Received: 4 March 2024 | *Revised: 25 April 2024* | *Accepted: 24 May 2024*
DOI: 10.37917/ijeee.22.1.18 *Vol. 22 | Issue 1 | June 2026*

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

IJEEE University of Basrah College of Engineering

Enhanced Hybrid Model in Federated Learning Environment for Medical Heterogeneous Images

Tiba Saad Mohammed*, Hilal Al-Libawy
Department of Electrical Engineering, College of Engineering, University of Babylon, Babel, Iraq

Correspondance
*Tiba Saad Mohammed
Department of Electrical Engineering, College of Engineering, University of Babylon, Babel, Iraq
Email: sth.tiba.mohammed@student.uobabylon.edu.iq

Abstract
Federated learning (FL) is one of the newest and most significant fields for developing artificial intelligence applications. This technology trains its models in a distributed way, using data from different clients who work together in the system without sharing their data. The training process is kept local to protect the privacy of the data. Among the many difficulties that have arisen due to the novelty of this technology is the issue of heterogeneous data between typical clients. Client's data may differ from each other in different respects, for example non identically and independent distribution (non-IID) between clients and the difference in the type of data used in each client. This can lead to inconsistencies in the model's predictions and other undesirable outcomes. This paper discussed ways to solve this problem where clients with heterogeneous data were dealt with in terms of number and type. Because there are different types of image data through which doctors can diagnose coronavirus, such as x-rays, CT-scan. A hybrid convolution neural network (CNN) and long short-term memory model (LSTM) has been proposed in a federated learning system to predict the incidence of this disease by using two clients, each with one of these different data. Good results were obtained with an accuracy of more than 99% in one customer and more than 95% in the second client while maintaining the privacy of this data.

Keywords
Federated Learning, X-Ray Images, CT-Scan Images, Hybrid Model (LSTM & CNN).

I. Introduction

Artificial intelligence first appeared in 1950 when they developed a program to sense, understand and make decisions. After that, they developed machine learning, considered one of the most essential branches and fields of artificial intelligence. Machine learning is algorithms built by mathematical models that depend on bound data we enter into the machine. The algorithms analyses this data and decide according to the function it is designed for. As a result of the abundance of data at the present time and the importance of this data for the development of areas of artificial intelligence, they developed deep learning, which is considered one of the branches of machine learning and depends on a lot of data. Deep learning differs from machine learning as deep learning does not require organizing data and extracting features. Still, we enter the data directly, and its algorithm, in turn, extracts the features from the data and analyzes it to perform the task it was made for [1]. In recent years, obtaining data has become very difficult, especially in the medical field, to protect data privacy, as strict laws have been set against data privacy violators in many world countries [2]. This made researchers seek to develop technology that contributes to preserving data privacy to develop artificial intelligence models. In 2016, federated learning was proposed to solve data protection issues [3]. Federated learning is a distributed machine learning in which many clients participate collaboratively to solve machine learning problems. The process of training models takes place in place of the data and, therefore, does not need to be moved. The data and the data remain with its owner, thus solving the data privacy problem. On the other hand, it allows the use of data from different places simultaneously and the use of a lot of data to develop artificial intelligence models. It

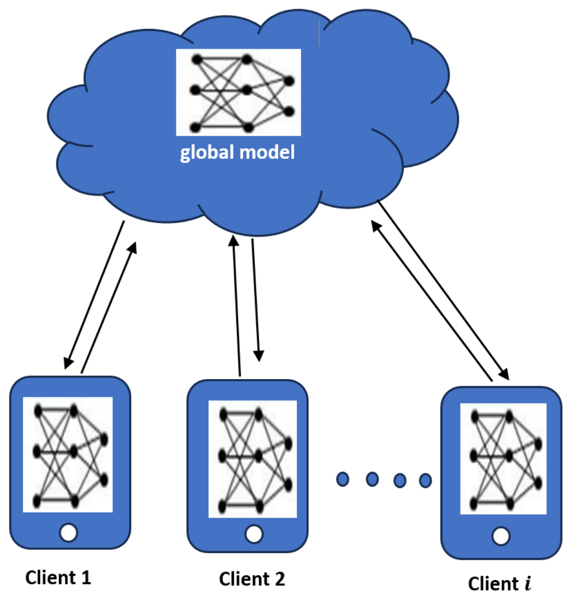

Fig. 1. Federated learning process

is used in different applications [4]. Recently, data acquisition has become one of the important issues facing researchers because of the laws that have been put in place to protect data. Because of this, researchers tended to discover a new technique that protects data and helps researchers train models using enough data to develop AI journals. This technology is called federated learning, and it is a distributed machine learning. Federated learning deals with many clients with data, and training takes place within these clients in the data's location to preserve the data's privacy [1]. The basic idea of federated learning consists of a server that builds a model and transfers it to the clients participating in the system to train the model locally with the data it owns. After training the locally distributed model, the client sends the trained model with new parameters to the server. The server collects the models from all contributing clients, and the models are collected, and a new global model is formed, which is considered a prototype for the cycle. Second, [5] this process is repeated several cycles until the required accuracy of the system is obtained. Fig. 1 shows the Federated learning process in a simplified way. As previously mentioned, federated learning was discovered to solve machine learning problems. In federated learning, the data is trained on a single learning model. It is more difficult in the case of data heterogeneity in different clients. Devices often make and receive data in a way that is not evenly spread across the network., which may differ in type for each client. This could make planning, analyzing, and evaluating harder [6]. There are many other challenges that researchers seek to address, such as Expensive Communication [7], Systems Heterogeneity [8–10] and Privacy Concerns [11]. The main contributions of our work could be summarized as follows:

1. Solving data Heterogeneous issue, In this thesis, different data were used for each client (CT-Scan and X-Ray dataset) and unbalanced data distribution among clients. As far as we know, such data was used for the first time to train a federated learning model.
2. Implement data augmentation strategies to increase the number of training data to get a robust system and good results.
3. Improving the system's accuracy: improving the accuracy of FL models is one of the current research hotspots and challenging tasks. We propose a hybrid model (CNN+LSTM) to train a better learning model that deals with data heterogeny and achieves high accuracy.
4. To improve the precision of sentiment analysis for medical data, a new approach, FL, has been proposed based on a deep hybrid Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) model to identify COVID-19 automatically.

The remainder of this paper can be organized as follows: Part II. discusses our work related to previous work. Part III. provides a justification for the fundamental principles of FL simplicity. Part IV. proposes our proposed method to solve the problem of heterogeneous data in federated learning. Part V. presents the results of the experiment used in our work. Finally, Part VI. concludes this paper.

II. Related Work

In 2017, McMahan et al. [12] developed (FL) method to resolve the conflict between the machine learning training process and data privacy protection which involves a big number of data that shared its samples. FL is based on sharing model parameters that can be combined into a single model. Adaptive enhancers for federated learning were used in 2021 to solve the problem of controlling and displaying unfavourable convergence behavior that lacks control and display in federated averaging (FedAvg). The results showed, after doing many experiments, that these improvement methods can significantly improve how well cooperative learning works, so federated optimization (FedOpt) [13] was used In this work with heterogeneous data for the first time an attempt to improve federated learning work with this type of standardized optimization method. In federated learning, each client has data with a different appearance that is not identical and distributed independently. It is called (non-IID) [14]. This is one of the critical challenges in federated learning because the difference in data will lead to a significant difference in local models. When the server collects it, it will reduce the system's efficiency. Recent research [15] indicates that no algorithm wins over an elementary empirical risk reduction (ERM) algorithm when equipping distributed clients with data augmentation. This can be explained by the fact that data augmentation works as a static mechanism, whereby data augmentation constitutes an effective and straightforward solution to mitigate these differences in FL clients. It also doesn't consider that false correlations are common in each area in the domain generalization (DG). [16] technique that was previously used to address the problem of data heterogeneity. We can use data augmentation technology on each client's data because it builds well-distributed and similar data distributions while protecting privacy. This allows distributed models to converge and makes it easy to combine data using the simplest algorithms.

III. Fundamentals of Federated Learning

In federated learning systems, the system consists of a group of N_i distributed clients where $i = 1, 2, 3, \ldots n$ and a central server S. The clients train the model under the supervision of server S collaboratively on its own data locally D_i. The server identifies participating clients within the group G, for example, there is client N_1 that trains the model on Its owned data set B_1, and the second client N_2, trains the model on the basis of its local data set B_2, and so on for all clients participating in the system. Each client belonging to group G updates their model parameters p_k since k is an element of group G. After that, the server performs By assembling the updated models to form the global model that show in (1).

$$f_g = \frac{1}{|G|} \sum_{i=1}^{|G|} p_k w_k \tag{1}$$

Where w_k is the aggregation weight, and $|G|$ is the number of elements in G. Then the server sends the global form again to the clients to repeat the same process several times until convergence is obtained

IV. Proposed Method

Training data are the most crucial component in the FL paradigm since they determine how well FL models perform. There are several issues with the data. So, in this work, a new system was introduced to solve the problems of heterogeneous data. A novel solution called Heterogeneous Data Federated Learning (HDFL) Has been proposed. This section first introduces the architecture of the proposed FL system (see A.). We introduce a data augmentation approach to solve the problem of heterogeneous data (see B.). After that, Finally, We present a new Hybrid model to train a better learning model that deals with data heterogeny it was summarized all the system to form a heterogeneous data Federated learning solution to achieve high accuracy (see C.).

A. Architecture of the System

Infrastructure is needed for federated learning to transfer machine learning models back and forth, train and test them on local data, and then combine the updated models. The infrastructure to do that in a simple, scalable, and secure manner is provided by Flower. Shortly put, Flower offers a unifying strategy for federated learning. We must aggregate all the model updates we received from the client nodes to obtain a single model. Aggregation is the term for this procedure, and there are numerous methods for doing it. This paper used a technique of federated averaging to collect different models from clients participating in the system and then applied an adaptive server optimizer to improve the result. Fig. 2 shows the proposed system.

In Fig. 2 the number (1) indicates the model used to train the data may be described A convolutional neural network (CNN) uses sliding convolutional filters to process input picture data. Feature information can be learned by a CNN in both the spatial and temporal dimensions. Long short-term memory (LSTM) networks learn long-term dependencies between time steps and interpret visual data by looping over them. The training data is used by a CNN-LSTM network, which combines convolutional and LSTM layers. When trained, the model sends the updated model with the new parameters to the server, shown in No. (2). After that, the server collects the new models from both clients to form a new global model, and this is step No. (3). After that, the new global model is sent a second time to the clients for training again in the second round, and this step is illustrated by No. 4. Steps from 1 to 4 are repeated for several rounds until the required results are obtained.

B. Heterogeneous Data

This work's heterogeneous data and data augmentation approach selected a heterogeneous data set for different clients. The heterogeneity of the data comes from two aspects. First, the data regarding the number of clients is not balanced, as shown in Fig. 3. On the other hand, different data were used in terms of type as show in Fig. 4.

In this work, different data were used for each client (CT-Scan [17] and X-Ray dataset [18]) and unbalanced data distribution among clients [19]. As far as we know, such data was used for the first time to train a federated learning model.

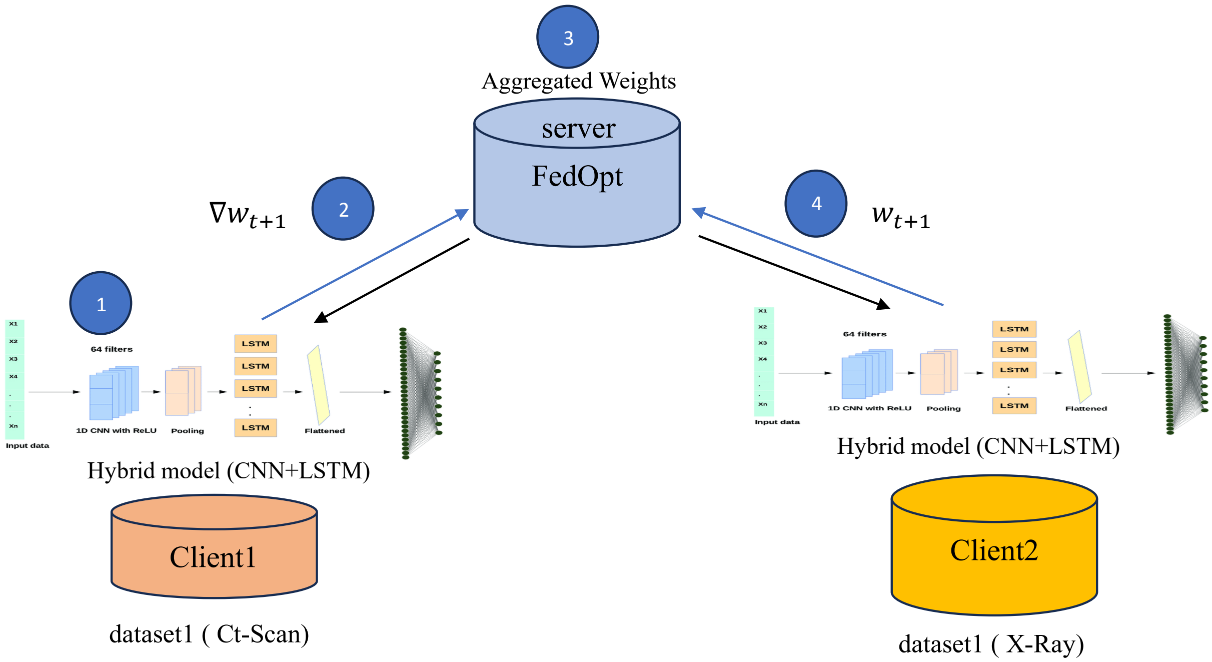

Fig. 2. The proposed system

Implementing data augmentation strategies in federal learning has two advantages: first, to reduce heterogeneous data problems by improving the similarity between data owned by the different clients. Another advantage of data augmentation is that most applications in federal learning need more data to make the model more robust. Therefore, data augmentation is one of the techniques often used to improve the performance of AI systems. The simplest way to increment the data is to reverse the vertical axis. Another commonly used technique is random farming. You can also use things like spin, cut, rescale and others. To illustrate the mechanism of data augmentation, we rely on the causal model [20]. A causal model has been proposed that explains the data augmentation approach to understand better how this approach works.

In FL, we have different client each client i has its simulated data D_i, and for each client, i used random variable $€_i$. Let g is the function that allows to generation new data Y_i depending on $€_i$ for each client i can be represented by the mechanism in (2):

$$Y_i = g(D_i, €_i) \text{ where } D_i \perp €_i \tag{2}$$

Note that D_i and $€_i$ are independent. The function g remains invariant across clients and represents re-scaling operation of D_i with random degree $€_i$ to increase the amount of data. the data augmentation A for each Y_i improved the result in this system. See Fig. 5.

In this work, have been used data augmentation technique that expand the training set by generating modified versions

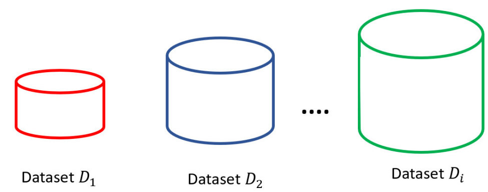

Fig. 3. Unbalanced dataset on each client

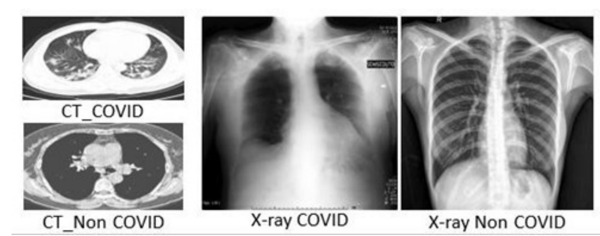

Fig. 4. Different datasets on each client

of an existing dataset through the utilization of available data. It was used to enhance the result and get good performance.

C. Proposed Hybrid Model

We propose a Hybrid model (CNN+LSTM) to train a better learning model deals with data heterogeny and achieve high accuracy Model training relies heavily on data at each client [21]. In our work, each client has data consisting of one group for training and one group for testing. The Fig. 6 shows the architecture of our hybrid model that used in this works.The

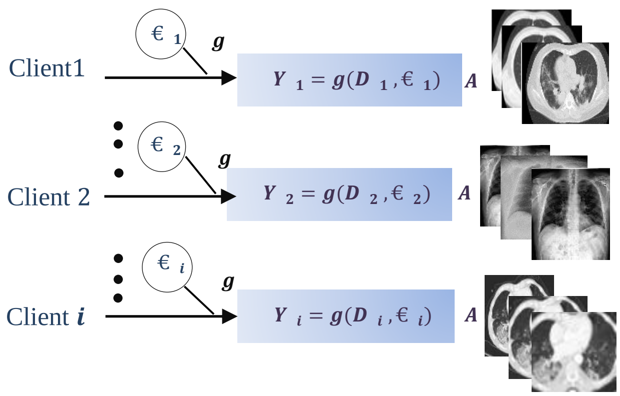

Fig. 5. Data augmentation mechanism

values of the architectural parameters can be summarized as follows

- Conv Layer (64 Filter size (3,3))
- Max Pool Layer (Filter size (2,2))
- Conv Layer (128 Filter size (3,3))
- Max Pool Layer (Filter size (2,2))
- Conv Layer (128 Filter size (3,3))
- Max Pool Layer (Filter size (2,2))
- Dropout Layer (Prob of dropout 0.2)
- FC Layer (36992 neurons)
- Dropout Layer (Prob of dropout 0.5)
- FC Layer (512 neurons)
- Repeat vector Layer (size(13, 512))
- recurrent LSTM Layer (size(128))
- recurrent LSTM Layer (size(64))
- Dropout Layer (Prob of dropout 0.25)
- FC Layer, SoftMax (2 neurons)

We note from the previous architecture that the SoftMax function converts the previous layer's output into potential distributions, which is what we want for our classification process to use in detecting the Coronavirus. The following flowchart that shown in Fig. 7, From client_1 and client_2, there are parameters like epochs, batch size, image height, image width, and input shape that are required at the time of data augmentation process. It used data augmentation to generate the data for which the dataset has been passed and returns three outputs: train, test and valid datasets. The batch size of The local training for each client is set as 64. In the FL process, each client exchanges the desired parameter at every local round, which is 5, denoted as epoch, and global round is also 5. To transport machine learning models back and forth, train and test them on local data, and then aggregate the updated models, federated learning needs the necessary infrastructure. That can be done easily, flexibly, and infrastructure. Shortly put, Flower offers a unifying strategy for federated learning. We must aggregate all the model's updates we received from the client nodes to obtain a single model. from the client nodes received. This method is known as aggregation, and there are many different ways to do it.

The most important way to do it is called Federated optimization, that is used in the system. Fedopt is the first method that used adaptive server optimization in FL [13].

In the context of FL, the client updates the local model using the parameters it received from the server after the server delivers it the global model parameters. The model is then trained using the local data, which it is modifies the model parameters locally. The updated/modified model parameters are then sent back to the server. The server contains the logic for starting the server and the weight for its clients to be executed. To address data heterogeneity issues [22], including heterogeneity Data in terms of type and heterogeneity in terms of number and, therefore, models heterogeneity. We propose a general solution to this problem and explain the method proposed in Algorithm.1 that described proposed method to solve Heterogeneous Data in Federated Learning.

V. Result And Discussion

In this part, we evaluate our method by using various Data sets such as an X-ray dataset and a CT-scan dataset for human lung to show our effectiveness on the heterogeneous data set. The results of the experiment are determined on Keras package and the Platform TensorFlow by using pycharm program. The data that was used in each client was divided into a set of training data and validation data. Our proposed framework trains the hybrid CNN+LSTM model to collect the heterogenous data set from different clients collaboratively and train a global model to detect covid 19. In this work, accuracy represents training accuracy and validation accuracy measures accuracy on validation data. Fig. 8 indicates that accuracy and Fig. 9 indicates the validation accuracy. Thea are increases significantly when the rounds are increasing. Also, the loss represents a measure of loss during the training process, and the validation loss measures loss during the validation process.

From Fig. 8 we notice the accuracy of the model increases with each round in each of the different clients, and we get good accuracy with the least possible number of rounds

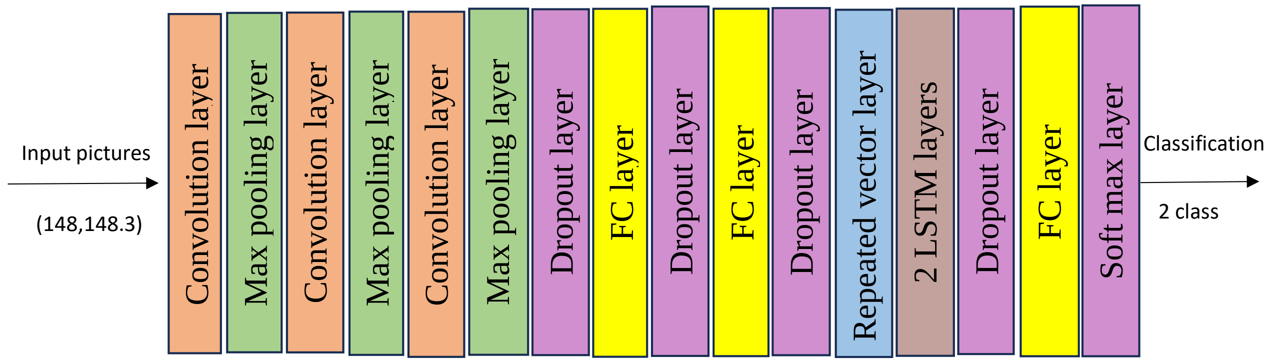

Fig. 6. Proposed model architecture

Algorithm 1 Heterogeneous Data in Federated Learning

Input:
Central supervise server S
corresponding client N_i.
n client N_i, where $i = 1, 2, 3 \ldots n$
n local dataset B_i: available for N_i clients
Output:
global model f_g for the central server.
n local model f_i for each client N_i.

1: Requesting initial parameters p_i from one random client by the server
2: one random client c trains on B_1 to obtain initial parameters p_1 and send it to the server.
3: The central server S Received initial parameters from one random client N_1
4: Initializing global model f_g its form in the server Model update:
5: The specified client N_i calculates the degree of its output class $f_i(x_n)$ where $X_n \in$ local data set B_i
6: The specified client N_i upload $f_i(X_n)$ to the server S.
7: The Server S calculates the average scores of this output class $f'(X_n) = \sum f_i(X_n)m$
8: The Server S calculates global model f_g from $f'(X_n)$
9: The server S transmits f_g to all clients N_i.
10: different client N_i downloads the global model f_g.
11: different client N_i used data augmentation to create new random samples Y_i to produce less data heterogeneity.
12: different client N_i updates local dataset: $B_i \leftarrow B_i + Y_i$.
13: different client N_i trains on new B_i to obtain a local model f_i.
14: Repeat Steps 11 ~ 19 until f_g and f_i get converged.

compared to the previous works. As well as, in the case of Validation accuracy in the shape, we notice Fig. 9, that validation accuracy increases with the increase in the number of rounds and obtaining very good accuracy compared to previous works. Else, Table II. shows accuracy and verification of accuracy in degrees at each round. Fig. 10. and Fig. 11. Show the training loss and validation loss of the system.

Fig. 9 and Fig. 11 show that the convergence of losses, as in the case of accuracy, does not change smoothly in terms of type and taken from different places. In addition, shows a decrease in the amount of losses with the progression of the number of rounds, and thus an increase in the accuracy of the model. Table II. Shows Loss and Validation Loss for each round in client1 and client2. Finally, we compared our work with the previous work.

Many previous studies were conducted to detect Covid 19, as shown in Table III. However, this research does not take into account the heterogeneity of data between different clients, especially the difference in the type of data and the unequal amount of data between clients. In our proposed model, a better disease prediction model was built with the heterogeneity of the data used. Where a hybrid model (CNN+LSTM) was built to train heterogeneous data and obtain the best accuracy among all previous research

TABLE I.
ACCURACY AND VALIDATION ACCURACY FOR EACH ROUND IN CLIENT_1 AND CLIENT_2

Round		1	2	3	4	5
Training	Client 1	0.729	0.87	0.917	0.946	0.9517
Accuracy	Client2	0.799	0.862	0.95	0.98	0.985
Validation	Client1	0.77	0.864	0.9125	0.92	0.929
Accuracy	Client2	0.64	0.87	0.98	0.99	0.992

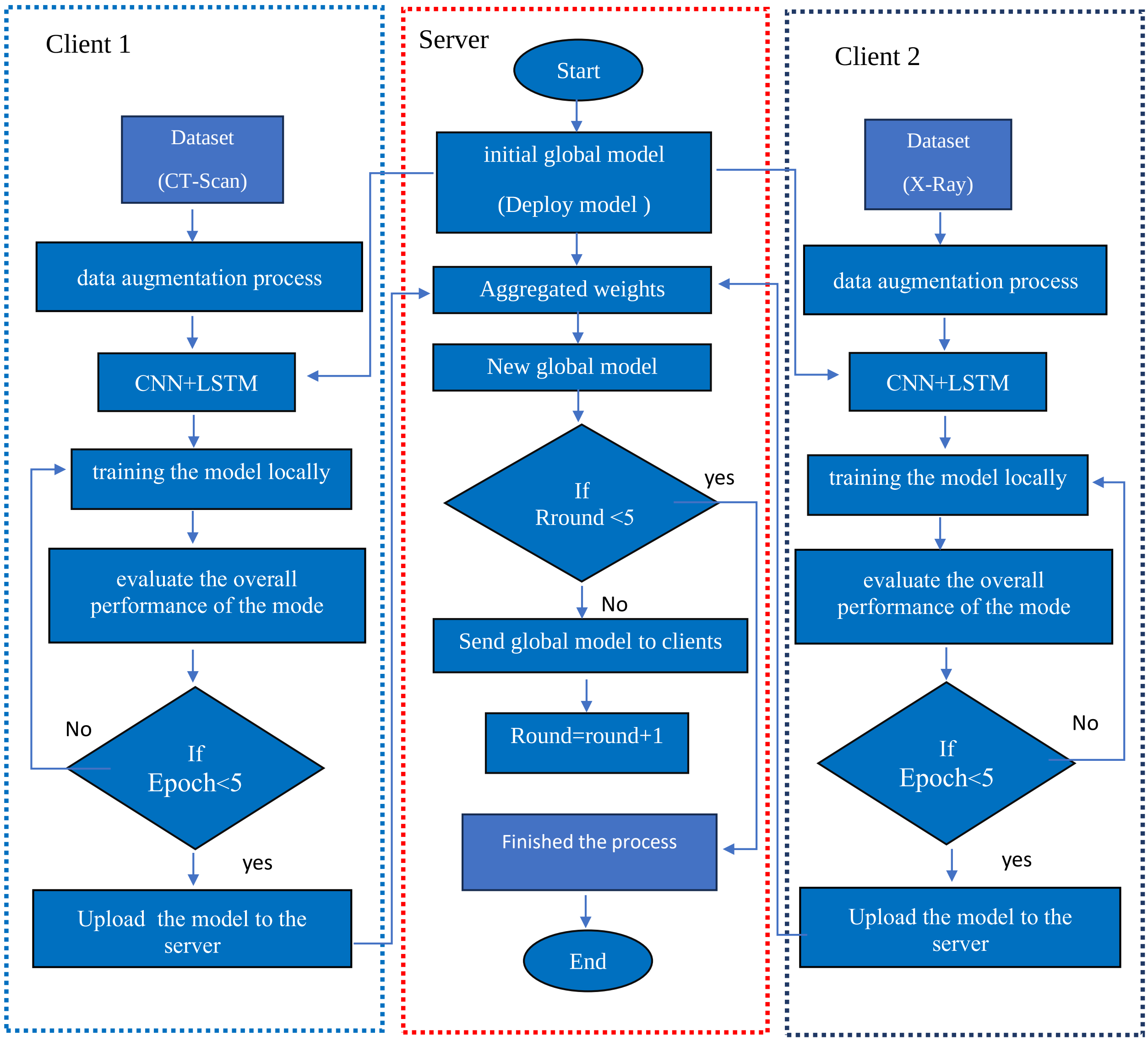

Fig. 7. A flowchart explaining the mechanism of action of the proposed system

TABLE II.
TRAINING LOSS AND VALIDATION LOSS FOR EACH ROUND IN CLIENT_1 AND CLIENT_2

Round		1	2	3	4	5
Training Accuracy	Client 1	0.729	0.87	0.917	0.946	0.9517
	Client2	0.799	0.862	0.95	0.98	0.985
Validation Accuracy	Client1	0.77	0.864	0.9125	0.92	0.929
	Client2	0.64	0.87	0.98	0.99	0.992

VI. Conclusion

A hybrid model was built for training different clients in the federated learning technique. This model is trained on heterogeneous data that's owned it these clients. Data heterogeneity is one of the open challenges that we were able in this research to deal with such a problem and obtain very good results. The proposed system was used to predict Covid 19 and it showed The results are that an accuracy of more than 99% was obtained, and this result is the best predictor of this disease in comparison to previous works. In our next work, We propose expanding the system by increasing the number of clients who have different types and numbers of data. We expect to obtain

TABLE III.
LIST OF PREVIOUS PAPERS USING FEDERATED LEARNING TO RECOGNITION OF COVID-19

Backbone method	contributions	dataset	accuracy
Proposed hybrid CNN+LSTM Data Augmentation Fedopt	COVID-19 Identification on Data Heterogeneous Improve accuracy	X-ray+ct- scan	99% for client1 95% for client2
a blockchain-empowered method proposes a data normalisation technique	The data is collected from different sources (i.e., Hospitals) and devices.	CT-scan [23]	97%
dynamic fusion-based federated learning approach	To improve communication efficiency COVID-19 detection	CT scan [24]	94%
FedDPGAN (Federated Differentially Private Generative Adversarial Networks)	Detection of COVID- 19 Pneumonia	X-ray [25]	94.45%
a deep learning proposed to build convolutional neural network (CNN) FL-VGG16, FL-ResNet50	validated on COVID- 19 screening on unbalanced data	X-ray images [26]	test-set accuracy 92% test-set accuracy 92.7%.
The study involves the development of two distinct machine learning models, namely a federated learning model and a classical machine learning model.	we examined the comparative effectiveness of federated learning in contrast to traditional learning methods.	x-ray [27]	98%
genetic clustered FL (Genetic CFL)	Detection of COVID- 19	patient personal records [28]	92.08%
deep Federated learning is used	detecting corona virous lung abnormalities	chest CT [29]	95%
Convolutional Neural Networks (CNNs) cyclic weight transfer (CWT)	COVID-19 detection	CT-slices [30]	94%

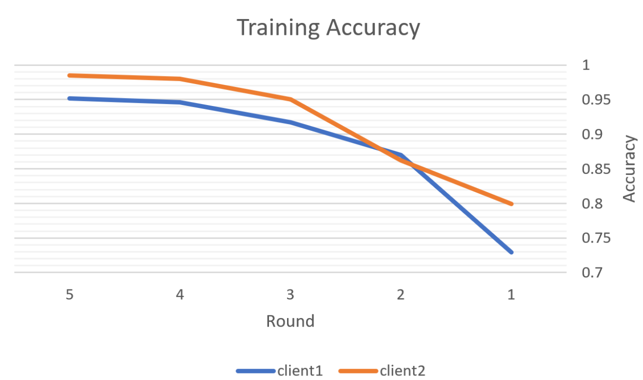

Fig. 8. Training accuracy for each round in client_1 and client_2

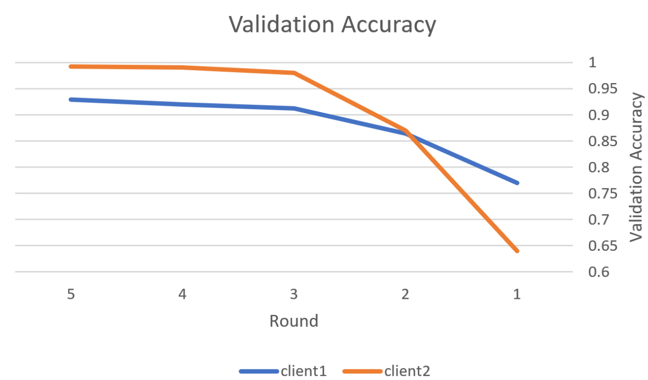

Fig. 9. Validation accuracy for each round in client_1 and client_2

positive results for all clients when using the same proposed system. We have also studied the effect of increasing the number of clients on the accuracy of the model.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

References

[1] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, *et al.*, "Advances and open problems in federated learning," *Foundations and trends® in machine learning*, vol. 14, no. 1–2, pp. 1–210, 2021.

[2] B. Pfitzner, N. Steckhan, and B. Arnrich, "Federated learning in a medical context: a systematic literature review," *ACM Transactions on Internet Technology (TOIT)*, vol. 21, no. 2, pp. 1–31, 2021.

[3] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*, vol. 54, pp. 1273–1282, PMLR, 2017.

Fig. 10. Training loss for each round in client_1 and client_2

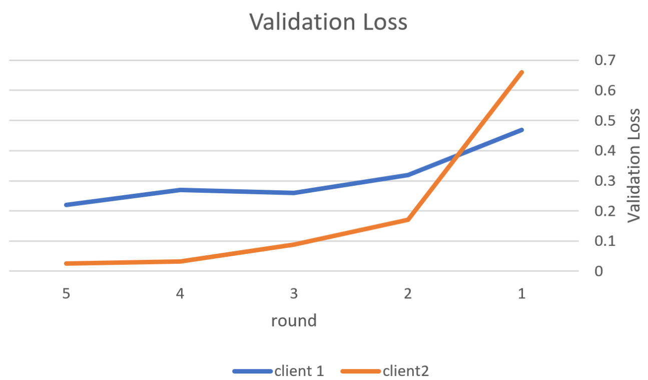

Fig. 11. Validation Loss for each round in client_1 and client_2

[4] L. Li, Y. Fan, M. Tse, and K.-Y. Lin, "A review of applications in federated learning," *Computers & Industrial Engineering*, vol. 149, p. 106854, 2020.

[5] B. Liu, N. Lv, Y. Guo, and Y. Li, "Recent advances on federated learning: A systematic survey," *Neurocomputing*, p. 128019, 2024.

[6] M. Jiang, Z. Wang, and Q. Dou, "Harmofl: Harmonizing local and global drifts in federated learning on heterogeneous medical images," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 36, no. 1, pp. 1087–1095, 2022.

[7] M. Asad, A. Moustafa, and T. Ito, "Fedopt: Towards communication efficiency and privacy preservation in federated learning," *Applied Sciences*, vol. 10, no. 8, p. 2864, 2020.

[8] X. Li, Z. Qu, B. Tang, and Z. Lu, "Fedlga: Toward system-heterogeneity of federated learning via local gradient approximation," *IEEE Transactions on Cybernetics*, vol. 54, no. 1, pp. 401–414, 2023.

[9] J. Cao, Z. Lian, W. Liu, Z. Zhu, and C. Ji, "Hadfl: Heterogeneity-aware decentralized federated learning framework," in *2021 58th ACM/IEEE Design Automation Conference (DAC)*, (San Francisco, CA, USA), pp. 1–6, IEEE, 2021.

[10] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," *Proceedings of Machine learning and systems*, vol. 2, pp. 429–450, 2020.

[11] M. Malekzadeh, B. Hasircioglu, N. Mital, K. Katarya, M. E. Ozfatura, and D. Gündüz, "Dopamine: Differentially private federated learning on medical data," *arXiv:2101.11693*, 2021.

[12] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*, vol. 54, pp. 1273–1282, PMLR, 2017.

[13] S. Reddi, Z. Charles, M. Zaheer, Z. Garrett, K. Rush, J. Konečnỳ, S. Kumar, and H. B. McMahan, "Adaptive federated optimization," *arXiv:2003.00295*, 2020.

[14] Y. Zhao, M. Li, L. Lai, N. Suda, D. Civin, and V. Chandra, "Federated learning with non-iid data," *arXiv:1806.00582*, 2018.

[15] I. Gulrajani and D. Lopez-Paz, "In search of lost domain generalization," *arXiv:2007.01434*, 2020.

[16] D. Krueger, E. Caballero, J.-H. Jacobsen, A. Zhang, J. Binas, D. Zhang, R. Le Priol, and A. Courville, "Out-of-distribution generalization via risk extrapolation (rex)," in *International conference on machine learning*, pp. 5815–5826, PMLR, 2021.

[17] M. Maftouni, "Large covid-19 ct scan slice dataset," 2021. https://www.kaggle.com/dsv/2321803.

[18] P. Bhowal, S. Sen, J. H. Yoon, Z. W. Geem, and R. Sarkar, "Large covid-19 ct scan slice dataset," 2021. https://paperswithcode.com/dataset/novel-covid-19-chestxray-repository.

[19] Z. Liu, F. Wu, Y. Wang, M. Yang, and X. Pan, "Fedcl: Federated contrastive learning for multi-center medical image classification," *Pattern Recognition*, vol. 143, p. 109739, 2023.

[20] J. Peters, D. Janzing, and B. Schölkopf, *Elements of causal inference: foundations and learning algorithms*. The MIT Press, 2017.

[21] G. Q. Ali and H. Al-Libawy, "Time-series deep-learning classifier for human activity recognition based on smartphone built-in sensors," *Journal of Physics: Conference Series*, vol. 1973, no. 1, p. 012127, 2021.

[22] K. Chen, X. Zhang, X. Zhou, B. Mi, Y. Xiao, L. Zhou, Z. Wu, L. Wu, and X. Wang, "Privacy preserving federated learning for full heterogeneity," *ISA transactions*, vol. 141, pp. 73–83, 2023.

[23] R. Kumar, A. A. Khan, J. Kumar, N. A. Golilarz, S. Zhang, Y. Ting, C. Zheng, W. Wang, *et al.*, "Blockchain-federated-learning and deep learning models for covid-19 detection using ct imaging," *IEEE Sensors Journal*, vol. 21, no. 14, pp. 16301–16314, 2021.

[24] W. Zhang, T. Zhou, Q. Lu, X. Wang, C. Zhu, H. Sun, Z. Wang, S. K. Lo, and F.-Y. Wang, "Dynamic-fusion-based federated learning for covid-19 detection," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 15884–15891, 2021.

[25] L. Zhang, B. Shen, A. Barnawi, S. Xi, N. Kumar, and Y. Wu, "Feddpgan: federated differentially private generative adversarial networks framework for the detection of covid-19 pneumonia," *Information Systems Frontiers*, vol. 23, no. 6, pp. 1403–1415, 2021.

[26] I. Feki, S. Ammar, Y. Kessentini, and K. Muhammad, "Federated learning for covid-19 screening from chest x-ray images," *Applied Soft Computing*, vol. 106, p. 107330, 2021.

[27] M. Abdul Salam, S. Taha, and M. Ramadan, "Covid-19 detection using federated machine learning," *Plos one*, vol. 16, no. 6, p. e0252573, 2021.

[28] D. R. Kandati and T. R. Gadekallu, "Genetic clustered federated learning for covid-19 detection," *Electronics*, vol. 11, no. 17, p. 2714, 2022.

[29] Q. Dou, T. Y. So, M. Jiang, Q. Liu, V. Vardhanabhuti, G. Kaissis, Z. Li, W. Si, H. H. Lee, K. Yu, *et al.*, "Federated deep learning for detecting covid-19 lung abnormalities in ct: a privacy-preserving multinational validation study," *NPJ digital medicine*, vol. 4, no. 1, p. 60, 2021.

[30] E. Darzi, N. M. Sijtsema, and P. van Ooijen, "A comparative study of federated learning methods for covid-19 detection," *Scientific Reports*, vol. 14, no. 1, p. 3944, 2024.