
Accuracy	0.96	0.89	0.82	0.96	0.97	1.00
Precision	0.95	0.80	0.80	1.00	0.97	1.00
Recall	0.96	0.94	0.00	0.96	0.97	1.00
F1-score	0.96	0.86	0.88	0.00	0.97	1.00

Figure. 13 Comparative of DL models in 3D COVID 19

Table 3. A comparison with deep learning models on COVID-19 dataset

Previous Works	Used algorithm	Dataset	Accuracy	Precision	Recall	F1-score
S. Pathan *et al* [11]	CNN	SARS-CoV-2 CT	0.96	0.95	0.96	0.96
P. Silva *et al* [44]	EfficientNets	SARS-CoV-2 CT	0.89	0.80	0.94	0.86
S. He, *et al* [45]	3D-Resnet	Mosmed-1110 CT	0.82	0.80	×	0.88
S. Serte *et al* [41]	ResNet50	Mosmed-1110 CT	0.96	1.00	0.96	×
Proposed model	**3D CNN**	**SARS-CoV-2 CT**	**0.97**	**0.97**	**0.97**	**0.97**
Proposed model	**3D CNN**	**Mosmed-1110 CT**	**1.00**	**1.00**	**1.00**	**1.00**

followed classification task to the extracted features using softmax classifier. This approach accomplished best architecture of 3D CNN among multiple models for diagnosing 3D COVID-19 based CT scan technique. While previous works less emphasis on poor estimates of the optimal CNN model because the ensemble or transfer learning dependenting on only architecture that could be not generated optimal results. In conclusion, the proposed method's performance results show that the proposed model is more robust and accurate than the 3D- ResNet18 and 3D-ResNet50 models.

8. Conclusion

COVID-19 are highly sensitive and serious diseases that need to reliable and effective a deep learning model that is free from false positivity or negativity. In this paper, GTA approach is proposed to build an efficient 3D CNN model for predicting 3D COVID-19 CT scans, where GTA approach trains a group of 3D CNN models that have different parameters such as weights and baises in stage 1, and optimal 3D CNN model is selected among them based on highest accuracy in stage 2. In fact, GTA can be a greedy search in many solutions for reaching an optimal accuray and lowest false positives over two stages. To the best of our knowledge, this is the first effort to do appraoch for the problem at hand, and we think the GTA approach to be a potential and viable alternative to the mate heuristic or ensemble approaches for a greedy search to obtain the best results or detection. An efficient model was evaluated based on two large COVID-19 datasets, the realistic findings of evaluation shows that our DL framework may more reasonable by achieving a high recognition with accuracy (1.00), precision (1.00), and F1-Score (1.00) for Mosmed-1110 as well as 0.97 of accuracy, precision, and F1-Score for SARS-CoV-2 CT scan.. We have also planned to enhance the quality of the COVID-19 images by collecting more images of CT scan and using some well-established pre-trained 3D CNN models to have better features at the initial stage to improve the generalization of the model.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by first author. The supervision, and project administration, have been done by second author and the thierd auther.

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