A Deep-Learning-Based Edge-Centric COVID-19-Like Pandemic Screening and Diagnosis System within a B5G Framework Using Blockchain

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Abstract

Beyond 5G (B5G) has the potential of realizing all three pillars of 5G, which are massive type communication, ultra-reliable low latency communication, and enhanced mobile broadband. Currently, a COVID-19-like pandemic can utilize B5G to combat the pandemic by using real-time processing of massive volumes of test data at the edge of hospitals and by leveraging seamless communication between the edge and a global core cloud to update any diagnosis or predicting model globally. In this article, we propose an artificial-intelligence-enabled edge-centric COVID-19 screening and diagnosis system using the B5G network. Furthermore, we use blockchain-based secure transmission of patients' data in the edge. The proposed system uses screening and diagnosis in the edge by using powerful edge devices that can run deep learning (DL) models. The DL models can be downloaded from the core cloud to the edge server or uploaded to the core cloud when necessary.

Introduction

The three main pillars of 5G communication are massive machine type communication (mMTC) spread over many terminals and sensors, ultra-reliable low-latency communication (URLLC), which ensures rapid feedback for real-time applications, and enhanced mobile broadband (eMBB), which transmits multiple gigabytes of data on demand. With these pillars, 5G is expected to have 1 million devices/km^2, where the devices will have 10 years of battery life, communication will have zero mobility interruption and less than 1 ms radio latency, peak data rate of gigabits per second, and on-demand data rate of hundreds of megabits per second. The one problem of the 5G network is that it is not possible to achieve all three pillars simultaneously because of the limitation of the radio spectrum in the microwave band. The problem can be solved by using the beyond 5G (B5G) network, which promises to use free-space optics and radio spectrum of millimeter-wave and Terahertz wave [1]. The B5G technology has great potential for application in many critical and important aspects of our lives, including industrial applications, smart healthcare applications, and business transactions [2]. As healthcare applications deal with patients' private data, the data should be handled securely and confidentially, for example, by using the blockchain technique.

The COVID-19 pandemic has halted the life of the world, and we do not know how long it will last and how much damage it will impose on the world. There is a huge mismatch between the number of suspected patients and the number of available beds and test facilities in the hospitals. The hospitals are not able to test all the suspected patients and admit them. Therefore, a B5G network-based COVID-19 screening and diagnosis system can help doctors and hospitals to reduce this huge burden. B5G provides a resolution of sensing, imaging, positioning, and wireless transmission that the COVID-19 pandemic can utilize to combat the virus. The three pillars of 5G can be effectively achieved by deep learning (DL)-based distribution of COVID-19-specific edge devices and efficient allocation of software-defined network (SDN) resources [3]. For example, training a deep learning (DL) model using a lot of chest computer tomography (CT) scan images or chest X-ray images in the cloud needs very high bandwidth, and a URLLC network for uninterrupted and seamless training of the models. Furthermore, the images may come from many hospitals and clinic sources, which means the network should handle many machines or devices at the same time with high spectrum demand and massive data sharing between them. B5G has the capability of dynamic network slicing, where each slice can be configured based on a client's demand, available GPU and processing power, edge configuration, and energy-efficient devices.

Patients' data are considered to be private and should be handled with care so that there is no security breach of the data. Fortunately, the advancement of mobile edge computing (MEC) allows us to use high processing power devices at the edge [4]. This feature of MEC augments B5G realization. Now, moderate DL models can run on edge devices, which means that URLLC of B5G can be achieved by performing the first-tier processing of medical data at the edge more securely and reliably. Data processing at the edge also can ensure data privacy preservation, which is essential for a hospital. Real-time processing can also be ensured, which can help patients who need immediate decisions from the processed data. This will especially help incentive care unit patients who need a certain level

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of oxygen supply and medication depending on the decision.

To combat COVID-19, a huge amount of data from thousands of heterogeneous networks must be acquired, processed, and responded to in a reliable, efficient, secure, and speedy manner. Vital signs can be captured by the user's smartphone, and the processed data from vital signs should be transferred to a local hospital repository for a possible alert. As there are millions of people, a massive amount of data should be processed in a URLLC network to provide an immediate decision on whether the person needs to go to a hospital or not. The MEC layer can adopt a decentralized trusted mechanism such as blockchain to process the data in a secure and private manner before they are shared with the stakeholders.

Hospitals generate massive volumes of data every day, which need to be stored and processed without breaking the privacy of the data. The data include X-ray images, CT scan images, ultrasound images, protease sequences, and ocular surface images. There are many patients in one hospital, so all these data combined create a huge volume. If there is no edge computing facility, this huge volume of data needs to be transmitted to the cloud for distributed computing. This will create many problems related to limited bandwidth, interrupted transmission, and security breach. A B5G network with edge computing can solve these problems efficiently. Suppose chest X-ray images from many hospitals around the world are available in the central data storage of a cloud. A DL model uses these images to train an automatic COVID-19 detection system. This trained model can then be used by any hospital after loading it to the edge. A hospital may have new patients, which means a new dataset is generated in the hospital. The loaded DL model can be fine-tuned by this new dataset. A chest X-ray image can be classified as COVID-19 or non-COVID-19 by using the fine-tuned model using edge inference. The fine-tuned model can be uploaded to the cloud, and the model can be updated further by new images gathered in the cloud by different hospitals. This cloud-hosted DL model can be managed by the World Health Organization (WHO). A 5G mMTC pillar can be realized by edge learning of deep models in several edge devices, URLLC can be realized by assigning edge devices where the signal strength is the maximum, and eMBB can be utilized by doctors from different hospitals at various locations to consult on diagnoses for specific cases, and to share the results and thereby realize the virtual reality experience to combat COVID-19.

In this article, we propose a DL-based edge-centric COVID-19 screening and diagnosis system. The system will analyze vital signs such as body temperature, blood pressure, pulse rate, and cough sound, which will be acquired from a suspected patient via a smartphone app. After analysis, the system will give an output (suspected or not) of whether the patient has the potential to be a COVID-19 patient or not for screening purposes. With this screening, non-suspected people will not go to the hospital. If suspected, the patient will be admitted to the hospital for further tests in the form of chest

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X-ray, CT scan, lung ultrasound, or ocular surface. The proposed system will process these images using DL models and visualize the suspected regions in the images. The outputs of these models will be fused using decision-level fusion to provide a suggestion to the doctor as to whether the patient is a COVID-19 patient or not. With this suggestion and visualization, the doctor can make the final decision. The whole system will be based on edge and cloud, and the test phase and visualization will be at the edge.

Literature Review

The COVID-19 pandemic broke out in Wuhan, China, in December 2019. Since then, it has spread to over more than 200 countries claiming many human lives and affecting others, which we had not seen for many decades. According to the American College of Radiology (ACR), the most reliable method of diagnosing COVID-19 is to analyze the protease sequence of RNA. Also, it recommends not to use radiograph images as a first-line screening of this disease. It can only be used in combination with other signs.

The WHO provided some symptoms and signs of COVID-19. These symptoms and signs include high fever (> 38°C), dry cough, mental fatigue (for some patients), and shortness of breath (for a few patients). The diagnosis can be made accurate by a real-time reverse transcription-polymerase chain reaction (rRT-PCR) test; however, the sensitivity of this test has a wide range of reporting. Medical imaging, such as chest X-ray and CT scan, is only advised if the patient shows a worsening respiratory status and there is a risk of disease progression. Chest radiographs can be normal during the early stage of the disease; however, after more than 10 days, findings are evident. Therefore, we should not be confused with the chest radiograph images of a patient at an early stage.

Already some research studies [5, 6] have focused on the classification of COVID-19 and normal chest X-rays. Although this research is in its early stages, the studies lay a good platform on which to continue the research in this direction. Before mentioning any of this research, we note that there are only a few COVID-19 radiograph images available publicly at this moment, although every week the image set is updated.

Rahman *et al.* [7] have proposed a COVID-19 diagnosis framework that leverages the B5G ultra-low latency advancement to offer privacy and security of the DL model's dataset. The proposed system uses a distributed DL process where each local edge node trains a local model with its private dataset without sharing the training dataset with the outside world. A set of collaborating nodes can then aggregate the local models to obtain a more accurate global model, which can then be shared with the distributed clients. The framework has been tested with an X-ray dataset of COVID-19 patients. The authors reported promising results.

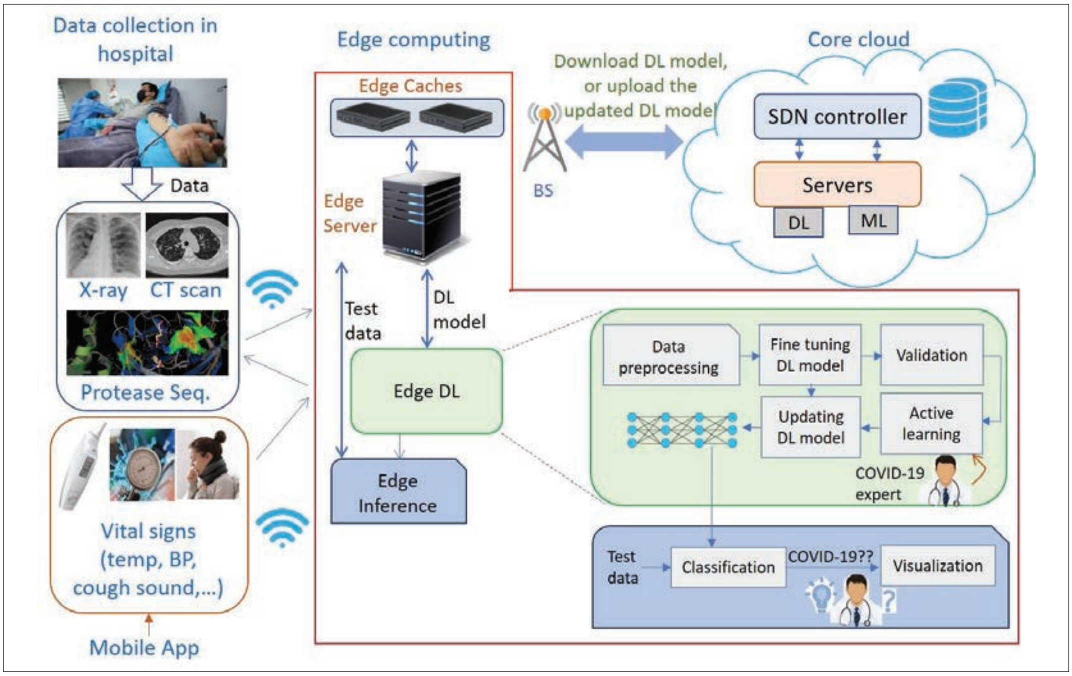


FIGURE 1. Schematic diagram of the proposed AI-driven edge-centric COVID-19 diagnosis system.

Narin *et al.* [8] used the InceptionV3, Inception-ResNetV2, and ResNet50 DL models to classify the images. The highest accuracy of 98 percent was obtained by ResNet50. As only a few images were used in the experiments, we cannot rely on the findings. In [9], the authors used a convolutional neural network (CNN) model called DeTraC to classify COVID-19 chest X-ray images from normal and SARS X-ray images. The principal component analysis was used to compress the feature vector. In the experiments, they used 80 normal samples, 105 COVID-19 samples, and 11 SARS samples. The maximum accuracy of 95.1 percent was obtained. The number of samples was unbalanced and very few.

The authors in [10] developed a DL model called COVID-Net to detect COVID-19 from chest X-ray images. The proposed network used residual projection-expansion-projection-expansion modules. The authors collected samples of normal and non-COVID-19 pneumonia, around 8000 each, and 76 COVID-19 samples. An accuracy of 92.4 percent was achieved. In [11], a generative adversarial network (GAN) was used to increase the number of sample images of COVID-19. Three different deep models were investigated. The number of COVID-19 samples was 69. The best accuracy was 87.2 percent using AlexNet for a 3-class problem.

In [6], an interesting tool of segmentation to measure the volume of the infection was proposed using CT scan images. More than 500 COVID-19 samples were used; however, they were not made public. An accuracy of 91.6 percent was obtained. Apart from chest X-ray images and CT scan images, other tests can reveal the presence and progress of COVID-19. Lung ultrasound is one of them. Lung ultrasound can give enough evidence of COVID-19 if diagnosed properly, and it is much cheaper and easier for the patient than the CT scan image.

As this is an early stage of enough data availability regarding COVID-19, most of these methods have experimented with less data. The visualization and proper explanation are almost absent in these methods.

Research Methodology

Figure 1 shows a schematic diagram of the proposed COVID-19 diagnosis system. The system has three main components: data collection, edge computing, and core cloud computing. In the data collection component, different modalities of data are collected. This collection can be done using an app for vital signs such as body temperature, blood pressure, pulse rate, and cough sound. A suspected patient can use his or her mobile phone app to record the vital signs and upload them to a data center in a hospital. An artificial intelligence (AI)-driven module will classify whether these signals belong to normal or to a case that needs further investigation.

If a suspected patient needs further investigation, he or she will be admitted to the hospital and will undergo several tests including radiographic images such as chest X-ray image and chest CT scan, rRT-PCR test, ocular surface test, and lung ultrasound. The proposed AI-driven edge-centric diagnosis system will automatically classify the sample as COVID-19 or non-COVID-19. The proposed system will also have a visualization option for each of these signals using heat maps so that the doctors can pinpoint the area of diagnosis. We leave the final judgment to the doctors, but our system will provide them with decision and visualization support.

Currently, radiographic images are being uploaded daily at some public depositories. At the moment of writing this article, the number of COVID-19 samples in these depositories is low, although we believe that it will grow at a fast rate soon. In the proposed system, a DL model is trained using the samples available in the cloud and putting the trained model in a core cloud. When more samples are available in the public depositories, the trained model will be updated with the new data.

As for the hospital side, there will be an interface program that can be maintained by an edge computing service. B5G technology will be used at the hospital premises to find the available edge resources with strong signal coverage. Due to the advancement of edge computing, now edge devices are capable of running the DL model using a massive volume of data such as radiographic images. Intel, Google, and NVIDIA are offering edge nodes with GPU capability to run in the edge. The DL models can run in an edge node within lightweight Docker containers.

When some data are available at the hospital, the trained DL model will be downloaded from the core cloud to the edge and fine-tuned with the data at the hospital. Active learning will take place during fine-tuning, where specialist doctors will manually verify the output and validate it. With this active input from humans, the DL model will be done with fine-tuning.

To test a particular sample, an edge inference will load this data to the system, and the system will classify the sample as COVID-19 or not by the fine-tuned DL model. To assist the doctor in deciding, the system will also provide a visualization of the sample. The visualization will have marks in the affected area of the image.

The fine-tuned DL model will be uploaded to the core cloud and will be there as an updated model. Hospitals in different regions will have access to the core cloud with proper authentication so that the updated DL model is readily available to the hospitals. The proposed system does not need to send the hospitals' classified data (samples) to the cloud. Therefore, the data will remain private to the hospital.

Figure 2 shows the screening and diagnosis stages of the proposed system. In the screening stage, the person has his/her screening via vital signs. If there is a suspicion of COVID-19 based on the processing of the signs, the person can visit a hospital where some tests are carried out. If the tests are positive, the patient is admitted to the hospital for treatment.

Figure 3 shows the proposed multi-modal COVID-19 diagnosis modules inside the proposed system. The modules are divided into two types: screening modules and test modules. In the screen modules, various vital sign signals are the inputs. The vital sign signals include body temperature, blood pressure, pulse rate, and cough sound. A simple mobile app records these signals of the user, and a light DL model processes the signals using long short-term memory (LSTM) separately. A decision-level fusion in the form of a logical regression is applied to these models' outputs. The final output is a binary decision on whether the person of these signals needs further investigation in the hospital or not. Only if this screening recommends that the person be admitted to the hospital do we go to the test modules. The light LSTM is computationally inexpensive and can easily run on a smartphone or PDA. For the processing of the cough sound, we first extract a color spectrogram and then feed it to a CNN model.

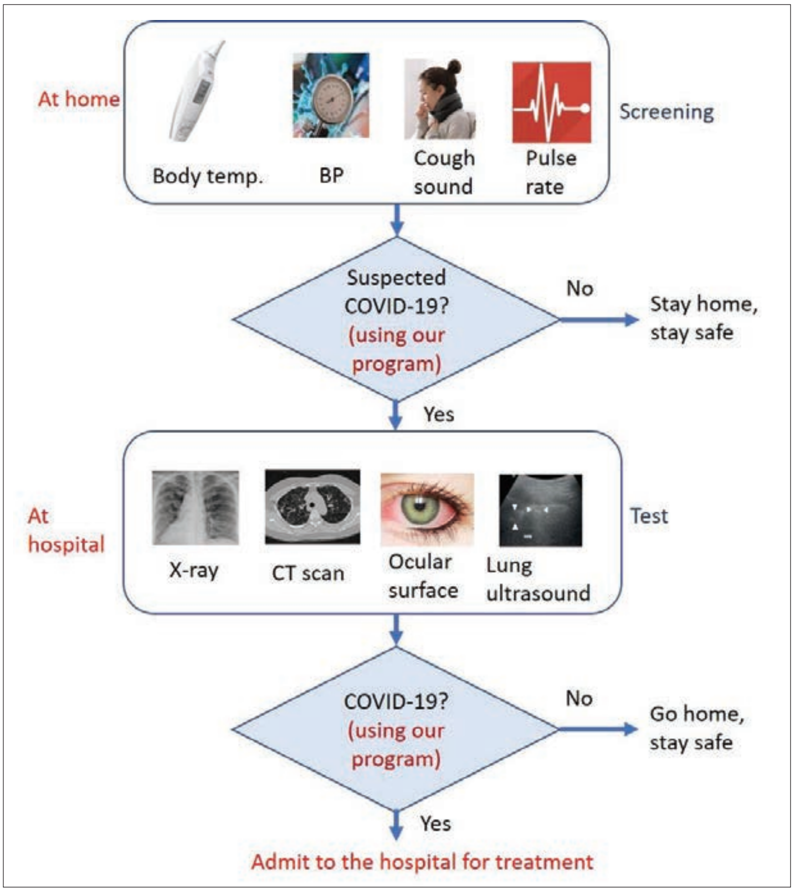


FIGURE 2. Flowchart of the screening and diagnosis process using the proposed system.

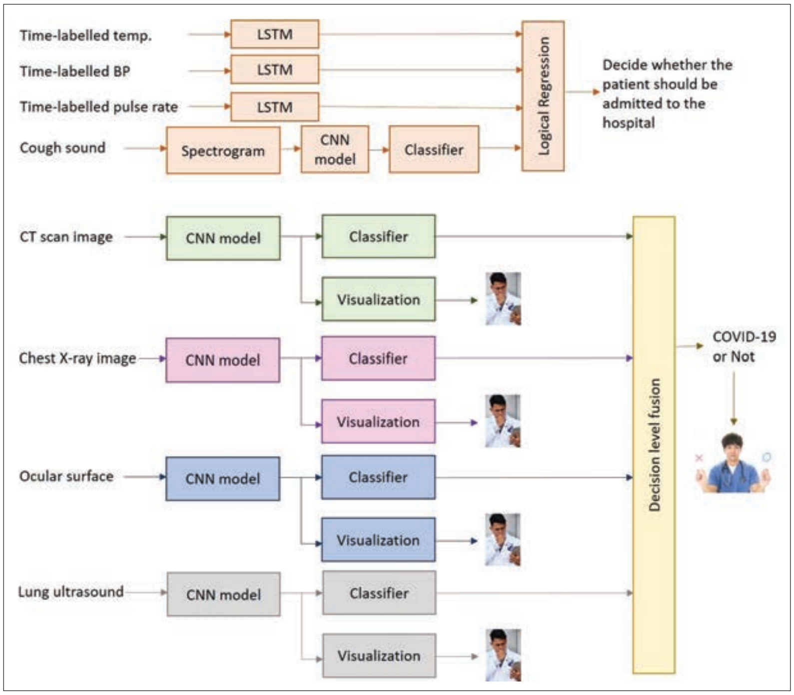


FIGURE 3. Block diagram of the proposed multi-modal COVID-19 diagnosis modules.

In the test modules, different test images are the inputs. The images include chest X-ray, CT scan, ocular surface, and lung ultrasound. All these images are processed separately in parallel CNN models. Different CNN models are investigated in terms of accuracy and number of parameters. One of the major points of focus is on the

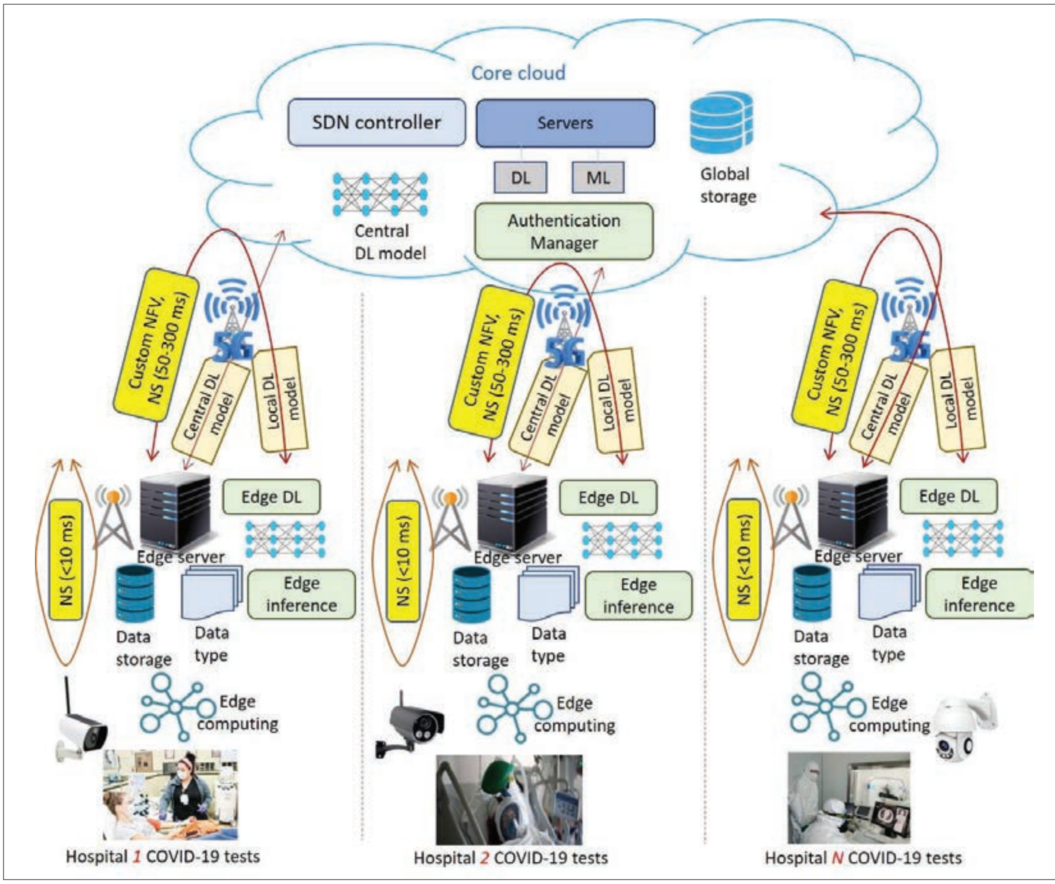


FIGURE 4. Schematic diagram of B5G supported COVID-19 management.

false negative rate. We have already done some preliminary experiments, which are described later. Most doctors are not comfortable with the decision of a computer program and would prefer to see some visual cues in images. Therefore, the proposed system also visualizes the images using heatmaps showing the doctor which parts need more attention. We fuse the outputs of CNN and classifiers at the decision level because some modalities may not be present or required. Visualization before the fusion enables doctors to investigate the results of each modality. If any modality result is positive, the patient will be tested for COVID-19 positivity.

B5G Supported COVID-19 Management

The COVID-19 management in this proposed system can be supported by B5G. With the help of B5G, user equipment (UE) devices or an edge server of a hospital within the maximum signal strength can work in edge computing. A tree-based DL model can be used to optimize the distribution of edge devices for an uninterrupted experience of the users [12]. The hospital can also utilize the DL facility to fine-tune the weights of the DL for an mMTC using a 5G cell. Multiple dedicated virtual networks from different hospitals can be allowed B5G network slicing (NS) facility. Each NS will be in the range between 50 ms and 200 ms. Each hospital can have its own NS of less than 10 ms to fine-tune the DL model, to process data, and to execute blockchain modules in the edge computing. An overall platform of the proposed system using the B5G network is shown in Fig. 4 The DL model can always monitor the NS metrics for the best usage of the edge devices in terms of signal strength, data volume, and availability of the device. For example, the data volume of the protease sequence model is much higher than that of a chest X-ray or lung ultrasound.

The distributed edge-cloud-based COVID-19-like pandemic diagnosis system can meet the expectation of users, patients, hospitals, and stakeholders across the globe. With the facility of edge computing using the B5G network, the DL model can be trained, fine-tuned, validated, and tested at the edges of the hospitals to provide real-time processing of huge volumes of data and accurate results locally and globally.

Let us consider a scenario where there are *N* number of hospitals and health clinics connected to a global core cloud server. The server has several components such as authentication module, SDN controller, several layers of machine learning (ML) and DL modules, and global storage. In the global storage, there are many normal, COVID-19, and non-COVID-19 samples available, which were uploaded by many hospitals and clinics after applying blockchain [13]. A central DL model is trained using this huge number of samples. The model is also validated by a small subset of samples, which are mutually exclusive with the training samples. This trained and validated DL model is now ready to be downloaded by the client hospitals and clinics. All the hospitals connected to the core cloud also have a local edge computing facility powered by B5G. Suppose hospital 1

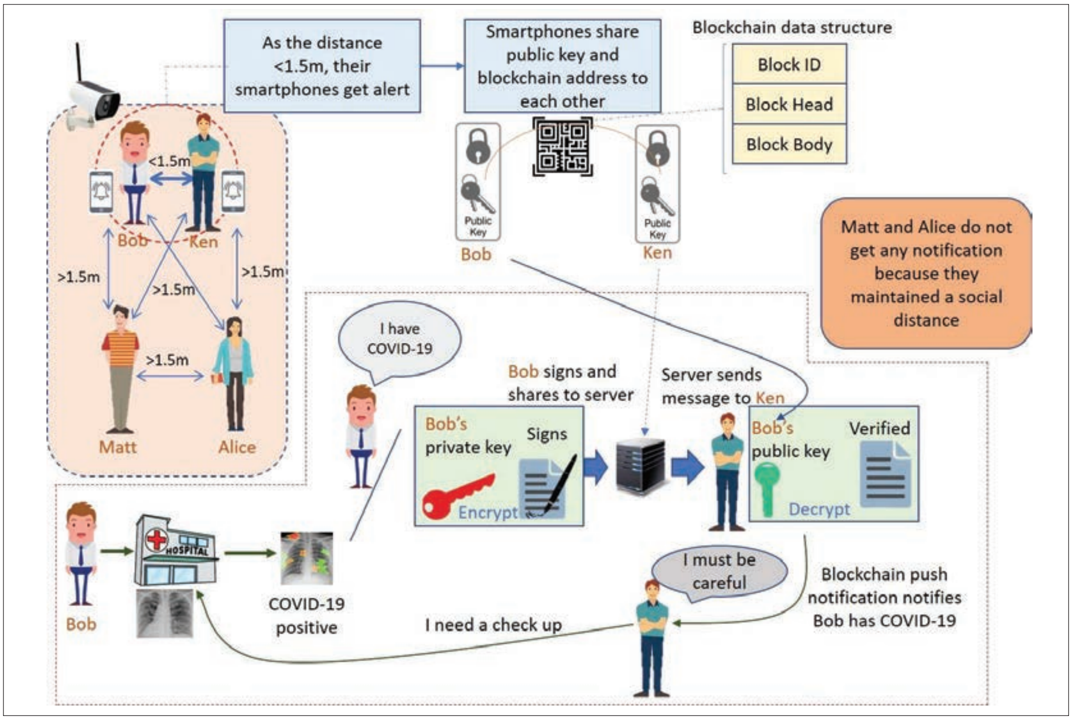


FIGURE 5. Illustration of a blockchain-based COVID-19 transaction.

has some COVID-19 X-ray test images manually classified as COVID-19 or non-COVID-19. The edge server of the hospital receives the images, downloads the DL model from the core cloud, and manages the edge devices to fine-tune the DL model with these new images. For a new test image, the edge inference does automatic diagnosis and visualization using the fine-tuned DL model. After visualizing, a doctor can manually segment the important parts and feed the images back to the DL model. We call this procedure active learning. Active learning helps the DL training to be accurate. Once this fine-tuning and active learning are finished, the edge server uploads the updated DL model to the core cloud. During this process, hospital 2 has collected many COVID-19 CT scan images, and hospital 3 has gathered many COVID-19 ultrasound images. The edge servers of these hospitals do the same thing as the server of hospital 1 does. Due to the dynamic NS, the downloading and uploading of DL models of different hospitals do not affect each other, and the transmission and processing become seamless.

Blockchain-Based Secure COVID-19 Transaction

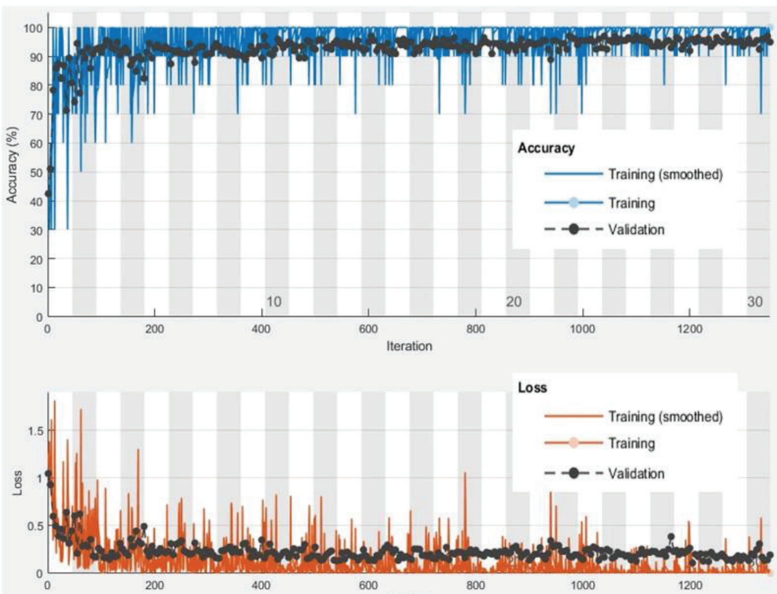
As the health data is strictly private, they should be handled with a high degree of privacy and in a secure manner. In the proposed system, we adopt the blockchain-based COVID-19 transaction [13]. Figure 5 shows an example scenario of the blockchain-based COVID-19 transaction using social distancing. We assume that all the residents of a town have smartphones, and IP wireless surveillance cameras are mounted in various places where there is a possibility of gathering such as marketplaces, hospital waiting-areas, and emergency healthcare service [14]. In such a place, there are four persons: Bob, Ken, Matt, and Alice. Bob and Ken have distance between them less than 1.5 m, which is the cutoff distance for social distancing for COVID-19. Matt and Alice have a distance of more than 1.5 m from others. The camera captures the distance, and when the distance between two persons (Bob and Ken) is less than 1.5 m, the DL module sends a notification to these two persons. In this example, Bob and Ken get alerts on their smartphones. Once alerted, the smartphones share anonymous public key/blockchain addresses between each other. The blockchain data is structured in three layers: block ID, block head, and block body. Within a couple of days, Bob is feeling unwell, and measures his blood pressure, pulse rate, and body temperature, and records his cough sound. The proposed system (screening modules) processes the data locally and makes a decision that Bob needs to visit a hospital for further tests. The hospital has his chest X-ray and CT scan images taken and uses the pretrained DL model to make a diagnosis; suppose this diagnosis is COVID-19 positive. As a socially aware person, Bob finds all the anonymous keys that are gathered in his smartphone due to the close distance with other persons. He signs all the keys with his private key (encryption) and shares them with the hospital server. The server sends a message to all persons with those anonymous public keys. As a result, Ken receives the encrypted message and decrypts it by using Bob's public key, which is stored in his smartphone due to being within close distance with Bob. Ken now understands that as Bob has COVID-19, he (Ken) should go into isolation or to the hospital for COVID-19 tests.

Experiments and Results

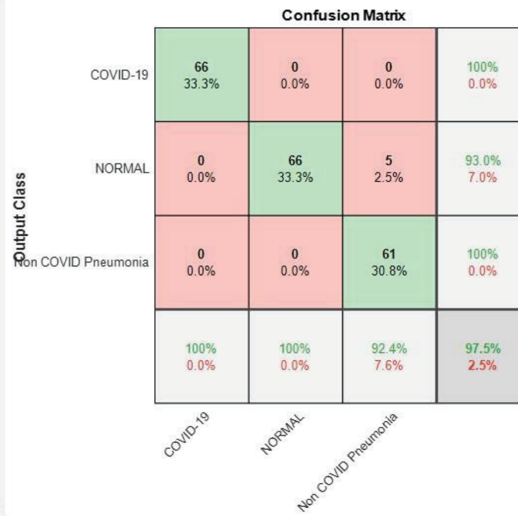
As proof of concept, we performed several experiments on chest X-ray images to classify whether they belong to normal, non-COVID-19 pneumonia, or COVID-19 patients. Currently,

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	AUC
ResNet18	93.1	92.8	96.4	96.3	0.965
ResNet50	95.3	94.4	100.0	98.1	0.971
ResNet101	97.5	96.3	100.0	100	1.0
InceptionV3	97.1	95.5	99.3	99.5	1.0
DenseNet201	96.7	94.2	98.5	98.7	0.984
SqueezeNet	95.1	92.1	96.9	97.8	0.965
xception	95.8	92.5	97.4	98.1	0.968
MobileNetv2	94.5	90.7	95.8	95.4	0.975

(a)



(b)



(c)

FIGURE 6. Results of the proposed system using different DL models: a) performance metrics of different deep models using chest X-ray images.; b) the learning progress of ResNet101, which showed the best accuracy of 97.5 percent. From the figure, we find that we can even apply early stopping of the training to minimize the time; c) confusion matrix of the system using ResNet101.

there are limited data of COVID-19 available in a public depository that can be used in the proposed AI-based approach. There is no continuous data recording of body temperature, blood pressure, pulse rate, and cough sound for COVID-19 patients. There are several Kaggle and Github repositories to host chest X-ray images and CT scan images. For the experiments, the images are separated into a training set and a testing set. The number of images per set is as follows: in the training set, 5000, 7000, and 210 images of normal, pneumonia (non-COVID-19), and COVID-19 classes, respectively; in the testing set, the corresponding numbers are 100, 100, and 10, respectively. We performed the experiments in five folds, in which each fold contained a different set of test images. The samples in the training and testing sets were disjoint. The training images were augmented by random rotation between $-15°$ and $15°$, reflection horizontally and vertically, and the scale between 0.8 and 1.2. The parameters were set the same for all the models as follows: mini-batch stochastic gradient descent for optimizing the weights, mini-batch size of 10, the maximum epoch was 10, and the initial learning rate was $1e^{-4}$. We tried different values of learning rate and mini-batch size; however, the mentioned values produced the optimum results.

For the vital sign signals, we used Kito+ Health Tracker Smart Cover Case and iHealth Air Wireless Fingertip Pulse Oximeter. The NVIDIA Jetson Nano Developer Kit with CPU of 64-bit Quad-core ARM A57 @ 1.43 GHz and GPU of 128-core NVIDIA Maxwell @ 921 MHz was used for the processing. DeepStream SDK was installed in the kit to enable AI-enabled video and image processing and multi-sensor processing. Several python libraries were used to test 5G edge server protocols at UE and base station. Using these libraries, 5G multiple-input multiple-output (MIMO) beam selection, NS, scheduling of URLLC, and eMBB were controlled [15].

Figure 6 shows the results of the experiments. The results are for chest X-ray detection using different pretrained DL models. We chose these specific DL models because they were shown to achieve good results in various applications. The learning process of ResNet101, which provided the best accuracy, for the training and validation test is also shown. The confusion matrix obtained by ResNet101 is shown in Fig. 6c. We also performed similar experiments using CT scan images. The best accuracy was obtained again by ResNet101, and the accuracy was 97.1 percent.

Conclusion and Future Work

We propose an AI-enabled edge-centric COVID-19 screening and diagnosis system. The system was implemented using a B5G network, where the system could leverage the benefits of a low-latency network, mMTC, and eMBB. The blockchain was applied to the COVID-19 transaction to process and transmit data privately and securely. A hospital's data were processed in the edge using the recent development of high-power edge devices, where the DL models could be fine-tuned and tested. The proposed COVID-19 screening and diagnosis system can be applied to any communicable disease like COVID-19. It will help reduce the congestion of patients in the hospital to screen out non-COVID-19 patients and to handle the confidential patients' data in the edge to maintain privacy.

The future directions of this research can be as follows:

- Apply mobile DL models to reduce the number of weights in the model.
- Apply parallel processing in the edge devices.

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The proposed COVID-19 screening and diagnosis system can be applied to any communicable disease like COVID-19. It will help reducing the congestion of patients in the hospital, to screen-out non-COVID-19 patients, to handle the confidential patients' data in the edge to maintain privacy.

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