B5G-Enabled Distributed Artificial Intelligence on Edges for COVID-19 Pandemic Outbreak Prediction

Md Rafiul Hassan, Mohammad Mehedi Hassan, Meteb Altaf, Mostafa Shamin Yeasar, M. Imtiaz Hossain, Kanis Fatema, Rubya Shaharin, and Adel F Ahmed

Abstract

In this study, we leverage the fusion of edge computing, artificial intelligence (AI) methods, and facilities provided by B5G to build a heterogeneous set of AI techniques for COVID-19 outbreak prediction. Advancement in the areas of AI, edge computing, the Internet of Things (IoT), and fast communication networks provided by beyond 5G (B5G) networks has opened doors for new possibilities by fusing these technologies and techniques. In a pandemic outbreak, such as COVID-19, the need for rapid analysis, decision making, and prediction of future trends becomes paramount. On a global map, the distributed processing and analysis of data at the source is now possible and much more efficient. With the features provided by B5G, such as low latency, larger area coverage, higher data rate, and real-time communication, building new intelligent and efficient frameworks is becoming easier. In this study, our aim is to achieve higher accuracy in prediction by fusing multiple AI methods and leveraging the B5G communication architecture. We propose a distributed architecture for training AI methods on edge devices, with the results of edge-trained models then propagated to a central cloud AI method, which then combines all the received edge-trained models into a global and final prediction model. The experimental results of five countries (United States, India, Italy, Bangladesh, and Saudi Arabia) show that the proposed distributed AI on edges can predict COVID-19 outbreak better than that of each individual AI method in terms of correlation coefficient scores.

Introduction

Artificial intelligence (AI) is considered capable of solving any problem in which the intrinsic relationships between input and output are unknown. The challenge of the majority of AI techniques is that they require a long training time not only to analyze and identify the input–output relationship but also to capture the data produced in real time for processing and analysis by these AI algorithms. Furthermore, if the input–output relationship is complex, no single AI technique can provide accurate performance with a high level of confidence. Hence, fusion of multiple AI techniques has been attempted to enhance performance.

Edge computing can play a vital role in developing and training individual AI techniques by combining the concepts of the Internet of Things (IoT) and cloud-based architectures in cyber-physical systems by utilizing the features of beyond 5G (B5G). The facilities provided by B5G (e.g., low latency, larger area coverage, energy efficiency, data rate, spectrum) offer a suitable communication medium to further enhance AI's applicability to edge computing. The recent COVID-19 pandemic can be considered one of the applications of combining AI techniques with edge computing, IoT, and B5G [1].

For instance, a COVID-19 patient might undergo a CT scan or X-ray for diagnosis of his or her health status. Automatic analysis of a CT scan or X-ray dataset can be possible using an AI technique (e.g., deep learning or deep neural network [DNN]). However, training a deep network (DN) for such a dataset in a networking environment would require reliable and large bandwidth, along with a highly efficient communication channel. We can leverage the high efficiency and extremely low latency and high bandwidth of B5G for training AI models in distributed networking environments. It should be noted that in such environments, each node of the network is utilized to train part of the DN in parallel with other nodes of the network. Thus, training efficiency would be enhanced, while massive datasets would be shared among the nodes connected via the network.

The invention of mobile edge computing allows us to apply the features of B5G for training distributed AI techniques to analyzing COVID-19 pandemic data and for predicting COVID-19 cases (e.g., the total number of expected COVID-19 patients in the future). In analyzing COVID-19 pandemic data by fusing different AI techniques, data can be analyzed by individual AI techniques at edge levels [1–3]. The results of the analyses using the respective AI techniques can be communicated to other edges to generate the final results. Data processing at the edge level will ascertain the privacy and security of confidential data related to COVID-19 patients. Thus edge computing seems suitable not only for enhancing

Md Rafiul Hassan is with the University of Maine at Presque Isle; Mohammad Mehedi Hassan (corresponding author) is with the Research Chair of Smart Technologies, King Saud University; Meteb Altaf is with King Abdulaziz City for Science and Technology; Mostafa Shamin Yeasar, Kanis Fatema, and Rubya Shaharin are with Jatiyo Kabi Kazi Nazrul Islam University; M. Imtiaz Hossain is with the University of Malaya; Adel F Ahmed is with King Fahd University of Petroleum and Minerals.

Digital Object Identifier: 10.1109/MNET.011.2000713

0890-8044/21/$25.00 © 2021 IEEE

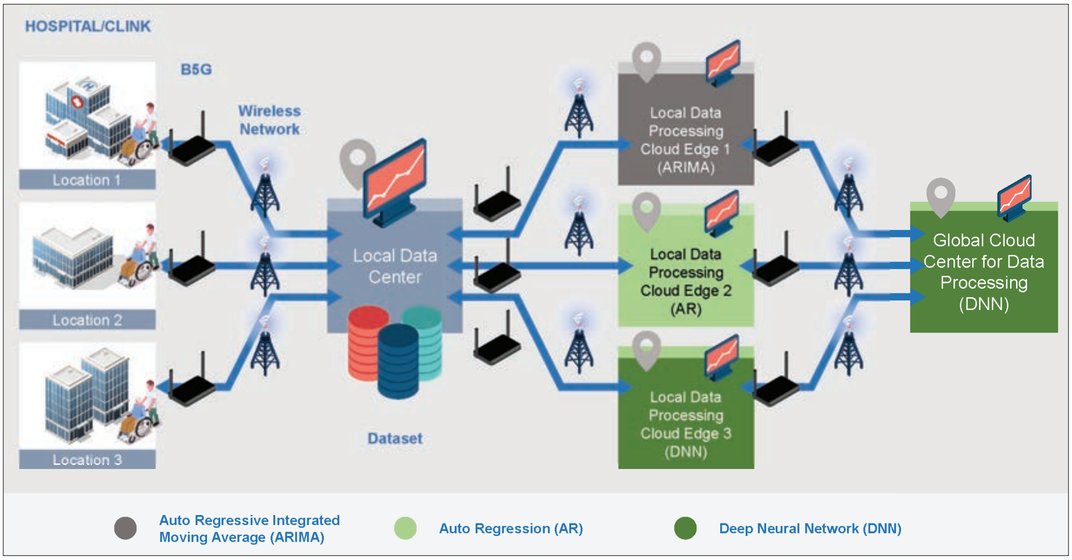

FIGURE 1. A framework for COVID-19 pandemic outburst prediction through applications of B5G and different AI techniques at distributed edges.

the data analysis by fusing different AI techniques, but also providing security of the data. Within the framework of combined edge computing and AI techniques, B5G features will provide ultra-low-latency communication among edges.

Analysis of pandemic datasets like COVID-19 is beneficial for all stakeholders, from physicians at local hospitals to policymakers. Hence, it is important to enhance the efficiency of the training in AI techniques, as well as their accuracy. Most of the existing studies focused on the enhancement of the AI approach for improved COVID-19 outbreak prediction performance. For example, Wang *et al*. [4] proposed an ensemble of logistic models with a Prophet model to predict COVID-19 outbursts. In this article, we propose to utilize the strengths of edge computing combined with B5G facilities, which would certainly be beneficial in the enhancement of AI efficiency and accuracy. For example, if the data are collected at spot A, the edge computing facility available at that spot can develop an AI model and analyze the data. Similarly, another edge can analyze data at spot B. Both AI models from spots A and B would send the analyzed results to a third computing facility that would combine the results through developing and training on another AI technique (the global AI model) to produce the final outcome. The efficiency of communication among the edges can be enhanced through B5G features, while each edge can perform data analysis locally. Furthermore, the overall accuracy of the analysis would be enhanced because each individual edge would deploy an individual AI technique that is different from the others. Thus, an individual AI technique would make up for the limitations of the others. We conjecture that one such framework would provide better performance for COVID-19 data analysis and prediction. During the current pandemic, the global AI model can also communicate with similar frameworks developed at other locations, thereby improving the analysis of COVID-19 data even further.

Figure 1 shows a framework for how data can be processed locally at edges and the results transferred to a central cloud data processing center. In this framework, to achieve efficient communication between hospitals or clinics and the local edge processing center, a B5G wireless network is deployed. We assume that each local edge is located in a city or hospital, while the global cloud edge data processing center is located in each country.

As of October 27, 2020, many professionals anticipated a second wave of the COVID-19 pandemic. Hence, there is a need for a method to predict the exact number of COVID-19 cases. By using advanced communication technologies such as B5G and edge computing facilities, distributed AI techniques can be deployed on the cloud to analyze and predict COVID-19 outbreaks and to encourage necessary actions accordingly. In this article, we design and develop a distributed AI to be deployed on cloud edges to support predictions of COVID-19 outbreaks. In brief, we make the following contributions in this article:

- We propose a framework for edge computing using B5G network architecture for the enhancement of communication among the edges to predict COVID-19 cases. The characteristic high bandwidth and low latency provided by B5G technology will enhance data communication between edges, making the decision making process faster.
- We propose a distributed ensemble of different AI methodologies that are known for time-series data, such as those presented in the analyses of COVID-19 cases. Each individual AI method is deployed on an edge, and the outcome of each edge is propagated to a cloud edge to combine all the results using another AI method.
- We conducted experiments on real-world data for five countries and compare the prediction performance of our proposed distributed AI method with that of other individual AI methods.

The remainder of the article is organized as follows. In the following section, we describe the history of the COVID-19 outbreak. We then pro-

Study	Name of the epidemic disease	AI technique used	Goal and achievements
Liang *et al.* [9]	African swine fever	Cfs-subset-evaluator-based feature selection combined with the random forest algorithm.	Predicted ASF outbreak prediction with accuracies from 76.02% to 84.64%.
Anno *et al.* [10]	Dengue fever	Transfer-learning-based Deep AlexNet	Worked on 3 Dengue hotspots in southeast Taiwan and identified spatiotemporal connections among those spots with sea surface temperatures for the Dengue fever outbreak. A deep AlexNet model has been used with 100% accuracy on an 8-fold cross validation scheme. Sea surface temperature images were used in the experimentation.
Tapak *et al.* [11]	Influenza	Random forest, artificial neural network, support vector machine	The identified random forest time series model is a suitable method to predict weekly influenza-like illness in Iran compared to ANN and SVM.
Iqbal and Islam [12]	Dengue fever	LogitBoost Ensemble Model	Predicted Dengue outbreak using a number of methods. Identified that LogitBoost ensemble method can provide the best classificaiton accuracy of 92%.
Ardabili *et al.* [13]	COVID-19 outbreak prediction	Multi-layered perceptron (MLP) and adaptive neuro fuzzy interference System (ANFIS)	Provided a comparative analysis between machine learning and soft computing models for prediction of COVID-19 outbreak without susceptible-infected-recovered (SIR) and susceptible-exposed-infected-recovered (SEIR) models. Experimental results show that MLP and ANFIS can provide good performance.
Malki *et al.* [14]	Investigated the association between weather data and COVID-19 pandemic mortality rate	Decision tree regressor, *K*-nearest regressor, AdaBoost regressor, support vector regressor.	Used and investigated different regressor models to identify any association between weather features (humidity, temperature, etc.) and COVID-19 mortality rate prediction.
Wang *et al.* [4]	COVID-19 trend prediction	Logistic model, FbProphet (Facebook Prophet) model	To predict the epidemic trend of COVID–19, used combination of logistic model and prophet model. Experimental result suggested that there would be a peak in the trend of COVID–19 in October 2020.
Gao *et al.* [15]	Prediction of mortality risk due to COVID-19	Logistic regression (LR), support vector machine, gradient boosted decision tree (GBDT), and neural network (NN)	Developed and applied an ensemble of machine learning models combining LR, SVM, GBDT, and NN to predict mortality rate for COVID-19. They achieved a maximum area under curve of 0.9760.

TABLE 1. List of studies that proposed application of AI methods for pandemic outbreak prediction.

vide a brief description of the few existing studies whose authors developed and implemented a computational methodology for pandemic outbreak prediction. Following this, we formally describe the framework of our proposed system. Before concluding the article, we outline the implementation of the framework and discuss the experimental results.

History of the COVID-19 Outbreak

On December 31, 2019, a COVID-19 outbreak was first reported in Wuhan, China, and had spread all over the world to more than 216 countries as of September 5, 2020 [5]. There have been more than 35 million people infected with COVID-19, and more than one million confirmed deaths. The outbreak was declared a public health emergency of international concern by the World Health Organization (WHO) on January 30, 2020 [6].

The outbreak of an infectious disease is the occurrence of a disease that is not usually expected in a particular community, geographical region, or period. The cause of COVID-19 is a new type of coronavirus, which was previously named 2019-nCoV by the WHO. It is the seventh member of the coronavirus family that can spread to humans, together with MERS-nCoV and SARS-nCoV [5]. There are several symptoms of the infection, including fever, cough, shortness of breath, and diarrhea. In more severe cases, COVID-19 can cause pneumonia and even death. The incubation period of COVID-19 can last for 14 days or longer [6]. The disease may still be infectious during the latency period. Through respiratory droplets and close contact, the virus can spread from person to person [6].

The WHO issues information and advice about COVID-19, which is accessible on its website and social media channels (including Weibo, Twitter, Facebook, Instagram, LinkedIn, and Pinterest) [6]. It is a tedious task to model the COVID-19 outbreak through analysis of the publicly available myth busters as well as collecting actual information from each hospitals/clinics. Scientists have questioned the ability of standard models to deliver accurate results, given the clear difference between this outbreak and other recent outbreaks [7]. In various geopolitical areas and under different containment strategies, the complexity of population-wide behavior has dramatically increased model uncertainty, because many known and unknown variables are involved in the spread [8].

Pandemic Outbreak Prediction and Classification

There is a gap in the COVID-19 literature, even though many methods have been assayed with varying success in modeling former pandemics (e.g., Ebola, cholera, swine fever, H1N1 influenza, Dengue fever, Zika, and oyster norovirus). Some notable AI methods used for outbreak prediction are presented in Table 1. The basic methods of random forest, NNs, Bayesian networks, naïve Bayes, genetic programming, and classification and regression tree are limited. AI application in modeling epidemics is still in the early stages. Table 1 lists a few recent studies whose authors proposed and used different AI methods for predicting pandemic outbreaks including COVID-19. As described in the table, none of these scholars used the facilities of edge computing to deal with the huge amounts of COVID-19 data accumulated every second. Furthermore, because new data are added constantly, the trends of COVID-19 data are continuously changing. Hence, new AI methods need to be developed that will efficiently deal with big data and continuously self-update. In this article, we propose a distributed AI on the edge that is able to deal with big data (because data are processed at distributed edges on the cloud) and to accurately predict the course of the pandemic.

System Design

Distributed AI Methods at the Edge

In the proposed distributed AI methods at the edge, we assume that each edge uses collected data within a country and then applies an AI method to analyze the data for predicting COVID-19 outbreaks. Each individual edge will then transfer the results of the analysis to the cloud edge. The cloud edge will apply another AI method to combine all the received results from the edges and produce a final prediction for COVID-19 outbreaks. This system design is depicted in Fig. 2. In our proposed simulation model, we analyzed COVID-19 data of countries using three edges with the following three AI methods:

- Autoregressive integrated moving average (ARIMA)
- Autoregression (AR)
- DNN

The cloud edge utilizes another DNN to combine the results of each of the edges. The communication among the edges is assumed to use B5G's characteristic enhanced communication quality, high bandwidth, and low latency. We define each of the AI methods below.

Autoregression: Autoregression (AR) is a popular time-series analysis technique that considers a sequence of past historical data to predict the future. AR utilizes an equation of a traditional linear regression model in which the independent variables are considered to be the past values of the time-series data, while the dependent variable is the predicted value for the future. In AR, the length of the past sequential data can be varied to identify a suitable length to produce an accurate prediction. Because AR is a linear regression model, it is highly efficient in identifying the trend of time-series data if the data follow a linear trend. However, if the data are chaotic (i.e., there are numerous fluctuations or changes in trends), AR might fail to produce good predictions. The AR model evinces the realization that time t is a linear combination of the previous realization with some noise term.

ARIMA: ARIMA is one of the best-performing models for time-series data analysis. The COVID-19 dataset is time-series data in nature; thus, we use ARIMA at one of the edges of our proposed distributed AI model. ARIMA is a generalized form of the AR moving average (ARMA) method. In ARMA, two methods, AR and moving average (MA), are combined such that AR considers the effect of past data to identify trends in the time series, while MA generalizes the past data by removing fluctuation noises in the time-series data. However, ARMA is unable to tackle any non-stationarity that might appear in the dataset. In ARIMA, a differencing value I is introduced to remove non-stationarity of the dataset, and thereby it can enhance the performance of the base ARMA model further. In brief, d is the number of times the sequence becomes stationary through difference disposal. It is a tedious task to select optimal values of the parameters of ARIMA, which are p (representing the order of AR), d (representing the value of the differencing parameter I), and q (representing the order of MA). In our methodology, we analyzed past COVID-19 time-series data and empirically selected optimal values for p, d, and q.

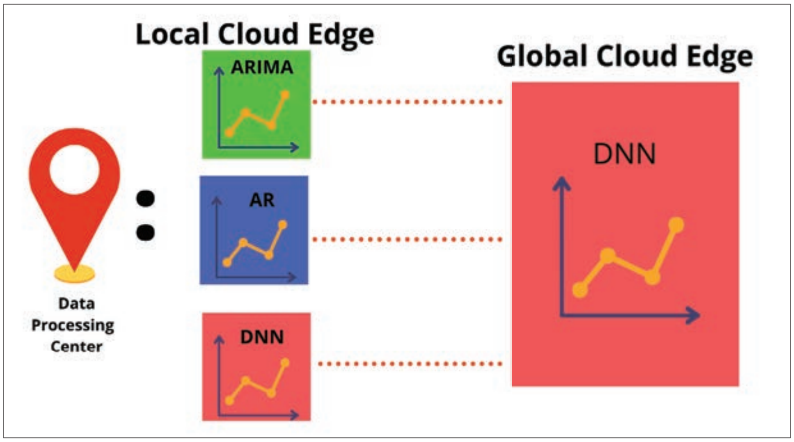

FIGURE 2. Framework of the distributed AI on edges for COVID-19 outburst prediction.

Deep Neural Network: Deep learning uses DNN, which consists of multiple artificial neurons, called nodes, arranged in a layered configuration. Typically, there are three types of layers of nodes in a DNN:

- An input layer
- One or more hidden layers
- An output layer

Each node in the NN implements an activation function that maps the weighted inputs to the outputs of each node. The activation functions are a crucial component of deep learning. They determine whether a node should be activated or not. There are three types of activation functions:

- Binary step activation function (a threshold-based activation function)
- Linear activation function that takes the form $y = cx$
- Nonlinear activation function, which allows the models to create complex mapping between inputs and outputs

Nonlinear activation functions have gained popularity recently because almost any process imaginable can be represented as a functional computation in a DNN, provided that the activation function is nonlinear. Nonlinear activation functions allow backpropagation, a learning tech-

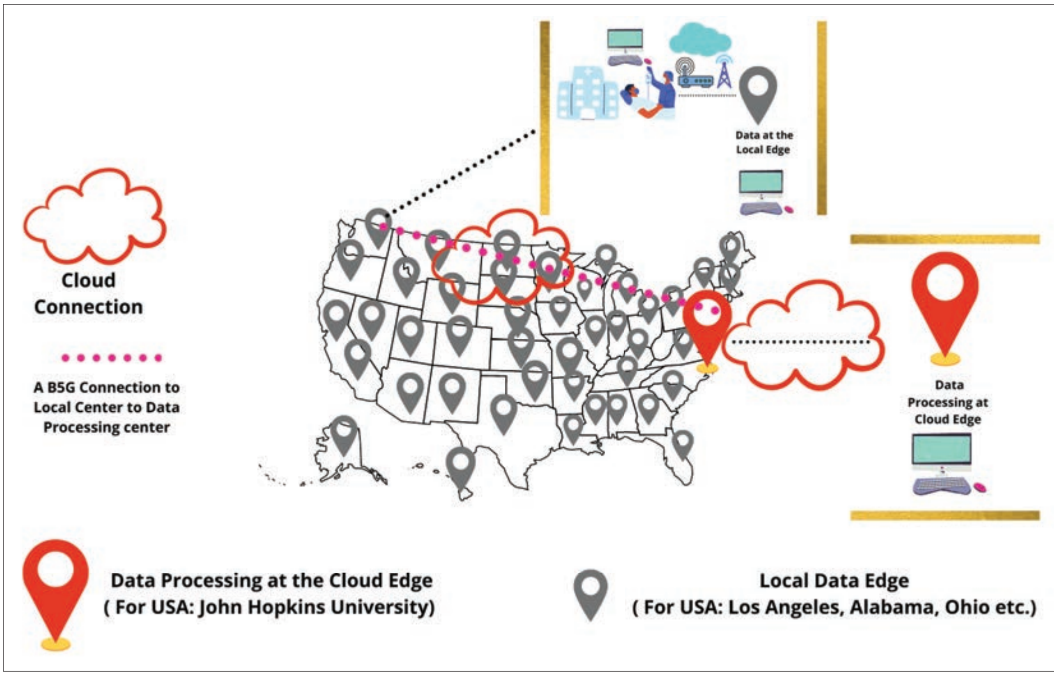

FIGURE 3. Data collection, data processing, and prediction at local edges and generating COVID-19 outburst prediction at cloud edge: a sample framework for the United States.

nique for DNNs, and also allow stacking of multiple layers of neurons. There are a few common nonlinear activation functions that have proven useful in the literature, each with its pros and cons:

- Sigmoid, which most often maps values in the range of zero to one or minus one to one
- Hyperbolic tangent (TanH)
- Rectified linear unit (ReLU), with its many variants including Leaky ReLU and Parametric ReLU
- Softmax, which can handle multiple classes
- Swish, a self-gated activation function that performs better than ReLU with reasonable computation efficiency

DNN at Cloud Edge: As shown in Fig. 3, a DNN is deployed at the edge of the cloud to combine all the predictions generated at individual edges. It should be noted that the communication between edges and the cloud edge takes place through B5G because of enhanced performance in terms of latency and bandwidth. We contend that the DNN at the cloud edge will provide improved COVID-19 outbreak prediction by combining the individual predictions from each edge.

Implementation

We designed and developed the distributed AI on edges for COVID-19 outbreak prediction following Fig. 3. We used open library sources, such as TensorFlow, Keras, Pandas, NumPy, sklearn, pickle, matplotlib, and seaborn. We also used Matlab libraries such as NNtool, statistics tools, and plotting tools in our implementation. We built edges at three different locations, where the configurations of each edge device varied in terms of computational capacity. The previous 10 days' data were used to predict the COVID-19 outbreak for day 11. Hence, for the DNN at Edge 3, the input layer utilized 10 neurons. Only one hidden layer was chosen, which utilized five neurons, whereas the output layer used one neuron. For the DNN in CloudEdge, the input layer consisted of three neurons, while the hidden layer used three neurons and the output layer had only one neuron. The Bayesian regularization back-propagation algorithm was used to train both DNNs (Edge3 and CloudEdge), while the Levenberg-Marquardt optimization approach was used to adapt the weights. Parameters of the DNN and AR used in our framework were chosen empirically, while the parameters of ARIMA were chosen by analyzing the ACF and PACF plots. To overcome the over-fitting problem of DNN training, a validation dataset was used to test how the trained model performs for an unseen dataset.

Dataset

Daily COVID-19 outburst data is accumulated at ourworldindata.org, which relies on data from the European Center for Disease Prevention and Control (ECDC). We simulated our experiment for the following list of countries:

- United States
- India
- Bangladesh
- Italy
- Saudi Arabia

Our distributed AI model on edges was trained using a dataset ranging from December 31, 2019 to May 15, 2020, and each of the individual AI methods running at individual local edges was used to predict the COVID-19 outburst number for the following day. That is, as soon as the data for the day were collected locally through the B5G network, the model could predict the total number of COVID-19 patients for the next day. We predicted COVID-19 outbreak data from May 16, 2020 to August 31, 2020 and compared the prediction with the actual COVID-19 data.

Country	Correlation coefficient (R-square)				MAPE			
	Edge1 (ARIMA)	Edge2 (AR)	Edge3 (DNN)	CloudEdge (DNN)	Edge1 (ARIMA)	Edge2 (AR)	Edge3 (DeepNN)	CloudEdge (DeepNN)
USA	0.9644	0.9661	0.9524	0.9994	8.91206292	8.31160441	9.65384203	6.84942372
India	0.9943	0.9913	0.9863	0.9951	5.28996426	6.05022261	7.64208275	4.98347836
Bangladesh	0.7825	0.8583	0.8435	0.9501	15.4564656	18.768055	15.8973075	13.7891872
Italy	0.9101	0.9024	0.9077	0.9999	25.4953303	26.0378425	24.7468502	23.2527571
Saudi Arabia	0.9612	0.9598	0.9595	0.9998	7.98227452	9.21986404	9.47143366	7.49919554

TABLE 2. Prediction results comparison among the individual AI methods and the AI at cloudEdge.

Results

We implemented all the programs and executed them on some edge devices and the cloud edge to predict COVID-19 outbreak for a few countries. At each of the edges, we employed different AI methods in the Python application. Table 2 shows the sample results for five countries in terms of R-squared values and mean absolute percentage error (MAPE). R-squared represents the correlation between the actual and predicted COVID-19 patients. An R-squared value equal to 1 represents a 100 percent match with the actual value. An R-squared value close to 1 represents very good prediction performance because the predicted value follows the same trend as the actual value. As shown in the table, the distributed AI on the edges can provide an R-squared value close to 1 for each of the countries considered in the experiment. It is interesting to note that at each edge device, the achieved R-squared value was also highly impressive. However, once the cloud edge combined all the predicted results of all edges, the achieved R-squared value was further enhanced (e.g., for Bangladesh, using Edge1 [ARIMA], Edge2 [AR], and Edge3 [DNN], we achieved R-squared values of 0.7825, 0.8583, and 0.8435, respectively). The cloud edge (DNN) combined all the predicted values and generated a final prediction with an R-squared of 0.9501, a 10.66 percent improvement compared to DNN, a 9.18 percent improvement compared to AR, and a 16.76 percent compared to ARIMA. A similar improvement in the prediction result by combining the outcomes of individual AI methods was achieved for other countries. Figure 4 shows the predicted vs. actual COVID-19 cases for India and Italy, respectively. As these figures show, after combining the outcome of individual AR, ARIMA, and DNN at CloudEdge(DNN), the predicted values become closer to the actual COVID-19 cases compared to that of AR, ARIMA, and individual DNN. The predicted values by ARIMA are also as impressive as the combined results generated by CloudEdge(DNN). These results justify that AI techniques can guide policy makers in predicting future COVID-19 cases to take necessary steps for controlling the further spread of COVID-19.

We further evaluated the distributed AI on the edges using another popular performance metric: MAPE. The last columns of Table 2 show the MAPE prediction performance for each of the edges deployed in our distributed AI on the edge model. As shown in the table, the combined result at CloudEdge(DNN) provided better performance compared to the predictions generated at each individual edge. It should be noted that the lower the value of MAPE, the better the prediction performance. As shown in the table, the MAPE score for India was 4.98 percent using the proposed approach, which was lower than those achieved using individual ARIMA (5.29 percent), AR (6.05 percent), and DNN (7.64 percent). For the United States, the MAPE score improvements of our proposed approach compared to ARIMA, AR and DNN are (8.91 – 6.85 =) 2.06 percent, (8.31 – 6.85 =) 1.46 percent, and (9.65 – 6.85 =) 2.8 percent, respectively. A similar MAPE score improvement trend was observed for the other countries used in the experiment. We notice that for Italy and Bangladesh, the MAPE values are comparatively higher than the other countries' values. This is because in those countries, a comparatively lower number of people were diagnosed with COVID-19 during the pertinent period, leading to a fractional error in prediction results in countries with a high MAPE score. The combination of impressive R-squared values with moderate MAPE scores indicates that the AI methods are able to predict the changes in trends of COVID-19 outbursts in all the countries, while the prediction of the exact number of COVID-19 patients was achieved with an error range from 7 to 23 percent.

Comparison with Other Approaches Applied in Other Studies: In the literature. Ardabili *et al.* [13] found an MLP to be an efficient approach to predict COVID-19 outbreak. Table 2 reports the COVID-19 outbreak prediction using DNN (Edge3). As shown in the table, our AI at CloudeEdge outperforms the performance of individual DNNs. Note that DNN is an updated variant of an MLP, and hence we opt to compare it with DNN instead of a vanilla MLP. In another study, Want *et al.* [4] proposed using the logistic model (which is a variant of an MLP) to predict COVID-19 outbreaks. As mentioned before, in our experiment, we use the advanced variation of the MLP (i.e., DNN), and our proposed approach is superior to that of individual DNN in terms of prediction performance. It should be noted that we opt to use the state-of-the-art variant of the MLP to predict COVID-19 outburst prediction in place of using vanilla MLP or logistic regression.

Conclusions

We introduce a COVID-19 pandemic-outbreak prediction framework based on B5G network architecture, edge computing, and distributed AI techniques. The proposed framework leverages the high-bandwidth and low-latency characteristics of B5G technology with edge computing for enhancement of the intercommunication among

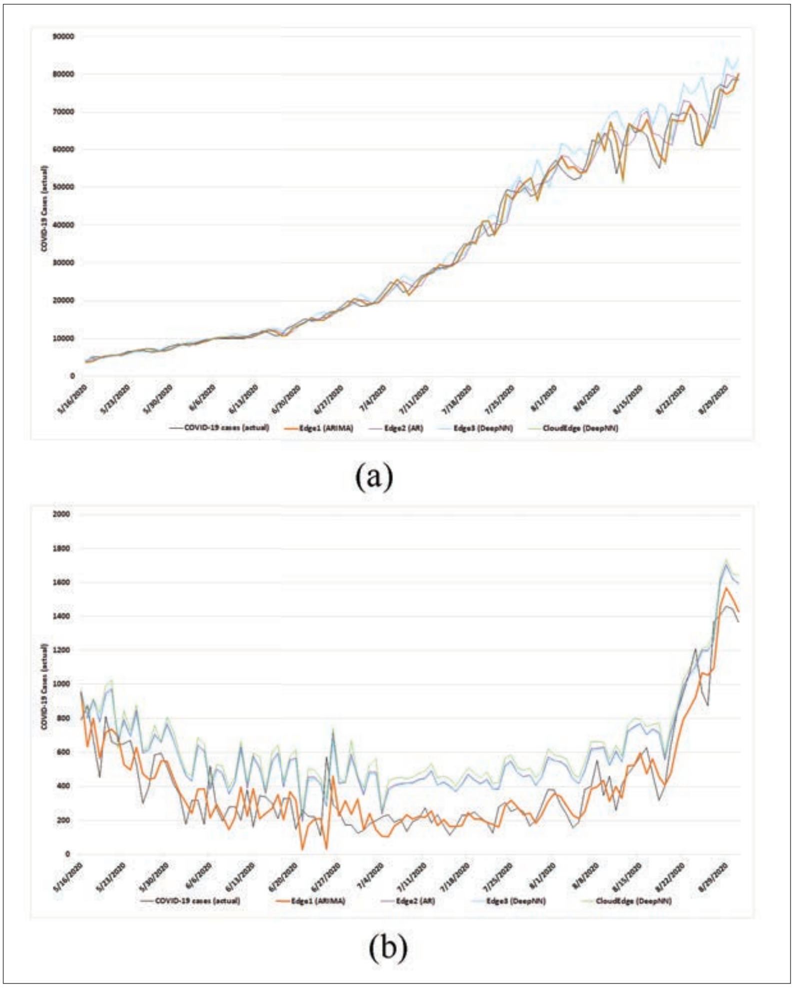

FIGURE 4. a) Prediction vs. actual COVID-19 cases for India; b) prediction vs. actual COVID-19 cases for Italy.

the edges. It then uses a distributed ensemble of different AI methodologies to support COVID-19 outbreak predictions, where each individual AI method is deployed on an edge, and the outcome of each edge is propagated to a cloud edge for combining all the results using another AI method. We conducted various experiments with real-world data for five countries, and the results clearly show the improved prediction performance of our proposed distributed AI with the edge method using existing state-of-the-art approaches. In a future study, we plan to work on more real-world datasets from other countries for timely prediction of the exact number of COVID-19 cases to reduce the impact of an anticipated second wave of the COVID-19 pandemic. Moreover, a recurrent AI approach will be implemented at the edges to enhance the framework's capacity to produce long-term prediction.

Acknowledgment

The authors are grateful to the Deanship of Scientific Research at King Saud University for funding this work through the Vice Deanship of Scientific Research Chairs: Chair of Smart Technologies.

References

[1] M. S. Hossain, G. Muhammad, and N. Guizani, "Explainable AI and Mass Surveillance System-Based Healthcare Framework to Combat COVID-19 Like Pandemics," *IEEE Network*, vol. 34, no. 4, July/Aug. 2020, pp. 126–32.

[2] Y. Abdulsalam and M. S. Hossain, "Covid-19 Networking Demand: An Auction-Based Mechanism for Automated Selection of Edge Computing Services," *IEEE Trans. Network Science and Engineering*, 2020.

[3] M. A. Rahman *et al.*, "B5G and Explainable Deep Learning Assisted Healthcare Vertical at the Edge: Covid-19 Perspective," *IEEE Network*, vol. 34, no. 4, July/Aug. 2020, pp. 98–105.

[4] P. Wang *et al.*, "Prediction of Epidemic Trends in Covid-19 With Logistic Model and Machine Learning Technics," *Chaos, Solitons & Fractals*, vol. 139, 2020, p. 110,058.

[5] D. S. Hui *et al.*, "The Continuing 2019-Ncov Epidemic Threat of Novel Coronaviruses to Global Health — The Latest 2019 Novel Coronavirus Outbreak in Wuhan, China," *Int'l. J. Infectious Diseases*, vol. 91, 2020, pp. 264–66.

[6] W. H. Organization *et al.*, "Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (Covid-19); Novel Coronavirus (2019-Ncov): Situation Report, 13 and Statement on the Second Meeting of the International Health Regulations, Emergency Committee Regarding the Outbreak of Novel Coronavirus (2019-ncov); 2005," 2020.

[7] I. S. Koolhof *et al.*, "The Forecasting of Dynamical Ross River Virus Outbreaks: Victoria, Australia," *Epidemics*, vol. 30, 2020, p. 100,377.

[8] A. Darwish, Y. Rahhal, and A. Jafar, "A Comparative Study on Predicting Influenza Outbreaks Using Different Feature Spaces: Application of Influenza-Like Illness Data from Early Warning Alert and Response System in Syria," *BMC Research Notes*, vol. 13, no. 1, 2020, pp. 1–8.

[9] R. Liang *et al.*, "Prediction for Global African Swine Fever Outbreaks Based on a Combination of Random Forest Algorithms and Meteorological Data," *Transboundary and Emerging Diseases*, vol. 67, no. 2, 2020, pp. 935–46.

[10] S. Anno *et al.*, "Spatio-Temporal Dengue Fever Hotspots Associated with Climatic Factors in Taiwan Including Outbreak Predictions Based on Machine-Learning," *Geospatial Health*, vol. 14, no. 2, 2019.

[11] L. Tapak *et al.*, "Comparative Evaluation of Time Series Models for Predicting Influenza Outbreaks: Application of Influenza-Like Illness Data from Sentinel Sites of Healthcare Centers in Iran," *BMC Research Notes*, vol. 12, no. 1, 2019, p. 353.

[12] N. Iqbal and M. Islam, "Machine Learning for Dengue Outbreak Prediction: A Performance Evaluation of Different Prominent Classifiers," *Informatica*, vol. 43, no. 3, 2019.

[13] S. F. Ardabili *et al.*, "Covid-19 Outbreak Prediction with Machine Learning," SSRN 3580188, 2020.

[14] Z. Malki *et al.*, "Association Between Weather Data and Covid-19 Pandemic Predicting Mortality Rate: Machine Learning Approaches," *Chaos, Solitons & Fractals*, vol. 138, p. 110,137.

[15] Y. Gao *et al.*, "Machine Learning Based Early Warning System Enables Accurate Mortality Risk Prediction for Covid-19," *Nature Commun.*, vol. 11, no. 1, 2020, pp. 1–10.

Biographies

Md Rafiul Hassan [M] received his Ph.D. degree in computer science and software engineering from the University of Melbourne, Victoria, Australia, in 2007. He is currently an associate professor with the Department of Computer Science, University of Maine at Presque Isle. He has authored or coauthored 60 research papers in internationally reputed journals and conference proceedings. His research interests include artificial intelligence, deep learning, machine learning, and computational intelligence with a focus on developing new data mining and machine learning techniques for big data analysis and 5G-enabled IoT. He has secured more than $1.5 million of funding from different agencies (e.g., University of Maine Small Campus Initiative, Early Career Research Grant, ARAMCO research project) to support his research works. He acted as Guest Editor of *Applied Soft Computing* (Elsevier) and *IET Software* (Wiley).

Mohammad Mehedi Hassan [SM] received his Ph.D. degree in computer engineering from Kyung Hee University, Seoul, South Korea, in February 2011. He is currently a full professor with the Information Systems Department, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. He has authored and co-authored around 260+ publications including refereed IEEE/ACM/Springer/Elsevier journals, conference papers, books, and book chapters. He is a recipient of a number of awards including the Distinguished Research Award from College of Computer and Information Sciences, the KSU 2020, Best Journal Paper Award from the *IEEE Systems Journal* in 2018, and the Excellence in Research Award from the College of Computer and Information Sciences, KSU (2015 and 2016). He is listed as one of the top 2% Scientists of the World in the Networking and Telecommunication field. His research

interests include edge/cloud computing, the Internet of Things, cyber security, artificial intelligence, body sensor networks, and 5G networks.

Meteb Altaf received his PhD degree from Brunel University London, United Kingdom, in 2009. He is currently an associate professor at King Abdulaziz City for Science and Technology (KACST), Riyadh, Saudi Arabia, and Director of the 3Advanced Manufacturing and Industry 4.0 Center at KACST. He has published a great number of papers in different well-known ISI journals and in well recognized conferences as well. He is also a visiting lecturer in the Biomedical Technology Department at King Saud University. His research interests include pervasive healthcare, the Internet of Things, Industry 4.0, manufacturing, robotics, and smart city.

Mostofa Shamim Yeasir is a B.S. student in computer science and engineering at Jatiya Kabi Kazi Nazrul Islam University, Trishal, Mymensingh, Bangladesh. He has been conducting research under the supervision of associate professor Md Rafiul Hassan since early 2020. His research interests include machine learning and artificial intelligence with real-world applications. He also works as a freelancer (data analyst).

Muhammad Imtiaz Hossain is a Ph.D. candidate in the Department of Artificial Intelligence at the University of Malaya, Malaysia. His research interests include developing novel hybrid and ensemble machine learning models for forecasting and classification.

Kanis Fatema is studying for her B.Sc.Eng. in computer science and engineering at Jatiya Kabi Kazi Nazrul Islam University. She looks forward to solving challenging research problems in the areas of machine learning, IoT, and 5G networking. Her research interests include machine learning, deep learning image processing, robotics, and network security.

Rubya Shaharin is an assistant professor in the Department of Computer Science and Engineering at Jatiya Kabi Kazi Nazrul Islam University. She received her B.Sc. and M.Sc. degrees from the same university. Her research interests are speech recognition, smart health, telemedicine, machine learning, and image processing. She has several international journal publications. She received an ICT fellowship for her Master's research.

Adel F Ahmed received his B.S. degree in mathematics from King Saud University in 1995, his M.S. degree in computer science from King Fahd University of Petroleum and Minerals (KFUPM), Saudi Arabia, in 2001, and his Ph.D. degree in computer science from the University of Sydney, Australia, in 2008. He is currently a Dean with the College of Computer Science & Engineering at KFUPM. Conveying knowledge via visualizations using computing power has been his passion ever since he was introduced to computers in the 1980s.