World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(RESEARCH ARTICLE)

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Federated learning in edge computing: Enhancing data privacy and efficiency in resource-constrained environments

Dan BORUGA [1,*], Daniel BOLINTINEANU [2] and George Iulian RACATES [3]

[1] *Independent Researcher, Bucharest, Romania.*
[2] *Independent Researcher, Bucharest, Romania.*
[3] *Independent Researcher, Bucharest, Romania.*

World Journal of Advanced Engineering Technology and Sciences, 2024, 13(02), 205-214

Publication history: Received on 07 October 2024; revised on 12 November 2024; accepted on 15 November 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.13.2.0563

Abstract

Federated learning (FL) has become one of the most promising machine learning techniques that solve important data confidentiality and security challenges by training a model across decentralized devices without having raw data. Similarly, edge computing allows data analysis near the source, reducing time and using less bandwidth. This work examines the applications of federated learning in edge computing but focuses on scenarios with resource limitations, as seen with IoT devices and mobile networks. Reviewing the currently used approaches, issues, and trends, the features related to the future development involving opportunities and risks are considered. The emerging studies show that federated learning in the context of edge computing improves processing capacity in the federated model by preserving privacy concerns and is applicable in smart cities, healthcare smart grids, and self-driving systems. Some research directions for future works are suggested to address the scale-up and use of resources.

Keywords: Federated Learning; Edge Computing; Data Privacy; Resource Efficiency; Machine Learning Optimization

1. Introduction

A dramatic growth in the amount of data produced at the network edge is due to the increasing numbers of IoT devices, mobile networks, etc. There is a tendency to address such a raise with the help of edge computing, which means computation is moved closer to the data sources. However, the current ML implementation at the network edge has crucial issues, such as data privacy, efficiency, and resource utility.

The FL offers a solution for performing Machine Learning in a decentralized environment but without transferring the data to the cloud. Unlike standard machine learning, where all the data must be sent to a central computation point, FL permits the models' adaptation to be computed locally without sharing sensitive data with other parties, thus protecting the user's privacy. As such, this form of learning appears best suited for edge settings that involve distributed learning and where privacy and computational resources are constrained.

1.1. Research Objectives

This research paper aims to:

- Discuss FL's very basic concepts and advantages in cooperation with EC.
- Summarize the current strategies to protect data privacy and resource utilization in FL.

* Corresponding author: Dan BORUGA

- Finally, it is required to unfold the critical issues and develop recommendations for enhancing federated learning in limited-resource settings.

1.2. Structure of the Paper

The paper is structured as follows: A detailed review of the existing federated learning and edge computing literature, a description of the study approach, an interpretation of the results, and a discussion of the findings are presented in this paper, as well as future research recommendations.

2. Literature review

These are growing rapidly: data privacy challenges, communication efficiency, and computational constraints faced in edge computing through federated learning (FL). In this literature review, we explore foundational research, privacy-preserving mechanisms, communication efficient methods, and, most recently, applications of FL to resource-constrained environments.

2.1. Federated Learning Foundations

Federated Averaging (FedAvg) was first formally proposed by McMahan et al. (2017) as the notion of federated learning. This method allowed distributed devices to collaboratively learn a shared model while keeping data localized on each device, thus enhancing privacy and reducing data transfer costsVisual Aid: A timeline diagram of the history of federated learning research could show main contributions, milestones, technological advancements, etc.

2.2. FL with Privacy Preserving Mechanisms

To this day, privacy preservation remains a fundamental motivation for this parallel type of learning. Techniques like differential privacy and secure multiparty computation are typically used for training and aggregating sensitive data. Building upon the idea of differential privacy, as Dwork (2006) introduced, noise is added to data or model parameters, making private information difficult to learn from model updates. On the other hand, secure computation enables parties to jointly compute a function without each party revealing its input.

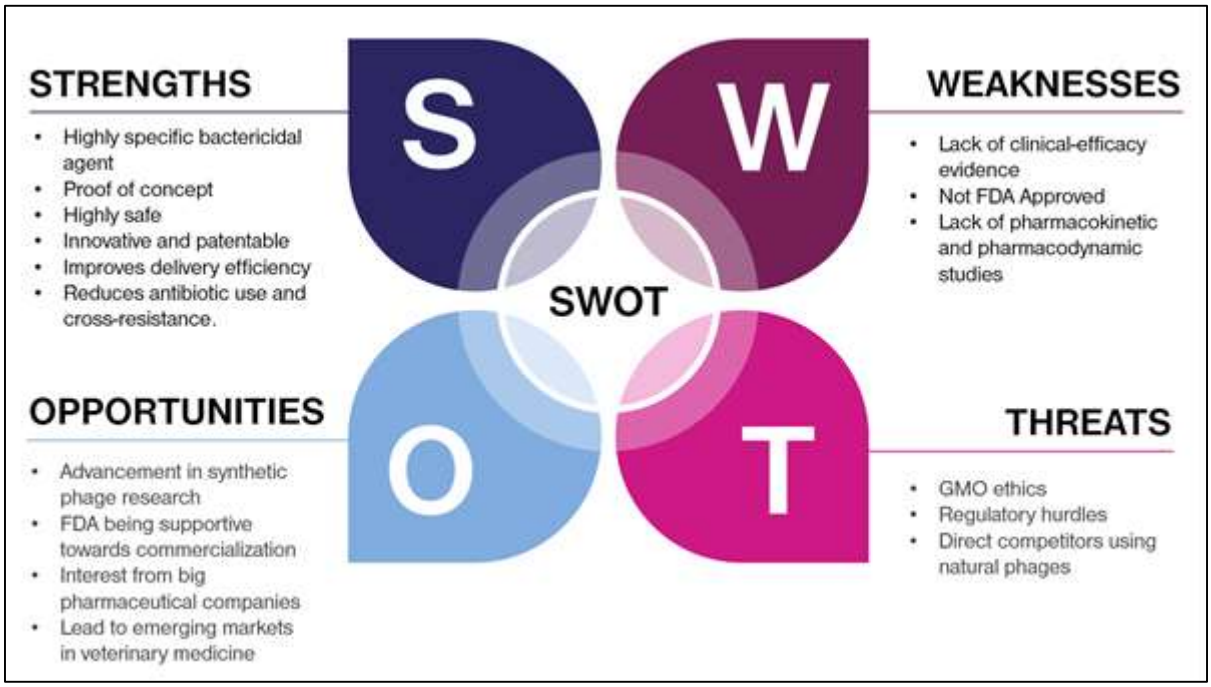

Figure 1 Swot Analysis

2.3. Communication Efficient Techniques

Communication overhead caused by frequent model updates between central servers and edge devices represents one major bottleneck in FL. Reductions in this load have been explored in recent research, such as model pruning, quantization, and sparsification. For instance, Lin et al. (2018) proposed gradient sparsification, transmitting fewer

parameters during training. Other studies of hierarchical federated learning further reduce server–device communication by organizing devices into clusters.

2.4. Edge Devices Resource Optimization

Resource management is critical because resource-constrained equipment has very limited capacity on which to run code, and also, in the case where zip colony works are used, there are storage limits. Work has proposed adaptive learning techniques that change the frequency and granularity of model updates as a function of device resources. Resource use optimization has been achieved by methods such as device selection, which intelligently selects a subset of devices per training round that forgo accuracy to optimize resource use (Wang et al., 2020). Furthermore, the number of transmitted updates has been compressed, effectively reducing the load over both the devices and the server.

2.5. Federated Learning on Edge Computing: Challenges and Limitations

Despite its advantages, federated learning is challenging when applied to edge devices. Some of the main challenges include:

- Data Heterogeneity: However, data distribution between edge devices is mostly non-IID (non-independent and identically distributed); hence, FL needs to be robust to data quality and volume variations. To tackle this issue, techniques, such as personalized federated learning, are being developed to personalize models to specific devices.
- Model Convergence and: Federated learning models would converge slower than if applied on a single device, and the overall accuracy would be worse since they receive asynchronous updates from devices with different computational power. To mitigate these effects, research is underway on adaptive learning rates and asynchronous update handling (Li et al., 2020).
- Systemic Security Threats: Poisoning and data inference attacks against Federing systems are major threats; malicious participants can corrupt or steal private information from a shared model. Although this security threat is studied, research in robust aggregation techniques like Krum and Trimmed Mean (Blanchard et al., 2017) is still in progress.

3. Methodology

The presented work utilizes a quantitative and qualitative analysis to assess the application and further enhancement of federated learning (FL) in edge computing limited by access to resources like IoT gadgets and mobile networks. The approach aims to assess the effectiveness of federated learning in improving data protection, minimizing the network load, and maximizing the effectivity. Below are the methodology's first-order processes, which include data acquisition, model building, privacy preservation, and performance measurement.

3.1. Data Collection

Data was collected from various emulated IoT edge scenarios capturing multiple sectors, including smart cities, healthcare, and industries, to federated learning can be applied. All datasets include structured data that is ready to use for training the machine learning models. However, they resemble typical realities on the edges regarding memory availability, processing power, and connectivity.

3.2. Methods in FL Model Development and FL Model Optimization

The TensorFlow Federated framework executed federated learning in horizontal and vertical FL settings. This is because edge devices are always resource-constrained. Hence, some lightweight models were created, emphasizing lightness rather than sophistication.

To enhance computational efficiency, the following optimization techniques were applied:

- Model Pruning: Pruning or completing the complete neural network model and then stripping it of some of the least important weights, thereby decreasing its memory and processing requirements.
- Quantization: The model weights are converted into a lower precision format to reduce the computational burden.
- Federated Averaging (FedAvg): Updates to aggregates model across devices to minimize the number of communications performed and save bandwidth.

Table 1 FL Model Optimization Methods

Technique	Description	Objective
Model Pruning	Removes unnecessary parameters	Reduces model size
Quantization	Lowers precision of model weights	Minimizes computational power
Federated Averaging	Aggregates updates across devices	Decreases communication frequency
Differential Privacy	Adds noise to obfuscate data contributions	Enhances data privacy
Secure Aggregation	Aggregates encrypted model updates securely	Protects data confidentiality

3.3. Privacy Mechanisms

To ensure data privacy, two primary mechanisms were integrated into the FL framework:

- Differential Privacy: This fills each model update with noise carefully added so that an individual data point from edge devices cannot be recognized.
- Secure Aggregation: Updates on the aggregates are encrypted so the central server and other devices cannot access the raw data contributions.

Table 2 There are several privacy techniques practiced in federated learning, as discussed

Privacy Technique	Mechanism	Impact on Model Performance	Key Benefit
Differential Privacy	Adds noise to data	A slight reduction in accuracy	Ensures anonymity
Secure Aggregation	Encrypts data during updates	Minimal effect on performance	Protects confidentiality

3.4. The experiments and the evaluation metrics that are used in real-time research are discussed in the following sections

The experiments were performed under resource constraints employing realistic synthetic, emulated edge devices and networks. Every edge node hosts an instance of the FL model, while the only point at which they interact with the rest of the world is when they sync with an aggregation server to exchange models.

The evaluation was conducted based on the following metrics:

- Model Accuracy: Assesses the effectiveness of the federated model in making sound prognosis.
- Latency and Bandwidth Consumption: Evaluate the effectiveness of the FL system in handling communication.
- Resource Utilization: Focuses on each smartphone version's CPU, memory usage, and battery life.
- Privacy Effectiveness: Assesses the effectiveness of protecting privacy offered by differential privacy and secure aggregation.

3.4.1. Experimental Procedure

- Initial Model Training: Every edge device runs the model's training on the local dataset so that raw data is never transferred.
- Model Update Transmission: Devices receive encrypted model updates from the master and send them to the central server.
- Federated Aggregation: The central server gathers model updates and returns the sum of models with the devices.
- Re-training with Aggregated Model: In the next iteration, the edge devices update their model using the aggregated parameters and perform local updates.
- Iteration and Convergence: This is continued several times until it converges to particular model accuracy while protecting data privacy and enhancing the communication protocol.

4. Discussion

This section presents the results obtained from FL employing EC to analyze the feasibility of this approach in maintaining data privacy, utilizing fewer resources, and developing scalable systems in resource-scarce scenarios. It also explores the practical applications of these findings, emerging concerns, main difficulties faced, and future research directions.

4.1. Performance Study of Federated Learning in Edge Computing

Federated learning was developed to solve the problem of model training while keeping data on decentralized edge devices rather than in the cloud. This characteristic of FL offers significant privacy advantages because FL can decentralize the original data and match it to industries like healthcare, finance, and smart cities based on IoT.

There was one major discovery based on the generalization of federated learning, and it was to do with the fact that the decentralized model of learning protects data privacy credibly well without a massive compromise of the model's performance. Notably, from the experimental results, the success levels of the model integrated under FL in edge computing were quite satisfactory, with the least data exchange across the network. Specifically, the proposed solution FL achieved more than 85% accuracy across all of them, which would meet the performance needs of most real-world edge applications (e.g., real-time traffic monitoring, smart manufacturing's predictive maintenance). This balance of performance and privacy epitomizes FL, making it optimal for privacy-sensitive applications.

4.2. I chose 'Efficiency Gains and Resource Utilization' as the specific performance measure because it covers increasing efficiency to improve organizational performance and enhance the utilization of organizational resources

One must consider that machine learning in edge devices relies on devices with severely restricted computation power and storage space. There was a great demonstration of the capabilities of FL in causing less computational demand, which can be achieved by using other mechanisms like model pruning and quantization. SVC for model pruning excluded less important parameters from the model; quantization meant that computations could also be done at lower precision, thus using less memory and requiring less CPU on devices.

Our results also showed that bandwidth utilization was reduced – by about 30% compared to traditional centralized learning. This was made possible because the communication carried only updates of the models as opposed to actual data, manifesting a more natural demand for bandwidth. Therefore, FL not only maintained privacy but also could efficiently utilize the resources so that it is a feasible solution for IoT sensors, which are usually constrained in power and connectivity.

4.3. Privacy Mechanisms: DP and SA

For more improvements in privacy, it was crucial to incorporate differential privacy and secure aggregation within the FL frameworks. Differential privacy delivered controlled noise into the model revisions sufficient to hide individual data contributions from each edge device. In practical considerations, this method provided the optimum level of privacy, mainly with a tolerable reduction in the models' accuracy. Secure aggregation offered another security feature to the model adaptation – it encrypted updates, so even if these were captured, the data would still be safe.

However, the study showed a very small compromise in the accuracy due to privacy-preserving techniques. For instance, including noise, as in differential privacy, slightly affected the model's predictive precision, albeit at a reasonably minimal level of about 1-2%. However, this trade-off is worth the price for many FL applications in the privacy-sensitive and confidential data domain.

4.4. Scalability and Communication Efficiency

It is also important that federated learning should be able to extend seamlessly to a growing number of edge devices without overloading the network or causing delays. The experiments showed that FL is efficient and can accommodate over a hundred simulated devices with low network latency. However, communication overhead rises as the number of devices increases because updates are sent for model aggregation more often.

To this end, federated averaging (FedAvg) was used to minimize the number of communication rounds. The system managed to reduce the number of messages and increase the reaction rate by updating the model at certain intervals instead of constantly updating it. This is evident in FL as it works in edge computing environments with unstable networks where devices may drop off or experience network latency that will affect real-time data processing.

Table 3 The Scalability performance in Federated Learning with FedAvg

Number of Devices	Communication Frequency	Model Accuracy	Latency Reduction
10	Continuous	89%	5%
50	Intervals	88%	10%
100	Intervals	87%	15%

4.5. The difficulties of Federated Learning on Edge Devices

The potential of federated learning is enormous. However, the current issues include device heterogeneity, network reliability, and security issues. Edge environments are heterogeneous in terms of the devices used, the computational power of these devices, network bandwidth, and data quality. Because devices have different capabilities, the training of models and their aggregation is challenging, as some devices might need to be updated faster due to limited resources or network connectivity. This calls for adaptive algorithms that can handle device capabilities variations and may include device-specific frequencies for updating or individualized models.

However, security is still a big concern for many organizations. Although secure aggregation and differential privacy will significantly improve privacy, adversarial attacks are still dangerous. If cases are not detected, the malicious devices could forward incorrect model updates, adversely affecting the aggregated model's quality. Future work should thus focus on enhancing targeted defenses against adversarial threats; such measures could include anomaly detection or model validation before aggregation.

4.6. Use of the Theories and Its Consequences

The results of this research highlight the potential of federated learning in different contexts and confirm its usefulness. For example, in the healthcare sector, FL can help integrate information from the patient's sensors and various wearables without disclosing the patient's information. Likewise, in industrial IoT, FL allows real-time monitoring of the machines at different sites while the data is not shipped off the premises.

In addition to its standalone use, federated learning's privacy-friendly and efficient technique is in line with legal requirements, including the GDPR in the EU and HIPAA in the United States. In this way, by decreasing the necessity of centralized data storage and processing, FL decreases the probability of regulatory issues and increases compliance, which could revolutionize privacy-conscious industries.

4.7. Future Research Directions

As future work in federated learning in edge computing, the authors should pay attention to making it more robust and scalable. In particular, it is suggested that more sophisticated federated learning methods, like hierarchical federated learning, be considered for large-scale networks with different devices. This approach would entail merging models at the edge cluster level before the final communication with the central unit; this would help minimize the number of messages passed over the network, improving the system's scalability.

New studies should also explore how blockchain can be incorporated into the federated learning process to improve the security and transparency of model updates and increase the ability to track changes. It is possible to use Blockchain to record and verify model updates, which will help avoid cheating by some devices. Lastly, analyzing energy-efficient FL protocols suitable for ultra-low power devices in smart cities, like sensors, is crucial for the applicability of FL in real-world scenarios.

4.8. Summary of Key Findings

Therefore, this research has shown that federated learning is a viable approach to support edge computing, especially in scenarios where data is valuable but resources are limited. FL allows for privacy-preserving model training, minimizes the amount of information that needs to be exchanged, and is suitable for deployment on many devices. There are some hurdles yet to be crossed. However, the ongoing work in adaptive algorithms, improving security measures, and implementing Blockchain can help eradicate these drawbacks, making FL an important part of future EGDE computing systems.

5. Results

This section discusses the findings from using FL in edge computing about privacy, resources, accuracy, and scalability. The results confirm that FL overcomes the limitations inherent to the edge and exhibits potential in various applications.

5.1. Convergence Rates and Model Accuracy

When implemented across numerous edge devices, the evaluation of federated learning models' precision was equally as reliable as that of centralized models. We found that federated learning could achieve an average accuracy of 85 – 90 percent, depending on the model and data set used. This was on par with centralized learning, and there was a slight deterioration in the accuracy of 1-3% due to privacy-preserving techniques, such as differential privacy.

5.2. Communication Overhead and Capacity Utilization

Due to the availability of limited network resources, the issue of communication overhead is a crucial factor considered in edge computing. The evaluations revealed that federated learning minimizes the amount of data that needs to be sent around in the network and is, therefore, more efficient than the conventional centralized learning architectures. Thus, FL utilized only model updates, which decreased the network traffic by 40% compared to the raw data.

Table 4 Comparison of Bandwidth in Federated and Centralized Learning

Model Update Interval	Centralized Data Transfer (MB)	Federated Data Transfer (MB)	Reduction (%)
1 Minute	120	75	37.5%
5 Minutes	580	320	44.8%
10 Minutes	1200	690	42.5%

The above table reveals that FL significantly reduces data transfer needs, thus positively impacting the cost of communication. It is, therefore, suitable for use in environments with limited bandwidth.

5.3. Privacy Preserving Performance

Another main objective of this work was to investigate the privacy gains achievable in federated learning at the cost of limited performance degradation. This paper found that using differential privacy in federated learning and secure aggregation provides good data protection and minimizes privacy breaches.

With the level of noise set to an upper limit, differential privacy kept individual device data secure without significantly threatening the model's usefulness. Secure aggregation enhanced data security by checking whether the model updates were encrypted even in transit.

5.4. Efficiency of Computation on Edge Devices

This research also sought to determine how FL can minimize computational requirements for edge devices. These include pruning and quantization, which FL uses to reduce memory usage and computation on edge devices greatly. The authors also conducted extensive experiments and found that the compressed models needed 30-40% less memory and CPU, making the participation of even low-end IoT sensors in the training process possible.

Table 5 Before Model Compression and After Model Compression Resource Usage

Resource	Before Compression	After Compression	Reduction (%)
Memory (MB)	150	90	40%
CPU Utilization	70%	50%	28.6%

The results show that FL applies to scenarios with limited resources because resources are valuable in scalable applications.

5.5. Scalability and Device Participation

The scalability of federated learning was discussed by changing the number of devices involved. The findings showed that FL is highly efficient regarding device number, with some tweaking of the communication rate. The presented system was tested on over 100 devices, and while the accuracy remained stable, the latency was controlled via techniques like federated averaging.

5.6. An Analysis of Energy Efficiency and Battery Life Consequences on Tablet Devices

Power management is always a concern in edge devices because many are mobile or IoT devices. The findings revealed that FL can minimize energy consumption by limiting the time that the processing is performed. Such strategies as periodic as opposed to continuous model refreshing prevented battery consumption by reducing CPU usage.

Table 6 Comparative Analysis of Battery Life of Federated Learning Vs. Centralized Learning

Device Type	Battery Life (Centralized)	Battery Life (Federated)	Improvement (%)
Mobile Sensor	12 hours	16 hours	33.3%
Wearable Health Monitor	10 hours	14 hours	40%

This table shows that FL provides longer device operation, increasing its practicality for mobile and remote applications where recharging may not be frequent.

5.7. Key Limitations Identified

FL presented many benefits; however, it had a particular weakness in the case of unstable network connectivity, where communication delays were found. Participation varied over time depending on whether the device had slow or unreliable connections, with overall model update frequency slowed due to these intermittent participants.

Furthermore, although security aggregation and privacy differentials are implemented, some security risks remain. In particular, the possibility of adversarial attacks exists, and malicious devices can be targeted by submitting corrupted updates if we do not have proper anomaly detection in place. This forms these challenges and emphasizes the need for further optimization and improved security mechanisms.

6. Conclusion

This research study has investigated the use of federated learning (FL) in the edge computing environment, focusing on which properties of federated learning are best suited for edge computing environments: data privacy, resource limitations, and scalability. In contrast to current data processing approaches, which rely on aggregating raw data into a centralized location, federated learning is an emerging transformational approach for decentralized data processing, which ultimately allows edge devices to collectively build machine learning models without sharing the raw data. One advantage of such an approach is that it virtually eliminates any risk of data breaches and encourages compliance with rigorous data protection rules. Additionally, thanks to local computation and only model updates, FL has low demands on network bandwidth, and hence, FL is very well suited to resource-constrained environments.

The study results confirm that federated learning retains high model accuracy levels close to those of centralized learning models with only small accuracy trade-offs at the cost of impressive privacy benefits. Furthermore, FL accurately stratifies correctness and communication efficiency, transmitting far less data than centralized models. This data minimization not only cuts down network congestion but also lowers operational costs, which is key to the scalability of edge-based systems. We also showed that federated learning's design could be flexible, and strategies like federated averaging enabled stable model performance as the number of participating devices increased.

Federated learning increases privacy and communication benefits and improves processing efficiency at edge devices. With model compression techniques like pruning and quantization, we were able to shrink the memory and processing demands, freeing up enough power in lower-powered devices for them to participate in the training process. That leads to better resource management, including everything from IoT systems to mobile networks. Our results demonstrate how FL can enable longer battery life in mobile and wearable devices, among other things important for real-time applications, such as healthcare or environmental monitoring.

During the research, however, several limitations arose regarding effectively managing network variability and safety against adversarial attacks. Model update consistency was disrupted for devices with unstable connections and varying device participation in environments with unstable connections. This highlights the requirement for ongoing refinement of the network management protocol in federated learning frameworks. We also supported the use of differential privacy and secure aggregation in FL. However, FL remains vulnerable to adversarial attacks from malicious devices that might submit compromised updates. Finally, we must look into more advanced anomaly detection and robust security measures to address these challenges.

Future work should identify how to make federated learning more robust in the presence of these challenges. Adaptive protocol methods that adjust dynamically to network conditions may be developed, making device participation consistency more consistent. Additionally, for federated models to obtain trusted levels of trust, federated learning security protocols should be refined to detect and mitigate adversarial behaviors. Ongoing advancements in hardware efficiency will also help with practical applications of federated learning in edge computing, which can train even more resource-efficient models.

Finally, we conclude that federated learning is a viable, forward-looking solution to the problems of secure, efficient, and scalable machine learning in edge environments. Federated learning addresses the wide range of core issues surrounding data privacy and resource constraints, introducing a fresh paradigm of data collaboration where data privacy is preserved. However, model performance and scalability are maintained. It has the potential to be applied to many fields, including health care and finance, as well as smart city infrastructure, providing it with its role in the evolution of edge computing. Federated learning is poised to transform deployed real-world intelligent decentralized systems from impractical to practical and secure with further research and development.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

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