B5G and Explainable Deep Learning Assisted Healthcare Vertical at the Edge: COVID-19 Perspective

Md. Abdur Rahman, M. Shamim Hossain, Nabil A. Alrajeh, and Nadra Guizani

Abstract

B5G-based tactile edge learning shows promise as a solution to handle infectious diseases such as COVID-19 at a global level. By leveraging edge computing with the 5G RAN, management of epidemic diseases such as COVID-19 can be conducted efficiently. Deploying a hierarchical edge computing architecture offers several benefits such as scalability, low latency, and privacy for the data and the training model, which enables analysis of COVID-19 by a local trusted edge server. However, existing deep learning (DL) algorithms suffer from two crucial drawbacks: first, the training requires a large COVID-19 dataset on various dimensions, which is difficult for any local authority to manage. Second, the DL results require ethical approval and explanations from healthcare providers and other stakeholders in order to be accepted. In this article, we propose a B5G framework that supports COVID-19 diagnosis, leveraging the low-latency, high-bandwidth features of the 5G network at the edge. Our framework employs a distributed DL paradigm where each COVID-19 edge employs its own local DL framework and uses a three-phase reconciliation with the global DL framework. The local DL model runs on edge nodes while the global DL model runs on a cloud environment. The training of a local DL model is performed with the dataset available from the edge; it is applied to the global model after receiving approval from the subject matter experts at the edge. Our framework adds semantics to existing DL models so that human domain experts on COVID-19 can gain insight and semantic visualization of the key decision-making activities that take place within the deep learning ecosystem. We have implemented a subset of various COVID-19 scenarios using distributed DL at the edge and in the cloud. The test results are promising.

Introduction

The potential features of Beyond 5G (B5G) offer several key advancements such as energy efficiency, area traffic capacity, peak data rate, user expected data rate, spectrum efficiency, user mobility, low latency, and high connection density [1]. On top of these pillars, 5G can offer next-generation services for any particular vertical. The sudden appearance of the global pandemic COVID-19 has demonstrated the importance and essence of these 5G pillars, which we call B5G [2]. B5G provides key tools that can be leveraged in the pandemic situation, such as wireless cognition, sensing, imaging, communication, and positioning [3]. The three pillars of 5G — massive machine-type communications (mMTC), ultra-reliable, low-latency communications (uRLLC), and enhanced mobile broadband (eMBB) — can be configured for COVID-19-specific heterogeneous edge devices with an intelligent and flexible allocation of software-defined network resources in response to network dynamics. For instance, a CT-scan dataset for training a deep learning algorithm requires a highly reliable extreme bandwidth and a low-latency network to enable the rapid training of a deep learning model. Furthermore, B5G has the capacity to leverage deep learning models to support dynamic network slicing, in which each slice can be customized based on the underlying COVID-19 deep learning algorithm's need for GPU, edge/cloud resources, spectrum demand, and energy efficiency for use in applications such as mobile broadband, tactile Internet, device-to-device communications, and massive dataset sharing.

Recent advancements in mobile edge computing have made B5G even more appealing [4]. The true power of ultra-low-latency communication is that it can leverage the first tier of data processing at the edge where the data is generated. In the case of COVID-19, this particular aspect is crucial from regulatory and data privacy perspectives. In addition, the speed, time and latency, cost, and volume of data transfers are optimized through edge-based processing. The need for data analysis at the edge arises in cases where decisions based on data processing must be made immediately for a patient. For example, there may be insufficient time for patient data to be transferred to cloud servers; there may be no connectivity at all. An intensive care unit (ICU) set up for COVID-19 patients is an area that could benefit from edge-based deep learning, where real-time data processing and decision making are important for closed-loop systems that must maintain critical physiological parameters, such as oxygen level, within a specific range of values.

Due to recent developments in edge computing capabilities and machine learning algorithms for edge devices [5], massive volumes of COVID-19 data on radiological images, DNA/RNA, thermal images, drug discovery, and vaccine research,

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can be processed at the edge [6]. For example, machines with a large RAM, SSD, and GPU memory can be easily afforded by any hospital's edge node. Intel, Google, Nvidia, and other vendors offer edge nodes that have the GPU capability to run deep neural network algorithms on the edge. Additionally, specialized deep learning algorithms can now be run on these edge nodes within lightweight docker containers. All such recent advancements have created the possibility of a distributed COVID-19 deep learning platform in which a three-phase reconciliation can take place [7].

During phase one, the local deep learning model can learn from an available dataset or one generated at the edge. For example, the CT-scan images of patients, available from a hospital anywhere in the world, can be used to train and recognize COVID-19 patterns from CT-scan images [2, 8]. After a human subject-matter expert approves the result, the local edge node can transmit the new dataset and updated deep learning model to the global model, which we consider phase two. Once a sufficient number of global subject-matter experts have observed the local updates and the dataset used to train the model, this model can be applied to the global model. Subsequently, during phase three, the global update can be tested with a global dataset of certain data types (e.g., CT-scan images available from multiple hospital sources around the globe), which will increase the accuracy of the global model. Once its accuracy has been established, the model can be distributed to interested local models running at different spatial edge nodes around the globe. This global deep learning model could be hosted by the World Health Organization (WHO). Edge learning can allow 5G mMTC phenomena to be realized by deploying deep learning models to recognize blood pressure cuffs, bed monitors, infusion pumps, and other monitoring devices, tracking staff with proper PPE, and monitoring COVID-19 inventory and patients [9]. Leveraging the eMBB pillar of 5G, COVID-19 treatment-supporting doctors and nurses around the globe can share results, perform rural telemedicine, and leverage augmented and virtual reality experiences to manage COVID-19 patients, all without risking infection.

During a pandemic such as COVID-19, it is crucial to have a distributed edge/cloud-based deep learning model in which training, validation, testing, and inferencing can take place at the edge of hospital networks, in order to support global efforts toward real-time massive data processing and deduce accurate results at both local and global levels. The hotspot or epicenter of disease spread, which faces the highest number of COVID-19 patients, can provide a large number of live datasets of different dimensions; these can be shared through 5G networks and used by the global AI and Deep Neural Network community to train the respective DL models. Finally, the globally trained model can be shared with local edge servers around the world to facilitate rapid screening. For example, a large dataset of RNA sequences available from COVID-19 patients at an epicenter could enable drug and vaccine research institutes in another location to produce a COVID-19 vaccine [10].

B5G coupled with deep learning for a COVID-19 vertical would allow low-latency, high-quality data sharing that could help healthcare providers administer patients remotely, greatly improve ubiquitous access to state of the art advancements, allow professionals outside of locked-down epicenters to diagnose patients remotely, and alleviate immense pressure on frontline caregiver personnel [11]. This would also lower the risk of healthcare support personnel being exposed to the virus, including remote medical personnel and patients with co-morbidities who need hospital and laboratory facilities that are currently overburdened with coronavirus subjects' treatment.

B5G can also facilitate a new wave of medical IoT devices at the edge, with drones delivering drugs and reading thermal images and robots checking patients' temperatures, delivering advice, and disinfecting hospital rooms, thus reducing virus spreading. Current medical IoT advancements allow hospitals equipped with 5G-powered DL modules to track the safe movements of subjects and hospital personnel. This high-speed 5G network allows efficient distribution of services and support staff as they are needed the most. Beyond the COVID-19 medical crisis, preventative quarantine has the potential to leverage 5G and DL algorithms. Tactile Internet features of B5G, such as mixed reality, can support real-time hands-on experience sharing among geographically separate hospitals.

As of May 25, 2020, there have been 5,555,752 confirmed cases of COVID-19, with 348,220 deaths. COVID-19 symptom-testing can yield false positives, as the genomic structure of the virus closely resembles other coronaviruses; there is also a possibility that it could co-exist with other respiratory infections. Experts suggest conducting multimodal tests to attain better accuracy and insight. Unfortunately, due to time constraints in addressing the pandemic, it is difficult to manually conduct many such tests on each test subject. Thanks to recent advancements in DL algorithms and B5G networks, it is now possible to investigate COVID-19 phenomena both at network edges and in the cloud in almost real-time. In this article, we investigate a set of distributed deep learning applications that can support COVID-19 tracking, diagnosis, and reporting and assist in vaccine development. In this article, we make the following contributions:

- We propose a B5G network architecture suitable for COVID-19 diagnosis, which leverages the low-latency, high-bandwidth features of 5G networks along with functionalities such as network slicing through network function virtualization and a software-defined network at the edge.
- We propose a distributed DL paradigm, in which each edge node employs its local DL datasets and training models and uses a three-phase reconciliation with global DL models after receiving approval from subject-matter experts at the edge. Similarly, the global optimum model is distributed to the edge nodes after acceptance by global subject-matter experts.
- We propose adding explainability and semantics to existing deep learning models so that human domain experts on COVID-19 can gain insight and semantic visualization of the key decision-making activities that occur within the deep learning ecosystem.

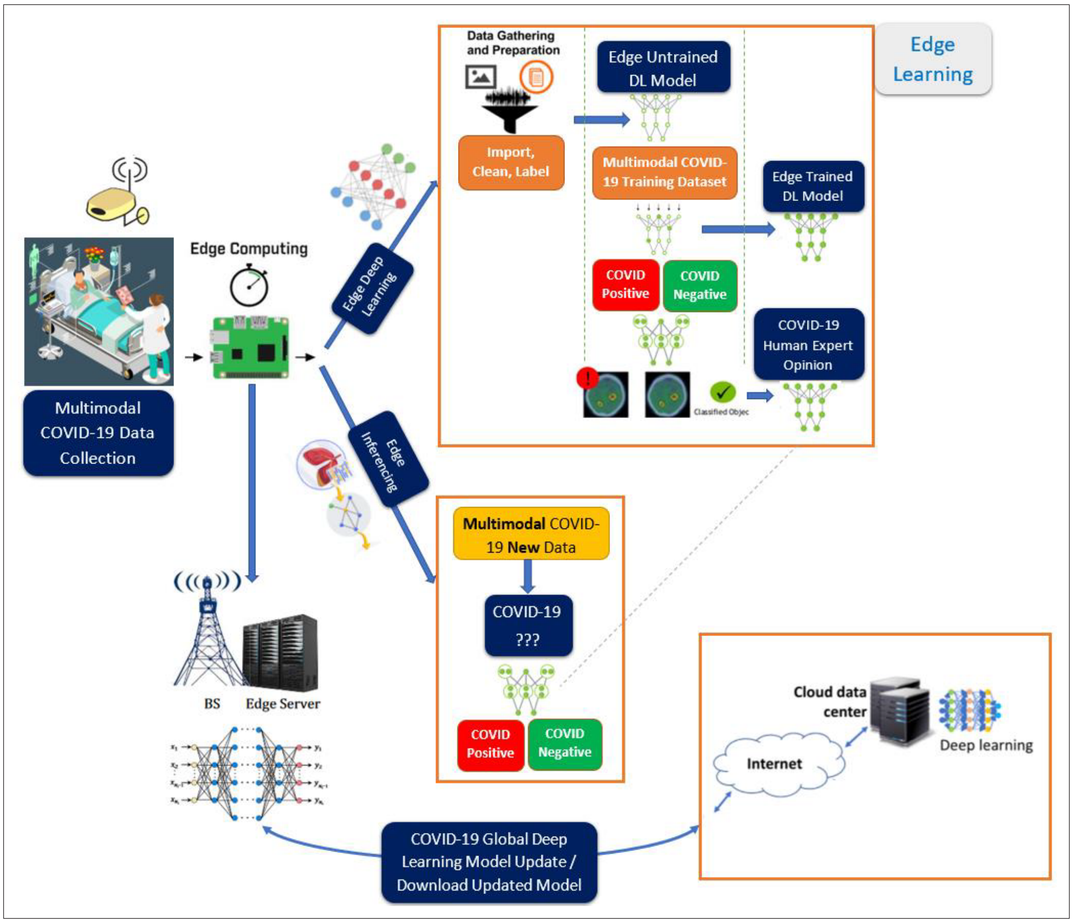

FIGURE 1. High level COVID-19 edge learning platform.

The remainder of the article is organized as follows. The following section describes the proposed system design. We then outline the implementation of the framework. Following that we give preliminary test results and then conclude the article.

System Design

Distributed Deep Learning at the Edge

We have developed a COVID-19 epidemic management system (Fig. 1), which utilizes the three-phase reconciliation process described earlier. The framework leverages mobile edge nodes that are assumed to be deployed in hospital premises, in which local COVID-19 DL algorithms can run local or global datasets. The local edge node can also download the necessary DL models from the global space. For example, if a local hospital in a certain country wants to update the human-to-human spreading pattern, it can publish the local dataset on national and global sites, allowing people with COVID-19 to mark their past locations to warn others who might have come into contact with them. In another example, a hospital may be identifying targets for a vaccine against SARS-CoV-2, the virus that causes COVID-19. Vaccines act by recognizing pathogens; each vaccine has its own targets. By scanning the sequences of all pathogenic targets for each vaccine, vaccines can be matched to their recognized targets. A DL model could predict these associations, compare all vaccines, and identify which one recognizes sequences similar to those of COVID-19. A third example is that of a hospital receiving patients and using the following steps to detect COVID-19 via X-ray images [8]:

- Use the local X-Ray dataset available from COVID-19 patients and non-infected patients.
- Train deep learning algorithms at the edge.
- Complete inferencing on the results using hospital experts or regional experts.
- Once approved, share the local model in the global space.

A fourth hospital might specialize in identifying COVID-19 patients through CT scan images [12], while an RNA-sequencing laboratory might specialize in molecular tracking inside human cells and developing deep learning algorithms that can assess existing drugs' effects on the virus. The laboratory might design an AI-based honeypot using pathogenic proteins with tiny chemical tags attached to an infected cell to lure them into attacking lab-grown human cells. A deep learning algorithm can monitor genomic dynamics to observe the induced changes in the human proteins that the virus hijacks during infection. Once an accurate deep learning model is developed, the model and the RNA sequence(s) could be shared with the global community. Similarly, different types and modalities of COVID-19 tests can be performed at the edge and integrated with other results from around the world. This design allows each local hospital or region to support global COVID-19 pandemic management and receive support in turn.

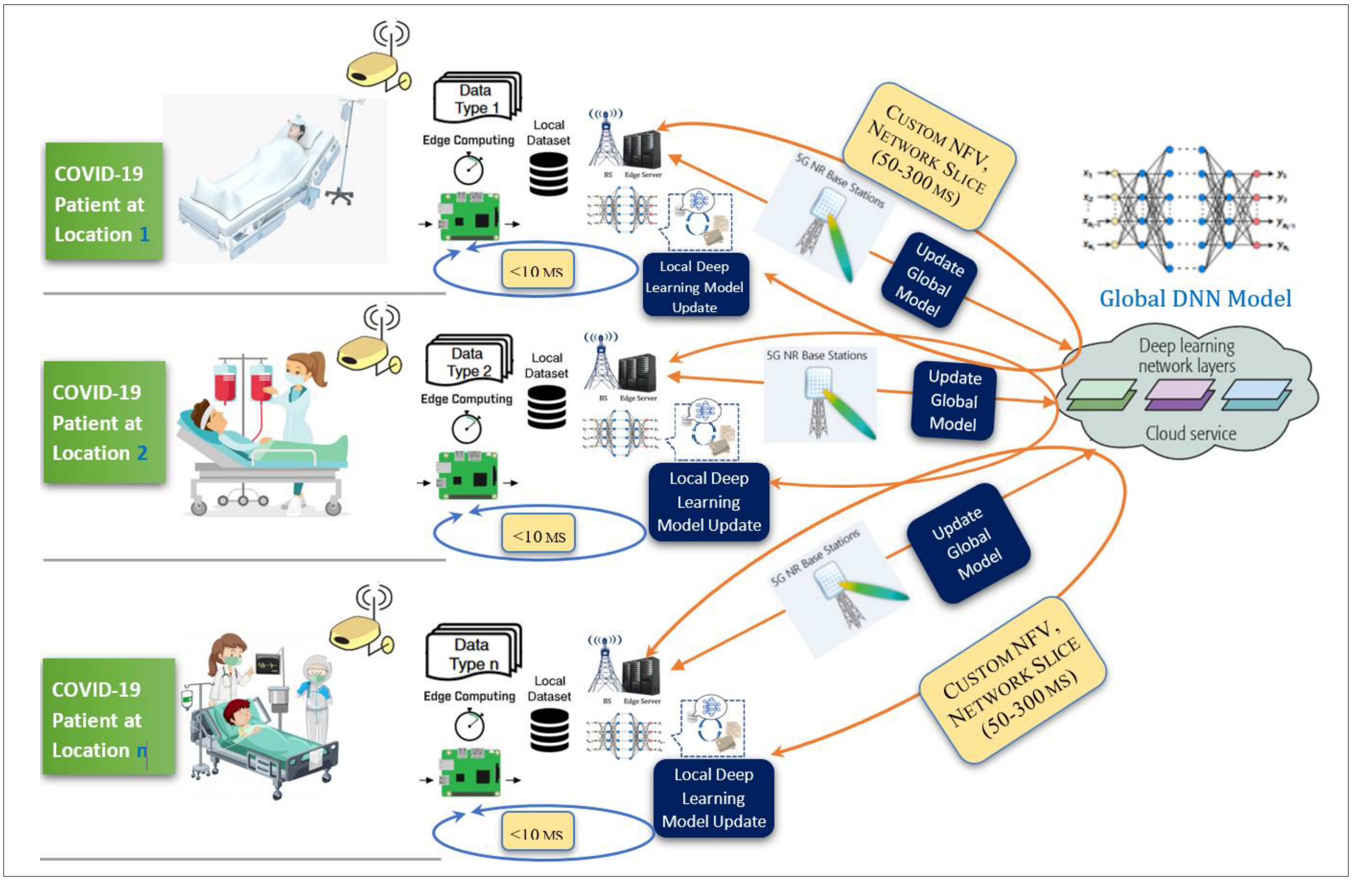

FIGURE 2. B5G network slicing and network function virtualization to support quality of service for the deep learning COVID-19 applications.

B5G for COVID-19

Figure 2 shows how B5G could support COVID-19 management. B5G could allow a COVID-19 treatment site to deploy deep learning algorithms running at the edge UE device or edge server to find the optimum beam with the highest signal strength [13, 14]. Another B5G feature that hospitals treating COVID-19 could deploy is deep learning models that optimize the weights for antenna elements for a massive MIMO 5G cell site. The DL model can learn at the edge environment to optimize Massive MIMO, which can enhance the COVID-19 treatment experience. B5G offers network slicing support for COVID-19 verticals by allowing 5G RAN or multiple dedicated virtual networks at the edge. Each hospital, institution, or research center treating COVID-19 could deploy its own network slicing DL model by conducting training that applies datasets related to COVID-19 users, network characteristics, and security parameters.

As shown in Fig. 2, the framework can leverage network functions virtualization (NFV) to monitor the network slicing metrics for the most optimum usage of each deep learning model. For example, the bandwidth requirements for models based on CT scans and thermal imagery, with corresponding datasets, are different than those of an RNA-sequencing model.

Figure 3 shows our proposed design of various COVID-19 applications by depicting each application with an explainability layer [15]. Each application shown in the COVID-19 DNN modules employs the relevant dataset available from the COVID-19 Datasets modules. Each application employs the DL algorithm and libraries and adds explainability for human experts to interact with. Each of the applications houses the necessary DL models. For example, the body temperature module can be trained to accurately and non-invasively monitor a COVID-19 patient's body temperature in real-time and issue alerts on abnormal temperatures. In order to augment the temperature data with a privacy-oriented dataset of human motion videos, an Openpose external library could be utilized. B5G can facilitate continuous remote monitoring and diagnosis by supporting mobile edge devices with DL models and 5G networks' fast data-load speeds.

An intriguing characteristic of COVID-19 is that symptoms appear over a period of 15 days. Some symptoms are visible at certain time points, when some tests will be effective and others will yield negative results. For example, using reverse transcription-polymerase chain reaction (RT-PCR) to detect SARS-CoV-2 RNA from sputum or a nasopharyngeal swab might yield inconclusive results at some time points. On the other hand, the temporal development of the radiological manifestation of COVID-19 in human lungs begins exhibiting at a different point than that of other types of viral pneumonia. Thus, performing multiple types of deep learning-based tests at different temporal dimensions would provide better insight into the development of COVID-19 within individual patients and the broader population.

In this study, we investigate 16 dimensions of datasets related to COVID-19; we test various deep learning algorithms for different types of applications. For example, some of these applications concern computer vision problems while others belong to other areas of deep learning, as shown in Fig. 3.

Implementation

We developed each of the applications as shown in Fig. 3 to test various aspects of COVID-19 treatment within a 5G application scenario. To comply with data security requirements, we utilized FIPS 140-2 validated cryptographic algorithms. We implemented each of the applications as part of proof-of-concept through different open-source libraries such as pysim5G, fiona, shapely, PyTorch, Tensorflow, Keras, Pandas, CV2, Openpose, NumPy, flirimageextractor, nodejs, docker, sklearn, matplotlib, flask, Django, nginx, react, imutils, paho, pickle, scipy, seaborn, plotly, dash, skimage, shap, PIL, BeautifulSoup, and selenium. We installed the local edge server with NVIDIA GeForce RTX 2080 Ti 11GB GPU drivers, CUDA 10.0, and cuDNN v7.6.4 for TensorFlow 2.0 on an Ubuntu Linux machine. We tested several edge devices such as Intel NCS2, Raspberry PI 4 with 4GB memory, and NVIDIA Jetson Tx2 with drivers such as TensorFlow Lite, Caffe, OpenVino toolkit, Tensorflow, PyTorch, and Apache MXNet. The NVIDIA Jetson Nano developer board packs 472GFLOPS of computational horsepower that can run TensorFlow, Keras, NumPy, SciPy, and OpenCV with CUDA support. We have used NVIDIA's Jetpack 4.2 Ubuntu-based OS image to run on Raspberry Pi. We have installed Python virtual environments on the Jetson Nano. We have also used TensorFlow's Object Detection API (TFOD API) for developing object detection models and optimizing the models for the Nano's GPU. In addition, we used Flask, a Python micro web server, and Jupyter, a web-based Python environment. We configured the NVIDIA Jetson Nano camera to be used by either a PiCamera or a USB camera. We also added the necessary environment to be able to train custom Caffe plus TensorFlow models for the Movidius Neural Compute Stick 2.

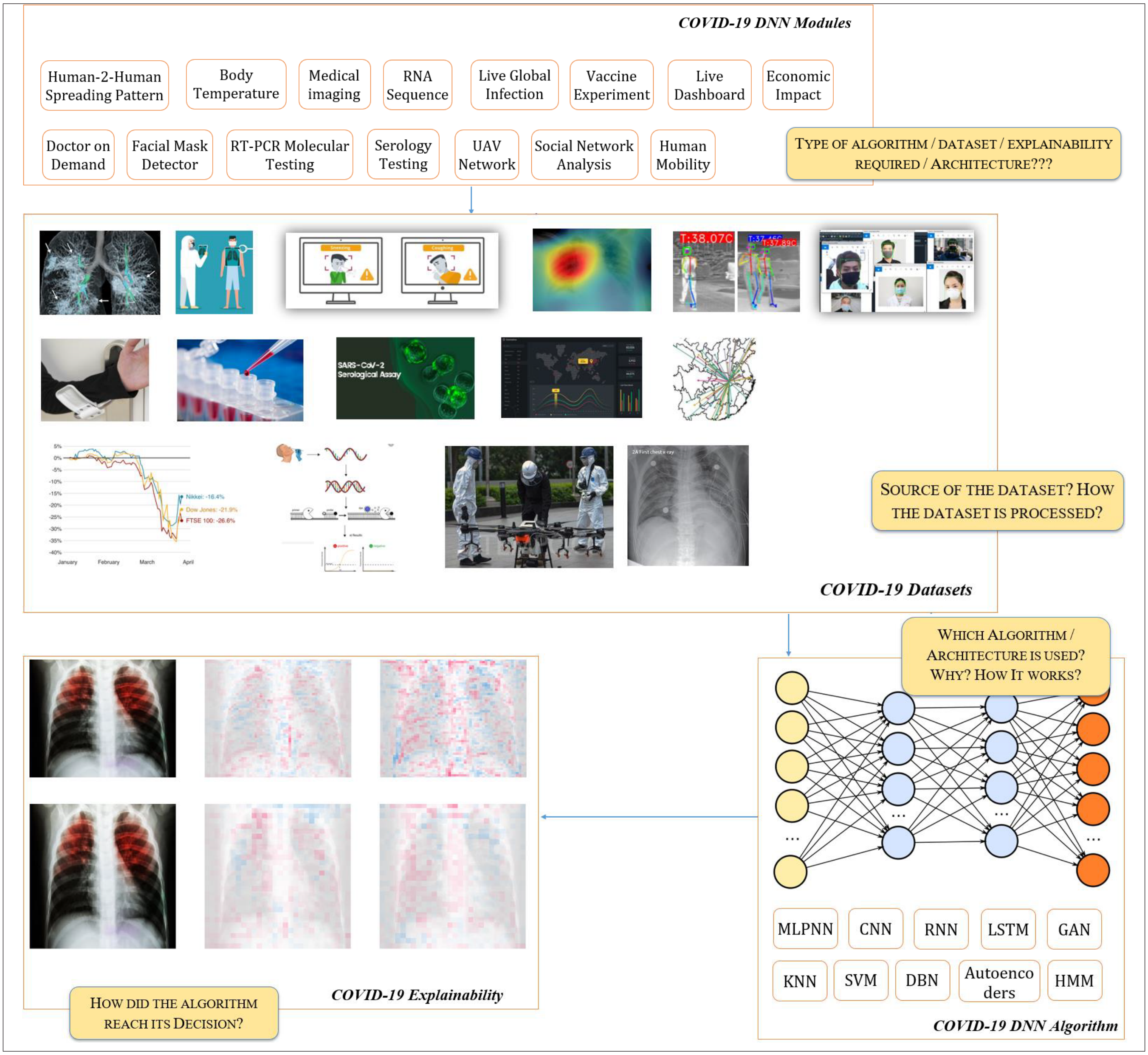

FIGURE 3. Wrapping up the COVID-19 framework with the workflow of explainability and semantics.

The COVID-19 non-invasive body temperature module was implemented using an off-the-shelf body pose detector; the location of the face was identified by the DL algorithm where the temperature value is augmented. We used images from a thermal camera with correct radiometric calibration and radiometric Exif data loaded onto the image. We developed the code in Python and tested it on both Windows 10 and Ubuntu 19.10 with the NVidia driver, Cuda 10.0, and Cudnn 7.6.5. In order to facilitate use in portable sites, we also tested an Adafruit AMG8833 thermal camera sensor mounted on our Jetson Nano-embedded environment so that it could be deployed to mobile sites as needed by health or law enforcement officials. We tested the UAV capability with the DJI Mavic 2 Enterprise Dual drone with FLIR MSX Thermal imaging, Dynamic zoom functionality, and Password protection for data security. The thermal images from the drone were used by Openpose and OpenCV libraries to detect the live body temperature of COVID-19 patients or subjects.

We used several python libraries for testing 5G edge server protocols at UE and edge base stations. We tested various deep learning scenarios, such as making handoff decisions in a sliced 5G network, efficient and reliable network slicing in 5G networks, 5G MIMO Beam-Selection, integrated modeling of 5G at the edge, reinforcement learning and automated planning for 5G network slicing, joint scheduling problems of URLLC and eMBB in 5G NR, and 5G mmWave MIMO systems involving mobility. We also tested other 5G edge server modules, such as a software-defined network (SDN) supporting Packet Forwarding Control Protocol (PFCP) for 5G Next Generation Core Network, so that the SDN controller can communicate with the remote user-plane elements via the PFCP protocol. The 5G python network function modules include UE, gNB (RAN), AMF, AUSF, SMF, PCF, UDM, and UPF. We also tested Deep Learning algorithms at the edge with NVIDIA Jetson TX2, which enables accurate positioning from 5G mmWave transmissions.

We set up an anaconda environment with Jupyter Notebook and Spyder editors along with PyCharm Professional Edition. We developed the proof-of-concept deep learning applications and packaged each application within a docker image. Each docker image holds only one application, as shown in Fig. 3. Each docker image is equipped with the python libraries needed to execute the functionalities as necessary for COVID-19 management. When a change or upgrade in a docker image is needed, the local edge server sends the image to the Travis-CI to build the image. After successful building, the image is published to the docker hub. The docker hub is configured to automatically push the docker image to the Amazon Elastic Container Registry (ECR), from which the docker image can be instantiated within a serverless ECS Fargate cluster. The whole process is automated via GitHub, by which any deep learning model can be migrated and merged with the master branch of the global deep learning model. Figure 4 shows two different containers running two different applications from our local edge machine. Once a global commit takes place at the docker hub, any edge server can pull the docker image containing the latest release of the COVID-19 application. This ensures that the container contains the global deep learning model.

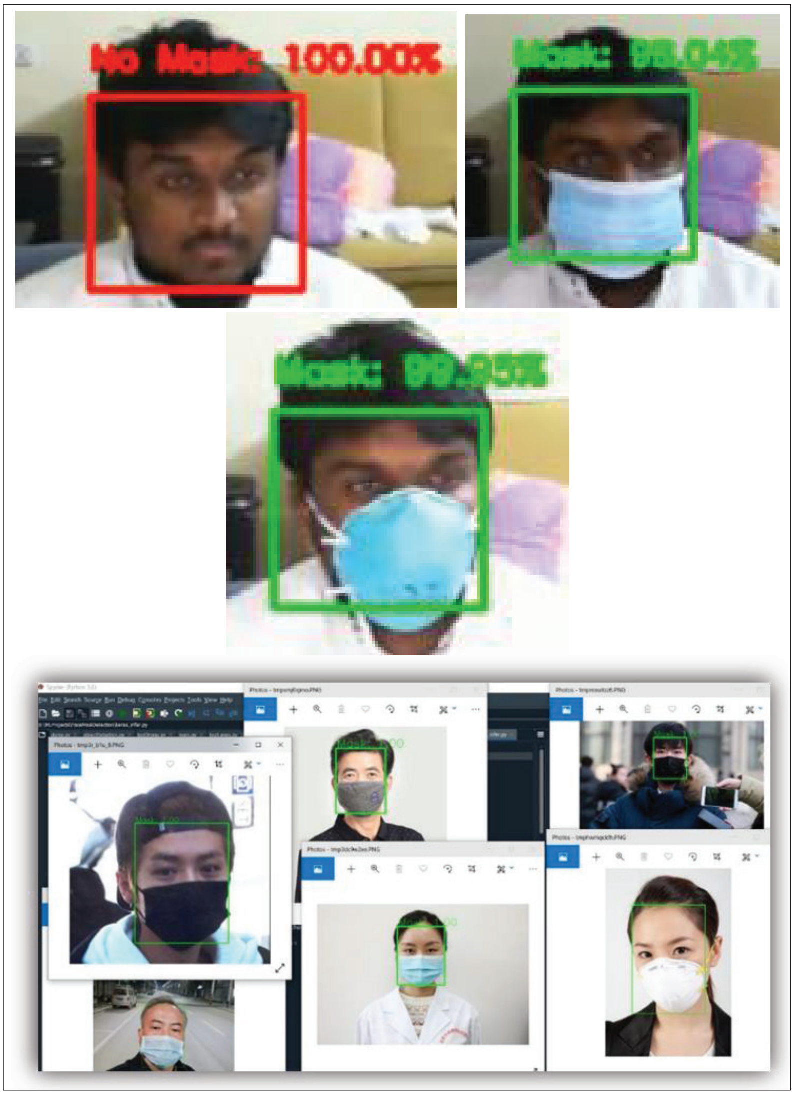

FIGURE 4. Sample deployment of the COVID-19 applications on an Amazon ECS Fargate cluster — live mask detector of different types at the edge.

Test Results

We collected datasets for each of the applications mentioned in Fig. 3, consisting of COVID-19 positive and negative class of features, that are freely available from the Internet. For some applications (e.g., X-Ray), we received a much larger number of datasets, while for other types we had fewer datasets of diversified genders and ages. We have leveraged existing open-source COVID-19 Python applications and dockerized them for deployment to local and global hubs. Figure 5 shows two sample test results. Figure 5a shows a Deep Neural Network model containing a "scoring system" to measure how well a country is responding to the COVID-19 emergency (a higher score indicates a better response). Figure 5B gives a sample visualization of the impact of COVID-19 concerning a projection of local capacity data.

In order to add semantics, we have resorted to the Class Activation Mapping (CAM) method for our proposed applications. To analyze the performance of the algorithm further, we determined the probability that a given case is COVID-19 pos-

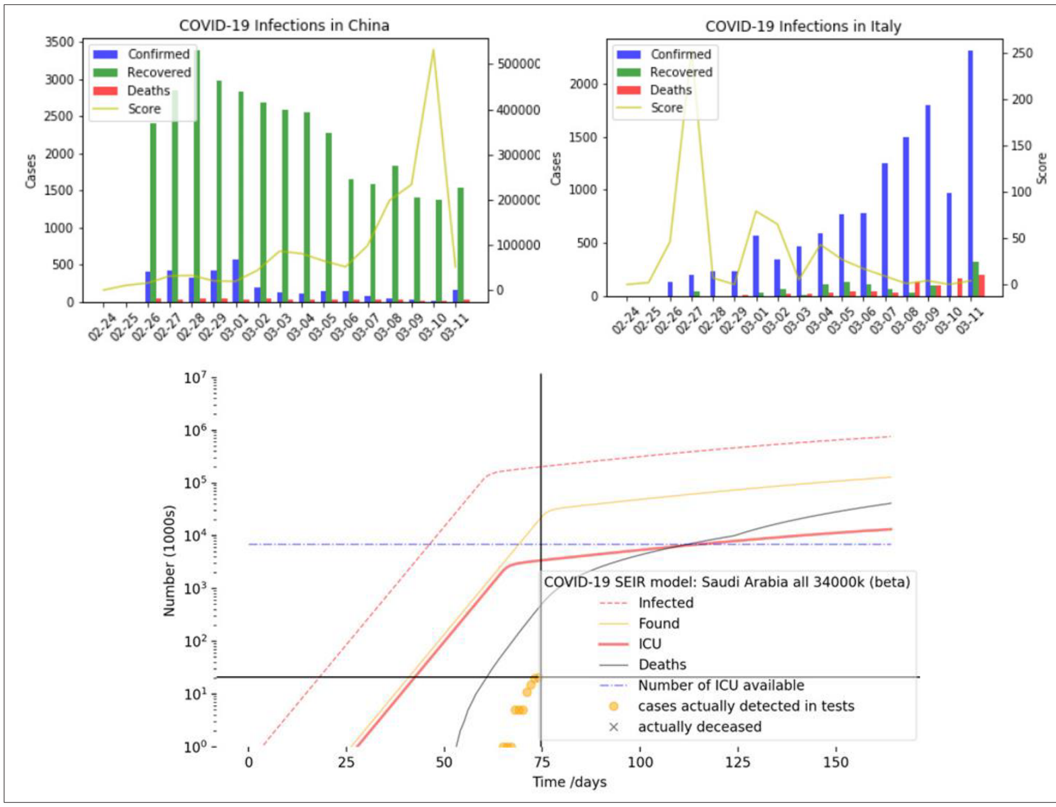

FIGURE 5. Sample graphical user interface of two COVID-19 applications running on docker container: (top) how successful each nation has been in flattening the spread; (bottom) hospital readiness statistics for COVID-19.

itive by benchmarking our dataset with that of the publicly available similar datasets classified as Normal, other influenza types, or COVID-19 by radiologists [2]. Each application was trained with the relevant dataset. In order to assess the effectiveness of different types of COVID-19 applications, the following metrics were observed:

- Accuracy: 0.9817
- Sensitivity: .8400
- Specificity: 1.0000

The sensitivity measures the ratio of COVID-19 positive subjects that are correctly identified by our DL algorithm while the specificity results in correctly identifying the COVID-19 negative subjects, that is, healthy subjects or subjects having other types of co-morbidity. We have considered all four cases, that is, COVID-19 positive subjects that are correctly identified as positive; healthy subjects incorrectly identified as COVID-19 positive; healthy subjects correctly identified as COVID-19 negative; and COVID-19 positive subjects incorrectly identified as COVID-19 negative. The results obtained show approximately 98 percent accuracy, 84 percent sensitivity (true positive), and 100 percent specificity (true negative). For each type of application, we identified a mechanism for adding a semantic layer so that human experts can submit a query and evidence can be presented in response. An example of this phenomenon is shown in Fig. 6, in which the 7th and 14th intermediate layers of semantic predictions are shown. Similarly, for each DL application, we have measured the accuracy, sensitivity, and specificity values, along with confusion metrics that facilitate releasing each application to global space for further development.

Conclusion and Future Work

In this article, we have introduced a COVID-19 management framework based on a distributed deep learning neural network. The framework leverages mobile edge computing, in which deep learning takes place both at the edge and in the cloud deep learning environment. The local edge deep learning model benefits from the recent advancement of B5G verticals and thus offers a tactile Internet experience for COVID-19 solutions. As part of the distributed learning, each local DL platform updates the global DL model, which can be shared with edge servers around the world that are serving COVID-19 patients. To conduct proof-of-concept, we have developed a set of deep learning models that can run on edge or cloud nodes and perform edge or global model-training, testing, validation, and inference operations. We have also introduced the explainability layer for each algorithm so that the DL algorithms reveal semantics that will be needed by medical doctors for COVID-19 diagnosis.

In a future study, we plan to work with local hospitals to deploy our model and perform clinical trials. We will be dedicating our time to improving the accuracy of the DL models so that the clinical trials yield acceptable results. Another crucial aspect that we will focus on is adversarial attacks on the DL algorithms. We will construct defense mechanisms to filter adversarial attacks on our COVID-19 DL applications. We will develop efficient deployment models by supporting lightweight containers housing B5G-based DL algorithms packed inside for deployment to institutions treating COVID-19 globally, thus improving explainability and supporting clinicians through trust and transparency.

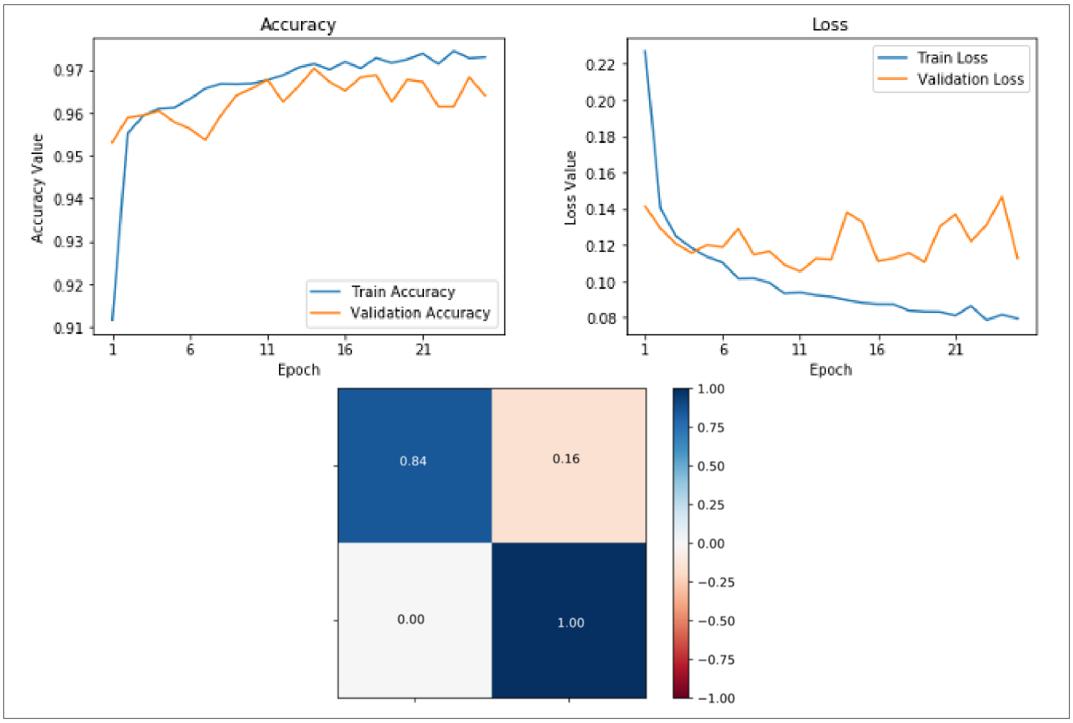

FIGURE 6. Process of edge-based training, accuracy, and confusion matrix of COVID-19 applications before release to a global model: (top) training and validation accuracy and loss are measured for each run respectively, and (bottom) the confusion matrix is measured.

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