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Advancements in Federated Learning for Health Applications: A Concise Survey

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***Abstract*—Smart solutions in the healthcare domain have garnered considerable attention due to their potential to enhance standard treatment methods and improve overall health. However, privacy concerns often prevent the sharing of healthcare data, which can limit the scope for improvement. In this context, Federated Learning (FL) has emerged as a transformative paradigm in machine learning. It enables collaborative model training across decentralised devices while preserving data privacy and security. This approach has gained significant traction in recent years, particularly within the healthcare sector. It offers unprecedented opportunities to harness collective intelligence from diverse healthcare datasets without compromising sensitive patient information. This survey paper summarises numerous research works that focus on the application of FL to address various healthcare challenges. Moreover, a comparison of these works is conducted, summarising the different technologies employed in each case. Therefore, in light of the previous remarks, this paper provides an up-to-date overview of the state of the art in the application of FL in the healthcare industry.**

***Index Terms*—Artificial Intelligence, Deep Learning, Federated Learning, Machine Learning, Healthcare**

I. Introduction

The healthcare sector is a prolific generator of a vast array of sensitive data. This includes but is not limited to, patient records, medical images, and genetic information. The importance of this data cannot be overstated, as it plays a pivotal role in advancing medical research, developing personalised treatments tailored to individual patients, and improving the overall delivery of healthcare services. However, the effective use of this data for machine learning applications has been hindered by several factors. The decentralised nature of healthcare data, coupled with concerns about privacy and security, have posed significant challenges. In response to these challenges, Federated Learning (FL) has emerged as a promising solution. The main advantage of FL is that it enables collaborative model training without compromising data privacy.

In the specific context of FL, the data always remains in the possession of the data owner, such as hospitals, and is never shared with a third party. These data owners train local models on their own data and only share the model updates with a central server. This central server then aggregates these updates to create a global federated model, which is subsequently distributed back to the data owners. Federated Learning can provide significant benefits in the healthcare sector, particularly for several health-related applications. For instance, personalized medicine could see substantial improvements through the application of FL. It can be used to develop specialized treatment plans tailored to individual patient profiles and specific information. Another potential application of FL is in the research of rare diseases. Currently, data related to rare diseases are considered sensitive and are not widely shared. However, FL could enable access to a much larger dataset by allowing data owners to contribute to the learning process without actually sharing the sensitive data. Federated Learning can also be used to monitor trends and identify potential outbreaks of infectious diseases. By analyzing data from wearable devices and other sources, it can provide early warning signals to health authorities, thereby enabling timely interventions. Moreover, FL can contribute to the design of clinical trials. By using patient data, clinical trials can be designed more efficiently, reducing costs while simultaneously enhancing the development of new treatments. This is achieved by leveraging the insights gained from the federated learning process, which can help identify the most promising treatment strategies based on real-world data.

Despite the numerous advantages of Federated Learning (FL), it is accompanied by several challenges. One of the primary challenges is data heterogeneity. Data originating from different sources, such as hospitals, can exhibit diverse distributions and characteristics. This is particularly true if a hospital specializes in specific treatments, which can lead to a unique data distribution. Another challenge is related to bias and fairness. Models could potentially inherit biases from the available training data. Therefore, it is crucial to

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consider bias mitigation techniques when developing and training these models. Security and privacy present another significant challenge. While FL was developed with the intention of addressing these concerns, data leakage can still occur during the model exchange process. Therefore, it is essential to incorporate encryption techniques during the transfer of updates to ensure the privacy and security of the data. Lastly, communication overhead is an aspect that cannot be overlooked. In scenarios where several hospitals participate in the process, the communication overhead increases. This could potentially limit the scalability of the FL models. Therefore, efficient communication protocols and strategies need to be developed to ensure the scalability and efficiency of FL in real-world applications.

Both academia and industry are actively working to address these challenges and develop more efficient, robust, and equitable FL methods tailored to the specific needs of the healthcare domain. As FL technology evolves, it is set to play a pivotal role in propelling healthcare innovation and enhancing patient outcomes. In this paper, we examine various research works that explore the diverse applications of FL within the healthcare sector. Next, based on this study, particular research directions are provided. Therefore, the contributions of this paper are summarised as follows:

- **C1 – State-of-the-Art Analysis**: We conduct an analysis and comparison of various research works that have applied FL in the healthcare domain.
- **C2 – Trends and Gaps**: We discuss potential future directions and identify gaps in the current research before concluding our paper.

Therefore, in light of the aforementioned remarks, this paper is structured as follows. Section II provides an overview of FL. Section III analyses existing works on FL applications in the healthcare domain. Next, section IV discusses directions for future work in this research area. Finally, section V concludes this paper.

II. Overview of Federated Learning

During the FL procedure, multiple clients (e.g. hospitals) create individual models using their local data samples without exchanging them. These models are then aggregated by a central server into a single, unified model. This approach is particularly beneficial for preserving privacy and reducing communication costs. This process can be visualised in Figure 1. The detailed steps involved in the FL procedure are summarised below.

- **Local Training**: Each participating client in the federated network uses its local data (e.g. local patient data) to train a Machine Learning (ML) or Deep Learning (DL) model. The important aspect here is that all computations are performed on the local device and the raw data is not sent anywhere, thus preserving data privacy.
- **Model Update Sharing**: After local training, each client generates an update to the model. The parameters of this model (such as the weights of a DL model), and not the raw data or the locally trained model, are sent to a central server (responsible for the aggregation process). During the exchange of updates, encryption and anonymisation methods may be employed to further enhance security, as these updates could potentially lead to data leakage.
- **Aggregation**: The central server collects the updates from all clients. It then aggregates these updates to generate a global model update. The aggregation process can be as simple as averaging or more complex, employing various schemes.
- **Global Update**: The aggregated global model update is then sent back to each participating client.
- **Iteration**: Steps 1-4 are repeated for several rounds until the model's performance is satisfactory or a stopping criterion is met.

This way, FL allows for a machine learning model to learn from many entities without needing to access the raw data from these entities, thus addressing privacy and security concerns. It also reduces the amount of data that needs to be transmitted, which can lead to lower communication costs. However, it also presents new challenges, such as dealing with devices that have different computational capabilities, varying amounts of data, or are only intermittently connected.

III. Analysis of Existing Federated Applications in the Healthcare Sector

In [1], A. Qayyum et al. proposed a clustered FL approach that focuses on multimodal Covid-19 diagnosis. More specifically, they utilized X-ray data or ultrasound images from different clients to predict Covid-19, while ensuring data privacy by keeping the data on the client's side. The authors considered different clusters of clients depending on the specific data they used, such as X-ray or ultrasound images. They also employed differential privacy to further enhance privacy during the transfer of weights from the local clients to the global server. The models were implemented using TensorFlow and their performance was evaluated against two baseline approaches: FL with separate models for each image type and FL with a single multimodal model trained on all data. They found that their proposed clustered FL approach achieved the best results, demonstrating its effectiveness in improving diagnostic accuracy and efficiency while also ensuring the privacy of the data.

In [2], the authors conducted a study on the application of FL in cancer diagnosis, with a specific focus on enhancing the efficiency of the FL process. They opted for the Message Queuing Telemetry Transport (MQTT) protocol to exchange model parameters during the FL process, as it was deemed superior in terms of bandwidth efficiency compared to traditional application-layer protocols. For the purpose of aggregating model weights, they employed two strategies: FedAvg and Consensus-driven Federated Averaging (CFA). The effectiveness of the proposed FL approach was evaluated using three publicly accessible datasets for brain tumor segmentation: BraTS 2018, BraTS 2020, and the Athens dataset. In addition, a real-world scenario involving five medical nodes

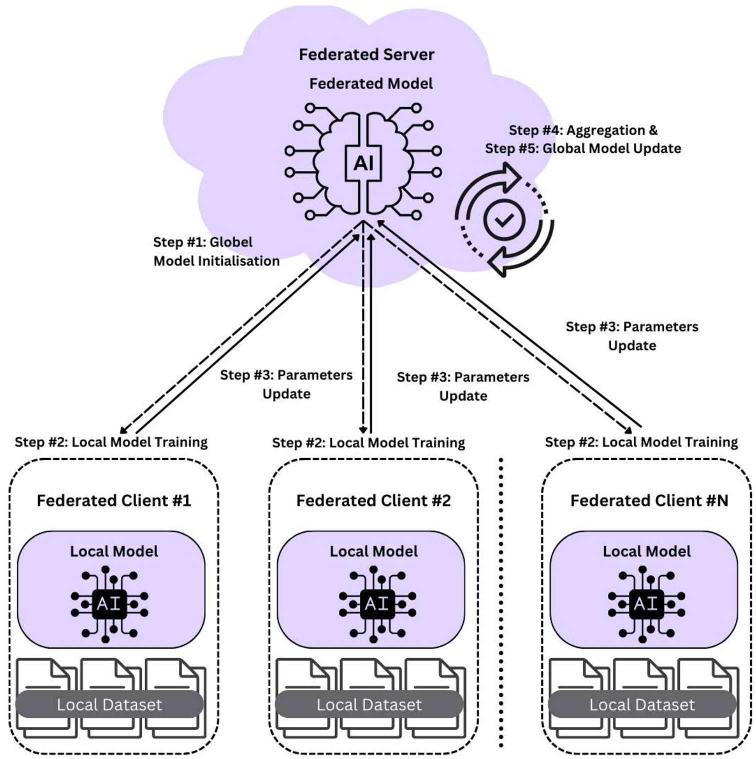

Fig. 1. Overview of Federated Learning Procedure

spread across Europe was set up to test the practicality of the FL framework. The Dice Similarity Coefficient (DSC) was used as the main metric for validation to assess the accuracy of the segmentation predictions. The results indicated that the combination of the proposed FL structure and the MQTT protocol effectively optimized the FL process, leading to enhanced model performance and a reduction in communication overhead.

In the study [3], I. Dayan et al. proposed the EXAM AI model, which is capable of utilizing Electronic Medical Records (EMRs), chest X-rays, vital signs, and laboratory data to effectively predict the oxygen requirements of COVID-19 patients. The EXAM model is an extension of the SARS-COV-2 Clinical Decision Support (CDS) model. It leverages the FL approach to combine data from 20 different medical institutions. In order to further enhance data privacy and ensure that the data remains protected, they implemented the Secure Sockets Layer (SSL) and differential privacy techniques during the FL procedure. For the evaluation metrics, they used the ROC curve and confusion matrix. The results of their study indicated that the proposed model outperforms local models and demonstrates superior performance across diverse healthcare settings.

In [4], the authors introduce a system that uses FL and blockchain technology to protect privacy in healthcare environments. The framework's data management components encompass three main tiers: the sensor network, the blockchain cloud network, and the healthcare equipment layer. Data from IoT-connected sensors resides on the sensor network and is securely transferred to the blockchain cloud network for validation, processing, and dissemination to healthcare equipment, such as Magnetic Resonance Imaging (MRI) machines and display terminals. The FL architecture comprises the blockchain cloud repository, federation manager, integrity manager, privacy broker, feature manager, and model manager. The blockchain cloud repository stores the model's features, while the feature manager selects the relevant sub-features for training. The federation manager selects participating clients for local model training, and the privacy broker ensures data privacy throughout the process. The integrity manager monitors and resolves potential errors within sub-models. The framework's effectiveness is demonstrated in a case study within the healthcare domain.

In [5], the authors introduce FRESH, a FL framework that leverages ring signatures to safeguard user privacy and enhance the performance of healthcare applications. By employing ring signatures to obfuscate the source of model updates, FRESH effectively thwarts source inference attacks, ensuring the confidentiality of sensitive health data. FRESH's architecture comprises four key components: wearable devices, clients, a signature server, and an aggregation server. Wearables collect physiological data from patients and transmit it to clients, which locally train machine learning models to predict diagnoses. The signature server coordinates interactions between clients, verifying signatures on model updates before forwarding them to the aggregation server. The aggregation

TABLE I
APPLICATIONS OF FEDERATED LEARNING IN THE HEALTH DOMAIN

Ref	Problem Statement	Data Type	Aggregation Techniques	Privacy and Security Mechanisms	Datasets	Tools	Performance Evaluation
[1]	Predicting COVID-19 patient outcomes while safeguarding patient privacy through the application of federated learning.	Images, Numerical	Federated averaging	Differential privacy	Data from 20 medical institutes.	Tensorlflow	ROC curve, Confusion Matrix
[2]	Federated learning strategies for cancer diagnosis, while optimizing model parameter exchange and enhancing federated learning training efficiency.	Images	Federated averaging, Consensus-driven federated averaging	Differential privacy, Authentication	BraTS 2018, BraTS 2020, Athens dataset	N/A	Dice Similarity Coefficient over time
[3]	Predicting oxygen needs in COVID-19 patients using federated learning.	Images, Numerical	Federated averaging	Secure sockets layer (SSL) Encryption, Differential privacy	Data from 20 medical institutes.	Tensorflow	ROC curve, Confusion Matrix
[4]	Leveraging federated learning and blockchain to securely collaborate on healthcare data.	All types	Federated averaging	Blockchain, Differential privacy, Homomorphic encryption	Patient-related data (blood pressure, glucose meter, insulin pump, and others)	N/A	Overheads (ms)
[5]	Addressing the privacy vulnerabilities inherent in federated learning.	Numerical	Sum of weighted parameters	Ring signatures	Collected physiological data from users	JPBC library	Signature time, Verification time
[6]	Federated learning-enabled person movement identification using wearable device data for personalized health monitoring.	Numerical, Text	Federated averaging	Blockchain	UniMiB SHAR, Human activity recognition	N/A	Accuracy, Precision, Recall, and F1-score
[7]	Predicting the level of user depression using federated learning.	Text	Federated averaging	N/A	The Global Sentiment Dictionary	Tensorflow	Accuracy, Precision, Recall, and F1-score
[8]	Addressing the data privacy and efficiency challenges of mental health monitoring systems using federated learning.	Numerical	Federated averaging	Encrypted communication	Collected data from devices.	CoreML	Average memory usage (KB), Average power consumption (%)
[9]	Using user-generated data for healthcare data analytics utilizing the federated learning approach.	Numerical	Federated averaging	Homomorphic encryption	Health-related data from wearable devices	N/A	N/A
[10]	Federated learning for chronic kidney disease prediction.	Images, Numerical	Federated averaging	N/A	Image dataset collected from kaggle	Tophat for image enhancement	Sensitivity, Specificity, Accuracy, Efficiency
[11]	Addressing the non-IID data distribution challenge in the healthcare domain using a clustered federated learning approach.	Numerical	Federated averaging	N/A	HRV dataset (Gathered for research at Samsung Medical Center Department of Psychiatry).	Tensorflow (Keras)	Accuracy
[12]	Privacy-preserving federated learning framework tailored for IoT-driven SmartHealth Systems.	Images	Federated averaging	Differential privacy	MNIST, CIFAR10, STL10, COVID19 Chest X-RAY	Pysift, Pytorch	MAE, Accuracy, Computation time.

server, finally, aggregates the validated model updates to form a global model. This novel framework empowers healthcare providers to harness the power of FL while preserving patient privacy, enabling accurate diagnosis prediction without compromising sensitive health information. FRESH marks a significant step forward in safeguarding patient data and promoting the adoption of privacy-preserving FL in healthcare applications.

In [6], the authors introduce a novel FL and deep reinforcement learning framework for improving person movement identification in smart healthcare systems. This system, leveraging wearable devices equipped with sensors, addresses the challenge of processing vast amounts of unlabeled data by utilizing a DRL framework for auto-labelling and FL for efficient data training. Therefore, the proposed system significantly reduces the need for transferring massive data to cloud servers, thus minimising memory usage, computational costs, and enhancing data privacy. The use of bidirectional long short-term memory networks enables high accuracy in data classification, with simulation results showing a remarkable 99.67% accuracy, alongside a substantial reduction in memory and computational demands and a 36.73% decrease in data transmission. This collaborative effort spans multiple global institutions, demonstrating the potential of federated learning in advancing smart healthcare technologies by making them more efficient, secure, and scalable.

In [7], the authors delve into predicting user depression levels using their social media posts, leveraging the synergy of FL and DL methodologies. Local edge devices train Recurrent Neural Network (RNN) models on their respective datasets, while the global FL model arises from the aggregation of these local models on a central server. The global FL model seamlessly integrates into an alert system embedded within user devices, notifying them about their evolving depression levels. Experimental evaluation employing social media post sentences revealed the model's remarkable prowess, achieving an accuracy of 93.6% in predicting depression levels.

In [8], B. Suruliraj and R. Orji introduce an FL architecture tailored for Mental Health Monitoring Systems (MHMS), effectively addressing the challenges of data transmission, processing on centralised servers, and safeguarding user privacy in MHMS. The proposed solution embodies a mobile sensing application that captures contextual data from users' surroundings, enabling the prediction of depression symptoms. The collected data encompasses location information, movement patterns, and call logs. The authors devised an anomaly detection algorithm that analyses user data locally on their smartphones, leveraging FL to train the algorithm for robust anomaly detection. Experimental validation demonstrated that FL implementation significantly minimised power consumption, storage requirements, and internet data usage.

S. Hakak et al. in [9] introduce a conceptual framework for healthcare data analytics, leveraging FL to harness user-generated data for enhanced healthcare insights. The framework comprises three distinct modules: Cloud Module, Edge Module, and Application Module. The Cloud Module, overseen by a model owner such as a healthcare digital manager, orchestrates cloud-based tasks, manages patient registration, and hosts trained models. The Edge Module, the heart of model optimisation, comprises three sub-modules: FL server, Local Storage Controller (LSC), and Aggregator. The FL server facilitates model updates, the LSC manages local data storage, and the Aggregator consolidates updates from edge devices. The Application Module handles the integration of new smart-input devices, broadening the scope of healthcare data collection.

The work in [10] proposes a FL approach designed to predict the severity of Chronic Kidney Disease (CKD) by utilizing patient data from a variety of decentralized sources. The proposed model employs FL to train a Convolutional Neural Network (CNN) specifically for the prediction of CKD severity. The model is trained on a dataset comprised of patient records, which include a range of clinical parameters pertinent to kidney function. The CNN is capable of identifying complex patterns within the data, which enables it to accurately determine the severity of CKD based on the specific characteristics of the patient. The study reveals that the CNN, when trained using the FL approach, achieves a high level of prediction accuracy. This level of accuracy is comparable to, and in some cases surpasses, that of traditional Machine Learning (ML) models that are trained on centralized data. This suggests that the FL-based approach could potentially offer a more effective and privacy-preserving method for predicting CKD severity.

In [11], the authors present a novel FL model for wellness detection is proposed. The FL model addresses the non-Independent and Identically Distributed (IID) problem in the healthcare domain by clustering clients based on their data distribution. The model is trained in two steps. In the first step, a global model is created using the standard FL procedure. Clients then train local models using their local data. Instead of storing the weights of the local models, they store the differences between the local weights and the global weights. This process is repeated for several cycles. In the second step, the model from the first step is used as a starting point for further training. At each round, the differences in the weights are examined, and clusters are created. These clusters are then trained separately until a limit is reached, at which point a final global model is created by averaging the weights of all the clusters. The system was implemented using TensorFlow and evaluated on the HRV dataset collected for research at Samsung Medical Center's Department of Psychiatry. The results showed that classical machine learning achieved higher accuracy, but the FL model had the advantage of preserving user privacy.

In [12], the authors propose a conceptual three-fold hierarchical privacy-preserving FL framework specifically tailored for IoT-based SmartHealth Systems. The framework tackles the sensitive information leakage issue inherent to FL by introducing an intermediate layer between clients and the central server, termed edged aggregator or edge intelligence. This layer serves as a proxy for processing the learned models before their incorporation into the global model. For distinct sectors, such as pathology or isolated patients' vitals data, separate edged aggregators are established, each responsible for handling data originating from its respective domain. Edged aggregators receive differentially private encrypted model parameters from clients within their assigned sectors and broadcast updated models back to the clients. After a series of iterations, when the blended model converges, all edged aggregators relay the blended models for global aggregation, ensuring the preservation of privacy throughout the learning process. The proposed solution was compared against other baselines and demonstrated superior performance in terms of both privacy protection and model accuracy.

IV. Trends and Research Directions

Our examination of the current state of research and development in FL for healthcare has uncovered several significant trends and directions for future research:

FL Process Optimisation: There is active research into strategies for optimizing the FL process to enhance its efficiency and effectiveness. Significant reductions in training time and resource consumption can be achieved by optimizing the communication and aggregation of model updates. Techniques such as clustered FL aim to tackle the challenge of non-identically distributed (non-IID) data by clustering clients based on their data characteristics, which can improve model performance by ensuring that similar data is aggregated together.

Privacy-Preserving FL: Preserving privacy is of great importance for healthcare applications, and data can significantly aid in the development of new AI-powered applications. Therefore, FL is an essential approach to ensure the usage of patient data while ensuring data privacy.

Explainable Artificial Intelligence (XAI): XAI is vital in FL as it enhances trust, transparency, and comprehensibility in decentralized machine learning models. In healthcare and other sensitive areas, XAI allows those involved to understand how models make predictions, which aids in making better decisions and ensures ethical and fair results. By combining XAI with FL, it's feasible to address privacy issues while still offering insights into the decision-making process of AI models trained on distributed data, making the technology more user-friendly and acceptable to both users and regulators.

The current trends and research directions underscore the growing significance of FL within the healthcare sector. As the technology moves forward, FL continues to evolve and mature, and as mechanisms designed to preserve privacy become increasingly sophisticated, it is expected that the influence of FL on healthcare will expand. This expansion is likely to result in enhancements in several key areas including the accuracy of diagnoses, the personalization of health monitoring, and an overall enhancement in the quality of patient care.

V. Conclusions

Federated Learning is a technology anticipated to bring about significant advancements in the healthcare sector. The recent applications of Federated Learning in healthcare, as discussed in this article, demonstrate its potential to effect substantial improvements in various healthcare aspects. By harnessing data from a variety of sources while preserving data privacy, Federated Learning can aid in the early detection of diseases, potentially saving lives and reducing healthcare costs. Furthermore, it can facilitate real-time health surveillance, enabling healthcare providers to continuously monitor patients' health status. As Federated Learning continues to evolve, we can look forward to a future where healthcare is more precise, personalized, and of superior quality.

References

[1] A. Qayyum, K. Ahmad, M. A. Ahsan, A. Al-Fuqaha and J. Qadir, "Collaborative Federated Learning for Healthcare: Multi-Modal COVID-19 Diagnosis at the Edge", IEEE Open Journal of the Computer Society, vol. 3, pp. 172-184, 2022

[2] B. C. Tedeschini, S. Savazzi, R. Stoklasa, L. Barbieri, I. Stathopoulos, M. Nicoli, L. Serio, "Decentralized Federated Learning for Healthcare Networks: A Case Study on Tumor Segmentation", IEEE Access, vol. 10, pp. 8693 - 8708, 2022

[3] I. Dayan, H. R. Roth, A. Zhong, A. Harouni, A. Gentili, A. Z. Abidin, et al., "Federated learning for predicting clinical outcomes in patients with COVID-19", Nature Medicine, vol. 27, pp. 1735–1743, 2021

[4] S. Singh, S. Rathore, O. Alfarraj, A. Tolba, B. Yoon, "A framework for privacy-preservation of IoT healthcare data using Federated Learning and blockchain technology", Future Generation Computer Systems, vol. 129, pp. 380-388, 2022

[5] W. Wang, X. Li, X. Qiu, X. Zhang, V. Brusic, J. Zhao, "A privacy preserving framework for federated learning in smart healthcare systems", Information Processing & Management, vol. 60, no. 1, 2023

[6] K. S. Arikumar, S. B. Prathiba, M. Alazab, T. R. Gadekallu, S. Pandya, J. M. Khan and R. S. Moorthy, "FL-PMI: Federated Learning-Based Person Movement Identification through Wearable Devices in Smart Healthcare Systems", Sensors, vol. 22, no. 4, 2022

[7] M. A. M. Pranto and N. Al Asad, "A Comprehensive Model to Monitor Mental Health based on Federated Learning and Deep Learning", in IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON), 2021

[8] B. Suruliraj and R. Orji, "Federated Learning Framework for Mobile Sensing Apps in Mental Health", in IEEE 10th International Conference on Serious Games and Applications for Health(SeGAH), 2022

[9] S. Hakak, S. Ray, W. Z. Khan and E. Scheme, "A Framework for Edge-Assisted Healthcare Data Analytics using Federated Learning", in IEEE International Conference on Big Data (Big Data), 2020

[10] J.M. Nandhini, S. Joshi, K. Anuratha, "Federated Learning Based Prediction of Chronic Kidney Diseases", in 1st International Conference on Computational Science and Technology (ICCST), 2022

[11] A. Gupta, C. Maurya, K. Dhere and V. K. Chaurasiya, "Wellness Detection Using Clustered Federated Learning", in IEEE 6th Conference on Information and Communication Technology (CICT), 2022

[12] M. Akter, N. Moustafa, T. Lynar and I. Razzak, "Edge Intelligence-based Privacy Protection Framework for IoT-based Smart Healthcare Systems", IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 12, pp. 5805 - 5816, 2022