Based on deep convolutional neural network, COVID-19 identification utilizing computed tomography scans

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ABSTRACT

In the year 2019 specifically, on March 11th, the coronavirus illness two thousand nineteen (COVID-19) was announced a worldwide epidemic due to its rapid spread and lack of treatment options. As a result, infected individuals must be identified and quarantined quickly to prevent the illness from spreading. The method used to test for COVID-19 is called real-time-polymerase chain reaction (RT-PCR), which has problems with having low sensitivity and taking an extended amount of time. Because chest computed tomography (CT) scans are more sensitive than RT-PCR, it follows that such scans can be employed for diagnostic purposes. This study developed a deep convolutional neural network (CNN) approach to detect COVID-19 using CT scan images. An architecture of deep learning (DL) called convolutional neural network computed tomography scans (CT-CNN) was utilized to efficiently identify COVID-19. The findings of our suggested model are highly encouraging, with an accuracy of 96.14%, an F1 score of 96.21%, and a recall of 97.53% when it comes to classifying CT scans as either infected or not infected by COVID-19.

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1. INTRODUCTION

Coronavirus illness two thousand nineteen (COVID-19) is a viral ill health from which new varieties are constantly being created [1], [2]. Real-time polymerase chain reaction (RT-PCR) is the most common method utilized for earlier detection of COVID-19 [3], [4]. Consequently, chest computed tomography (CT) is crucial in determining lung problems in sicker with mild-to-severe COVID-19 pneumonic illnes. CT take place the most common methods for determining the extent of a pulmonary oedema illness [5]–[10]. This method permits the stratification of patients into risk categories, offers prognostic estimations, and improves medical expert decision-making. Pulmonary hypertension and pneumonia are the most prevalent CT findings linked with clinical severity [11], [12]. On CT scans, symptoms of severe COVID-19 are ground glassy opacity (GGO), as well as pulmonary infiltrates (PIs) in a periphery pleural region; these symptoms often emerge within 14 days of virus exposure [13]. Through a pandemic, CT-based assessment became progressively more important of the treatment of critically ill COVID-19 suckers. According to the Radiological Association of North America [14], [15], CT exhibited abnormalities classed as frequent in COVID-19 pneumonia. CT is also a crucial component of intensive tomography in 2022.

Deep learning (DL) could be utilized to do the rigorous as well as quantitative laboratory analysis of the diseased level on computed tomography [16], [17]. DL allows us to undertake activities usually performed by humans [18], [19]. Relevant techniques against the COVID-19 epidemic are described in [20]. The objective of the current investigation was to identify and diagnose COVID-19 utilizing CT scans, as indicated by the authors of [21]–[26]. Mobiny *et al*. [21] presented a DL method known as detail-oriented capsule networks (DECAPS) for the categorization of COVID-19 from CT images. In CT images, Amyar *et al*. [22] proposed a model of new multitask deep learning to mutually recognize COVID-19 patient besides segment COVID-19 lesion starting chest CT images. A DL algorithm can segment as well as detect a COVID-19-infected area [23].

Li *et al*. [24] classifying COVID-19 CT images using a squeeze net-based simulation, for classify COVID-19 on CT scans, collected characteristics from 50 levels of (Covent). Konar *et al*. [25] classified COVID-19 from CT images using (PQIS-Net) assisted semi-supervised DL algorithm. Using CT scans, Wu *et al*. [26] suggested a joint classification with segmentation (JCS) approach for COVID-19 classification and diagnosis; this study is the next stage by employing imaging indicators as well as classification to identify the damage as well as classify the evolution of asthma over the (P.P.) in COVID-19 patients.

Deep convolutional neural network (CNN) models for COVID-19 diagnosis have been developed using CT scans and X-rays. Khan *et al*. [27] proposed the Coro-Net model for finding COVID-19 infection by applying CXR images. This method is based on severe inception and contains seventy-one layers trained utilizing an Image-Net dataset. According to the authors, the proposed Coro-Net model achieved 0.87 and 0.93 as an accuracy average and F1-score, respectively. Zhang *et al*. [28] proposed a residual CNN model consisting of 18 layers utilizing a dataset of 1531 chest X-ray images, achieving a 72.31% accuracy average.

COVID-19 chest X-ray studies can be broken down into two distinct groups. In other studies, a feature extraction method is used instead of raw data. The same holds true for the quantity of information analyzed during studies, which might range widely. Currently, the most popular method employs the utilization of CNN. In order to distinguish between healthy and sick COVID-19 cases, ApostolPoulos plus Bessiana used a typical COVID-19 induced pneumonia in combination with an advancing NN. The transfer learning strategy has been used in particular. Using transfer learning, researchers have been able to detect a wide variety of irregularities in incredibly small diagnostic imaging datasets, with sometimes astounding results [29].

To facilitate fast and accurate scanning, Apostolopoulos *et al*. [30] Aimed to build a DL-based system able to identify COVID-19 with high sensitivity using only chest X-rays. Using a CNN based multi-objective algorithm. Singh *et al*. [31] classified chest CT pictures of COVID-19-infected and uninfected patients. For determining if a patient has COVID-19 or not, Jaiswal *et al*. [32] proposed using a deep transfer learning approach built on top of the DenseNet201. To provide a foundation for qualitative diagnosis of COVID-19-related sinusitis using CT pictures, Chen *et al*. [33] suggested residual attention U-Net for automatic multi-class segmentation.

The research of Adhikari suggests a network called "auto diagnostic medical analysis" that searches for infected areas to assist the physician in identifying the diseased section if present. In the investigation, both X-ray and CT scans were utilized. A denseness network has been proposed [34] for removing and marking infected lung regions. Using chest X-ray scans, Alqudah *et al*. [35] used two distinct approaches to diagnose COVID-19 in their study. The first utilized the CNNs AOCT-Net, Mobile-Net, and Shuffle-Net. The photos were then categorized using the SoftMax classifier, K-neighbor, SVM, as well as random forest (RF) algorithms [36].

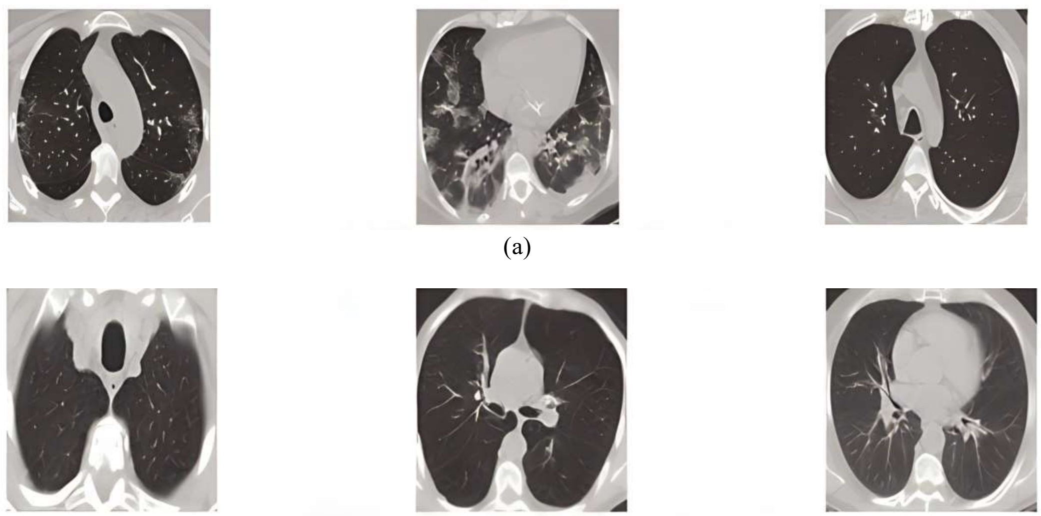
Khan *et al*. [27] used an exception architecture to detect COVID-19 infection in chest X-ray images of normal, bacterial, and viral pneumonia cases. To identify COVID-19 in chest X-rays, Ghoshal and Tucker [30] used a Bayesian CNN model with drop weights. The X-ray image dataset was used to train the VGG19 and Dense-Net algorithms that Hemdan *et al*. [37] used to analyze COVID-19.

Ucar and Korkmaz [38] assisted with the Squeeze-Net model's Bayesian optimization and worked on X-ray imaging for COVID-19 diagnostics. Apostolopoulos *et al*. [39] used CNNs trained to transfer learning to perform detection and recognition on X-ray images. For the identification of COVID-19, Sahinbas and Catak [40] utilized X-ray images coupled with the models VGG16, VGG19, Res-Net, Dense-Net, and InceptionV3. Through feature extraction and segmentation of X-ray images, Medhi *et al*. [41] were able to classify COVID-19 using CNN positively and commonly.

Barstugan *et al*. [42] utilized five different feature extraction methods: i) grey-level co-occurrence matrix (GLCM), ii) local directional patterns (LDPs), iii) grey-level run length matrix (GLRLM), iv) grey-level size zone matrix (GLSZM), and v) discrete wavelet transform (DWT). To classify X-ray images for the diagnosis of COVID-19 (DWT). SVM was used to categorize the collected features. They used 2-fold, 5-fold, and 10-fold cross-validation to ensure accuracy in our classifications. Using X-ray images and the Res-Net, InceptionV3, and Inception-Res-Net models, Punn and Agarwal [43] identified COVID-19.

2. METHOD
2.1. Dataset
In DL, data plays a significant role. It serves as fuel in the learning process; the most extensive and accurate dataset you have, the better result you can get. Thus, we have used SARS-CoV-2 CT scans, a publicly available dataset, to train our model. This dataset includes 2,482 CT scan images in total, with 1,252 CT scans for patients infected besides 1,230 CT scans for suckers non-diseased [44]. These chest scan images were collected for actual suckers from hospitals in Sao Paulo, Brazil. This data is available to download at [45]. Figure 1 shows tests of the SARS-CoV-2 C.T dataset Figure 1(a) COVID-19 CT scans images and Figure 1(b) non-COVID-19 CT scan images. In general, we train neural networks that require dataset images of similar sizes. However, the SARS-CoV-2 dataset consisted of images of many sizes; therefore, we first resized all images to [100×100] pixels as a pre-processing action [46].

It is standard in DL to split the dataset into training and test sets to train and evaluate a model train using the training set and then evaluate the model's performance using the testing set. Therefore, it is necessary to utilize unseen data in the testing phase. Thus, we decomposed the SARS-CoV-2 dataset into two parts: 80% for a training set of the total dataset and 20% for a testing set of the total dataset.



(a)

(b)

Figure 1. Tests of SARS-CoV-2 CT dataset; (a) COVID-19 CT scans images and (b) non-COVID-19 CT scan images

2.2. The proposed model
Our proposed model is named CT-CNN. It is a trainable model based on deep CNN, which is trained to classify COVID-19 infected patients by using chest CT scans. In the following, CT-CNN network architecture is described in detail. The whole CT-CNN model architecture is illustrated in Figure 2, which is implemented using two-dimensional CNNs; the model is composed of sequential layers, each of which plays a role in the classification process to predict infected cases. The CT-CNN aims to classify the CT scans into their correct class (COVID-19 or non-COVID-19). The network CT-CNN architecture decomposed into three main blocks to extract features from the dataset inputs. These three blocks are trained and tested as a single CNN network; however, it is much easier to explain them individually as the following:
- The first block layers, this block consists of a two-dimensional convolution layer with three filters and a receptive field size of [five by five]; convolutional layers are the critical component of the CNN for image classification tasks; this part is designed to get better features from an input image plus prepares the scans to be classified. Then, the convolution layer is tracked via a rectified linear unit (Relu) as an activation function. Next, the max-pooling layer was used with a kernel size of [three by three] and a stride of one to overwhelm the overfitting issue and minimize the size of the convolved features.
- The second block layer, this block consisted of a two-dimensional convolution layer with sixteen filters with a receptive field size of [five by five]. Then, the convolution layer is tracked via a Relu, tracked via a max pooling layer with a kernel size of [three by three] and stride of one. In the final block layers, this block consisted of a two-dimensional convolution layer with twenty-eight filters and a receptive field size

of [five by five]. Then, the convolution layer is followed by a Relu, followed by a max pooling layer (MPL) with a kernel size of [three by three] and stride size of one.
- Finally, after feature extraction from the previous blocks, the last step is classifying the images based on those features. Hence, fully connected SoftMax layers were used as a classifier. The overall details and parameters of the model are described in Table 1.

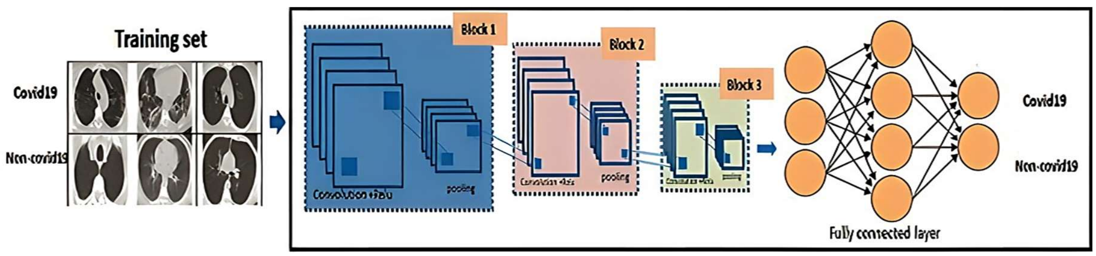


Figure 2. CT-NN architecture

Table 1. CT-CNN layers and parameters

Block 1	Block 2	Block 3	Classification
2-D Conv (3,5×5) layer	2-D Conv (16,5×5) layer	2-D Conv (28,5×5) layer	Fully connected layer
RELU layer	Relu layer	Relu layer	Softmax
Max pooling (3×3) layer	Max pooling (3×3) layer	Max pooling (3×3) layer	

2.3. Training

In this section, we described the training configurations to get better performance of the proposed CT-CNN and report more reliable results; stochastic gradient descent (SGDM) optimizer has been used for optimization, the momentum set to 0.9 and the learning rate remains constant with 0.1 while regularizations factor was set to 0.001. The loss function was used to decrease the error between the input label and the output label. Furthermore, we trained our model for thirty epochs, meaning that the whole data was fed to the network thirty times. Algorithm 1 describes the training process using the training set as input.

Algorithm 1: the proposed CT-CNN
Input: chest CT scans training set
Output: CT-CNN professional network.
Begin
Step1: T.R. ← Load CT scans training set.
 L ← Length (T.R.).
Step2: Resize (T.R) // [100 ×100] pixels.
Step3: Train a Net.
 For I ← L make
 Classify (T.R) // Sorting and classifying the Training Data
Step4: Analyze the contaminate network.
 End.

The experiments were performed on a PC running Windows 10 O.S. with intel inside core i7, CPU of 1.99 GHz, RAM of 16 GB, and Nvidia GPU GeForce MX130. The training took about (5) minutes using single GPU, the code of the CT-CNN model applied utilizing MATLAB environment with DL toolbox. The training curves of both loss function and accuracy are shown in Figures 3(a) and (b) (see appendix).

3. RESULTS EVALUATION

In this portion, we report the results of the CT-CNN model for COVID-19 classification. As mentioned, the dataset has been portioned into sets: i) 80% for the training set and ii) 20% for the testing set. A testing set and three calculation metrics were utilized to calculate a performance of CT-CNN method. The first and most important is accuracy, which determines the sum of correct values that are predicted out of all predictions. In other words, it tells how a model accurately classifies images to their proper class/label. The second metric is recall, which determines how many actual coronavirus cases are discovered. As well as a third metric is F1 score, representing the average mean between the recall and the precision. Figure 4 shows our model's results.

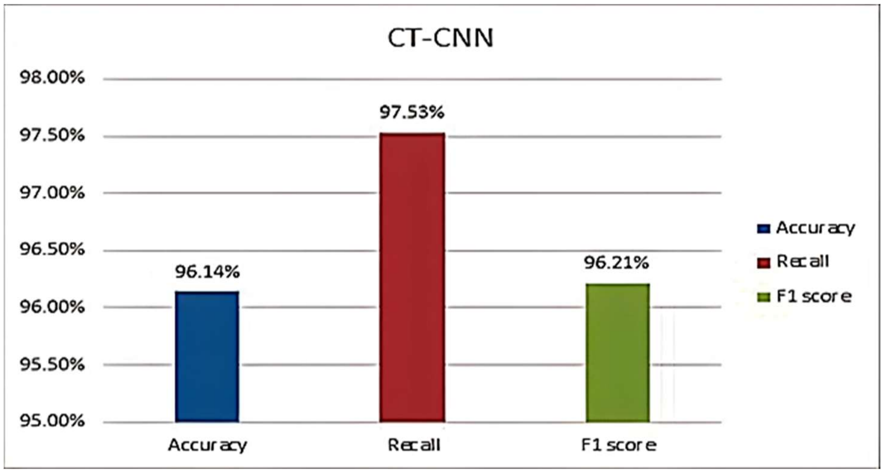


Figure 4. The CT-CNN model result

The confusion matrices were also used to show all details about the right or wrong classification for our CT-CNN proposed model, which is presented in Figure 5. Where true positive (TP) refers to correctly labelled scans, false negative (FN) to scans incorrectly identified as belonging to a different class, false positive (FP) to scans incorrectly labelled as belonging to any class at all, and true negative (TN) to scans not belonging to any class at all. To further analyze the effectiveness of the suggested scheme in real-world presentations, as well as to provide a comparative calculation. Table 2 compares the suggested method to various studies techniques, such as classic deep neural networks as well as pretrained networks. Figure 6 shows the difference of an efficacy of several methods for identifying COVID-19. As a result, the outcome in Table 2 indicate that CT-CNN have better performance and high efficiency on classification compared to other studies approaches.

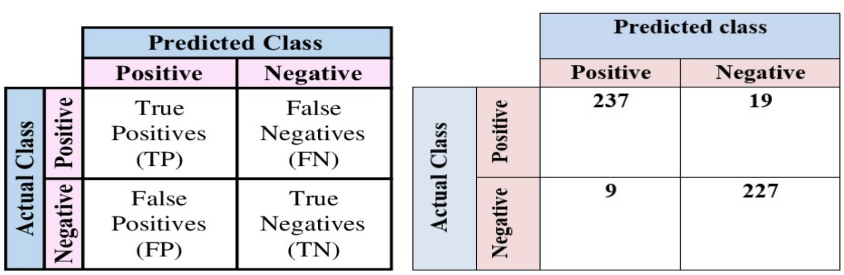


Figure 5. Confusion matrices for the COVID-19 class

Table 2. Utilizing a variety of calculation metrics, a comparison of the efficacy of various models for identifying COVID-19

Studies	Accuracy (%)	Recall (%)	F1 score (%)
Modified VGG-19 [1]	95	94	94
COVID CT-Net [47]	91	85	90
Contrastive learning (CL) [48]	91	86	91
Proposed model*s	96	96	97

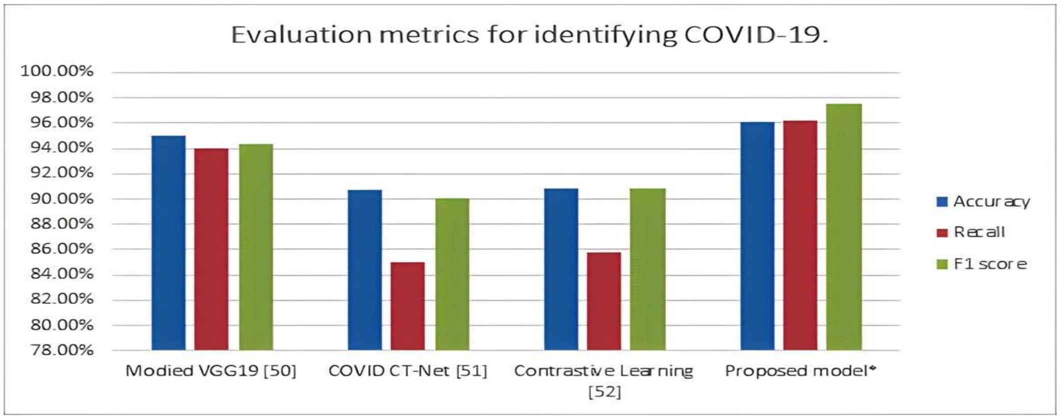


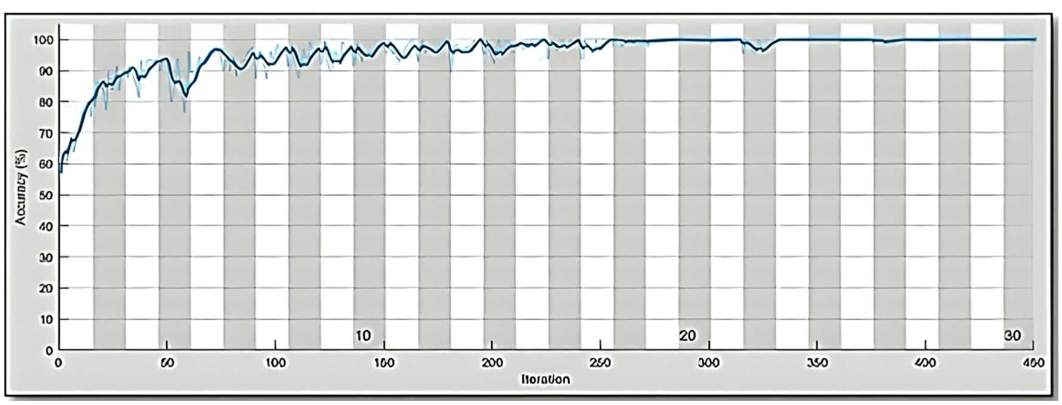
Figure 6. Comparison models' performance in detecting COVID-19

4. CONCLUSION

This paper proposes a CT-CNN classification model for COVID-19 diagnosis using the chest CT-scans dataset. Primarily, the chest CT scans dataset consists of two sets: the training set and the testing set. Then, a CT-CNN model's architecture was built with three core blocks of layers; next, the CT-CNN model was trained to utilize the training set and then examined and evaluated using the testing set. The results of our proposed model are auspicious, with the accurateness of 96 percentages, an F1 score of 96 percentages, as well as a recall of 97 percentage in classifying CT scans. Finally, the comparisons are illustrated between the CT-CNN method with other studies deep CNN classification models, which presented that CT-CNN method is more precise and effective in the COVID-19 classification mission. We comprehensively analyzed the published research on the infection-state identification in addition to COVID-19 categorization. We explained wherefore this simulation is the next phase the evolution of automatic CT image processing (telemedicine application). In the lack of a standardized framework for objectively comparing our outcomes, we discussed our findings while evaluating their originality and quality.

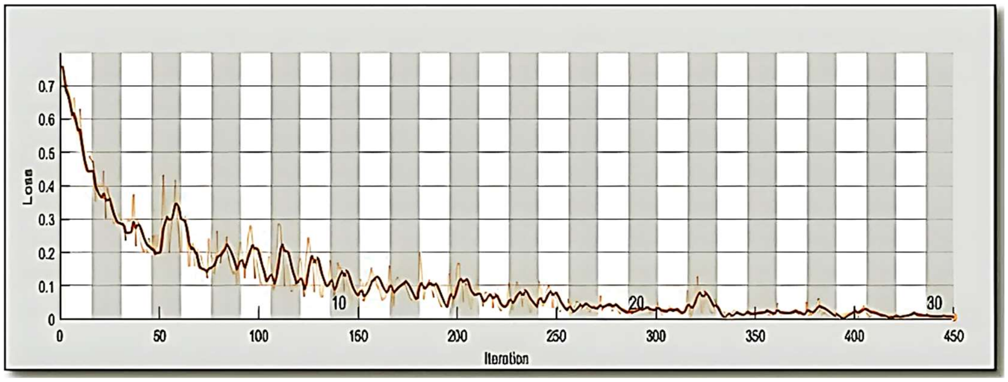
In addition, we demonstrated MATLAB-powered software. This interface provides RT-PCR with a visibility-fused, categorized, and recognized discovery that highlights the presence of COVID-19 by utilizing a combination of computed tomography and image analysis (early, progression, or peak phase). Due to the fact that the reference document is now digital, it is no longer essential to pass it around physically. This CAD can be linked into the picture archive and communication system of the radiology department to increase the future speed and accuracy of automated diagnosis.

APPENDIX



(a)

Figure 3. The training curves of both loss function and accuracy (a) training process accuracy and (b) training process loss function



(b)

Figure 3. The training curves of both loss function and accuracy (a) training process accuracy and (b) training process loss function (continue)

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