Auxiliary Diagnosis of COVID-19 Based on 5G-Enabled Federated Learning

Rui Wang, Jinfeng Xu, Yujun Ma, Muhammad Talha, Mabrook S. Al-Rakhami, and Ahmed Ghoneim

Abstract

The development of 5G and artificial intelligence technologies have brought novel ideas to the prevention, control, and diagnosis of disease. Due to the limitation of the privacy protection of medical big data, releasing the data of patients is not allowed. However, as COVID-19 spreads globally, it is urgent to develop a robust diagnostic model to serve as many institutions as possible. Therefore, we propose a 5G-enabled architecture of auxiliary diagnosis based on federated learning for multiple institutions and central cloud collaboration to realize the sharing of diagnosis models with high generalization performance. In order to exchange model and parameters between the central and distributed nodes, a framework of diagnosis model cognition is constructed for sharing and updating the model adaptively. The severity classification experiments of COVID-19 were carried out on the central cloud and three edge cloud servers to verify the effectiveness of the proposed architecture and model cognition strategy. At the same time, the aggregated model shows good performance with accuracy rates of 95.3, 79.4, and 97.7 percent on distributed nodes, and the recognition results can assist doctors in executing auxiliary diagnosis. Finally, the open issues of model fusion of multimodal data in the 5G network architecture are discussed.

Introduction

By 2021, the outbreak of COVID-19 has led to hundreds of millions of infected cases and millions of mortalities. The World Health Organization (WHO) announced that the outbreak of COVID-19 constitutes a public health emergency of international concern. It is a critical topic to explore a scheme of diagnosis and treatment for the epidemic [1]. The universal digitalization of patients' illness data and the extensive application of big data analysis techniques make the application of artificial intelligence (AI) techniques in the research of COVID-19 a novel solution and have sped up the transition of conventional medical services to smart medical services [2, 3].

The development of AI and 5G technology has greatly driven the intelligent trend of COVID-19 prevention, control, and diagnosis. Zhang *et al*. designed an AI system with computed tomography (CT) images to determine whether a patient is infected with COVID-19 and the prognosis of a given patient [4]. At the same time, Hossain *et al*. proposed a beyond 5G (B5G) framework that uses the low-latency and high-bandwidth capabilities of 5G networks to detect COVID-19 based on medical images [5]. Min *et al*. proposed a susceptible individuals, exposed individuals, infective individuals, recovered individuals (SEIR) model with characteristics of population migration, proving the importance of social distance and migration rate in reducing the number of infections and the basic amount of reproduction in order to prevent the spread of the COVID-19 pandemic [6]. In [7], a cloud-supported physical space positioning framework for patient monitoring is proposed to minimize the spread of viruses after the patient is monitored. Moreover, as the number of infections in various countries continues to be disclosed, numerous prediction models have been established. The utilization of a single point of data to achieve the diagnosis and prevention of COVID-19 has brought significant results.

AI technology plays a significant role in auxiliary diagnosis of COVID-19, and significant results have been achieved [8]. As the number of cases continues to increase, more data is needed to train deep learning algorithms to enhance the robustness of the model. However, due to the simplification of researchers' cooperative institutions and the limitation of patient information privacy protection, many researchers can only obtain the dataset from a hospital to conduct research, resulting in poor compliance of a trained model to the patients of other hospitals. As a result, the trained model only serves specific hospitals and cannot be widely promoted. Therefore, many people have trained a variety of models on similar types of data or the same research point, and due to the limitation of training data or trained models, the models have not been widely used. Federated learning has broad prospects in the medical field. In order to solve the problem of the inability to share data of patient among hospitals, Kim *et al*. proposed federated tensor decomposition for computational phenotyping. While respecting privacy, this method obtains an accuracy rate similar to the centralized training model [9]. Huang *et al.* designed a community-based federated machine learning algorithm that uses clustering data to train multiple community models. The experimental results show that the prediction accuracy of the algorithm is close to the method of centralized training. When privacy needs to be protected, the algorithm can be extended to other prediction tasks [10].

Digital Object Identifier:
10.1109/MNET.011.2000704

Rui Wang, Jinfeng Xu, and Yujun Ma (corresponding author) are with Huazhong University of Science and Technology; Muhammad Talha and Mabrook S. Al-Rakhami are with King Saud University; Ahmed Ghoneim (corresponding author) is with King Saud University and Menoufia University.

The coverage of 5G and the rapid development of related communication technologies have greatly increased the transmission rate of the network [11]. A key issue considered in this article is to use federated learning to diagnose COVID-19 in a 5G network environment, and realize the privacy protection and information sharing of each node's data through model aggregation and distribution under the premise of ensuring the diagnosis capability [12].

Most hospitals will examine the hematological indicators of COVID-19 patients and the symptom texts of patients when they are admitted, which are the most common types of data. This article is based on AI technology to train the model with multi-source heterogeneous data used for the implementation and deployment of federated learning at the same time [13]. Specifically, the auxiliary diagnosis includes identification and severity classification of COVID-19. Driven by 5G technology, the recognition model jointly established by multiple hospital nodes can accurately and quickly realize the detection and diversion of patients, which helps to allocate medical resources reasonably and reduce redundant consumption. In order to solve the above problems, the main contributions of this article are as follows:

- A 5G-enabled diagnosis architecture is used for cognition and protection of patients' data. Considering the requirements of low latency and high accuracy in COVID-19 diagnosis, an architecture is constructed to achieve privacy protection and condition awareness of patients. The integration of 5G technology and federated learning will achieve more accurate recognition, assisting doctors in decision making on the basis of ensuring high-speed data transmission.
- The diagnosis model cognition based on federated learning is designed to update and share the model. In order to achieve the utilization of multi-hospital nodes data and the improvement of model generalization performance, the idea of model design, initialization, updating, and aggregation based on federated learning to assist COVID-19 diagnosis is proposed. It helps multi-source data train a model on the basis of ensuring user privacy and multi-node sharing models.
- A severity classification task is implemented to verify the effectiveness of the proposed scheme. The data of patients from different hospitals are collected and analyzed. We use the severity classification as a case study to carry out a verification experiment. With the diagnostic model based on federated learning some better models can be attained by distributed nodes to predict the severity of COVID-19.

Our work provides a novel idea to improve the diagnosis performance of COVID-19 while ensuring protection of patients' privacy. The remainder of this article is organized as follows. The following section introduces the design of auxiliary diagnosis architecture. We then present the diagnosis model cognition with federated learning. Following that, we show data-driven evaluation for auxiliary severity diagnosis. Finally, we conclude the article.

The cloud will collect a variety of models from different edge clouds in order to shape a better model. Specifically, the three locations play different functions during the transmission of data and models. The architecture mainly includes three parts: data collection layer, diagnosis feedback layer, and model cognition layer.

Architecture of Auxiliary Diagnosis and Application for COVID-19

Introducing federated learning into the 5G-driven intelligent medical system will bring about novel evolution in the diagnosis and treatment of diseases. This section first presents a brand new disease-assisted diagnosis architecture, as shown in Fig. 1, and then takes COVID-19 as an example to carry out related applications to achieve auxiliary diagnosis.

Architecture Overview

In the architecture of auxiliary diagnosis based on federated learning, there are three locations where data and model are produced. Local devices deployed at local hospitals are used to examine and monitor physiological signals, which are the closest access to the source of data. The doctor-patient is the source of raw data, who is responsible for uploading the generated data to the node server where the hospital is located. Edge clouds are around the hospitals they serve, and give important guarantees of computation capability. The cloud will collect a variety of models from different edge clouds in order to shape a better model. Specifically, the three locations play different functions during the transmission of data and models. The architecture mainly includes three parts: data collection layer, diagnosis feedback layer, and model cognition layer.

Data Collection Layer: Considering infectious diseases under the epidemic, it is necessary to employ sensor technology, automation technology, and 5G to realize automatic data collection and transmission for local equipment deployed in hospitals. With high transmission speeds, quick real-time capabilities, and full-space connections, the 5G architecture is oriented to multi-scene collection environments, multi-service objects, and multi-device solutions, providing an important basic guarantee for model cognition and disease diagnosis.

Diagnosis Feedback Layer: The data collected by the local devices will be uploaded to the servers of the edge cloud nodes for disease identification and diagnosis. The layer is located on the edge cloud. It obtains mature diagnostic models from the cloud upward and receives data streaming from devices downward. After receiving the recognition result of the algorithm, it will be passed back to the data collection layer to help the doctor carry out the auxiliary diagnosis of the condition.

Model Cognition Layer: From raw data, common model to personalization model, finally a generalization model is generated. After receiving the initial model from the cloud, the edge cloud first conducts separate model training on the data from each hospital node, then uploads it to the cloud to learn the approximate distribution of the data of different nodes, and finally, the

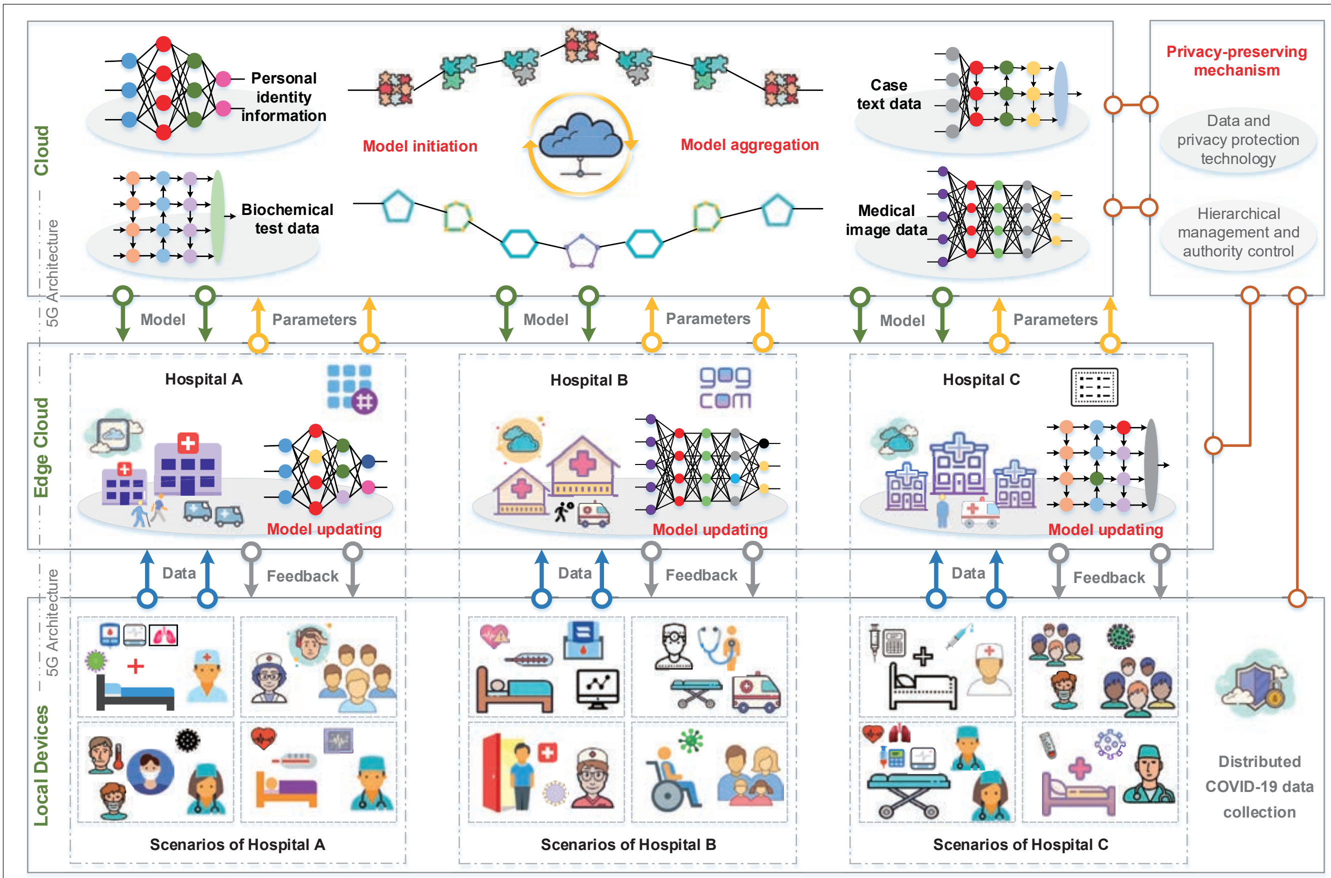

FIGURE 1. The architecture of auxiliary diagnosis based on federated learning.

central cloud sends an aggregation model to the edge node for model inference. There are lots of iterations and optimization based on federated learning to attain cognitive diagnosis models. Meanwhile, privacy-preserving mechanism (e.g., differential privacy) is used to preserve the information of patients, making it difficult to execute model anti-inference.

The data and model parameters can be transmitted smoothly on the three layers, making it convenient to train and test models based on federated learning.

Application for COVID-19

Patients with COVID-19 have more than one type information and data in order to receive comprehensive treatment. There are mainly multimodal data as follows.

Basic Identification Information: Basic identity information of patients is of great significance for determining the connection between patients, tracking the trajectory of patients, and finding potential contacts. This is not only conducive to the prevention and control of the COVID-19 epidemic, but also conducive to the discovery of the correlation of viral gene sequences. Generally, the patient's basic identity information is used to establish a COVID-19 knowledge graph to train end-to-end relationship discovery and entity recognition models, mainly based on long-term and short-term neural networks and convolutional neural networks.

Medical Record Text Data: The medical record mainly records the patient's symptoms, underlying diseases, and treatment plans, which can be employed to train diagnosis and treatment models based on symptoms and underlying diseases. It includes a text vectorized model and diagnosis and treatment model. Vectorized models (e.g., Word2Vec, BERT) used for diagnosis and treatment include convolutional neural network with attention mechanism, Transformer, and so on.

Biochemical Inspection Data: Generally, the test data is numerical data. Different machine learning and deep learning algorithms can be used according to different diagnostic tasks. Deep neural network can be used to train the classification or regression model for COVID-19 negative and positive judgments to predict the number of hospital stays.

Medical Image Data: Chest computed tomography images help provide accurate and rapid COVID-19 screening and detection. The transfer learning method is used to train a deep convolutional neural network, and a binary classification model is obtained to determine whether a CT image is positive or negative. Due to the limitation of the small dataset, there may be overfitting in the initial model, and the generalization performance of the model can be continuously improved in later adjustment.

In the application for COVID-19 patients, multi-task models are often required to run in parallel to achieve diagnosis and identification. After the patient is admitted to the hospital, nucleic acid testing will be carried out in the early stage for confirmation. During the course of treatment, a diagnosis of the severity of the disease will be performed to determine the appropriate treatment plan. Because of a variety of medical conditions and information levels of different hospital nodes, it is difficult for ordinary hospitals to obtain models with satisfactory performance, while top hospitals have the conditions to train high-performance models. After introducing federated learning, each medical node updates model parameters and other information through encryption, and the cloud server performs synthetic training without raw data. It is of great significance for alleviating the imbalance of medical resources and improving the clinical level of ordinary hospitals.

Diagnosis Model Cognition with Federated Learning

Because COVID-19 data is not centralized and there are privacy protection restrictions, we consider integrating federal learning into the COVID-19 diagnosis model. On one hand, federated learning solves the problem of decentralization of data and protects the privacy of patients. On the other hand, the joint diagnosis model of multiple nodes is beneficial to the improvement of model performance. The hospital manages the medical data of all patients in the hospital, and is responsible for receiving and updating the model transmitted by the cloud computing center. The cloud computing center is responsible for collecting models from various hospitals and distributing the improved models back to each hospital. Specifically, diagnosis model cognition includes four modules, namely model design, model initiation, model updating, and model aggregation, as shown in Fig. 2. Meanwhile, a privacy-preserving mechanism plays an important role in each module.

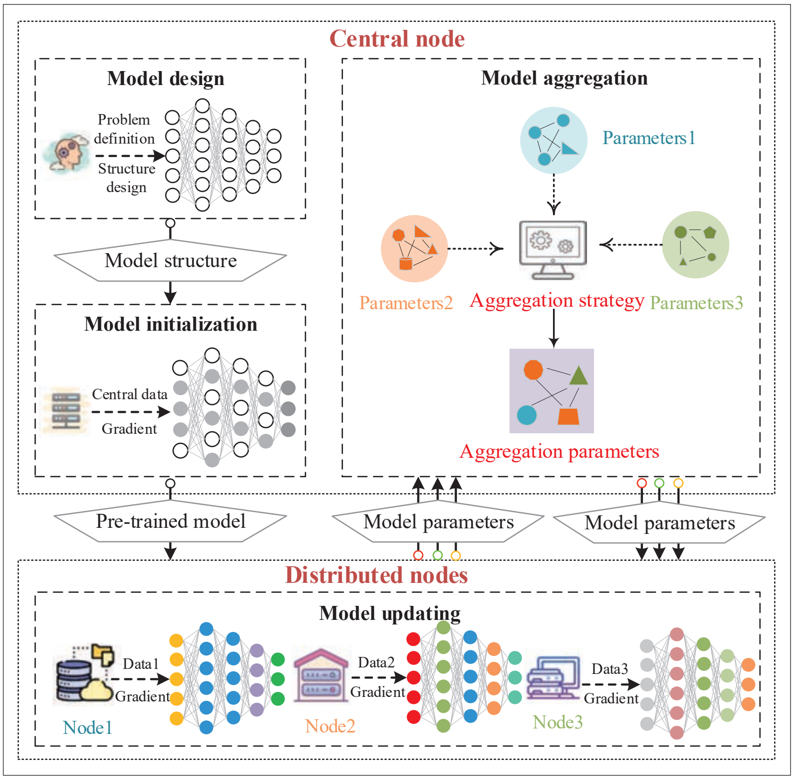

FIGURE 2. Diagnosis model cognition on central node and distributed nodes.

Model Design

After the central node knows about the requirement of distributed nodes, combined with the environment and conditions of the central server, the requirements will be defined, and the design for architecture of the model will be carried out at the same time. In the application of COVID-19, after a new patient is admitted to the hospital, it is necessary to decide the severity of the disease and dispatch appropriate medical resources to carry out treatment in a timely manner.

The patient's blood test indicators are used to identify the severity. The structure design and parameter settings of the model are shown in Table 1. Since blood indicators are only 85 simple numerical data, linear regression function is suitable to build neural networks. There all five layers in the network and first four linear layers are activated with ReLU function to enhance the fitting ability. In addition, adaptive moment estimation and cross entropy loss are utilized as the optimizer and loss function. It is notable that before training a pretrained network with biochemical data, they are going through some processing methods such as filling missing values and normalization operation.

Layer	Input	Output	Activation
1	85	128	ReLU
2	128	64	ReLU
3	64	32	ReLU
4	32	8	ReLU
5	8	3	–
Other params	Optimizer	Adaptive moment estimation	
	Loss	Cross entropy loss	

TABLE 1. Model design and parameters setting for severity recognition of patients with COVID-19.

Model Initiation

Model initiation means that the central node needs to use part of the data in the cloud to initialize the diagnostic model according to the structure of the model.

The data on the central server is used to pre-train the parameters of the deep neural network [14], and the parameters are updated by an adaptive gradient algorithm. It can dynamically adjust the learning rate of each parameter using small step size updates for frequently changing parameters and large step size updates for sparse parameters, which can be formulated as follows:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{g_t}{\sum_{i=1}^{t} g_t^2} \quad (1)$$

where θ is the parameter of the network, $g_t = \nabla_\theta J(\theta_{t-1})$ represents the gradient of the t time step, and η is the learning rate. When the pre-trained model is completed, it will be distributed to each sub-node.

Model Updating

After receiving the initiation diagnostic model sent by the central server, sub-nodes will use local data to fine-tune the parameters of the model to fit their conditions.

Node	Training dataset				Testing dataset				Server			
	Low	Medium	High	Sum	Low	Medium	High	Sum	Type	RAM	VRAM	Frequency
Central node	156	50	14	220	67	22	6	95	Tesla V100	512 GB	32 GB	5012 MHz
Sub-node1	126	39	5	170	54	17	2	73	RTX 2080 Ti	512 GB	8 GB	1920 MHz
Sub-node2	152	64	16	232	66	27	7	100	Tesla V100	512 GB	32 GB	5012 MHz
Sub-node3	54	16	16	86	23	7	7	37	GT 1030	4 GB	2 GB	60 HZ

TABLE 2. The dataset statistics and server configurations of central cloud and edge clouds.

The model updating of sub-nodes is executed on the basic pre-trained model to gain new knowledge from local samples and still retains the learning ability of the original model. At the same time, in the process of training the model, it is necessary to consider reducing the loss value of the model to improve the local recognition performance, and use an adaptive gradient optimizer to update the parameters of the network.

After the sub-node completes the training, the respective parameters will be uploaded to the central server for model aggregation. When the aggregation is completed, the parameters will be sent back to the sub-node to update the adaptive model, so as to loop until it meets the requirements of the sub-node.

Model Aggregation

In order to obtain valuable data from various distributed nodes without invasion of privacy of patients, the central cloud will aggregate updated models from various sub-nodes. The goal is to improve generalization capabilities while ensuring performance by integrating models trained with multi-source data. In order to maximize the utilization of the parameters of the optimal model, a parameter aggregation strategy named accuracy-first is constructed as follows:

$$\theta^{\tau} = \sum_{i=1}^{n} \theta_i^{\tau} \cdot \frac{\nu_i}{\sum_{i=1}^{n} \nu_i} \quad (2)$$

where θ_i^{τ} is the parameter of the τth layer of the sub-node i training network, ν_i is the accuracy rate of sub-node i on its testing set, and n represents the number of sub-nodes. After completing parameters aggregation, a new round of model recognition is opened. The central cloud iteratively trains the model and sends back the parameters to edge clouds until the sub-nodes are satisfied with the performance of the model.

Privacy-Preserving Mechanism

Although the risk of patient data leakage has been greatly reduced through federated learning, there are still privacy protection issues in the doctor-patient-hospital interaction. Therefore, it is necessary to strengthen the privacy protection in the medical network at the current connection point [15]. In the protection of COVID-19 data, privacy protection methods are divided into two aspects: technology and access control. Technical protection relies on cryptography in traditional data privacy protection. The data interaction node topology model of the cloud platform environment is constructed, and encryption algorithms are used to improve data security. Access control refers to the hierarchical management of medical data and users, and different rights are provided for each visitor based on the weight of different data in privacy protection. The established privacy protection system can form systematic protection in the storage, access, and transmission of COVID-19 data.

Data-Driven Evaluation for Auxiliary Severity Diagnosis

By using blood index data of COVID-19 patients, a cognitive classification model of severity based on federated learning was constructed, and data-driven evaluation experiments were carried out.

Experiment Setting

For the purpose of performing the severity auxiliary diagnosis based on federated learning, one central node is configured as remote cloud and three sub-nodes are configured as edge clouds. The details of configuration information and statistics of dataset deployed different nodes are shown in Table 2.

Due to the limitation of data source, the data are only from two hospitals. The dataset on sub-Node2 is from a hospital, and others on other nodes are from another hospital but different periods. Therefore, it is meaningful to carry out experiments with them. The severity of COVID-19 is recognized as three types: *low*, *medium*, and *high*. It can be seen due to the imbalance of patients that *low* and *medium* have more samples, but *high* has few. The training set and the testing set are divided at a ratio of 7:3 using a stratified sampling method, ensuring that the proportions of category samples divided into the two sets are balanced. There are 315 samples on the central node, and the total number of samples for sub-Node2 is 332, which has the most samples.

There are 85 blood index fields in a sample. However, in actual scenarios, since it is generally difficult to completely test all the index items for each patient, there is a problem: some indices are missing. Before training the model, the missing values need to be supplemented. During the experiments, after dividing the training and test datasets, each node calculates the average value of the different index items of each sample without null value on its own training dataset to add the corresponding missing values in the training and testing set item. Then the values of different indicators will have differences in magnitude. Min-Max Normalization is used for normalization processing. Similarly, the training dataset on each node is used as the standard to normalize the corresponding training and testing set. After the data preprocessing is complete, the model will be trained on each node server. The evaluation index for a model is accuracy rate.

Three kinds of server configurations are used as remote cloud and edge cloud. Tesla V100 servers are used on the central node and sub-Node2, while RTX 2080 Ti and GT 1030 are used on the other two nodes. According to the different types of servers, there is a variety of random access memory (RAM), video random access memory (VRAM), and frequency.

Comparisons of Aggregation Strategy

After each sub-node completes the model training, the parameter aggregation will be performed in the central node. It is very important to select a suitable aggregation strategy. In addition to the accuracy-first strategy proposed in this article, random and average methods are implemented. Since the sum of the weights of all node parameters is selected to be one, the random method randomly generates three decimals with a sum of one as the parameter weights of the three nodes. In the average method, the parameter weights of three nodes are 1/3. The evaluation experiment is carried out on the testing set of the central node. The central node will aggregate the parameters each epoch received from the sub-nodes and then evaluate it on the local testing dataset. The number of iterations for each sub-node is 100, and the number of parameter aggregations on the central node is also 100.

The comparison result is shown in Fig. 3. Since the accuracy of the first 40 epochs has changed greatly and is low, for the convenience of observation, the evaluation results between epoch 40 and epoch 100 are shown. It can be seen that the accuracy-first method has the highest accuracy rate of 72.9 percent, and the average method is inferior to accuracy-first with an accuracy rate of 67.7 percent, but its stability is stronger. The random method is less effective with 66.7 percent. Therefore, we can see that accuracy-first is a suitable method for pursuing high performance of the model. The average method can be used in systems that require high stability.

Evaluation of Distributed Nodes

By means of federated learning for auxiliary diagnosis of diseases, on one hand, it can well protect the privacy of patients, and on the other hand, it can solve the problem of data islands and employ multi-source data to improve the generalization ability of the diagnosis model. We evaluate the model performance of distributed nodes as shown in Fig. 4.

After the distributed node receives the aggregation parameters from the central node, it sets them as its own model parameters. At this time, the three distributed nodes have the same parameters. It can be seen that when the epoch is 0, the evaluation accuracy rates of the three models on their own testing datasets are 74.3, 65.7, and 62.1 percent, respectively. Then the three sub-nodes perform adaptive training of the model on their own training datasets with training size of 170, 232, and 86, respectively, to fine-tune the parameters. As the training epoch increases, the model performance of each node gradually improves until the epoch reaches 100 and processes of training are terminated. Finally, the evaluation accuracy rates of Node1, Node2, and Node3 on their own testing sets are 95.3, 79.4, and 97.7 percent, respectively. Although the final evaluation result of Node2 is low, its highest accuracy rate has reached 91.8 percent. In addition, we notice that since the dataset on Node2 comes from a completely different hospital than the other nodes, this may be one of the reasons why its accuracy rate is lower than the other two nodes. In general, model cognition based on federated learning performs well on each sub-node, which can help doctors assist in diagnosis, and determine the appropriate diagnosis and treatment plan for a patient.

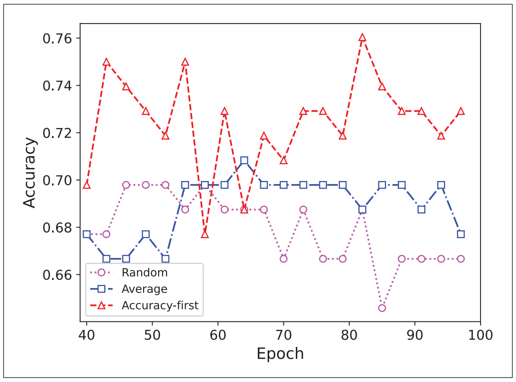

FIGURE 3. The comparison results of parameter aggregation methods.

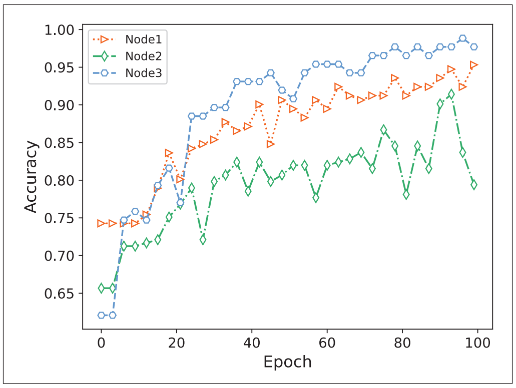

FIGURE 4. The evaluation results on three distributed nodes.

Conclusions and Open Issues

Combining the problems arising from the utilization of patient data and deep models during the COVID-19 epidemic, this article proposes a 5G-enabled deep learning framework based on federated learning to assist in the diagnosis of COVID-19. The data related to patients and models are stored and transmitted on three layers, which are data collection layer, diagnosis feedback layer, and model cognition layer. On the diagnosis model cognition layer, model design, initialization, updating, and aggregation are exe-

With increasing data types, the issue of data privacy protection becomes more important, and based on blockchain and federated learning will carry out effective model training under the premise of ensuring data security and exchange and training efficiency.

cuted. Based on the architecture of auxiliary diagnosis, hospital nodes can use powerful computing capability of the cloud to achieve low-latency, high-performance disease diagnosis on the basis of protecting patient privacy. Severity recognition of COVID-19 is taken as an application to validate the scheme. By using data from different hospitals to carry out experiments on four nodes, it is verified that the accuracy-first aggregation strategy has better performance. At the same time, after the aggregated parameters are trained on the three sub-nodes, the recognition accuracy rates of the severity are 95.3, 79.4, and 97.7 percent. The architecture proposed in this article can be used to assist doctors in diagnosis under the COVID-19 epidemic to help patients recover.

In medical diagnosis, it is difficult for multimodal data to achieve the desired effect. Especially in COVID-19, multiple data modalities are also required to provide doctors with a diagnosis basis. Therefore, in the joint federated learning of AI technology, it is also necessary to consider the 5G background multi-modal data fusion. The fusion and aggregation of multi-modal data models pose technical challenges for the cloud. The fusion method of multi-modal features and models is the key to improving the performance of the model at the child nodes. The aggregation of multiple parameters in the cloud node is a major test of the generalization performance of the model. With increasing data types, the issue of data privacy protection becomes more important, and based on blockchain and federated learning will carry out effective model training under the premise of ensuring data security and exchange and training efficiency. Finally, low-latency transmission of multi-modal data and super-large model parameters also puts a new test on the existing network architecture. The utilization of 5G technology to achieve synergy between edge cloud and cloud can help improve transmission performance.

Acknowledgment

The authors extend their appreciation to the Deanship of Scientific Research at King Saud University, Riyadh, Saudi Arabia, for funding this work through research group project no. RGP-229.

References

[1] C. Wang *et al.*, "A Novel Coronavirus Outbreak of Global Health Concern," *The Lancet*, vol. 395, no. 10223, 2020, pp. 470–73.

[2] M. Chen *et al.*, "Label-Less Learning for Emotion Cognition," *IEEE Trans. Neural Networks and Learning Systems*, vol. 31, no. 7, 2020, pp. 2430–40.

[3] I. D. Apostolopoulos *et al.*, "Covid-19: Automatic Detection from X-Ray Images Utilizing Transfer Learning with Convolutional Neural Networks," *Physical and Engineering Sciences in Medicine*, 2020, pp. 1–6.

[4] K. Zhang *et al.*, "Clinically Applicable AI System for Accurate Diagnosis, Quantitative Measurements, and Prognosis of Covid-19 Pneumonia Using Computed Tomography," *Cell*, 2020.

[5] M. S. Hossain *et al.*, "Explainable AI and Mass Surveillance System-Based Healthcare Framework to Combat COVID-I9 Like Pandemics," *IEEE Network*, vol. 34, no. 4, July/Aug. 2020, pp. 126–32.

[6] M. Chen *et al.*, "The Introduction of Population Migration to SEIAR for COVID-19 Epidemic Modeling with an Efficient Intervention Strategy," *Info. Fusion*, vol. 64, Dec. 2020, pp. 252–58.

[7] M. S. Hossain, "Cloud-Supported Cyber-Physical Localization Framework for Patients Monitoring," *IEEE Systems J.*, vol. 11, no. 1, Mar. 2017, pp. 118–27.

[8] L. Yan *et al.*, "An Interpretable Mortality Prediction Model for COVID-19 Patients," *Nature Machine Intelligence*, 2020, pp. 283–88.

[9] Y. Kim *et al.*, "Federated Tensor Factorization for Computational Phenotyping," *KDD: Proc.. Int'l. Conf. Knowledge Discovery & Data Mining*, Aug., 2017, vol. 2017, pp. 887–95.

[10] L. Huang *et al.*, "Patient Clustering Improves Efficiency of Federated Machine Learning to Predict Mortality and Hospital Stay Time Using Distributed Electronic Medical Records," *J. Biomedical Informatics*, vol. 99, 2019, 103291.

[11] Q. Yang *et al.*, "Federated Machine Learning: Concept and Applications," *ACM Trans. Intelligent Systems and Technology*, vol. 10, no. 2, 2019, pp. 1–19.

[12] Y. Abdulsalam *et al.*, "COVID-19 Networking Demand: An Auction-Based Mechanism for Automated Selection of Edge Computing Services," *IEEE Trans. Network Science and Engineering*. DOI: 10.1109/TNSE.2020.3026637.

[13] X. Wang *et al.*, "In-Edge AI: Intelligentizing Mobile Edge Computing, Caching, and Communication by Federated Learning," *IEEE Network*, vol. 33, no. 5, Sept./Oct. 2019, pp. 156–65.

[14] M. Chen *et al.*, "Label-less Learning for Traffic Control in an Edge Network," *IEEE Network*, vol. 32, no. 6, Nov./Dec. 2018, pp. 8–14.

[15] M. Hu *et al.*, "RAP: A Light-Weight Privacy-Preserving Framework for Recommender Systems," *IEEE Trans. Service Computing*, 2021. DOI: 10.1109/TSC.2021.3065035.

Biographies

Rui Wang (ruiwang2020@hust.edu.cn) is currently a Ph.D candidate in the School of Computer Science and Technology, HUST. She received her Bachelor's degree in computer science and technology from Lanzhou University, China, in 2018. Her research interests are computer vision, big data analysis, and reinforcement learning.

Jinfeng Xu (jinfengxuhust@hust.edu.cn) is currently a Ph.D candidate in the School of Computer Science and Technology, HUST. He received his Bachelor's degree in control science and engineering from Shandong University, China, in 2020. His research interests are edge computing and machine learning.

Yujun Ma (yujun.hust@gmail.com) is currently a special researcher in the School of Computer Science and Technology, HUST. He received his Ph.D. degree in computer science and technology from HUST in 2016. His research focuses on IoT, edge computing, body sensor networks, healthcare big data, and mobile cloud computing.

Muhammad Talha (mnaseem@ksu.edu.sa) received his Ph.D. degree in computer science from the Faculty of Computing, University of Technology Malaysia in 2015. He is a researcher in the Deanship of Scientific Research, King Saud University, Riyadh, Saudi Arabia. His research areas include image processing, pattern recognition, IoT, big data analysis, and artificial intelligence.

Mabrook S. Al-Rakhami (malrakhami@ksu.edu.sa) received a Master's degree in information systems from King Saud University, where he is currently pursuing a Ph.D. degree with the College of Computer and Information Sciences. He has authored several articles in peer-reviewed journals. His research interests include edge intelligence, cloud computing, IoT, and big data.

Ahmed Ghoneim (ghoneim@ksu.edu.sa) is currently an associate professor with the Department of Software Engineering, College of Computer and Information Sciences, King Saud University. He received his Ph.D. in software engineering from the University of Magdeburg, Germany, in 2007. His research interests are software evolution, edge computing, and IoT.