Real-Time Diagnosis System of COVID-19 Using X-Ray Images and Deep Learning

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The novel coronavirus named COVID-19 has quickly spread among humans worldwide, and the situation remains hazardous to the health system. The existence of this virus in the human body is identified through sputum or blood samples. Furthermore, computed tomography (CT) or X-ray has become a significant tool for quick diagnoses. Thus, it is essential to develop an online and real-time computer-aided diagnosis (CAD) approach to support physicians and avoid further spreading of the disease. In this research, a convolutional neural network (CNN) -based Residual neural network (ResNet50) has been employed to detect COVID-19 through chest X-ray images and achieved 98% accuracy. The proposed CAD system will receive the X-ray images from the remote hospitals/healthcare centers and perform diagnostic processes. Furthermore, the proposed CAD system uses advanced load balancer and resilience features to achieve fault tolerance with zero delays and perceives more infected cases during this pandemic.

COVID-19 was first perceived in Wuhan, China. This disease causes fever, cough, fatigue, and muscle pain during the initial phases.[1] Usually, people with COVID-19 indicate fever and minor respiratory after 5–6 days. Mostly, the infected cases of COVID-19 are not extreme. The findings show that this virus spreads from individual to individual. Around 80% of affirmed cases have a minor ailments and they are recuperating without special treatment. Infected individuals should be quarantined to avoid further spreading and must be treated within an isolation unit. Other complications like heart issues, respiratory problems, and lung infections are also possible. Infected individuals have observed serious respiratory issues in certain cases. However, the expanding numbers of recently suspected and infected cases have become disturbing because of the lack of resources and medications.[2,19] The existence of COVID-19 in the individual is identified through sputum or blood samples test. However, an X-ray and computed tomography (CT) scan are also advised.[3,4] The X-ray procedure is mostly advised to scan the affected organ, for example, lung infections, tumors finding, bone dislocations, pneumonia, and bone fractures. CT scan is an advanced type of X-ray advised to investigate the clearer images of the inner organs and soft tissues.[5,20] However, we are choosing an X-ray image dataset because the X-ray is a less harmful, and an easier and faster diagnostic procedure than a CT scan. Failure to rapidly identify the virus and delay in the treatment of coronavirus may lead to an increasing number of casualties. The clinicians require a chest X-ray to analyze the coronavirus at an early stage. Still, the enormous number of patients and inadequate radiologists prompted a high false-positive (FP) rate because of a substantial workload. Diagnosis of COVID-19's relies upon doctors' ability to recognize infected patients with a minimal

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false negative (FN). To reduce the workload of hospitals and physicians, a systematic approach is required for timely diagnosis. Computer-aided diagnosis (CAD) frameworks are the most demanding tool for hospitals to correctly diagnose suspected and infected cases through X-ray or CT scan images. Thus, the CAD system is the latest development in medical imaging for the initial finding of infected cases and a diagnostic tool that can enhance radiologists' performance. Currently, cloud computing achieves a great concentration in healthcare applications due to its capability to deliver medical services over the Internet. However, various applications employed in healthcare environments do not provide a real-time assessment for doctors. The demand for a timely, robust, and trustworthy health monitoring system is required.

Recent works on COVID-19 regarding the CAD system is presented in the "Literature Review." The "Proposed CAD Model" is presented; Results and Discussions are presented in "Experimental Work." Load balancer and resilience feature is presented in "Cloud Services for CAD System," and finally, "Conclusion and Future Works" is presented.

LITERATURE REVIEW

We briefly discus CAD systems and the importance of cloud computing in healthcare applications.

CAD System

Image processing and machine learning techniques are widely employed in the diagnostic field due to reliable, low-cost, and quick output. Several methods of the CAD system for COVID-19 have been proposed during this pandemic. The employment of machine learning techniques is a major development in medical imaging analysis, particularly convolutional neural network's-based architectures, which have generated encouraging results. Currently, deep learning is obtaining the most popularity for medical imaging analysis.[6] For example, Butt *et al.*[7] proposed a deep learning model using a dataset of 618 CT images to detect coronavirus. Among them, 219 images with coronavirus, 224 cases with pneumonia, and 175 images of normal people. The proposed paradigm accomplished an AUC of 0.996, a specificity of 92.2%, and a sensitivity of 98.2%. Shan *et al.*[8] proposed a deep learning framework and achieved a Dice similarity coefficient of 91.6%. Wang *et al.*[9] uses the inception migration-learning model and training is performed on 217 CT images and achieved with 82.9%, 80.5%, and 84% accuracy, specificity, and sensitivity, respectively. Xuanyang *et al.*[10] employed machine learning classifiers to differentiate typical pneumonia and SARS using X-ray images.

TABLE 1. Parameters For Resnet50.

ResNet50 model	Parameter
Image size	224 × 224
Weight	ImageNet
Optimizer	Adam
Random state	11
Pooling	GlobalAveragePooling2D
Patience	5
Epochs	20
Dropout	0.5
Initial learning rate	1e-4
factor	0.2
Batch size	16
Loss	Binary crossentropy
Training ratio	80%
Testing ratio	20%

Cloud Computing for Healthcare

In the healthcare environment, communication among device to device is performed to send, collect, and analyze data to transform the healthcare services, and facilitate people and institutions. Various resources in the form of Health Information Management System (HIMS) and Picture Archiving and Communication Systems (PACS) are employed to support clinicians and improve diagnosis.[11] Such resources require high processing, storage capabilities, real-time monitoring, and other technological skills. Nowadays, cloud computing is adopted in every human life domain, especially in healthcare, to avoid storage limitations and computational complexity. Therefore, data should be placed in the cloud rather than on limited storage and computing resources to provide diagnosis perfectly. Furthermore, real-time monitoring is a significant healthcare domain that needs a high response time and low latency.

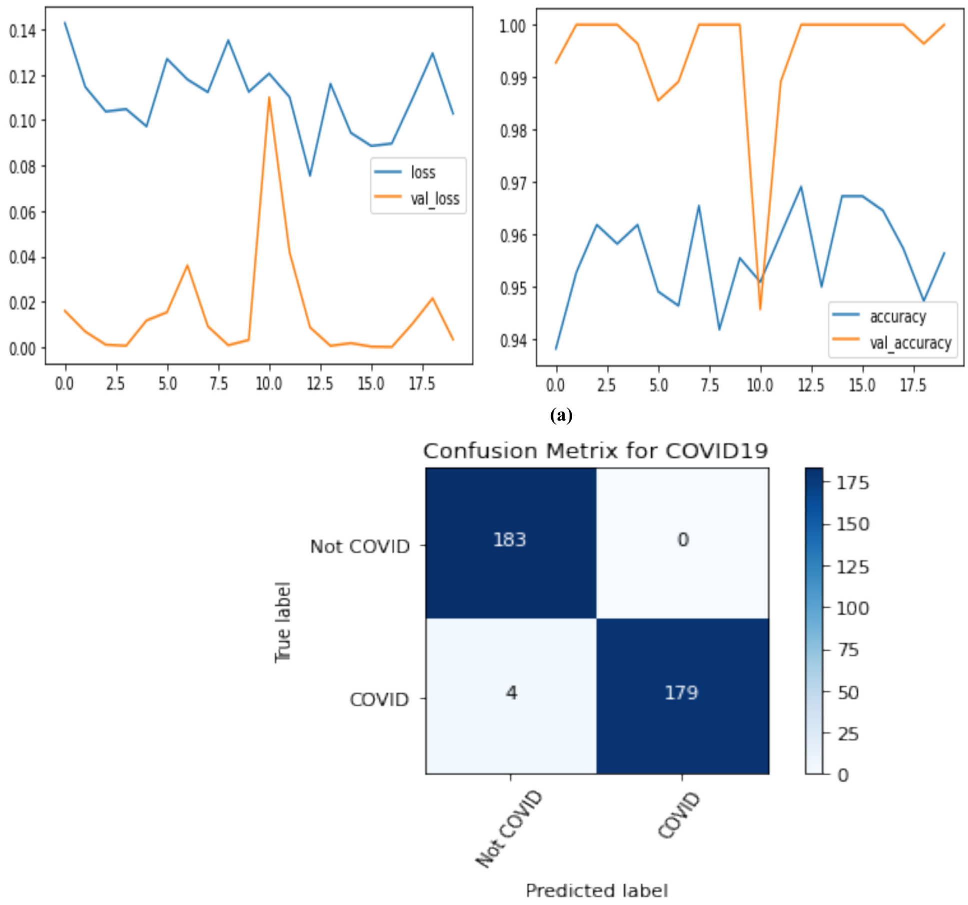
PROPOSED CAD MODEL

Database Description

Chest X-ray images have been acquired from the publicly available dataset.[12] This dataset is already augmented and contains 1824 images in which 912 belong to coronavirus and 912 belong to non-COVID images.

Background of CNN for Transfer Learning

CNN has a well-known process for image and pattern identification problems. Recently deep learning techniques show an impressive medical imaging outcome to conclude meaningful results from the diagnostic



(b)

FIGURE 1. (a) Accuracy graph using ResNet50. (b) Confusion matrix obtained using ResNet50.

procedure. The filters of CNN are convolved upon input for automatic feature extraction.

The previous architectures, like LeNet,[13] AlexNet,[14] and VGGNet[15] concentrated on expanding the level of the model to enhance accuracy. This bases a vanishing gradient problem because it generates too small value during back-propagation, causing poor learning. A deep CNN model known as ResNet is used to solve vanishing gradient problems by deploying skip functions and boosting architecture performance. ResNet50 model, a network of 50-layers, is employed to classify the chest X-ray images into COVID-19 and non-COVID categories. The main advantage of employing the ResNet50 model is that it adds shortcuts among layers to provide a quick solution. It avoids the distortion that arises as the architecture becomes complex and deeper. Furthermore, bottleneck blocks are employed to create faster training in the ResNet model.[16,17] A transfer learning-based approach has been employed through ImageNet dataset[14] to overwhelm the training cost and deficient data. ImageNet dataset comprises around 14 million images containing approximately 20,000 categories generated for image detection contests.[18] Two developments are made of transfer learning to extract significant features that are fine-tuned and freeze layers. This process causes transfer weights of the pretrained model from source-to-target dataset, for example, from ImageNet to X-ray images dataset in our proposed model. The input image is resized to 224×224 according to the network, and the output is provided in the form of classification accuracy.

EXPERIMENTAL WORK

Python was employed to train the proposed model and the experiment was carried out on Google Colab cloud services. The ResNet50 model is trained using the following parameters, as presented in Table 1.

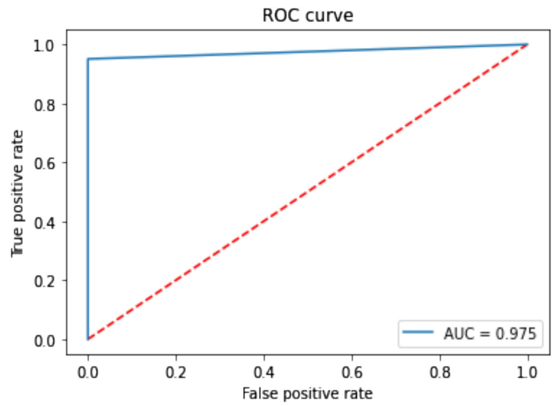


FIGURE 2. ROC curve obtained using ResNet50.

Results and Discussion

In this work, X-ray images have been employed for COVID-19 detection.[12] A well-known pretrained architecture known as ResNet50 has been employed using 80% training and 20% testing data, and achieved 98% accuracy. Moreover, other deep learning models like AlexNet[14] and VGG19[15] are also employed and achieved 92.9% and 94.2% accuracy, respectively. Figure 1(a) shows that training accuracy versus validation accuracy and training loss versus validation loss using the ResNet50 model are presented. It is observed that the loss values decrease quickly during the training stage. Figure 1 (b) shows the confusion matrix gained using the ResNet50 model of chest X-ray images on COVID and non-COVID categories.

The statistical analyses of the ResNet50 network are performed using the ROC curve and achieved the AUC value of 0.975, as illustrated in Figure 2. Furthermore, in this experiment, we tested the model and evaluated the visual prediction performance shown in Figure 3.

Cloud Services for CAD System

We know that it is challenging to control the spreading flow of COVID-19. Furthermore, most of the population is residing in rural areas, where no proper arrangement of diagnostic facilities is made available in healthcare facilitation services, including hospitals and daycare centers. Moreover, it will be beneficial if the CAD facility is extending to the rural areas' patients. Thus, online and real-time CAD framework is demanded. The proposed system will facilitate the patients around the clock with zero delays with the help of Internet of Medical Things (IoMT) devices and cloud services. This CAD system will receive images from remote hospitals/healthcare centers and will perform

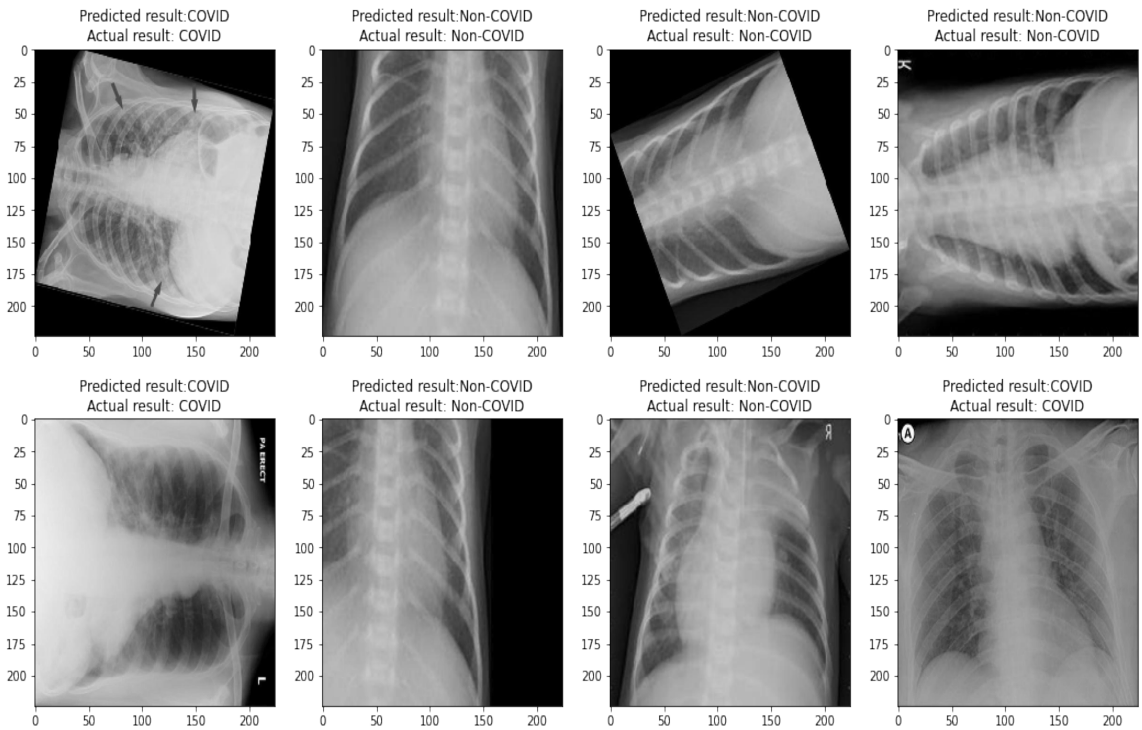


FIGURE 3 . Images prediction using ResNet50Cloud service for CAD system.

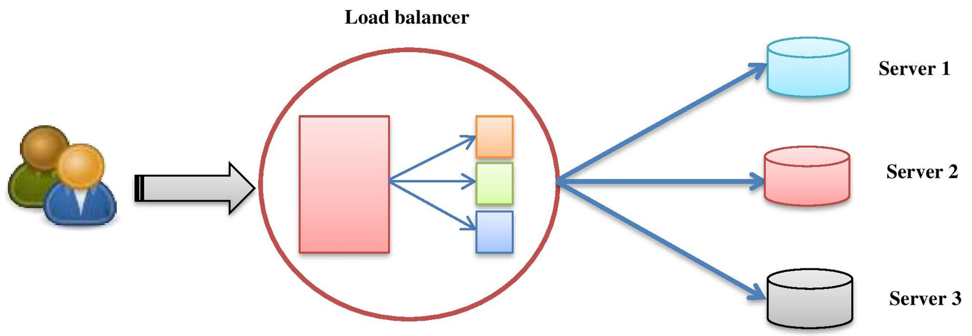


FIGURE 4. Cloud services with load balancer and resilience.

diagnostics. Thus, radiologists and physicians will be able to examine the patient's scan remotely with minimum cost and safety measures. Providing access on a global scale may degrade the performance of the proposed CAD system. Therefore, a load balancer will be placed before elastic provisioning of cloud services. In the proposed CAD system using deep learning, the concept of resilience will also be employed to provide and maintain an acceptable level of service during the fault and provide an efficient performance of the proposed CAD system remotely. The tool could be available online with features of load balancer to assist radiologists during this pandemic, as shown in Figure 4.

CONCLUSIONS AND FUTURE WORKS

Diagnosis of COVID-19 in the initial stage is significant to avoid further spreading of this ailment to others. In this work, transfer deep learning architecture through chest X-ray images is applied. The main reason for choosing chest X-ray images is their easy availability from any hospital without delay and difficulty. The experimental results illustrate that the ResNet50 model produced 98% accuracy. The deployment of such a model with cloud services and load balancers with resilience will facilitate the healthcare society, including doctors and patients. The main shortcoming of this research work is that a limited number of X-ray images are employed for the diagnosis of COVID-19. Future work may extend by adding more data and different models.

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