Impact of Federated Learning on Patient Healthcare Monitoring Model Approach

Muhammad Amjad[1], Muhammad Arslan Aslam[2], Ume Farwa Mushtaq[3], Asma Akhtar[4]
[1]University of Management and Technology (UMT), Lahore, Pakistan.
[2]The Islamia University of Bahawalpur, Bahawalpur, Pakistan
[3]World Health Organisation (WHO)
[4]Department of Computer Science, Virtual University of Pakistan, Lahore, and Pakistan
Corresponding Author: Muhammad Amjad: v31324@umt.edu.pk

Abstract- The integration of wearable devices, IoT, and mobile internet technology has led to the development of smart healthcare, which enables dynamic access to information, interconnectivity among individuals, materials, and institutions, and intelligent management of medical demands. In the context of a medical center in smart cities, real-time patient monitoring is crucial for accurate treatment outcomes. Despite the availability of several patient monitoring systems, their performance has not been optimal due to the lack of real-time patient monitoring. To address this challenge, this research proposes the use of a Federated Learning-based smart patient monitoring system. Federated Learning is a cutting-edge machine learning technique that trains algorithms across multiple decentralized devices or servers, each holding local data samples, without the need for data exchange. The proposed approach seeks to provide effective real-time monitoring of patients' healthcare records, thereby improving the accuracy and efficiency of patient treatment. By harnessing the power of Federated Learning, this proposed system is expected to revolutionize the way patients are monitored and treated in smart healthcare centers, leading to better health outcomes.

Keywords: Smart model, patient monitoring, federated learning

1 Introduction

The use of advanced medical care applications in light of the Internet of Medical Things (IoMT) framework have got be expanding step by step [1]. The IoMT framework gathers various clinical gadgets, remote innovations, and haze and cloud hubs dispersed all through the organization. The IoMT offers various administrations to computerized medical care applications and is by and large called IoT-empowered advanced medical services applications. This advanced medical care comprises different applications in which IoT-empowered administrations give omnipresent networks to the clients to screen their medical services all day, every day. The computerized medical services IoT applications store and move client information utilizing various associated hubs, for example, remote innovations and haze and distributed computing hubs for handling. Man-made reasoning empowered numerous powerful techniques to assist applications with dealing with their performance as well as information stockpiling in the IoT haze fog organization. Besides, current man-made reasoning methods are proposed to manage the protection safeguarding and misrepresentation oddity identification problems in the organization. IoT functions together with blockchain seek after different peculiarity recognition methods on conditional organization information of a municipal monetary blockchain known as bitcoin [2]. This blockchain-empowered arrangement is a model designed for a review that looks at irregularity discovery with regard to blockchain innovation and its monetary applications. It utilizes unaided AI strategies to eliminate conditional information after the bitcoin blockchain as well as dissect this for vindictive exchanges [3].

United education is a man-made reasoning worldview that surrenders figuring hubs to cooperatively determine a common standard. It does this by permitting different model preparation on isolated, free IoMT information of uses as only contribute to the prepared models, which have no private information. The client gadgets line their product information in the neighborhood as well as distribute it to the worldwide processing model used for implementation. This cycle is rehashed for a few emphases until a great model is created. The regionalized blockchain is the innovation that urges the IoT functions to perform at various hubs in the haze mist organization. Blockchain innovation can be carried out at the client-side as well as server-side through various plans like brilliant agreement, excavators, agreement, and different issue lenient plans. Be that as it may, static standards-based blockchain still experiences dynamic fakes and tricks, and the static educational experience in existing blockchain frameworks didn't work productively in the powerful climate [4].

Below the system of FL, all customers have a typical model design as well as preparing purposes. Every customer in the neighborhood prepares an ML simulation on their delicate information as well as afterward transfers the model boundaries. A focal server totals those transferred boundaries refreshes the worldwide model, as well as afterward disperses the model to every customer to refresh their neighborhood boundaries. Such a circle goes on until the preparation goal is accomplished. Albeit the above worldview keeps aggressors from getting to clients' confidential information straightforwardly, a few techniques have been created to extricate private data from the preparation interaction, for example, model reversal assaults enrollment assaults, and model extraction assaults [5].

Extraordinarily, utilized generative ill-disposed system (GAN) to surmise the personal information of the customer as of the common angles, and that implies that regardless of whether the model is prepared in FL, its protection can't be thoroughly ensured. To use such aberrant protection spillage, current functions mostly utilize two kinds of advances. One is differential protection (DP) which infuses suitable commotion to the common boundaries as indicated by the ideal security level. For instance, infused Laplace commotion to the slopes and specifically imparted the bothered inclinations to other people. The infused clamor to the goal capability of the brain organization to accomplish DP introduced a customer-sided difference protection FL plan to conceal customers' commitments in preparing. The new one is reliable multi-party calculation (SMC) in which different gatherings safely register a capability without uncovering their bits of feedback. In particular, future a multi-key completely homomorphic encryption (FHE) plan to permit various information proprietors to cooperatively become familiar with a brain network model safely in distributed computing applied limited underground distribution technique to refresh the worldwide model just once there are an adequate number of transferred clients used dispersed El Gamal encryption convention to fabricate a security safeguarding choice tree for the digital guard. Despite the accomplishments in security protecting FL, there are yet double downsides. The first is that the best DP-based techniques consume a lot of security spending plans because of the different emphases of profound learning calculations, prompting a high gamble of protection spillage. Accordingly, a few strategies will quite often forfeit a model exactness to adjust the security and utility [6].

The subsequent downside is that current SMC-based strategies typically require colossal calculation while utilizing cryptographic procedures like FHE, creating them wasteful in genuine products. Likewise, FL generally causes huge correspondence above, which is not set in stone by the collaboration among customers as well as a cloud server. We accept that security protecting FL methodology should be proficient in the calculation as well as correspondence but giving solid security safeguarding and helpful model utility. Considering the above issues, we propose an exceptionally productive unified learning major areas of strength for conservation in distributed computing (HFWP). By planning another encryption convention to execute SMC, we characterize straightforward security safeguarding FL methodology, which likewise permits a few clients to drop out during the preparation cycle.

In particular, we sum up the fundamental commitments as completely protection safeguarding combined learning technique called HFWP is introduced in view of a lightweight encryption convention rather than clamor infusion strategies, consequently giving provably security and helpful model utility at the same time. Under our characterized danger model, HFWP is exhibited to be powerful against intriguing gatherings and a genuine yet inquisitive server. We propose a productive enhancement procedure executed in three different ways: more nearby calculation, specific boundary contribution as well as the active investment of customers through the preparation interaction. We contrast equally hypothetically and tentatively HFWP and linked does, as well as Debased strategies and SMC-established techniques. Our standard solutions can give a manual for the determination of cryptographic methods for FL. This assesses the presence of HFWP on double genuine world datasets. The exploratory outcomes show that HFWP has clear progress equally in preparing productivity as well as correspondence price, but giving practically identical model exactness different strategies [7].

2 Literature Review

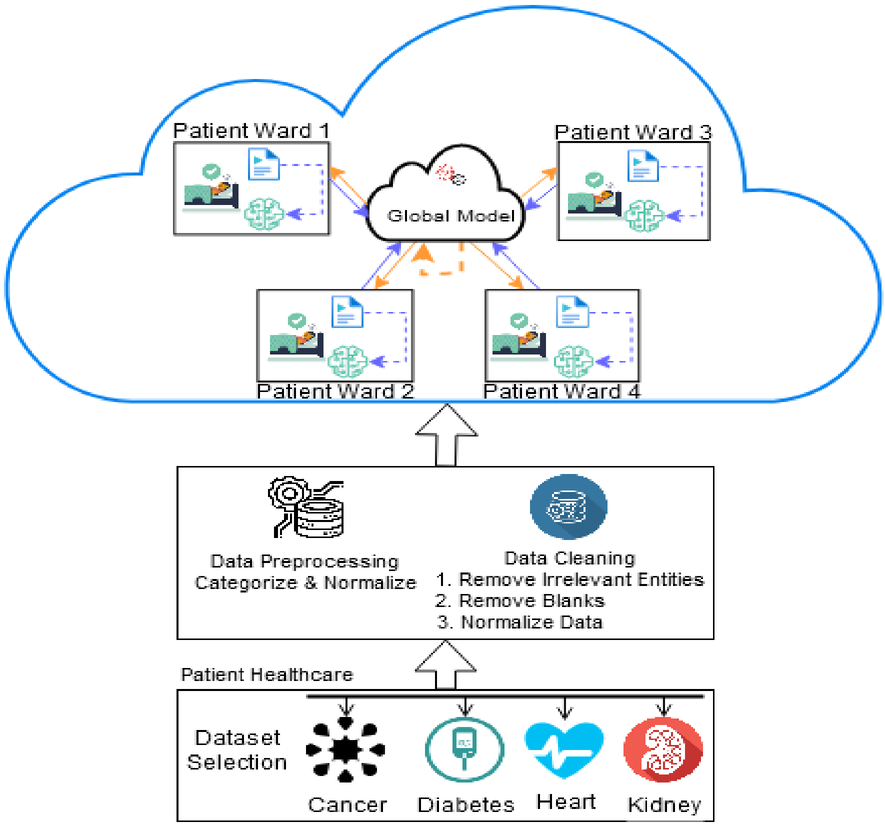
Federated learning addresses a class of AI calculations, which is basically a multi-facet brain network made from numerous nonlinear handling units. Each ensuing layer involves the result of the past sheet such as the info, so makes increment tasks as well as nonlinear handling, as well as result outcomes to the following sheet. All through this layer-by-layer highlight removal, it can gain proficiency with the perplexing capability among the information as well as result. The preparation of a profound understanding of calculations is the educational experience of mass boundaries in the multi-facet organization, which is a non-raised enhancement issue. Stochastic angle plummet (SGD) and its variations are particularly appropriate for tackling profoundly non-curved issues. The preparation cycle can be isolated interested in breast-feed-up as well as back-spread phases. In the feed-forward stage, the brain system progressively processes the result of every coating, as well as computes the mistake E (i.e., the cross-over randomness of the names as well as preparing yield) on the result layer [8].

Generally, unified profound learning requires preparing information to be assembled on a server farm. The model is prepared in a brought-together way. While unified learning permits information proprietors to hold a confidential learning organization, which trains with the nearby informational collection. From that point onward, every member transfers the angles of the neighborhood model to the cloud server. By refreshing with the worldwide angles assembled at the cloud server, the nearby model can abstain from being over-fitting. Furthermore, it additionally shields nearby information from being straightforwardly known to different members of the cloud server [9].

Distributed computing is the on-demand access of PC foundation assets, such as storage and processing power, without direct client management. Huge mists have capabilities spread across several places, each a server farm. There are a bunch of key motivations behind why industry chiefs are progressing from a customary cloud-based model to edge registering stages. The two central points that were at that point talked about in advance are low dormancy and high data transfer capacity. Nonetheless, the edge additionally accommodates more noteworthy security. For instance, sending information to an edge gadget will give any potential aggressors less chance to send off an assault when contrasted with the cloud just because the idleness is lower. In addition, assaults like DDoS which would typically be crippling in a cloud-based climate are delivered practically innocuous in an edge registering climate because the impacted edge gadgets can be eliminated from the organization without hampering the general usefulness of the organization all in all. This likewise implies that edge networks are considerably more dependable as they don't have a weak link. As examined momentarily ahead of time, edge networks are substantially more effectively adaptable because the gadgets have a lot more modest impression. For sure, a scale-out system of versatility, as opposed to a scale-up one, offers organizations an extremely alluring approach to getting great execution with minimal expense. Additionally, a portion of these edge gadgets or edge server farms may not be worked without any preparation by any one organization. Various partners can accomplice up to share the assets from the all-around existing IoT gadgets in the edge network Cloud figuring combined learning takes care of the information island issue by completely investigating the gigantic capability of the information on terminal gadgets without encroaching on client's protection, and it significantly works on the proficiency of model learning in distributed computing frameworks. Subsequently, it very well may be generally utilized in numerous situations where security assurance and asset usage are basic. In this part, we will examine a couple of situations for unified learning, and some new work applied in these situations [10]

3 Proposed Methodology

Patient health monitoring has become a crucial aspect of healthcare [11-13] in recent times. Accurate and timely detection of health parameters such as body temperature, pulse rate, galvanic skin reaction, and body position is critical to ensure patient well-being and prevent any adverse health outcomes. The importance of monitoring these parameters with precision cannot be overemphasized, as early detection of any deviations from the normal range can lead to prompt corrective action. This research proposes a Federated Learning-based patient healthcare monitoring model, in which sensors are used to gather vital health data from the patient. The proposed model leverages the power of Federated Learning to provide real-time monitoring of patients' health, ensuring that any deviations from the normal range are detected and acted upon promptly. The use of sensors and Federated Learning [14-16] in patient health monitoring is expected to revolutionize the way healthcare is delivered, leading to improved health outcomes and higher levels of patient safety. This proposed model represents a major step forward in the development of



intelligent health monitoring systems that can efficiently and effectively monitor patient well-being in real-time.

Figure 1: Proposed energy management model

The proposed patient monitoring system, as shown in Figure 1, utilizes data from multiple sensors connected to the patients for continuous monitoring of their health. The collected data undergoes preprocessing, which involves handling missing data through normalization, elimination of blank or irrelevant entities. The preprocessed data is then fed into a federated learning model, where 'n' number of healthcare monitoring models process the data and send it to the cloud for further training.The cloud contains a training layer (represented by blue dotted lines) that is used to predict patient health outcomes based on the data received from the 'n' number of healthcare monitoring models. This trained model is then uploaded to a local server (represented by blue lines) where it can be used for real-time monitoring of patient health.

After the trained models have been uploaded to the cloud, they are aggregated to develop a more efficient and intelligent healthcare monitoring system. The aggregated model is then updated and sent back to the 'n' number of smart patient monitoring systems, allowing for continuous monitoring and prediction of patient health, leading to a better quality of life for patients. It is important to note that this system provides a decentralized approach to healthcare monitoring, enabling data to be processed locally rather than relying on a central server. This enhances privacy and security of patient data and reduces the risk of data breaches. Additionally, the use of federated learning helps to improve the accuracy and robustness of the healthcare monitoring system.

4 Limitations and Future Directions

Advances in machine learning (ML) have enabled healthcare systems to monitor the health of patients in smart cities. Remote patient monitoring (RPM) utilities are widely used for accurate real-time health data acquisition, however, their limited accessibility, lack of provider engagement, and error rates cause a range of issues. To address this, this research proposes a federated learning-based healthcare model for patient monitoring. The model has the potential to overcome these issues and provide improved performance. In the future, the performance of such a model can be further enhanced with the use of fusion-based approaches. The proposed federated learning-based healthcare model for patient monitoring has the potential to not only resolve the existing issues related to RPM utilities, such as limited accessibility and lack of provider engagement, but also to provide better performance overall. This model could be further improved in the future by incorporating a fusion-based approach, which involves combining multiple data sources and techniques to generate a more reliable and accurate model. Through this approach, the performance of the model can be increased and potentially lead to better health outcomes for patients in smart cities.

5 Conclusion

After examining the current state of federated learning in patient healthcare monitoring, it is clear that this technology has the potential to improve the accuracy, speed, and scalability of patient healthcare systems. By utilizing distributed, privacy-preserving data, federated learning enables healthcare providers to more effectively monitor patients while protecting their privacy, and provides a more reliable method of data collection than traditional models. Furthermore, the use of federated learning in healthcare has the potential to reduce costs, as it eliminates the need for expensive data storage and sharing systems. Additionally, federated learning can be used to develop more accurate patient monitoring models, as it allows for the collection of data from multiple sources and enables healthcare providers to build models that are tailored to their specific needs. In the proposed research federated learning has the potential to revolutionize patient healthcare monitoring and lead to more effective and efficient healthcare systems. By providing a privacy-preserving, distributed data sharing system and enabling the development of more accurate models, federated learning can improve the accuracy, speed, and scalability of patient healthcare monitoring and lead to more efficient healthcare delivery.

6 References

[1] Badsha, S., Vakilinia, I., Sengupta, S., 2019. Privacy preserving cyber threat information sharing and learning for cyber defense. 2019 IEEE 9th Annu. Comput. Commun. Work. Conf. CCWC 2019 708–714.

[2] Phong, L.T., Aono, Y., Hayashi, T., Wang, L., Moriai, S., 2018. Privacy-Preserving Deep Learning via Additively Homomorphic Encryption. IEEE Trans. Inf. Forensics Secur. 13, 1333–1345.

[3] Hou, X., Li, Y., Chen, M., Wu, D., Jin, D., Chen, S., 2016. Vehicular Fog Computing: A Viewpoint of Vehicles as the Infrastructures. IEEE Trans. Veh. Technol. 65, 3860–3873.

[4] Yang, Q., Liu, Y., Chen, T., Tong, Y., 2019. Federated Machine Learning. ACM Trans. Intell. Syst. Technol. 10, 1–19.

[5] Geyer, R.C., Klein, T., Nabi, M., 2017. Differentially Private Federated Learning: A Client Level Perspective 1–7.

[6] Zhao, L., Wang, Q., Zou, Q., Zhang, Y., Chen, Y., 2020. Privacy-Preserving Collaborative Deep Learning with Unreliable Participants. IEEE Trans. Inf. Forensics Secur. 15, 1486–1500.

[7] Stojmenovic, I., Wen, S., 2014. The Fog computing paradigm: Scenarios and security issues. 2014 Fed. Conf. Comput. Sci. Inf. Syst. FedCSIS 2014 2, 1–8.

[8] Bhowal, P., Sen, S., Yoon, J.H., Geem, Z.W., Sarkar, R., 2021. Choquet Integral and Coalition Game-Based Ensemble of Deep Learning Models for COVID-19 Screening from Chest X-Ray Images. IEEE J. Biomed. Heal. Informatics 25, 4328–4339.

[9] Pustokhina, I.V., Pustokhin, D.A., Gupta, D., Khanna, A., Shankar, K., Nguyen, G.N., 2020. An Effective Training Scheme for Deep Neural Network in Edge Computing Enabled Internet of Medical Things (IoMT) Systems. IEEE Access 8, 107112–107123.

[10] Zyskind, G., Nathan, O., Pentland, A.S., 2015. Decentralizing privacy: Using blockchain to protect personal data. Proc. - 2015 IEEE Secur. Priv. Work. SPW 2015 180–184.

[11] Muneer S, Rasool MA. AA systematic review: Explainable Artificial Intelligence (XAI) based disease prediction. International Journal of Advanced Sciences and Computing. 2022 Jun 30;1(1):1-6.

[12] Nouman A, Muneer S. A systematic literature review on heart disease prediction using blockchain and machine learning techniques. International Journal of Computational and Innovative Sciences. 2022 Dec 30;1(4):1-6.

[13] Liu Z, Shi Y, Yang B. Open innovation in times of crisis: An overview of the healthcare sector in response to the COVID-19 Pandemic. Journal of Open Innovation: Technology, Market, and Complexity. 2022 Jan 14;8(1):21.

[14] Joshi M, Pal A, Sankarasubbu M. Federated learning for healthcare domain-Pipeline, applications and challenges. ACM Transactions on Computing for Healthcare. 2022 Nov 3;3(4):1-36.

[15] Rahman A, Hossain MS, Muhammad G, Kundu D, Debnath T, Rahman M, Khan MS, Tiwari P, Band SS. Federated learning-based AI approaches in smart healthcare: concepts, taxonomies, challenges and open issues. Cluster Computing. 2022 Aug 17:1-41.

[16] Nguyen DC, Pham QV, Pathirana PN, Ding M, Seneviratne A, Lin Z, Dobre O, Hwang WJ. Federated learning for smart healthcare: A survey. ACM Computing Surveys (CSUR). 2022 Feb 3;55(3):1-37.