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FEDERATED EDGE LEARNING FOR REAL-TIME IOT DATA PROCESSING

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ABSTRACT

Federal Learning (FL) recently attracted considerable attention as a promising approach to addressing data protection and scalability issues in industrial Internet of things (IIOT) enclosures, based on its powerful data protection capabilities. However, the effectiveness of the continuously developed clear streaming data on FL-enabled IIOT architectures is still under burden. Such data features can affect the accuracy of the model and may interfere with performance. To address the difficulties, associated with gaining dare of learning from streaming data within the IIOT framework for FL operations. Identify two main issues related to this context. It's slow convergence and catastrophic forgetting during training. Essentially, there is a simple but effective training strategy that uses some similarities to exchange older data samples with more relevant ones during iterative training. This method improves model accuracy, accelerates convergence, and reduces the risk of catastrophic forgetting. An extensive case study demonstrates the effectiveness of the proposed approach.This research provides valuable insight into overcoming key challenges and paves the way for the development and improvement of next-generation IIOT applications.

Keywords: Federal learning, Industrial Internet of Things.

INTRODUCTION

The Industrial Internet of Things (IIOT) plays an important role in the design of the Fourth Industrial Revolution, transforming traditional manufacturing processes by allowing interconnected devices to improve efficiency and productivity [1]. As these networks grow, the demand for intelligent data processing frames is becoming increasingly important for managing huge amounts of generated information [2]. The integration of artificial intelligence (KI) in IIOT devices further advances this area, enabling localized model training [3,4] and supporting effective operation in a variety of applications, such as smart homes, urban infrastructure, health systems [5,6] and intelligent transport [7]. IIOT scalability

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issues. FL ensures that FL ensures strong protection of data protection while maintaining scalability by collaboratively training global models without sending raw data. In particular, IIOT streaming data refers to real-time data that is continuously generated by the device during operation. This includes examples such as live video feeds for surveillance systems and current data traffic data from Smart Mobility Solutions. In contrast to static data records, streaming data continues to be developed, making it difficult to model with solid-state data distribution patterns. Key technologies that will drive this transformation include MEMS (microelectromechanical systems), sophisticated sensor systems, next-generation wireless communications and networks. However, intensive learning frames are subject to limitations, especially when sensitive data is involved. The risks associated with cloud-based data exchange take these approaches in real-time, real-time application, data protection and data protection approaches. These are not suitable for these approaches [10].

This allows real-time and intelligent decisions in a variety of areas, including smart cities, healthcare, transportation, and industrial automation. However, the large amounts of data, speeds and various data generated by the network edge are key issues in terms of latency, privacy, bandwidth consumption and scalability.

Furthermore, the central model has been increasingly criticized for its potential to undermine user privacy and overload network infrastructure. By incorporating computing resources into edge computing, bringing computing resources closer to data sources, this approach provides an effective solution for IoT data processing in real time. Fel ensures analysis with lower latency, improved data protection, reduced network traffic, and improved scalability.

RELATED WORK

Mendes et al. [11] examined the use of neuronal network-based approaches to support lifelong learning of gradually developed complex structures. In other words, they examine how neural networks can be used to continuously learn and adapt as increasingly complex patterns or structures emerge over time. These methods allow neural networks to dynamically scale their architecture, increasing adaptability and flexibility when faced with new tasks. In contrast to traditional approaches that use models that use both old and newer data, technology is more efficient when transforming real data streams.

Polikar et al. [12] Four important criteria for incremental learning systems: (1) the ability to learn and recognize leading class within new data. (2) Ability to identify and integrate completely new classes. (3) Update the model without reusing the original old data. (4) Previous data samples have been discarded, but maintain previous knowledge.

Castro et al. [13] proposed a method based on new data and a limited subgroup of previous samples. Technology uses a special loss function that combines the loss of distillation that can maintain previous knowledge with the cross loss to learn new information.

sisinni et al. [14] extended the Internet of Things conceptand enhanced frame by introducing a 3D model.

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Zhang et al. [15] presented Deep Model Integration (DMC), a class-based incremental learning strategy. This approach first trains a new class of date models exclusively, and then fuses existing models with double distillation goals. This strategy will help you overcome the limitations in access to the original training data.

CONTRIBUTION OF THIS WORK

1.Federation Learning Integration with Edge Computing in IoT

This work suggests a new architecture that combines federated learning and edge computing to process IoT data in real time. In contrast to traditional central learning, this approach maintains data on edge devices that improves data protection and reduces latency.

2.Real-time data processing power

Introducing systems that can handle real-time processing of sensor and device data in IoT networks. This framework allows models to be formed and updated on the spot without transferring datato cloud. It is suitable for intelligent cities and autonomous systems.

3.Communication - an efficient learning framework

The task includes techniques to optimize communication costs between edge nodes and central aggregators. This includes the use of model compression, asynchronous updates, or adaptive communication intervals to allow for learning to erupt in bandwidth-limited networks**.**

4.Scalability and Adaptability

A key contribution is to show how the proposed framework adapts to the increasing number of edge devices and the uneven hardware and non-IID data distributions common in real IoT environments.

5.Improved Security and Data Protection

Work can include mechanisms for data protection management (e.g. discriminatory privacy and secure aggregation) to ensure that systems meet data protection regulations and best practices in IoT networks.

The following is a summary of the remaining portion of this paper: The introduction and related works were found in Section 1 and 2, the suggested approach is explained more information on Section 3, the simulation results are presented in Section 4, and the conclusions and future research are explained in Section 5.

PROPOSED SYSTEM

Federated Learning

Recent progress in AI and the spread of IoT devices have led to exponential data growth. Additionally, concerns about data protection and data safety are rising. In response to these concerns, FL offers practical

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solutions to overcome these challenges by promoting joint ML without affecting individual privacy. FL uses the distributed nature of data to enable local learning on IoT devices. This will promote data protection models and simultaneously promote joint intelligence. Here we set up the basic concept of FL and present some important categories of FL, particularly for IoT networks. In particular, it provides an overview of the architecture of IoT FL.

Fundamental FL Concept

Federation Learning (FL) systems within an IoT network are made up of five key units, each of which plays a key role in ensuring functionality and effectiveness. Administrator entity monitors the entire FL system between the various components that manage system integrity and security agency, and manages the management of machine developer models, model models, and machine developer models. Perform training protocols and implementation reviews to evaluate the model output of the FL framework. Some implementations can use blockchain to ensure transparency and trust. Data protection plays a central role in maintaining data protection by storing raw data on devices.

Federated Edge Learning (FEL) is a new paradigm that integrates Federated Learning with edge computing to enable efficient and data protection processing in real-world data processing over the Internet of Things (IoT). In traditional cloud-based systems, raw data generated by IoT devices is sent to centralized servers for processing, leading to high latency, increased bandwidth usage, and potential data protection concerns. FEL deals with these issues by allowing IoT devices (or edge nodes) to train local machine learning models using their own data. Only model updates such as weights and gradients are transferred to the edge server or aggregator that combines them to create a global model. This decentralized approach significantly reduces the need for data transmission, reduces latency and reduces data protection. Therefore, it is suitable for critical applications of data protection like healthcare, industrial automation. However, FEL introduces challenges such as the processing of non-IID (non-dispersed) data about devices to ensure communication efficiency, handle resource limitations on edge devices, and ensure learning processes against controversy attacks. Despite these challenges, FEL offers a promising solution for scalable, real-time, secure IoT data processing in the network .

An effective framework for federated learning applied to continuous IIOT data

Central Server manages the overall coordination of the federated learning (FL) process. Responsibilities include configuring the training environment, distributing the global model to participating nodes, determining training parameters, and initializing the model version. Each knot contributes to the FL process by training the model with its own locally generated data.

Fed Stream Pipeline

The Fed Stream pipeline consists of three main stages: model initialization, data updates, and aggregation models. The following subsections provide a detailed description of each phase of the pipeline.

Level 1: Starting

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Step 1: Parameters -setup

To assumes the task of configuring some important parameters. Based on the size of the data record, these settings have been adjusted to ensure effective training. The main goal of this phase is to determine logical, well-tuned parameter values.

Step 2: Defining Performance measures

To evaluate the performance of FedStream within the data context of IIOT streaming, accuracy is chosen as the core evaluation metric. This choice is consistent with the objective of effectively measuring model performance in a real environment.

Step 3: The earliest worldwide framework

As soon as setup is complete, the central server sends the initialized global model to all connected IIOT nodes.The serves as a basic template for federated learning and as a consistent baseline for local training on nodes.

Level 2: Data Exchange

Step 1: Continuous Data Collection During Training

In this phase, each node will always collect new data while training is in progress. In this way, the model can remain up to date, adapt to data pattern changes, and improve performance in processing the actual data stream.

Step 2: Using Similarity Pairs for Data Selection

When a new sample is received, the node uses the similarity method to find and select historical data that matches the new input. This targeting agreement ensures that only the most relevant representative previous samples will be considered for exchange.

Step 3: Filter and Temporary Buffering

As soon as similar historical data is identified, it is filtered and temporarily stored in a special buffer. This prevents these very similar samples from being used repeatedly in future training, promotes training sentence diversity and improves model generalization.

Step 4: Data Integration for Continuous Training

The filtered statements of the remaining historical data, combined with the newly collected data, form the input for the next training cycle. This approach preserves the overall data distribution simultaneously involved in new knowledge, ensuring that the model continues to be effective and rise.

Algorithm 1

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FedStream's Algorithm Input: The K clients are indexed by k; a set of training sets Dk = {(Xj, Yj)}$n^k j$=1; One set to be added to the training set DN' = {(Xi, Yi)} N' i=1; number of communication rounds T; N' data are added every S rounds; number of local epochs E; learning rate η

Output: The optimal global model ωT

Server does:

initialize global model $\omega 0$

1.for t = 1, T do

2. Mt← (random set of m clients)

3.for each client $k \in Mt$ in parallel do

4.ωt+1 k ←Client Update (k, ωt, t)

5. end for

6.ωt+1 ← wt −$\eta tkn'$ kN' $\nabla \zeta k(wt)$

7.end for

Client does:

8.function Client Update (k, ωt, t)

9. if t = S then

10.Initialize anchor indices sets C ← ∅, Dk' ← ∅. for i = 1…, N' do

11. for j = 1…, nk do pij ← ($pj|i$ + $pi|j$) ⁄2

12.C ←C∪{pij}

13. end for

14.$C1$ ←max∑nkj=1 pij

15.end for

16.Dk' = {(Xj, Yj) ∈Dk|∃pij∈$C1$, s.t. j = i(pij)}

17.Dk← (Dk −Dk') ∪DN'

18.end if

19.for each local epoch i from 1 to E do

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20.$\omega \leftarrow \omega - \eta \nabla fk(wk)$

21.end for

22.return ω to server

23. end function

Level 3: Model Aggregation

Step 1 Integrating Local Model Updates

During the entire iterative training process, each IIOT node forwards the locally updated model parameters to a central server. The server combines these updates using aggregation algorithms such as FEDAVG to generate the updated global model. This sophisticated model is redistributed to all participating nodes. In addition, strategies from level 2, namely data replacement and dynamic memory, must continue to function in detail for effective processing. These mechanisms remain active until no new data reaches a stable convergence.

Details of the Algorithm

This section containscomprehensive overview of training process and implementation. The complete procedure is Algorithm. When new data is generated, similarity technology is used to compare it with existing data. Historical samples with high similarity to the new data will be placed aside and excluded from future training. This approach helps maintain the freshness and diversity of your data throughout your training.ClientWhen new data is introduced into the training process, initialize the set. For each new data point, compute its pairwise similarity with every data point in the original dataset. Update the setwith these similarity scores. Then, select the tophighest similarity values fromand identify the data points to update the set. During each training, use the updated dataset to train the local model, adjust the model parametersand send the updated parameters back to the central server for aggregation.

Federated learning framework for IIOT data

Data RecordsTo assess the effectiveness of the proposed FedStream framework, we perform extensive simulation experiments on the data records CIFAR-10 and MNIST. During the training phase, all data records are split into two main components. Client Page Data: Consists of 40,000 samples consisting of MNIST CIFAR-10 or 50,000 samples. The Dirichlet Distation concentration parameter is 0.3. This approach guarantees non-IID (same distributed as independence) data partitions, reflecting better learning scenarios for real federations. There are 32 filters and the second filter has 64 filters. Each folding layer continues from the Activation function. Level: The network closes with two fully connected layers. The first layer contains 512 neurons. The second layer outputs 10 neurons corresponding to the classification category.

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Performance Analysis

ComparativeEvaluation of FedStream and FedAvgTo trace the effectiveness of the proposed system FedStream framework, we conduct a comparative analysis against the classical FedAvg algorithm, which serves as the baseline.

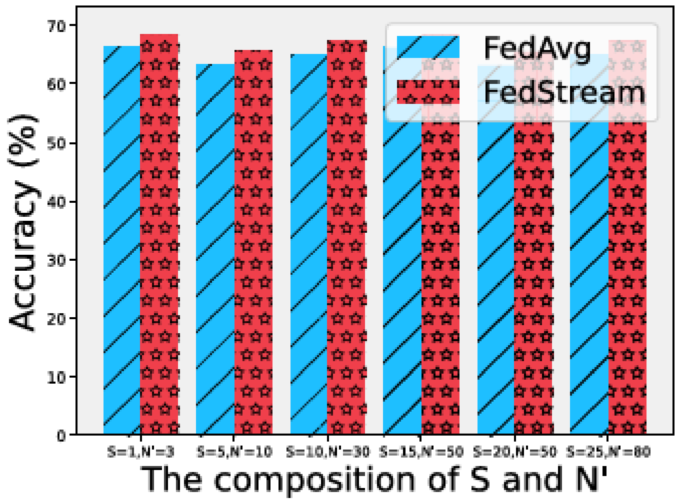

Fig. 1. Performance comparison betweenFedAvg andFedStream on the CIFAR-10 dataset under varying data addition intervals S and different sizes of newly added data N.

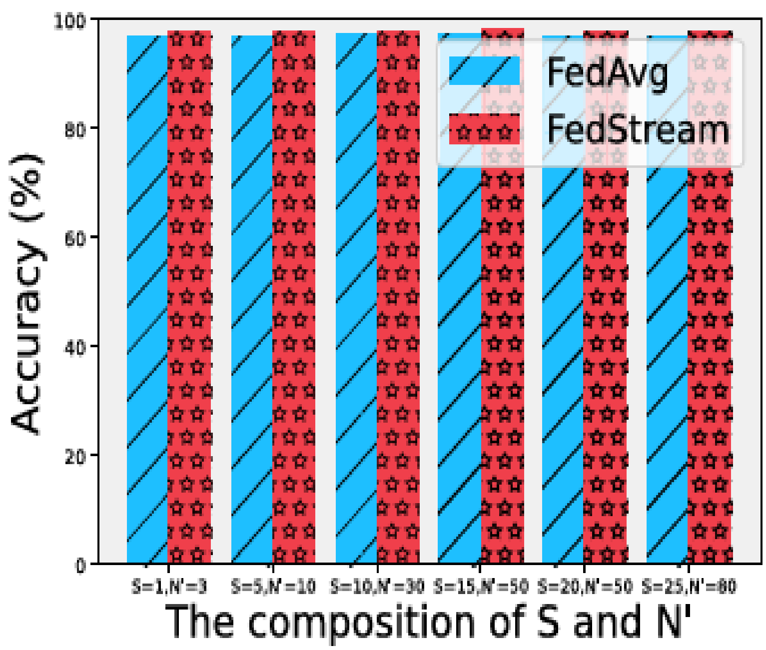

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Fig. 2. Performance comparison between FedStream and FedAvg on the MNIST dataset across various data addition intervals S and different sizes of added data N.

As depicted in Figures 1 and 2, under various parameter settings (e.g., values of S and N), FedStream consistently outperforms the standard FedAvg approach.These results highlight the superior performance of FedStream, particularly in its ability to address and reduce the negative impact of data heterogeneity and streaming dynamics in federated learning environments.

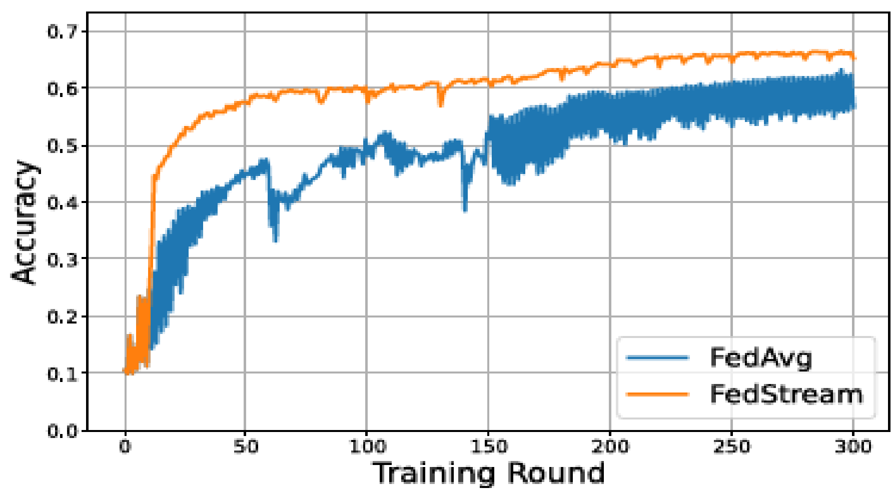

Fig. 3. Training performance comparison between FedStream and baseline methods on CIFAR-10 dataset.

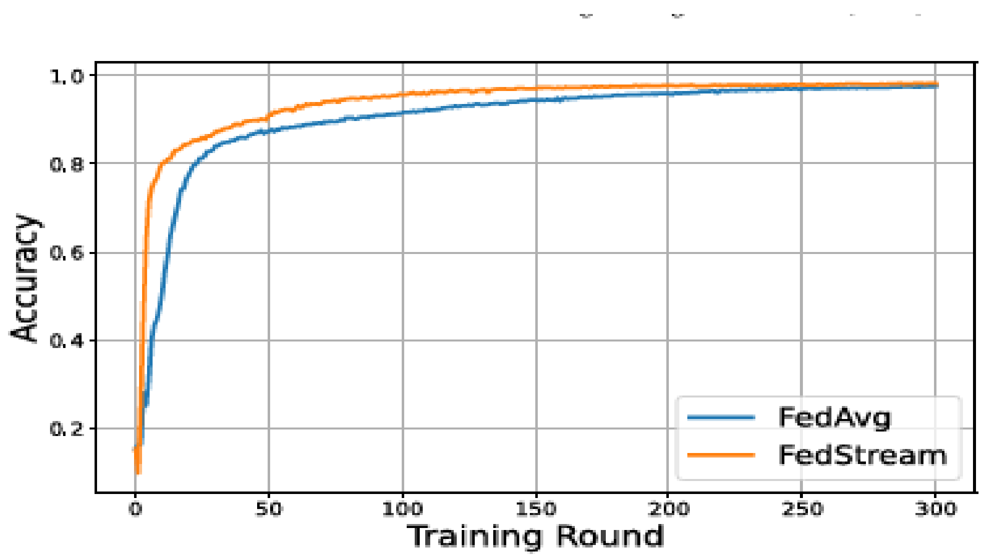

Fig. 4. Comparison of training performance between FedStream and baseline methods on the MNIST dataset.

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Table1 Experiment resultson CIFAR-10dataset.

(S, N)	(6,11)	(6,21)	(6,31)	(6,41)
ACC%	66.2	67.6	64.9	69.3
(S, N)	(6,40)	(11,49)	(25,40)	(15,40)
ACC%	67.1	45.9	45.8	56.0

Comparison between FedStream and FedAvgCurrentlyfocus on comparing the behaviour of the proposed FedStream with the traditional FEDAVG algorithm. The figure shown in 3 and 4, FedStream exhibits significantly faster convergence rates for both CIFAR 10 and MNIST datasets. For CIFAR 10 datasets, FedStream is relatively stable during MNIST dataset, convergence, convergence, convergence, convergence, convergence, convergence, transformation after about 50 training rounds. This indicates a strong convergence of the algorithm during the early training stage. In the CIFAR-10, the model begins to stabilize only after about 150 laps, and stability is observed at about 50 rounds in the MNIST.

Ablation Experiments

To further assess the effectiveness of the proposed framework, two sets of ablation studies were conducted using CIFAR 10 and MNIST data sets. In these studies, we examined the effects of two important hyperparameters: N^2 (number of new data) and S (data deduction interval). In the first sentence of the experiment, we kept the data ad data interval constant and evaluated how the newly added data changes affect the model output. In the second statement, we set ns^2 to see how different values of precision affect them. The results of these experiments are presented in Tables 1. The findings show that increasing the data size N'does not significantly affect the performance of the FedStream framework—the model maintains stable accuracy across all tested values. This demonstrates the robustness of the method under varying data volume conditions. Similarly, when adding 50 data samples per instance and varying the period S, the model continues to perform consistently, with minimal fluctuations in accuracy. These results further validate that FedStream is capable of sustaining high accuracy and stability, even when data is introduced at different rates.

Future Research

Federation Edge Learning (FEL) of real-time IoT data processing provides several exciting future research opportunities to improve privacy, efficiency and scalability of distributed systems. One important direction is to optimize federated learning models to reduce latency and improve decision-making processes in real time in IoT environments, particularly through the development of optical models that can be trained

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efficiently on resource-related edge devices. Researchers should also focus on improving data protection prescribing techniques such as secure multi-party calculations and different privacy to ensure that sensitive IoT data is still protected and enable collaborative learning across devices. Additionally, there is an increasing need for dynamic resource allocation strategies that take into account the non-uniform nature of IoT devices for optimal performance, compensating calculations, memory and communication resources. Particularly in the detection of anomalies and other important IoT tasks, real-time data power processing requires continuous updates of federation models, so it is important to develop algorithms that effectively process real-time data without affecting safety or accuracy. Furthermore, scalable solutions for managing large numbers of devices in federated learning systems, particularly through edge cloud hybrid architectures, are important that FEL systems can grow with the expansion of IoT networks. Therefore, research in this field will likely focus on developing more robust, energy efficient, safe federated learning frames that may work in a variety of dynamic IoT environments.

CONCLUSION

This work examined a federated edge learning framework specifically developed in real time for IoT data processing, addressing important issues such as data heterogeneity, privacy retention, and low latency in dynamic environments. The proposed FedStream approach improves traditional spring learning with adaptive data exchange strategies and dynamic training mechanisms for continuous data streams in industrial scenarios. Streaming data variation. The ablation studies also confirmed frame stability at various hyperparameter settings, enhancing practicality in actual deprivation. Future work can examine integration of more complex canteen scenarios to further improve multimodal sensor data, energy efficient optimization, and aspect system information.

REFERENCE

[1] D.C. Nguyen, M. Ding, P.N. Pathirana, A. Seneviratne, J. Li, H.V. Poor, Federated learning for internet of things: a comprehensive survey, IEEE Communications Surveys & Tutorials 23 (3) (2021) 1622–1658.

[2] M.H. ur Rehman, I. Yaqoob, K. Salah, M. Imran, P.P. Jayaraman, C. Perera, The role of big data analytics in industrial internet of things, Future Generation Computer Systems 99 (2019) 247–259.

[3] J. Kang, Z. Xiong, D. Niyato, S. Xie, J. Zhang, Incentive mechanism for reliable federated learning: a joint optimization approach to combining reputation and contract theory, IEEE Internet of Things Journal 6 (6) (2019) 10700–10714.

[4] M.S. Hossain, G. Muhammad, Cloud-assisted industrial internet of things (iiot)– enabled framework for health monitoring, Computer Networks 101 (2016) 192–202.

[5] A. Tripathi, N. Sindhwani, R. Anand, A. Dahiya, Role of iot in smart homes and smart cities: challenges, benefits, and applications, in: IoT Based Smart Applications, Springer, 2022, pp. 199–217.

Received: August 07 ,2025

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[6] M. Al-Hawawreh, M.S. Hossain, Federated learning-assisted distributed intrusion detection using mesh satellite nets for autonomous vehicle protection, IEEE Transactions on Consumer Electronics 70 (1) (2024) 854–862.

[7] T. Zhang, L. Gao, C. He, M. Zhang, B. Krishnamachari, A.S. Avestimehr, Federated learning for the internet of things: applications, challenges, and opportunities, IEEE Internet of Things Magazine 5 (1) (2022) 24–29.

[8] Wei Xian, Kan Yu, Fengling Han, Le Fang, Dehua He, Qing-Long Han, Advanced manufacturing in industry 5.0: A survey of key enabling technologies and future trends, IEEE Trans. Ind. Informat. (2023).

[9] Hao Ran Chi, Chung Kit Wu, Nen-Fu Huang, Kim Fung Tsang, Ayman Radwan, A survey of network automation for industrial internet-of-things towards industry 5.0, IEEE Trans. Ind. Informat. (2022).

[10] Qinbin Li, Zeyi Wen, Zhaomin Wu, Sixu Hu, Naibo Wang, Yuan Li, Xu Liu, Bingsheng He, A survey on federated learning systems: vision, hype and reality for data privacy and protection, IEEE Trans. Knowl. Data Eng. (2021).

[11] J.A. Mendez, E. Eaton, Lifelong learning of compositional structures, arXiv preprint arXiv:2007.07732 (2020).

[12] R. Polikar, L. Upda, S.S. Upda, V. Honavar, learn++: an incremental learning algorithm for supervised neural networks, IEEE transactions on systems, man, and cybernetics, part C (applications and reviews) 31 (4) (2001) 497–508.

[13] F.M. Castro, M.J. Marin-Jimenez, N. Guil, C. Schmid, K. Alahari, End-to-end incremental learning, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018.

[14] E. Sisinni, A. Saifullah, S. Han, U. Jennehag, M. Gidlund, Industrial internet of things: challenges, opportunities, and directions, IEEE Transactions on Indus trial Informatics 14 (11) (2018) 4724–4734.

[15] J. Zhang, J. Zhang, S. Ghosh, D. Li, S. Tasci, L. Heck, H. Zhang, C.-C.J. Kuo, Class-incremental learning via deep model consolidation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 2020.

[16] C.B. Mawuli, L. Che, J. Kumar, S.U. Din, Z. Qin, Q. Yang, J. Shao, Fedstream: prototype-based federated learning on distributed concept-drifting data streams, IEEE Transactions on Systems, Man, and Cybernetics: Systems (2023).

[17] A. Sari, A. Lekidis, I. Butun, Industrial networks and iiot: now and future trends, Industrial IoT: Challenges, Design Principles, Applications, and Security (2020) 3–55. [15] A. Mitra, H. Hassani, G.J. Pappas, online federated learning, in: 2021 60th IEEE Conference on Decision and Control (CDC), IEEE, 2021, pp. 4083–4090.

Received: August 07 ,2025

Volume 38 No. 5 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[18] G. Wei, X. Li, Knowledge lock: overcoming catastrophic forgetting in federated learning, in: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, 2022, pp. 601–612.

[19] Q. Li, Y. Diao, Q. Chen, B. He, Federated learning on non-iid data silos: an experimental study, in: 2022 IEEE 38th International Conference on Data Engineering (ICDE), IEEE, 2022, pp. 965–978.

[20] H. Wang, Z. Kaplan, D. Niu, B. Li, Optimizing federated learning on non-iid data with reinforcement learning, in: IEEE INFOCOM 2020-IEEE Conference on Computer Communications, IEEE, 2020, pp. 1698–1707.

[21] Y. Liu, S. Garg, J. Nie, Y. Zhang, Z. Xiong, J. Kang, M.S. Hossain, Deep anomaly detection for time-series data in industrial iot: a communication-efficient on device federated learning approach, IEEE Internet of Things Journal 8 (8) (2020) 6348–6358.

[22] Y. Zhao, H. Jiang, Y. Qin, H. Xie, Y. Wu, S. Liu, Z. Zhou, J. Xia, F. Zhou, et al., Preserving minority structures in graph sampling, IEEE Transactions on Visualization and Computer Graphics 27 (2) (2020) 1698–1708.

[23] M. Riemer, I. Cases, R. Ajemian, M. Liu, I. Rish, Y. Tu, G. Tesauro, learning to learn without forgetting by maximizing transfer and minimizing interference, preprint arXiv:1810.11910 (2018).

Received: August 07 ,2025