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# Enhancing Medical Data Analysis with Federated Learning in the Internet of Medical Things

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***Abstract:** The Internet of Things refers to physical items, which are equipped with software, sensors, computing power, and other technologies, and that communicate with other electronic devices and systems over communication networks or the Internet. A collection of medical devices and software programmes known as the Internet of Medical Things (IoMT) link to healthcare networks via internet computing. Machine-to-machine communication, which is the foundation of IoMT, is made feasible by medical equipment that includes Wi-Fi. IoMT devices have the ability to analyse and store collected data by connecting to cloud services. IoMT is a different moniker for IoT in healthcare. Since data is transferred via the internet and the IoMT creates a lot of data, privacy concerns are important. The vast volume of data produced by IoMT devices calls for big data processing, and federated learning tackles privacy issues as a way to overcome these difficulties. The big data health care framework for IoMT is discussed in this article. It is built on federated learning.*

***Keywords:** Federated Learning, Sensor, Medical Data, Iomt, Big Data Analytics, and Machine Learning.*

## 1. INTRODUCTION

The Internet of Things (IoT) is a network of physical objects connected through a network. These objects, acting as intelligent entities, make decisions based on their perception of the environment [1]. With the goal of automating processes without human intervention, IoT is extensively applied in various sectors such as industry, business, education, transportation, and healthcare [2]. Particularly within the healthcare field, the emergence of the Internet of Medical Things (IoMT) has seen IoT technology being widely implemented for medical and healthcare analytics [3].

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The development of lightweight transmission protocols, smart devices, and smart sensors accomplishes the ability of interconnection medical objects to observe biomedical signals. The disease diagnosis without the intervention of medical experts with the network of smart medical things is termed IoMT. The health of an individual is significant in leading a successful and peaceful life and healthcare is maintaining or enhancing health with the assistance of diagnosis, treatment, and prevention. Healthcare is effectively attained by the IoMT with the automation process [4,5].

The main advantage of IoMT based monitoring system accomplishes general events even if the patients are under observation continuously and minimizes hospital bills. IoMT monitors and also provides needed intimation to the patients as well as to the healthcare providers [6]. Medical data are stored and processed over the Internet whereas the generation of information is huge. The amount of data from IoMT has necessitated Big Data technology and healthcare analytics is accomplished by Big Data Technology [7]. Big Data based Healthcare analytics have been able to generate impactful decisions from medical data. The utilization of Big Data Analytics (BDA) has proved to be an efficient tool in handling large amounts of data and enhancing the decision-making process. IoT has introduced various advanced approaches and protocols, contributing significantly to the global communication system through the connection of millions of devices to the Internet[8].

Big data poses diversified challenges in processing and storing abundant data where the data process of handling those data is a complicated process due to its nature [9]. Federated learning is introduced into big data-based healthcare analytics. Federated learning is a form of collaborative machine learning technique that doesn’t need centralized training data [10]. The Federated learning process is different from the conventional methodology of machine learning [11]. Google's machine learning uses a cloud-based infrastructure for processing data, utilizing user-interaction information for model training[12]. Federated learning, initiated by a shared prediction model, allows for cooperative learning across devices [13].

The learning system stores the training knowledge on the devices, which dissociates machine learning's potential from the demand for cloud storage. This method extends beyond using a local predictive model, which makes predictions about electronic devices by bringing the training model to the right devices. Federated learning, addresses privacy issues of centralized methods by training models on local devices using model info, not raw data, thus sending only model variables between devices and internet[14]. This article discusses the IoMT and the data generated from IoMT is vast and also has different variety of data. This nature of IoMT has needed the assist of big data analytics and federated learning.

The rest of the text is structured as follows: Section 2 discusses the importance of federated learning and IoT-based healthcare analytics. Section 3 describes applications and works based on medical-based IoT technology. Section 4 provides a big data analytic framework for IoMT using federated learning. Section 5 concludes the article with a discussion of future scope.

## 2. RELATED WORKS

In recent years, there has been a significant expansion in the availability of advanced Internet of Things (IoT) devices. These sophisticated IoT devices necessitate the incorporation of

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efficient machine learning frameworks. Federated learning emerges as a potential solution that can facilitate the development of smart solutions based on IoT.
The Pustokhina, I. V. and Pustokhin, D. A. et al. [3] discussed the use of deep learning techniques to diagnose medical conditions and disorders through the application of artificial neural networks and mobile computing, with a focus on diagnosing hard-to-diagnose early-stage heart disease. Specifically, Edge computing is employed to reduce pressure on cloud platforms in analyzing massive medical data. Studies show that this methodology enhances disease diagnosis accuracy by a significantly higher percentage than traditional diagnostic methods. The technology was especially successful in type 2 diabetics with heart disease. Latif U.Khan et al. [24] discussed how to enable federated learning at network edge by optimizing resources and designing incentive mechanisms. Suraj Rajendran et al. [29] discussed various implementations of cloud-based federated learning across different institutions, providing machine learning (ML) models for health care that require larger training samples than typically afforded by one institution. Lee, G. H. and Shin, S. Y. [31] discussed the evaluation of federated learning on three benchmark datasets including a clinical benchmark dataset. It concludes that federated learning can achieve high performance while maintaining privacy protection because there is no requirement to centralize the data

**Federated Learning in IoT**
The increased accessibility of medical information and the rapid advancement of analytical techniques have a paradigm shift in the healthcare industry [15]. Among the huge volume of medical information, IoT has become a significant source of data. IoT has depicted huge potential in numerous medical applications namely fitness programs, monitoring individual health, elderly care, and chronic disease [16]. The significant benefits of the IoT approach is to aid the ability of the system that continuously monitors the clinical level patients and gathers diverse variants of bio-signals.
IoT data is typically collected, uploaded to the appropriate data center, and then used to train learning models. Additionally, information owners are very concerned with security and privacy [17], particularly in the healthcare industry to address privacy issues that are individually detectable by the medical data [18]. The solution to the data problem is to train a high-quality shared model for the entire world using centralised servers while dispersing the data across a large number of clients [19]. Figure 1 shows a comparison between ML and FL.

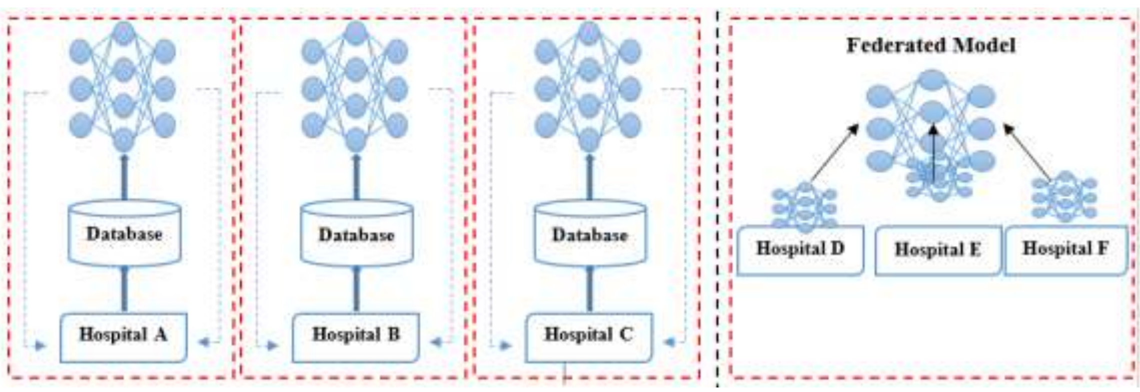

Figure 1. Architecture of ML vs FL in IoMT

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Federated learning distinguishes itself from distributed learning in several ways. It primarily emphasizes protecting user information, while distributed learning focuses on convergence speed. In federated learning, client device data distributions remain undisclosed, unlike in distributed learning where data sections can be allocated freely. Federated learning operates in a challenging environment due to vast, variably active clients with potential network inconsistencies. Often, devices like mobile phones may not maintain a consistent connection. The data distribution methods, referenced [22], previously associated with distributed learning, are now used to define federated learning. Unlike the traditional "whole dataset" approach, explaining federated data distribution is challenging. In a typical federated learning setup, M data owners train their unique models {k1, k2,...,kM} on separate datasets {L1, L2,..., LM}. The IoT healthcare problem aligns with horizontal federated learning, as outlined in [23], where datasets share features but differ in samples. The objective is minimizing the k(i) parameter w.

$$\underset{w}{min} k(i) = \sum_{j=1}^{M} k_j(w|L_j) \qquad (1)$$

After configuring the global model on the server, it's downloaded by all active clients. Each client then trains this model on their data over multiple epochs. Subsequently, the server receives the updated parameters or gradients from these clients, which highlight the differences between the updated and original models. It's crucial to understand that clients may differ in data volume and computational capabilities, preventing the server from handling simultaneous uploads from multiple clients. The server gathers the received uploads in order to update the global model. Continue doing the first two phases until convergence is reached. Figure 2 depicts the whole federated learning process.

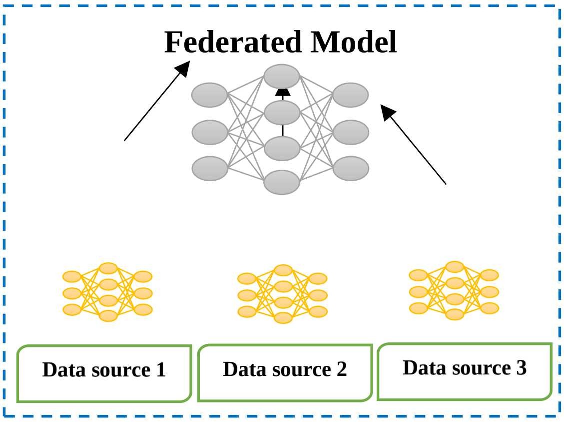


Figure 2. Overall Process of Federated Learning

In the context of Federated Learning, the training process begins with the employment of a linear regression model, optimized using the gradient descent method. During this process, it's paramount to maintain the secure transmission of both gradient values and loss metrics. Parameters integral to the training, such as the learning rate (represented by η) and the regularization coefficient (denoted as λ), are predefined. Furthermore, the model employs

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parameters ΘA and ΘB, each corresponding to the feature spaces Ma and Mb, respectively. The ultimate aim of this training process is.

$$\min_{\Theta_A,\Theta_B} \sum_i \left\| \Theta_A M_i^A + \Theta_B M_i^B - N_i \right\| + \frac{\lambda}{2}(\|\Theta_A\|^2 + \|\Theta_B\|^2) \quad \textbf{(2)}$$

Let $U_i^A = \Theta_A M_i^A, U_i^B = \Theta_B M_i^B$ then the encrypted loss is determined as

$[\![L]\!] = \left[\!\left[\sum_i((U_i^A + U_i^B - N_i))^2 + \frac{\lambda}{2}(\Theta_A^2 + \Theta_B^2)\right]\!\right]$, where additive homomorphic encryption is indicated as $[\![.]\!]$. Let $[\![L_A]\!] = \left[\!\left[\sum_i((U_i^A)^2 + \frac{\lambda}{2}\Theta_A^2)\right]\!\right], [\![L_B]\!] = \left[\!\left[\sum_i((U_i^B)^2 + \frac{\lambda}{2}\Theta_B^2)\right]\!\right]$ $and$ $[\![L_{AB}]\!] = [\![2\sum_i(U_i^A(U_i^B - N_i)^2]\!]$; then

$$[\![L]\!] = [\![L_A]\!] + [\![L_B]\!] + [\![L_{AB}]\!]$$

Similarly, let $[\![d_i]\!] = [\![U_i^A]\!] + [\![U_i^A - N_i]\!]$; then, the gradients are indicated as

$$\left[\!\left[\frac{\delta L}{\delta \Theta_A}\right]\!\right] = \sum_i [\![d_i]\!] M_i^A + [\![\lambda \Theta_A]\!]$$

$$\left[\!\left[\frac{\delta L}{\delta \Theta_B}\right]\!\right] = \sum_i [\![d_i]\!] M_i^B + [\![\lambda \Theta_B]\!]$$

While aligning entities and training the model, the data of A and B remain securely stored remotely, ensuring no compromise in privacy through data communication during training. It's important to highlight that any information potentially exposed to C might not necessarily be considered a privacy violation. To further enhance privacy, A and B could employ randomized masks to encrypt and thereby conceal their gradients from C."

**Applications of Medical IoT**

The hardship on medical staff has significantly expanded due to the rapid growth in population and disease around the world. The use of effective approaches to treating patients is a serious issue. Federated learning technology progress may improve "smart medicine." Previously, machine learning had limited data due to hospitals' independence and patient data confidentiality.

Due to the Personalized Medicine Initiative and creation of extensive general health electronic data, patient info is frequently stored in regional databases, making it hard for medical professionals to access needed info for diagnosis. A reliable medical assistant is crucial in while diagnosing a system. Horizontal federated learning can improve model performance, reducing costs for hospitals and enabling better diagnosis. As demand grows for aggregating medical data from multiple providers, this approach becomes increasingly valuable. Because it may be difficult to build a calibrating system that is successful enough locally.

An FL framework for privacy protection in multi-site medical imaging analysis minimizes distance correlation between raw data and intermediate presentations, reducing data transmission and important pattern leakage [24]. They looked similar to brain function where

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links could be used to categorize the access and privacy preservation of people with autism spectrum disorders and other health issues. Additionally, there are still some more techniques, which can effectively safeguard the fusion of medical-related information [25]. The medical applications based on FL is given in Table 1.

Table 1. Federated Learning Based Medical Application

| **Category** | **Significant Inference** | **Framework** |
|---|---|---|
| Medical Imaging | The FL paradigm, which evaluates the performance of five various designs, serves as the foundation for healthcare. In the comparison, the ResNet18 model performs admirably [26]. | FL |
| | A variation-aware FL (VAFL) framework that is more dependable was created. Information on prostate cancer was more accurately categorised using the FL framework [27]. | FL |
| Medical Information | On two independent data sets, the FL design was severely tested, and the outcomes were assessed. The FL technique often does not improve the precision of logistic regression [28]. | FL |
| | The efficacy of different products for death forecasting was evaluated using data from five hospitals [29]. | FL |
| | Under uneven, skewed, and severe data distributions, FL performs consistently [30]. | FL |
| | Based on FL, a privacy-preserving medical NER approach has been developed [31]. | FL |
| Processing of Medical Information | Using a dynamic fusion approach, model fusion was organised in accordance with the training period of participating clients. The COVID-19 identification process uses many types of medical diagnostic datasets with images [32]. | FL |
| | Using a knowledge extraction strategy, the FL communications bottleneck was overcome. The review discovered good results on three different medical datasets [33]. | FL |

## 3. METHODOLOGY

This research Enhancing Medical Data Analysis with Federated Learning in the Internet of Medical Things to meet Processing huge data generated by IoMT devices, federated learning overcomes these difficulties by solving privacy issues. In this approach, the fall detection dataset is used to perform Federated learning and machine learning methods. We evaluated performance using performance metrics such as accuracy, gain, and error rate and implementing FL models on IoT devices, combined with edge computing concepts. Make a comparison between ML and FL by determining the error rate for several iteration by multiplying the sum of the values of FP and FN by the sum of the values of TP, TN, FP and FN, as shown in Table 5, and it is calculated according to Equation(5). Big data analytics have been used in the field of healthcare to improve quality of life, reduce needless deaths, and cure epidemic diseases [34]. The system collects structured, unstructured, and semi-structured data in a variety of forms from wearable IoT sensor data, including temperature,

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climate, location, medical, and environmental data. The aggregated data is then visualised via cloud computing. In the database, the data is extracted, cleaned, and subjected to statistical analysis. The findings are then sent to doctors, remote users, and ambulances.

Wearable sensors generate large volumes of organized and unstructured data. analyzing this data for useful information is challenging, especially with cloud computing latency. This approach stores and maintains data on remote servers via the internet. IoT devices collect and share large data via a network. A fog layer gathers, analyzes, and processes data, reducing latency and increasing efficiency before storing it in the cloud for real-time decision making. The significant information generated from Big Data sources is connected to healthcare, which is hard to keep, manage, and evaluate.

A new framework, Meta Fog-Redirection (MF-R) with GC, addresses Big Data storage and analysis needs in IoT-based smart healthcare, providing security against unauthorized data access [35]. The user's heart rate, breathing rate, body temperature, blood sugar rate, and blood pressure are all collected by sensors in IoT devices and transferred to fog for analysis. The alert message is delivered to doctors using fog computing in emergency scenarios. Big Data is stored in the cloud platform using Apache HBase and Apache Pig.

Big Data management is a challenge in healthcare decision-making for real-time monitoring systems. Patient priority categorization is a key issue in Big Data analytics for telemedicine. The integration of patient prioritization and real-time monitoring systems in healthcare services is achieved using the six V's of Big Data [36]. For chronic illnesses like heart disease, high blood pressure, and diabetes, telemedicine involves continuous remote monitoring through sensors and real-time user data collection. This enables doctors to provide medical care remotely. Figure 3 illustrates Big Data usage in IoMT.

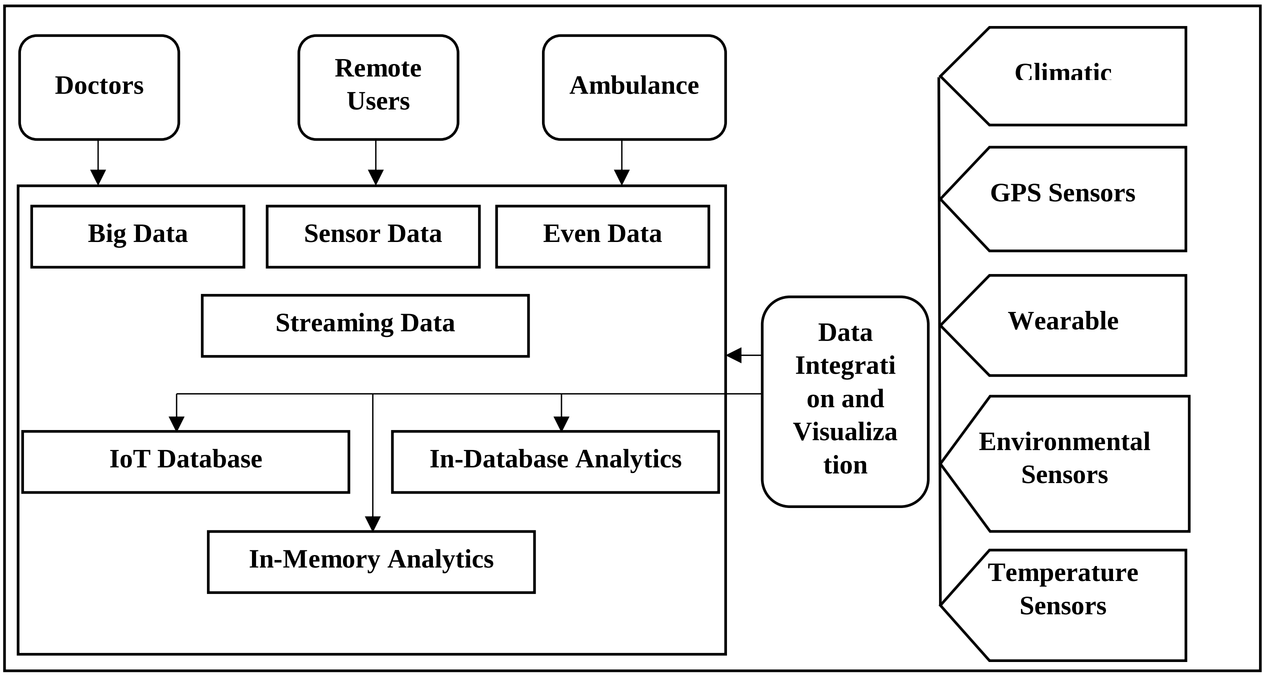


Figure 3. IoMT Architecture Based on Big Data

As patient numbers grow, deciding who to serve first becomes harder. Population aging and disasters are considered in telemedicine service planning. Patient prioritization occurs in transplantation, surgery, and OR access. Triage is used to treat patients based on severity. IoT and big data analytics can improve access to smart health services in developing nations.
There were three parts to the healthcare based IoT system and they are,

(i) Body sensor area network, which uses body-wear or embedded sensors to capture the patient's behaviour data as well as environmental parameters such as date, temperature, humidity, and time.
(ii) Data preparation, protocol transformation, data mining and filtering, and local alerting to patients are all performed via an Internet-connected smart gateway, also known as a fog layer or local access network.
(iii) A cloud and big data specific layer is used to retain all sensor data, analyse it, forecast a decision, and send an alert to caretakers in an emergency situation.

Electronic Health Records (EHR) are require big data analysis due to growing medical data. A compilation of an outpatient medical dataset is underway, with more doctors needed to assist. The Simultaneously Aided Diagnostic Model (SADM) is intended to boost outpatient doctors' productivity while reducing their workload [37]. Model performs data collection, preprocessing, storage, testing, feature extraction, machine learning, and aids in disease identification through comparison to clinical reference indices. The IoT-based healthcare system and its advantages, as well as disadvantages, are given in Table 2.

Table 2. IoT based Healthcare System Advantages and Disadvantages

| **Application Type** | **Advantages** | **Disadvantages** |
|---|---|---|
| Continuous observation of ICU patients | The observation system provide assistance to the doctors to make accurate decision. | The monitoring system hasn't been used yet, thus its accuracy hasn't been evaluated. |
| Study about the healthcare observation system | Energy minimises the power gap and power necessities are met. | Sensors in IoT devices consumes huge energy. |
| Prevention and diagnosis system to regulate the chickungunya virus | Feed-back system for real-time system. | Imbalanced security aspects. |
| Health observation system | Efficient healthcare related services are offered. | Fault tolerance towards handling the data. |
| Prevention and diagnosis of chickungunya virus | Alert generation is quick and huge bandwidth | Sensors in IoT devices consumes huge energy. |

During the data gathering step, information is gathered on outpatient medication records, treatment plans, charges, and outcomes of the treatment procedure. Machine learning employs a Support Vector Machine and a Neural Network approach to train the data with

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prior medical datasets to classify hyperlipidemia [35, 36]. Big Data analytics plays a crucial role in today's evolving medical environment by managing a huge amount and diversity of data and storing it in a way that makes it easy to rapidly obtain, update, and discard the information [37].

## 4. RESULT AND DISCUSSION

This section compares federated learning and existing machine learning algorithms using a fall detection dataset[38]. Performance is measured by accuracy, gain, and error.

### Accuracy

Accuracy is the measure of how well the value calculated from the categorised occurrences matches the actual value. Accuracy is the representation of quantitative bias and enduring errors. Along with the estimation's resemblance to the true value, it is also the acceptance (both TP and TN values) among some of the assessed classes. When accuracy is at its lowest, there is a difference between the result and the actual results values. It is the ratio of information examined to the number of successful fall detections. The rate of accuracy is given n Figure 4 and Table 3. It's calculated as follows:

$$\text{Acc} = \frac{\text{True Positive+True Negative}}{\text{True Positive+True Negative+False Positive+False Negative}} \quad (3)$$

Table 3. Comparison of Accuracy

| Iteration | ML | FL |
|---|---|---|
| 50 | 88 | 92 |
| 100 | 88.5 | 92.6 |
| 150 | 88.7 | 93 |
| 200 | 89 | 94 |

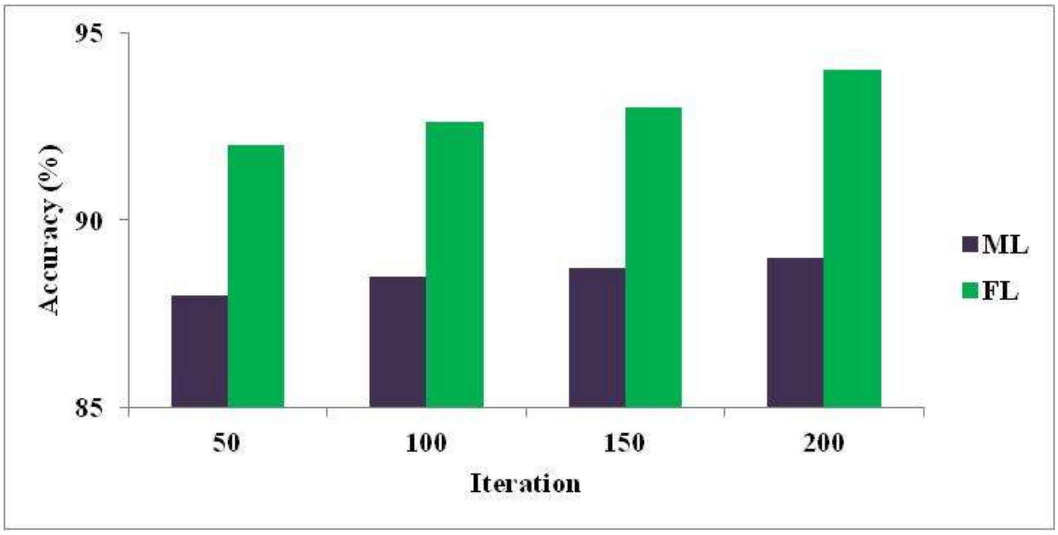


Figure 4. Comparison of Accuracy

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According to Figure 4, the suggested technique is quite successful, and the FL obtains a significant accuracy value.

### Gain

Information gain is the minimization in entropy value or surprise value by transforming a dataset that is often utilised in training. The rate of gain is given n Figure 5 and Table 4. It is computed as follows:

$$\text{Gain} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \quad \ldots.. (4)$$

Table 4. Comparison of Gain

| Iteration | ML | FL |
|---|---|---|
| 50 | 81 | 91 |
| 100 | 82 | 92 |
| 150 | 84 | 92.8 |
| 200 | 84.5 | 94 |

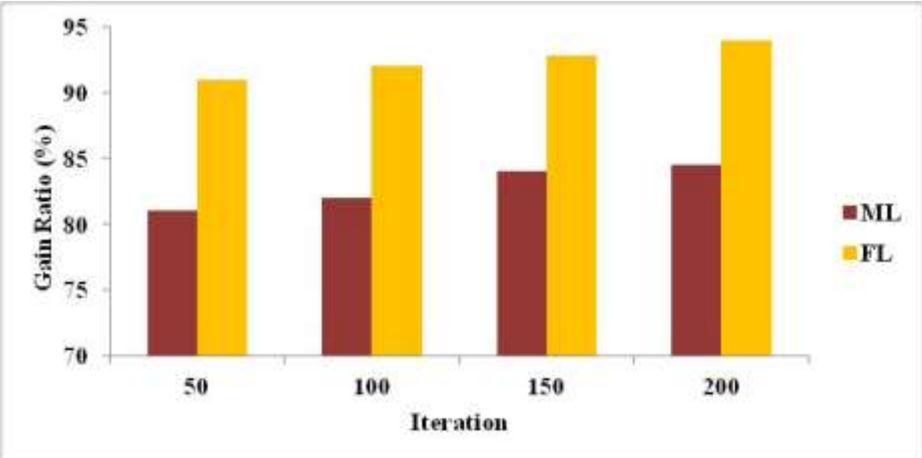


Figure 5. Comparison of Gain

Figure 5 shows that the proposed approach is very successful and FL achieves high gain values, which is evident from the observation.

### Error Rate

Different factors, such as noise, distortion, and disruption in the data processing, are to blame for the occurrence of mistake in the digitalization process. It is a ratio of competency rates. The percentage of patterns that the decision-making framework incorrectly categorises is known as the error rate. By multiplying the sum of the FP and FN values by the sum of the TP, TN, FP, and FN values, the error rate is determined. The value of error rate is depicted in Table 5 and Figure 5. It is calculated as follows:

$$\text{Error rate} = \frac{\text{FP+FN}}{\text{TP+TN+FP+FN}} \quad (5)$$

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Table 5. Comparison of Error Rate

| Iteration | ML | FL |
|---|---|---|
| 50 | 5.3 | 4.9 |
| 100 | 5.6 | 4.7 |
| 150 | 5.7 | 4.5 |
| 200 | 6.1 | 4.2 |

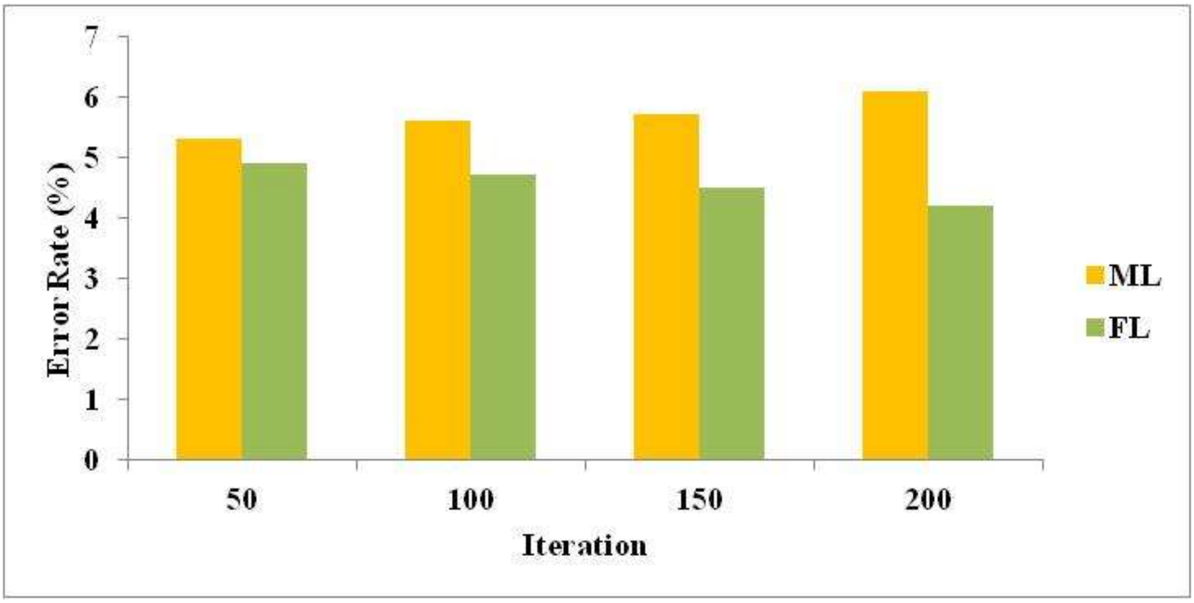


Figure 6. Comparison of Error Rate

The observation of Figure 6 demonstrates that the suggested strategy is quite successful and FL obtains a low error rate.

**Sensitivity**

The capacity of a machine learning methodology to detect positive features is represented by its sensitivity. The true positive rate (TPR) or recall are some other names for it. Given that it enables us to observe how many instances the approach was able to accurately detect, sensitivity is used to assess model performance.

Table 6. Comparison of Sensitivity

| Iteration | ML | FL |
|---|---|---|
| 50 | 78 | 95 |
| 100 | 75 | 89 |
| 150 | 79 | 90 |
| 200 | 84 | 91 |

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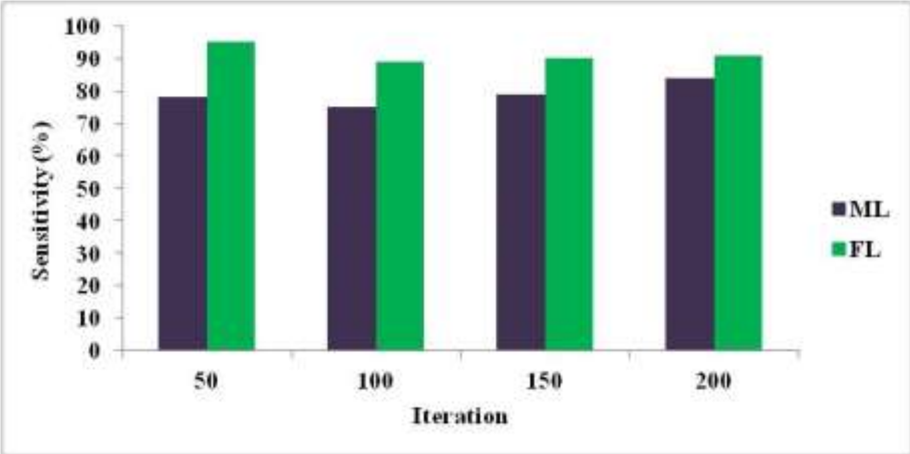


Figure 7. Comparison of Sensitivity

According to Figure 7 and Table 6, the suggested technique is extremely successful, and the FL obtains maximum sensitivity.

**Specificity**

The percentage of anticipated negatives that actually realized is known as specificity. As a result, there will be a higher proportion of actual negatives, often known as erroneous positives because they were first mistaken for good results. Sometimes, this proportion is referred to as the "false positive percentage".

Table 7. Comparison of Specificity

| Iteration | ML | FL |
|---|---|---|
| 50 | 76 | 92 |
| 100 | 73 | 91 |
| 150 | 76 | 95 |
| 200 | 78 | 97 |

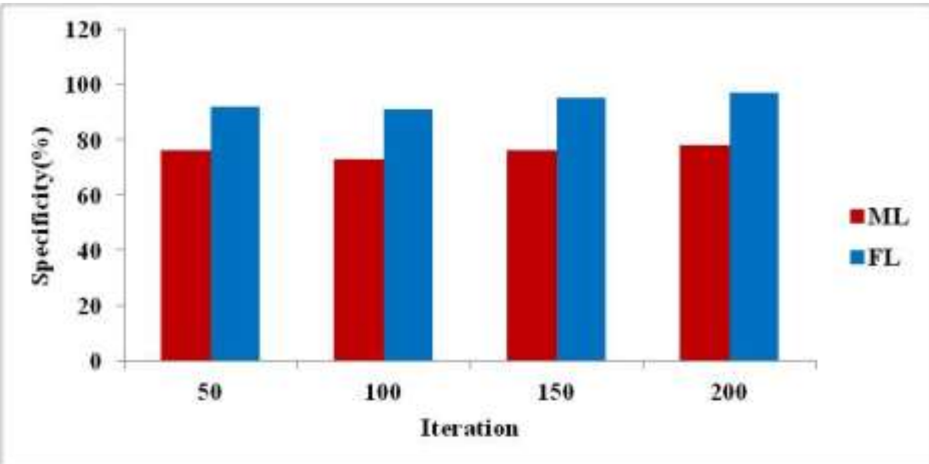


Figure 8. Comparison of Specificity

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According to Figure 8 and Table 7, the suggested technique is extremely successful, and the FL reaches maximal specificity.

## 5. CONCLUSION

This article discusses the significance of IoT and its role in health care field. The accumulation of medical things over internet facility is IoMT. The data generated from the sensors and devices are huge and it necessitated big data technology. Additionally, the data transmitted over internet poses several challenges namely integrity, privacy and security concerns. To handle this issue federated learning is introduced with the big data based healthcare analytics. Federated learning is derived from the machine learning that is entirely different from the learning schemes. The data generated from diverse sources will generate a learning model individually and an efficient model is generated with the already generated models. Newly constructed model is determined as federated model, which ensures privacy and security concerns. The data generated from sensors leads to enormous growth of data and it necessitated Big data based federated learning model for healthcare analytics. This article addressed the issues and depicted an effective big data based federated learning model.

## 6. REFERENCES

1. Cui, X. (2016). The internet of things. In Ethical ripples of creativity and innovation (pp. 61-68). Palgrave Macmillan, London.
2. Chen, C. H., & Lo, K. R. (2018). Applications of Internet of Things.
3. 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.
4. Alsubaei, F., Abuhussein, A., Shandilya, V., & Shiva, S. (2019). IoMT-SAF: Internet of medical things security assessment framework. Internet of Things, 8, 100123.
5. Tharini, V. J., & Vijayarani, S. (2020). IoT in Healthcare: Ecosystem, Pillars, Design Challenges, Applications, Vulnerabilities, Privacy, and Security Concerns. In Incorporating the Internet of Things in Healthcare Applications and Wearable Devices (pp. 1-22). IGI Global.
6. Joyia, G. J., Liaqat, R. M., Farooq, A., & Rehman, S. (2017). Internet of medical things (IoMT): Applications, benefits and future challenges in healthcare domain. J. Commun., 12(4), 240-247.
7. Kankanhalli, A., Hahn, J., Tan, S., & Gao, G. (2016). Big data and analytics in healthcare: introduction to the special section. Information Systems Frontiers, 18(2), 233-235.
8. Mehta, N., & Pandit, A. (2018). Concurrence of big data analytics and healthcare: A systematic review. International journal of medical informatics, 114, 57-65.
9. Kumar, S., & Singh, M. (2018). Big data analytics for healthcare industry: impact, applications, and tools. Big data mining and analytics, 2(1), 48-57.

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10. Yang, Q., Liu, Y., Cheng, Y., Kang, Y., Chen, T., & Yu, H. (2019). Federated learning. Synthesis Lectures on Artificial Intelligence and Machine Learning, 13(3), 1-207.
11. Bonawitz, K., Eichner, H., Grieskamp, W., Huba, D., Ingerman, A., Ivanov, V., & Roselander, J. (2019). Towards federated learning at scale: System design. arXiv preprint arXiv:1902.01046.
12. Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. IEEE Signal Processing Magazine, 37(3), 50-60.
13. Konečný, J., McMahan, H. B., Yu, F. X., Richtárik, P., Suresh, A. T., & Bacon, D. (2016). Federated learning: Strategies for improving communication efficiency. arXiv preprint arXiv:1610.05492.
14. Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., & Zhao, S. (2019). Advances and open problems in federated learning. arXiv preprint arXiv:1912.04977.
15. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2 (4), 230–243.
16. Islam, S. R., Kwak, D., Kabir, M. H., Hossain, M., & Kwak, K. S. (2018). The internet of things for healthcare: a comprehensive survey. IEEE Access. 2015; 3: 678–708.
17. Lim, W. Y. B., Luong, N. C., Hoang, D. T., Jiao, Y., Liang, Y. C., Yang, Q., ... & Miao, C. (2020). Federated learning in mobile edge networks: A comprehensive survey. IEEE Communications Surveys & Tutorials, 22(3), 2031-2063.
18. Konečný, J., McMahan, H. B., Ramage, D., & Richtárik, P. (2016). Federated optimization: Distributed machine learning for on-device intelligence. arXiv preprint arXiv:1610.02527.
19. McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017, April). Communication-efficient learning of deep networks from decentralized data. In Artificial intelligence and statistics (pp. 1273-1282). PMLR.
20. Xu, J., Glicksberg, B. S., Su, C., Walker, P., Bian, J., & Wang, F. (2021). Federated learning for healthcare informatics. Journal of Healthcare Informatics Research, 5(1), 1-19.
21. Firouzi, F., Rahmani, A. M., Mankodiya, K., Badaroglu, M., Merrett, G. V., Wong, P., & Farahani, B. (2018). Internet-of-Things and big data for smarter healthcare: From device to architecture, applications and analytics.
22. Pankajavalli, P. B., & Karthick, G. S. (2022). An Independent Constructive Multi-class Classification Algorithm for Predicting the Risk Level of Stress Using Multi-modal Data. Arabian Journal for Science and Engineering, 1-16.
23. Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2), 1-19.
24. Khan, L. U., Pandey, S. R., Tran, N. H., Saad, W., Han, Z., Nguyen, M. N., & Hong, C. S. (2020). Federated learning for edge networks: Resource optimization and incentive mechanism. IEEE Communications Magazine, 58(10), 88-93.

 

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25. Ahamad, S. S., & Khan Pathan, A. S. (2021). A formally verified authentication protocol in secure framework for mobile healthcare during COVID-19-like pandemic. Connection Science, 33(3), 532-554.
26. Karthick, G. S., & Pankajavalli, P. B. (2022). Chronic obstructive pulmonary disease prediction using Internet of things-spiro system and fuzzy-based quantum neural network classifier. Theoretical Computer Science.
27. Yan, B., Zhou, Y., Liu, B., Wang, J., Zhang, Y., Liu, L., ... & Liang, Z. (2020). A real-time contribution measurement method for participants in federated learning.
28. Yan, Z., Wicaksana, J., Wang, Z., Yang, X., & Cheng, K. T. (2020). Variation-Aware federated learning with multi-source decentralized medical image data. IEEE Journal of Biomedical and Health Informatics.
29. Rajendran, S., Obeid, J. S., Binol, H., Foley, K., Zhang, W., Austin, P., ... & Topaloglu, U. (2021). Cloud-based federated learning implementation across medical centers. JCO Clinical Cancer Informatics, 5, 1-11.
30. Pankajavalli, P. B., & Karthick, G. S. (Eds.). (2019). Incorporating the Internet of Things in Healthcare Applications and Wearable Devices. IGI Global.
31. Lee, G. H.,&Shin, S. Y. (2020). Federated learning on clinical benchmark data: Performance assessment. Journal of Medical Internet Research, 22(10), Article ID: e20891.
32. Ge, S., Wu, F., Wu, C., Qi, T., Huang, Y., & Xie, X. (2020). Fedner: Medical named entity recognition with federated learning. arXiv preprint arXiv:2003.09288.
33. Zhang, W., Zhou, T., Lu, Q., Wang, X., Zhu, C., Sun, H., ... & Wang, F. Y. (2021). Dynamic fusion-based federated learning for COVID-19 detection. IEEE Internet of Things Journal.
34. Sui, D., Chen, Y., Zhao, J., Jia, Y., Xie, Y., & Sun, W. (2020, November). Feded: Federated learning via ensemble distillation for medical relation extraction. In Proceedings of the 2020 conference on empirical methods in natural language processing (EMNLP) (pp. 2118-2128).
35. Karthick, G. S., & Pankajavalli, P. B. (2020). Architecting IoT based healthcare systems using machine learning algorithms: cloud-oriented healthcare model, streaming data analytics architecture, and case study. In Incorporating the Internet of Things in Healthcare Applications and Wearable Devices (pp. 40-66). IGI Global.
36. Sun, J., & Reddy, C. K. (2013, August). Big data analytics for healthcare. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 1525-1525).
37. Islam, M. S., Hasan, M. M., Wang, X., & Germack, H. D. (2018, June). A systematic review on healthcare analytics: application and theoretical perspective of data mining. In Healthcare (Vol. 6, No. 2, p. 54). Multidisciplinary Digital Publishing Institute.
38. Casilari, E., Santoyo-Ramón, J. A., & Cano-García, J. M. (2017). Umafall: A multisensor dataset for the research on automatic fall detection. Procedia Computer Science, 110, 32-39.