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Deep learning-based COVID-19 detection system using pulmonary CT scans

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Abstract: One of the most significant pandemics has been raised in the form of Coronavirus disease 2019 (COVID-19). Many researchers have faced various types of challenges for finding the accurate model, which can automatically detect the COVID-19 using computed pulmonary tomography (CT) scans of the chest. This paper has also focused on the same area, and a fully automatic model has been developed, which can predict the COVID-19 using the chest CT scans. The performance of the proposed method has been evaluated by classifying the CT scans of community-acquired pneumonia (CAP) and other non-pneumonia. The proposed deep learning model is based on ResNet 50, named CORNet for the detection of COVID-19, and also performed the retrospective and multicenter analysis for the extraction of visual characteristics from volumetric chest CT scans during COVID-19 detection. Between August 2016 and May 2020, the datasets were obtained from six hospitals. Results are evaluated on the image dataset consisting of a total of 10,052 CT scan images generated from 7850 patients, and the average age of the patients was 50 years. The implemented model has achieved the sensitivity and specificity of 90% and 96%, per scanned image with an AUC of 0. 95.

Key words: SARS-CoV-2, CT Scans, COVID-19, detection, deep learning, ResNet50, big medical data

1. Introduction

The latest coronavirus infection has spread worldwide since January 2020, which was first identified in Wuhan, China [1]. COVID-19 is characterized by fever, dry cough, nervous throat, loss of taste, and smell [2]. Additionally, tiredness, headaches, and respiratory problems (3%) are unidentified symptoms. Two related viruses, extreme acute respiratory syndrome coronavirus (SARS-CoV and MERS coronavirus), have been identified earlier [3, 4]. In China, the diagnosis was confirmed by the COVID-19 in a real-time polymerase chain reaction (RT-PCR) by the government [5].

RT-PCR is an effective test and takes a long time by the high false-negative rates. In the current pandemic situation, the low sensitivity RT-PCR test is unsatisfactory [6]. In some instances, the individual infected may not be detected immediately and may not be handled accordingly. Often, a fake negative result may be used as COVID-19 to allocate the infected to healthy people. A more reliable, practical, and faster technology available

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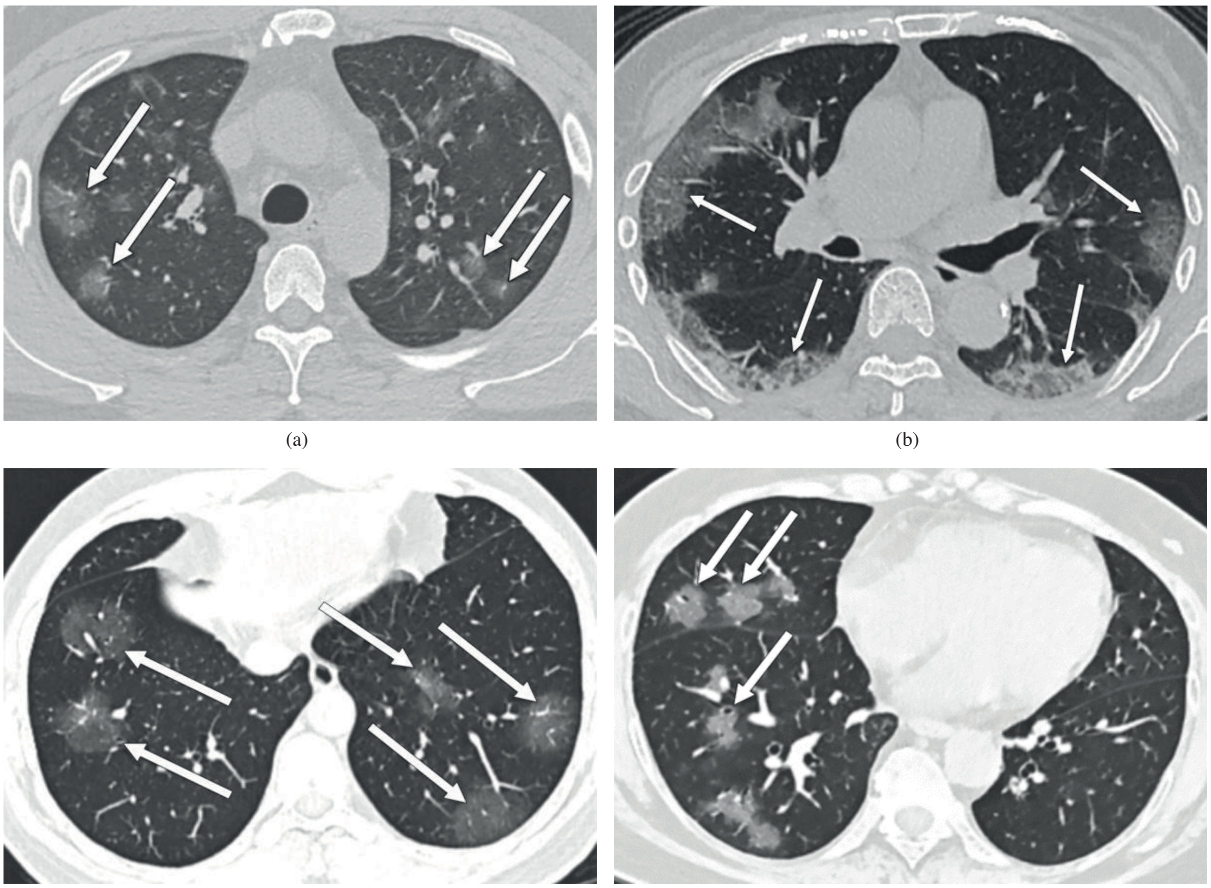
is computed tomography (CT) instead of RT-PCR for classifying and evaluating COVID-19 in the epidemic [7]. Figure 1 illustrates the images of Pulmonary CT scans. It is almost impossible to get a CT scan unless you're in a hospital that is why thoracic CT images for the early detection of COVID-19 patients are instrumental. Thus, finding COVID-19 using Thorax CT saves valuable time. Therefore, it is beneficial to save precious time of medical staff by automating analyses of the Thorax CT images.



(a) (b) (c) (d)

Figure 1. Images of Pulmonary CT scans.

The most powerful technology to use in medical research is deep learning. It is a simple and efficient way to diagnose and forecast different diseases with a reasonable precision rate. In the medical domain, various deep learning techniques have been used to differentiate between COVID-19 patients and healthy ones using CT scan images. One of the models is ultraprecise CTnet-10 model that is based on selfdesigned CT-10 process and is having accuracy of 82.1% [8]. Previous models are often used to improve the accuracy using CT scan images. One of the models presented is VGG-19 for detecting COVID-19 with an accuracy of 94.52% [9]. A number of authors have done various works on the detection of COVID-19, but still satisfactory results have yet to come. Therefore, in this paper, a deep learning-based model has been proposed, which can automatically detect the COVID-19 from pulmonary CT scan images.

The contributions of this work are as follows: (i) Introduced an approach based on deep learning that can classify the COVID-19 and nonCOVID-19 using Pulmonary CT scans images for the prediction of COVID-19.

(ii) Proposed model has been evaluated on the basis of parameters such as specificity, sensitivity and AUC.
(iii) Finally, it has been compared with the existing deep neural networks like AlexNet, VGG-16, SqueezeNet, VGG-19, etc.

The rest of the paper is organized as follows: Section 2 consists of the related work, whereas Section 3 and Section 4 have discussed the proposed work and result analysis, respectively. Lastly, Section 5 includes the discussion followed by references.

2. Related work

In the study of medical data processing, data scientists are making important contributions that eventually help in the development of medical sciences. Deep learning / machine learning / data extraction classifications were applied tremendously in order to extract specific features from image datasets for disease diagnosis and prediction. Human organ lungs become infected with COVID-19, and their diagnosis depends solely on the lungen ray [10]. Therefore, presearch data from lung image analysis is obvious, which helps in the evaluation of COVID-19 to achieve some sensible outcome by means of the profound learning process. The 121-layered convolutional neural network (CNN) uses a powerful CNN algorithm to detect the cases of pneumonia from chest X-rays. The model is trained in a data collection of over 100,000 pictures that include a frontal picture of the lung rays and outlines 14 forms of illnesses [11].

Rajpurkar et al. also stated likewise in the new COVID-19, the X-ray images of the chest were subject to the CNN methodology because they genuinely triggered more serious symptoms of pneumonia [12]. Alqudah et al.[13] has introduced an automated COVID-19 system using soft-max machine learning classifiers – support vector machine (SVM), random forest, k-nearest neighbor (KNN) with soft-max CNN to detect the problem with a 98% high level of accuracy. In the identification of malignant lung cancer from image evidence, the detection rate of Singh et al. [14] is 85.55%. Esteva et al. [15] based on the manifestation of skin lesion recognition, the diagnosis of various clinical skin images required a single CNN sheet. Two important cases – common cancer and deadly cancer – were listed in a research model for binary use. Liu et al. [16] has suggested a method of classifying the manifestations of tuberculosis in the chest, as seen in the tuberculosis datasets. The data collection used for X-ray images is unbalanced. The approach was CNN and transfer of learning and was stable with an excellent set of optimization strategies for different CNN architectures. However, during pre-processing of the data, it failed to consider regional information.

ResNet23 and classical ResNet-18 were used in the analysis carried out by Butt et al., and it achieved 86.7% accuracy [17]. The model has been educated on images from CT scans. In order to detect trends and forecast COVID-19 in different scenarios, Fanelli and Piazza used the publicly accessible dataset provided by John Hopkins University [18]. The median kinetics of the spread of the pandemic predicted the developments of the COVID-19 outbreak and how the government lockout placed affected the situation. Artificial intelligence (AI) has been introduced by Apostolopoulos and Mpesiana [11] with various transfer learning combinations and has obtained the best result with 98.75% accuracy of VGG19. The data collection used is also from GitHub, but the leakage of data may occur because many images of the same patient have been overlooked, and this may be a justification for high accuracy.

Li et al. [19] using AI, three-dimensional deep learning models in a dataset of 4356 CT scans of 3322 patients to detect patients of COVID-19. In order to forecast patterns and a potential cessation period of COVID-19 in different countries. Chimmula and Zhang [20] have developed an automated model using profound learning and AI, specifically Long Short Term Memory (LSTM) networks (rather than statistical methods). The diseases have patterns that are typically non-linear and linked to their propagation. The aim that can be accomplished with sequential networks is to identify these patterns. The model used transmission time series data and forecasted the coming patterns of viruses in Canada and that many infection clusters could continue until December 2020.

For the study of 77 CTs in the brain by Grewal et al. [21], DenseNet architecture and recurrent neural network layers were used. RADnet indicates a precision of CT-level hemorrhage of 81.82 percent. The Song et al. has performed lung cancer calcifications using three deep neural networks viz. CNN, Deep neural networks (DNN), and sparse autoencoders (SAE). Possibilities of the detection and prediction of ARD and mortality in smokers via pro food education, particularly CNN analyses, according to the findings of Gonzalez et al. [22]. During the epidemic period of COVID-19, CT was found to be useful for diagnosing COVID-19 patients. CT scan images of floor glass opacity, consolidation, crosshairs, and mad floor patterns were the primary factors for selecting COVID-19 for the sensing of COVID-19. CT chest findings and COVID-19 pneumonia were associated with each other by the group of researchers led by Zhao et al. [23]. This research, done by four universities in Huwan, China, and has found 101 cases of COVID-19 pneumonia. A basic understanding of clinical properties and detailed imagery characteristics was first assessed, and then these characteristics were compared. One hundred and twenty-one symptomatic Coronavirus-infected patients underwent a report on their chest CTs in the study published by Bernheim et al. [24]. These CT scans show bilateral and peripheral ground glass and consolidating pulmonary opacities in the lungs of patients treated with COVID-19.

A free-of-charge, open-source COVID-CT dataset created by Zhao et al. [25] holds 349 COVID-19 CTs of 216 patients and 463 non-COVID-19 CTs. The AI model for diagnosing COVID-19 in CT scans was developed by using the dataset. An automated image analysis platform based on AI was created by Gozes et al. [26] for the detection, quantification, and monitoring of coronaviruses in 157 international patients. The model's accuracy was 95 percent. The usual chest CT findings in both lungs include interlobular septal thickening, also seen under the pleura. The research team conducted research on an effective software system for accurate COVID-19 detection and determined that they had found it in the COVID-19 3D CT volumes [27].

UNet and a 3D deep neural network estimated the probability of COVID-19 infections on 630 CT scans. Among the total of 1,014 patients, 601 have tested positive for COVID-19, based on RT-PCR, and similar findings have been registered for chest CT. COVID-19's sensitivity for detecting lung lesions on a chest CT scan was reported to be 97% according to the research done by Ai et al. [5]. In a series of 51 patients with Chest CT and RT-PCR tests performed within three days by Fang et al. [28], generated COVID-19 sensitivity was 98% with CT while RT-PCR showed 71%. The CAD4COVID-Xray [29] system was trained on 29,000 CXR images, including 1,540 used solely for validation during training. The AI system was able to view six sets of x-rays independently. Using a pre-defined cut-off value (RT-PCR test results as a reference norm), the AI approach correctly identified CXR images as COVID-19 pneumonia, which has an AUC of 0.81.

There has been a wide variety of research activities using CNN, especially in the field of medical image analysis. Several methods have already been implemented in collaboration with health science which could reduce the wait for the broad diagnostic phase of some diseases. So, the next section will cover the materials and methods used for the prediction of COVID-19 disease.

3. Materials and methods

In this study, two factors have played a major role: proposed deep learning model and datasets used for the prediction purpose.

3.1. Dataset

The participating hospitals' ethics committees have entirely endorsed this retrospective research. To comply with informed written consent standards, this study no longer allows participants to obtain consent. A total of 3506 patients have been examined, all of whom had CT scans taken in the six medical centers over 15 months between August 16, 2016, and February 17, 2020, and all 3D CT scans were illustrated in Figure 1 as (a) Better CT scans for contrast materials, and (b) slice thickness scans with a thickness of more than 3 mm as shown in Figure 1. The mean age of the patients (standard deviation) was 49 years, and there were a substantially greater number of men (1838) than women (1484; p = .29). CT scans were present as part of a multiresolution image acquisition session that included multiple reconstruction kernels, each acquired at different times during the procedure. 1292 (30% of the 4352 scans in the final data set for COVID-19), 1735 (40% of the 4352 scans in the last data set for COVID-19), and 1325 (30% of the 4352 scans in the last data set for non-pneumonia abnormalities) were captured for the study. COVID-19 RT-PCR cases that have been acquired between December 31, 2019, and February 17, 2020, have all been confirmed positive. The time interval between the beginning of the first CT exam and the procedure's conclusion was seven days (range, 0-20 days). It lasted two days. Common signs were either cough (66% of 468 patients) or fever (81% of 468 patients).

The disease (average patient number of CT exams, 1.8; spectrum, 1–6) was accompanied by the administration of multiple CT tests on different days for each patient. In the participating hospitals, patients who had CAP and those who were not sick with pneumonia were randomly selected between August 16, 2016, and February 17, 2020. Although admissions into CAPS could take different forms, ambulatory, 46 percent (713 patients, 1551), and emergency, 3% (40 patients, 1551) were the most frequent admissions (46 patients). Of the 1551 CAP patients, 210 were confirmed as originating in the laboratory: 112 had a positive bacterial culture, and 98 had a negative bacterial culture. Patients with CAP and other non-pneumonia anomalies have been randomly selected from participating hospitals from August 16, 2016, to February 17, 2020. According to sources, both scans were apparently split into an exercise-based exercise kit with a 9:1 ratio and a patient-specific test.

The dataset for training the model was further divided, and internal validation was performed (10 percent of samples). For training and internal validation, the independent test set has not been used. Table 1 lists the patient illness statistics based on training and testing dataset, and Table 2 summarizes the patient population statistics, i.e. CORNet with the existing models.

Table 1. Comparison table of the CORNet with the existing models.

Dataset	No. of patients	Category	Number of scans
Training	1165 scans	nonpneumonia	1173
		CAP	1396
		COVID-19	400
Test	127 scans	nonpneumonia	130
		CAP	155
		COVID-19	68

Table 2. Comparison table of the CORNet with the existing models.

Model	Category	p value	AUC	Sensitivity(%)	Specificity(%)
Alexnet	Covid-19	-	0.89	89.21	68.63
VGG-16	Covid-19	-	0.928	80.39	86.27
SqueezeNet	Covid-19	-	0.899	78.43	87.25
VGG-19	Covid-19	-	0.94	92.16	78.43
ResNet-50	Covid-19	-	0.91	90.2	91.1
CORNet	nonpneumonia CAP COVID=19	<<.001	0.98 0.95 0.96	94 87 90	96 92 96

3.2. CORNet - proposed deep learning model

This study aims to build the COVID-19 prediction model using pulmonary CT scan images. It is observed that during the last 4 to 5 years, the deep learning model has performed significantly well in image classification. One of the primary reasons behind this is that the image consists of different components, so to process each component, different layers with several neurons are used in the deep learning model. These layers and neurons will generate better results during the classification. In this paper also, for the detection of COVID-19, called CORNet, a 3D deep learning system has been developed as illustrated in Figure 2. It can derive representative characteristics from both the local and 3D dimensions. The CORNet system consists of the backbone RestNet50 [30], which takes input from several CT trunks and provides functionality for the respective trunks. The extracted features are then combined with a pooling process from all slices. A completely linked layer and softmax activation feature for each species (COVID-19, CAP, nonpneumonia) is applied to the final characteristic plan. A unit based segmentation method has been employed for preprocessing and removal of lung regions as the area of concern with a 3D CT scan [31]. The image is then forwarded for the forecast to the proposed CORNet.

In this, ResNet-50 model is used as a backbone model with the Max Pooling approach using shared weights. The multiclass classification with the classes such as COVID-19, CAP and nonpneumonia is done using the proposed approach CORNet as shown in Figure 2.

4. Results and analysis

4.1. Statistical analysis

The proposed deep learning model's output was evaluated using an independent test set not used during model creation. Python software (version 3.6.3) has been used for statistical analysis with the help of Anaconda framework. Anaconda framework provides different type of libraries such as tensor flow, scikit-learn and many more for performing the analysis. Variance test analyses and x2 tests have been used to compare continuous and dichotomous variables between different classes. A statistically significant difference between the two-sides of p as .05 has been considered. Both COVID-19 and CAP sensitivity and specificities have been determined. The recipient operating characteristic curve has been plotted, and the area under the curve measured using the method by DeLong et al. [32] with 95% confidence intervals (CIs).

The parameters used for the evaluation of the model are as follows:

(i) Specificity and sensitivity - Sensitivity and specificity define how accurately a classifier predicts the true

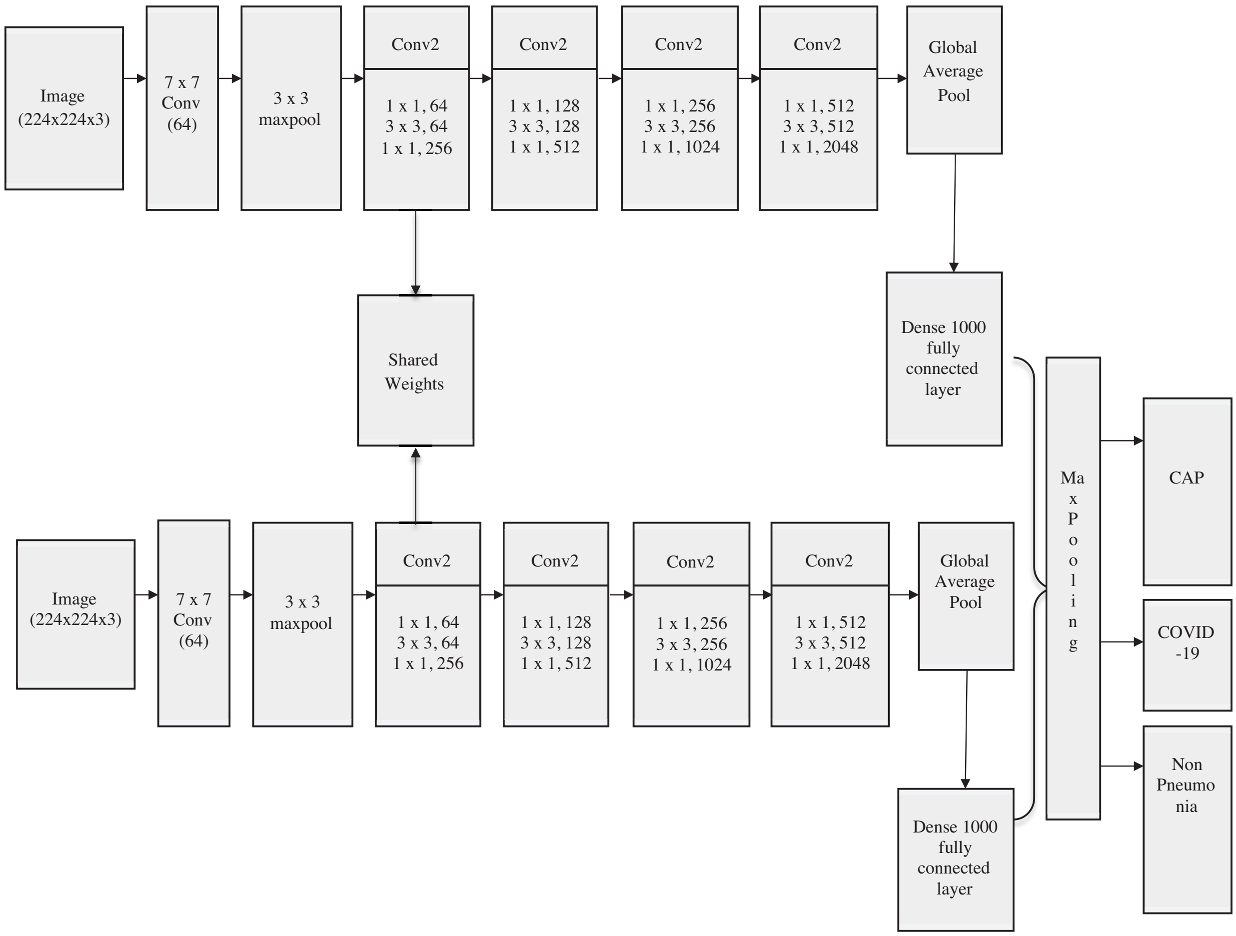


Figure 2. CORNet architecture.

positive rate and true negative rate for positive and negative labels that respectively represent the total positive and total negative count. In the given equation (1) & equation (2), TN and TP represents the true negative and true positive, respectively, whereas FP and FN shows the false positive and false negative, respectively. The given equation (1) & equation (2) show the specificity and sensitivity, respectively [33].

$$Specificity = TN/(TN + FP) \tag{1}$$

$$Sensitivity = TP/(TP + FN) \tag{2}$$

(ii) AUC - The AUC or ”Area under the ROC Curve” defines the total two-dimensional area underneath the entire ROC curve. This area is from the origin (0,0) to the value input (1,1). When the AUC is measured, it contains data from all possible threshold levels.

4.2. Model evaluation

The whole work is implemented using GPU, and the implementation has been done by Python programming language. From the results listed in Table 2, it has been indicated that the proposed model CORNet has outperformed the other existing algorithms. CORNet has achieved the AUC of 0.98, sensitivity of 94%, and specificity of 96%.

The comparative analysis of the proposed model with various networks has been performed on the basis of specificity. Figure 3, Figure 4 and Figure 5 illustrated the sensitivity, specificity, AUC comparison of the CORNet architecture with the existing networks. The graph has indicated that CORNet architecture has shown improved performance than other states-of-the-art algorithms.

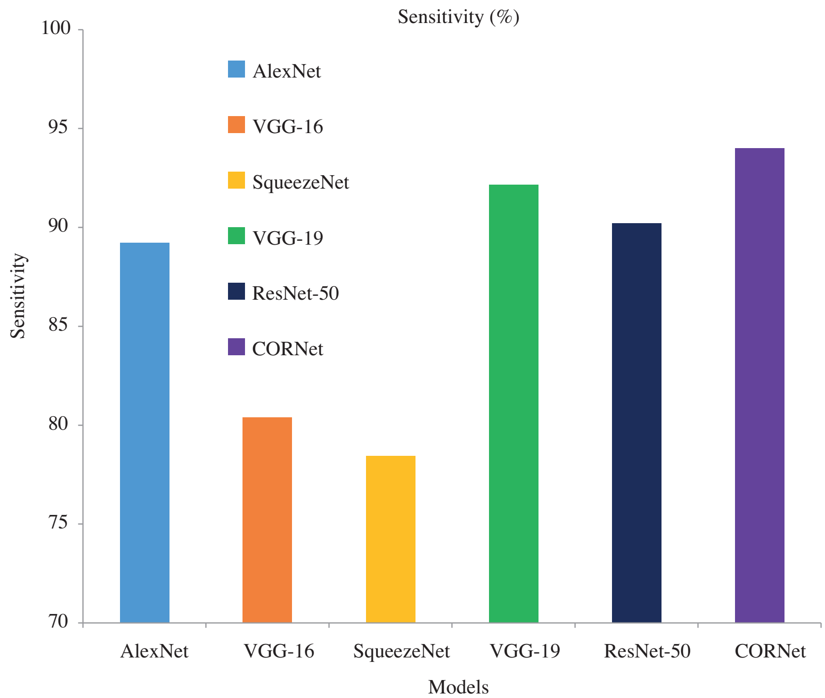


Figure 3. Sensitivity comparison of the CORNet architecture with existing networks.

It has been observed that CORNet has achieved the highest value of specificity [34] in comparison to AlexNet [35], VGG-16 [36], SqueezeNet [37], VGG-19 [38] and ResNet-50 [30]. It has also been noticed that SqueezeNet has shown very poor performance.

5. Discussion

A large number of CT scans, including 1292 COVID-19 CT scans, were performed in several hospitals. Additional control groups included 1735 CAPs and 1325 nonpneumonia CT scans to check detection robustness. Since different lung diseases and disorders had specific similar imaging characteristics, COVID-19 was detected in the control groups' scans. COVID-19 was first observed in the second half of 2019, and, as of the time of this writing, the virus has entered many other countries. As part of treatment, early diagnosis of the disease is vital to avoid the virus's spread. Reverse transcription-polymerase chain reaction (RT-PCR) is considered to be the reference standard. Still, chest computed tomography (CT) can scan for COVID-19 as a reliable and rapid approach.

It has been observed that the standard distribution of various CAP subtypes is adequate by the proposed sampling process. Non-COVID-19 viral pneumonia (e.g., flu-virus), bacterial pneumonia, and pneumonia from

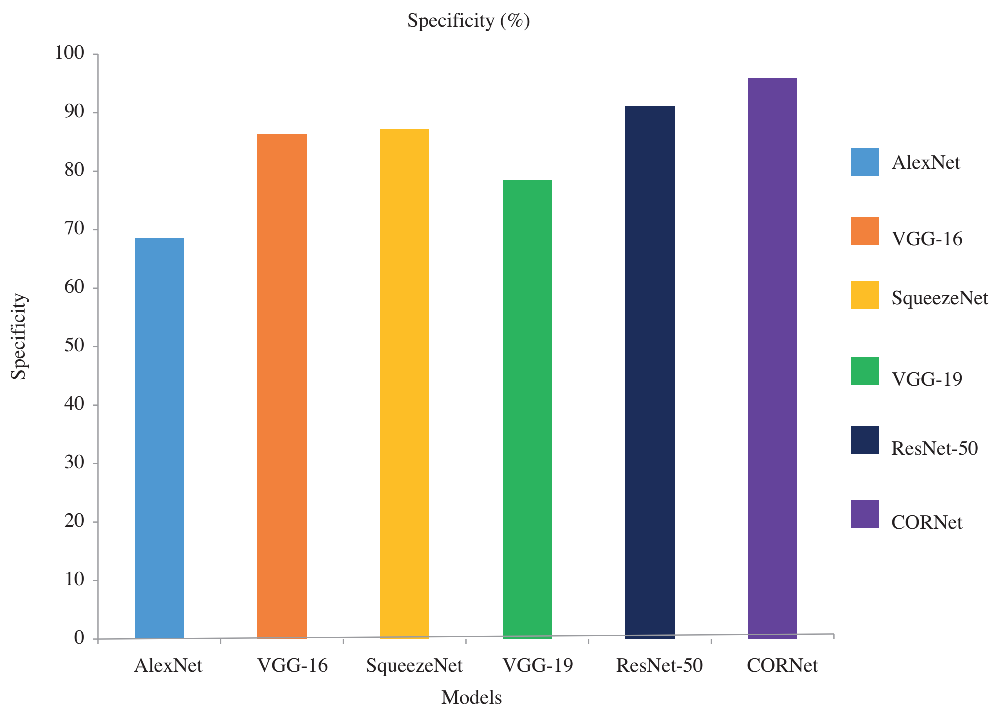


Figure 4. Specificity comparison of the CORNet architecture with existing networks.

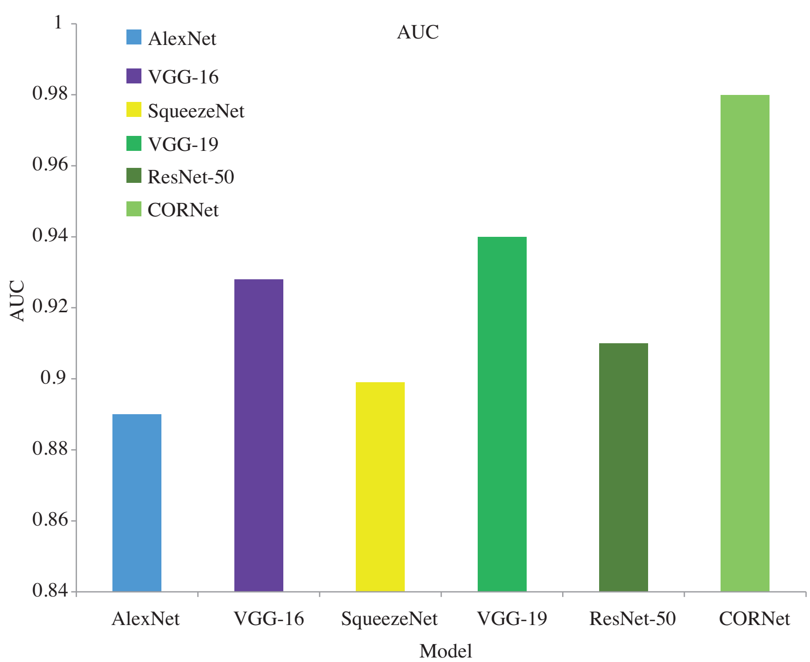


Figure 5. AUC comparison of the CORNet architecture with existing networks.

all causes should have been included in these cases. To validate the viral agent's real-time polymerase chain reaction, the results of CORNet should be checked. Another disadvantage of all deep learning techniques is their lack of clarity and interpretability (for example, it cannot be established what imagery is used to evaluate output). However, heat maps cannot provide the data necessary to picture how the model differentiates between COVID-19 and CAP with its distinctive features. Additionally, the lung's response to a variety of insults tends to overlap, which is linked to the presence of a variety of pulmonary diseases depending on various host factors, such as age, reactivity to drugs, immune status, and the number of other comorbidities. There is no single technique capable of identifying all of the different lung diseases detected by chest CT scans. It is proposed that a multidisciplinary approach should be required. The amount of data gathered in this study was huge, but both the training and test sets originated from the same healthcare facilities. As quickly as possible, we plan to perform more CT scans from different locations.

The study investigated whether one scan is COVID-19; and found no differentiation into different gravities when the disease diagnosis was not addressed. COVID-19 and the degree of control and treatment frequency will both play an essential role as a next step. A well-reasoned deep learning model is now in place to determine if a patient has coronavirus infection or a chest CT scan (COVID-19). This study demonstrates that an algorithm built with a convolutional neural network model can distinguish between COVID-19 and CAP.

6. Conclusion

In this study, a deep learning model named as CORNet has been developed for the detection of Coronavirus 2019 (COVID-19) from 3D chest CT scans. The proposed model has been evaluated with other existing networks. Concerning the independent testing results, this model has been shown to achieve high levels of sensitivity (94%, 87%, and 90%) and high specificity in the detection of COVID-19, respectively (96%, 92%, and 96%). For COVID-19 and communal-acquired pneumonia (CAP), the areas under the receptor operating characteristics were 0.96. This structure will extract representative features, both local and global, in two dimensions. Deep learning in the area of radiology has achieved superior achievement. Eventually, deep learning methods have been used successfully to diagnose pneumonia in pediatric chest x-rays and distinguish viral and bacterial pneumonia in bi-dimensional pediatric chest x-rays.In the future, the proposed method can be used to analysis other types of diseases such as cancer, diabetes and many more.

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Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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