ISSN: 2096-3246
Volume 58, Issue 02, June, 2026

IMPROVING COMPUTATIONAL EFFICIENCY IN FEDERATED LEARNING: APPLICATIONS IN MACHINE LEARNING AND DATA MINING

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Abstract
Federated Learning (FL) has emerged as a promising distributed machine learning paradigm that enables multiple devices to collaboratively train models without sharing raw data, thereby preserving privacy and enhancing data security. Despite its advantages, the practical deployment of FL is constrained by several computational challenges, including high communication overhead, intensive local computation, energy consumption, memory limitations, and statistical heterogeneity caused by non-IID data distributions. These issues are particularly critical in resource-constrained environments such as Internet of Things (IoT) devices, edge computing systems, and TinyML platforms.This survey presents a comprehensive review of recent advancements in improving computational efficiency in federated learning, with a focus on machine learning and data mining applications. The study analyzes 60 research articles published between 2022 and 2026 and examines key optimization techniques, including model compression through pruning, quantization, and knowledge distillation, feature selection and dimensionality reduction methods, gradient sparsification, clustered federated learning, and privacy-preserving mechanisms such as differential privacy and homomorphic encryption. The reviewed literature demonstrates that these approaches can significantly reduce communication costs, accelerate model convergence, and lower energy consumption while maintaining acceptable predictive performance. In many cases, communication overhead is reduced by 30–70%, with only minor accuracy degradation compared to centralized learning models.The survey further highlights the effectiveness of hybrid approaches that integrate clustering, compression, and sparsification strategies to address heterogeneity and scalability challenges. However, issues related to robustness, privacy-utility trade-offs, and cross-domain generalization remain open research problems. The findings emphasize the importance of computational efficiency for enabling scalable, practical, and sustainable federated learning systems in privacy-sensitive and resource-limited environments.

Keywords: Federated Learning, Computational Efficiency, Model Compression, Feature Selection, Communication Efficiency, Privacy-Preserving FL, Edge Computing, Data Mining, Non-IID Data

1. Introduction

Federated Learning (FL) has been gaining prominence quite fast as a decentralization method of ML, which enables different clients to develop one global model without leaking any of their private information to one another (Luzón et al., 2024). Even though it was invented with a purpose of solving the problem of data privacy in a distributed environment (Luzón et al., 2024), federated learning has proved to be useful in other fields, including medicine, mobility apps, IIoT and data mining. Despite all of the benefits that can be provided by federated learning, it brings a number of challenges that limit the usage of this technology (Villegas-Ch et al., 2024). The main obstacles associated with FL include the following: high communication cost for transferring data between client devices and a central server, high computation cost required by the devices, high energy consumption, lack of available memory space, and bad performance of systems with the presence of non-IID data distributions (Jung et al., 2024), It should be noted that when dealing with TinyML and IoT systems, these issues are even more critical as client devices suffer from poor computational capabilities, weak battery, and bandwidth capacity. (Borazjani et al., 2026). However, within the scope of TinyML and IoT platforms, these drawbacks are much more significant, considering that the hardware is constrained by computing, battery, and network capacities. On the other hand, during data mining operations where high-dimensional data sets are being used, these drawbacks could result in expensive and time-consuming processes. Therefore, enabling federated learning for its practical application in large scale (Dantas et al., 2024), privacy-preserving machine learning and data mining problems has made enhancing computational efficiency a highly significant research direction. Some of the latest efforts on this topic have focused on exploring various solutions, ranging from different compression methods (Bibi et al., 2024) (such as pruning, quantization, and knowledge distillation), efficient feature selection algorithms (Mahanipour & Khamfroush, 2025), (Gad et al., 2024) to solutions such as gradient sparsification and clustering aggregation (Kim et al., 2024).

The survey study tries to provide an extensive review on the most up-to-date approaches that could enhance the computational performance of federated learning, especially those pertaining to the machine learning and data mining application fields. As opposed to the prior studies concentrating solely on either theoretical aspects or specific subproblems, this study brings together empirical evidence derived from 60 relevant sources (mostly from the years 2022-2026) retrieved through Google Scholar searches and analyzes the success of the techniques in question in lowering communication overhead, computation complexity, and power consumption rates alongside their influence on the accuracy, convergence rate, and robustness of algorithms employed. In what follows, this paper will be structured as follows: the background and basics of federated learning efficiency will be introduced in Section 2; Section 3 will present a detailed classification of efficiency-related methods; regional and application-based implementations will be covered in Section 4. Next, the effectiveness of the methods will be analyzed in Section 5, followed by Section 6 dedicated to comparative analysis and Section 7 devoted to discussion of trends. Finally, Section 8 will focus on major challenges while Section 9 will bring conclusions.

2. Background and Foundations

The Federated Learning approach is a type of machine learning approach that allows multiple clients to train their global model in a distributed fashion by the help of a central server, without transferring any data between the clients themselves (Jung et al., 2024; Villegas-Ch et al., 2024). Contrary to conventional centralized learning techniques, in which all data are collected at one server for learning purposes, FL relies on locally trained updates on each client device and aggregates these updates on the server, using algorithms such as FedAvg that involve weighted averaging. Although such an approach is highly secure, it comes with several technical difficulties (Borazjani et al., 2026).

Efficiency of FL relies on four important criteria. The goal of communication efficiency is to minimize the amount of bandwidth and number of iterations involved in updating the model. Efficiency in computation and local training refers to minimizing the workload of each individual device. The latter two aspects (energy efficiency and memory efficiency) are especially crucial in the context of TinyML and edge devices due to their stringent resource requirements (Luzón et al., 2024). Finally, statistical efficiency deals with the problems associated with the non-IID distribution of data between the clients.

Federated Learning (FL) technology has found numerous applications in the fields of machine learning and data mining such as privacy-preserving analytics in healthcare (Haripriya et al., 2025), intrusion detection systems, industrial internet of things for predicting maintenance (Almalki et al., 2024), and applications in smart cities (Buyuktanir et al., 2025). FL's usefulness becomes apparent for all of these application areas because of its capability of dealing with private and distributed data. From 2022 to 2026, academic research has become increasingly inclined towards optimizing computational performance by resorting to model compression, feature selection, clustered federated learning, and privacy preservation (Takele & Villányi, 2025). This is necessary to enable federated learning at the edge on constrained devices such as Internet of Things (IoT) nodes and TinyML technologies (Zheng et al., 2025).

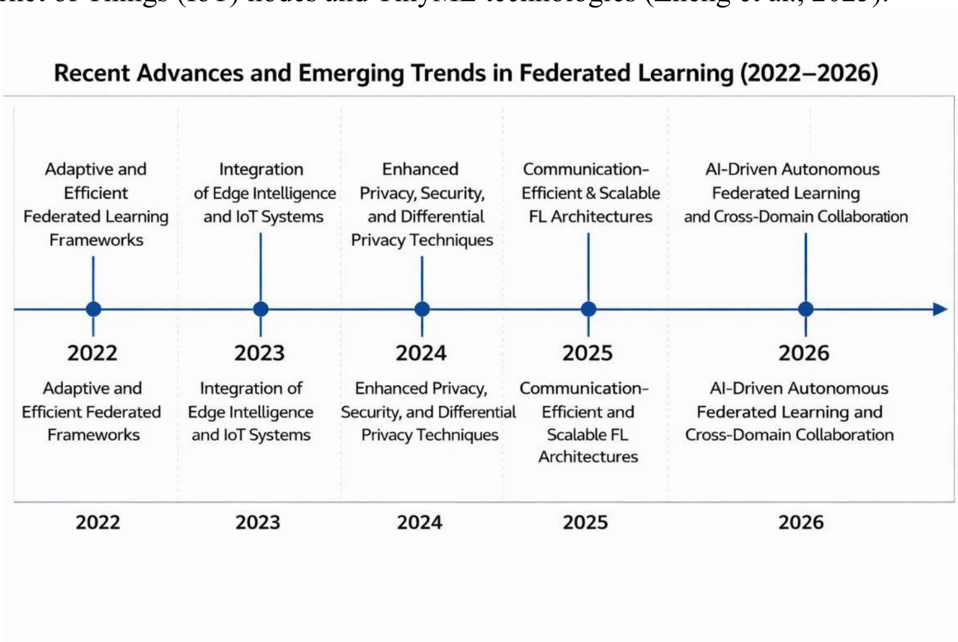

Figure 1: Evolution of Federated Learning Research and Advances

Figure 1 illustrates the timeline highlights key developments in federated learning from 2022 to 2026, emphasizing adaptive privacy preservation, communication-efficient training, edge intelligence integration, model optimization, scalable deployment, and AI-driven decentralized learning frameworks that support secure, efficient, and collaborative data analytics across distributed environments.

3. Classification Framework for Efficiency Techniques

The classification in this survey uses 60 articles written between 2022 to 2026 to categorize the methods that can be used to improve computational efficiency in federated learning. The three categories in the classification are created based on the main method used to overcome the efficiency problem.

3.1 Compression-Based Federated Learning

K Balaskas et al., (2024) Presents A hardware-aware deep neural network compression approach that combines various pruning techniques with mixed precision quantization for the purpose of improving the efficiency of neural networks when deployed on edge/embedded hardware architectures. This is achieved through the use of both neuron and weight pruning in combination with precision adaptively assigned depending on hardware sensitivity. The findings reveal that there are considerable reductions in storage, latency, and power consumption without affecting the accuracy rates. This approach makes it easier to deploy, but it incurs high optimization and hardware costs.

B Alhalabi et al., (2023) proposes FedNets as an efficient federated learning system that employs ensembles of pruned deep neural networks to achieve better computation and communication efficiency on edge devices. It uses model pruning along with ensemble learning to facilitate efficient learning on limited resources without compromising global model performance. The proposed framework proves to be more efficient regarding communication overhead, lower memory usage, and increased training speed on edge devices with comparable

prediction performance compared to traditional federated learning approaches. The system provides enhanced capabilities in terms of scalability, privacy preservation, and energy efficiency; nevertheless, complexity of ensembles, synchronization cost, and potential decrease in prediction performance due to non-IID data are main challenges.
NA Khan et al., (2025) provides an optimization method for deep learning via a hybrid of cluster-based quantization along with knowledge distillation. The knowledge distillation method is implemented by moving knowledge from the larger teacher model to the smaller student model through the use of the clustered weight quantization approach. The findings show that the technique is successful because of factors such as decreased model size, lower memory requirements, improved inference time, energy savings, and low model accuracy reduction. But there are some drawbacks of the technique that include increased training complexity and clustering.
X Lan et al., (2025) proposes a knowledge distillation methodology, which operates in the reverse direction (counterclockwise), in a block by block fashion, between teacher networks and student networks for compressing neural networks. This methodology improves the transfer of learned representations in a more systematic manner for better inference performance. Experiments show that this methodology achieves smaller model size, less computational complexity, and better inference performance while retaining competitive accuracy. Although this methodology allows more efficient deployment in edge devices, there are issues related to the high training complexity, dependence on good teachers, and high optimization overhead.
G Gad et al., (2024) proposes a federated learning architecture utilizing selective knowledge distillation for mitigating communication costs in bandwidth-limited wireless networks. Selective knowledge distillation ensures selective transmission of important knowledge representations instead of the entire model's parameters. Consequently, minimal communication costs are achieved while maintaining performance during federated training. Experimental evaluations confirm low communication delays, lower bandwidth utilization, and efficient training alongside high accuracy compared to traditional federated learning frameworks. Nevertheless, selective knowledge transfer is associated with risks such as potential information loss, unstable convergence, and poor performance when dealing with highly heterogeneous and non-IID distributions of data as well as unstable communication environments.
S Liu et al., (2025) presents a mutual knowledge distillation-based communication optimization technique for federated learning in cross-organizational federated learning, to minimize communication costs without compromising on the collaborative performance of the model. The technique allows the participating organizations to exchange knowledge distillation rather than complete models, enabling efficient decentralized training even when there is communication costs involved. The experimental results have proved that there is decreased communication overhead, better convergence rates, and higher learning efficiency, achieving comparable accuracy across different datasets. The proposed technique provides an improvement in terms of scalability, privacy, and compatibility across multiple organizations in a federated setting. However, it can face challenges such as knowledge inconsistency and synchronization.
U Bibi et al., (2024) proposed Recent advancements in pruning and quantization approaches towards efficient computations and minimizing memory usage of NLP models. This literature review explores pruning (both structured and unstructured), quantization (low-bit), and hybrid approaches in compressing transformers for natural language processing (NLP). Findings from experiments conducted as part of surveys on research papers indicate that a lot of improvement has been made in relation to size reduction, latency, and energy consumption without affecting the level of accuracy of natural language processing. However, some problems arise such as

accuracy trade-offs, difficulties in compressing bigger transformers, dependency on particular hardware architectures, and poor generalization ability of techniques.

P V Dantas et al. (2024) provides an exhaustive review of various ways to compress machine learning models such as pruning, quantization, knowledge distillation, low-rank approximation, and parameter sharing. By examining previously conducted studies, this study has identified the impact of the compression techniques on the size of the model, efficiency, power usage, and accuracy rates. In conclusion, it can be argued that the application of compression techniques increases the efficacy of implementing machine learning techniques as well as obtaining good accuracy levels while applying them in edge and mobile environments. However, poor performance, reliance on hardware, difficult optimization process, and poor generalization remain serious constraints.

W Villegas-Ch et al. (2024) proposed an efficient federated learning system for the TinyML-based Internet of Things devices, emphasizing privacy protection and efficient distributed learning. The algorithm utilizes techniques such as model optimization and efficient communication in order to implement learning algorithms at the edge using low-powered devices without exchanging sensitive data. Experiments show that the technique consumes less energy, reduces communication costs, provides more privacy, and ensures sufficient prediction accuracy. There are several limitations related to computational ability of the devices, communication issues, and the presence of highly heterogeneous non-IID data distribution.

J P Jung et al. (2024) proposes A mobile federated learning scheme that employs the Pareto optimality principle to achieve better resource management and faster model convergence is proposed in this study. This solution aims to optimize communication expense, power consumption, and learning efficiency by choosing proper client involvement and training schemes concurrently. From empirical tests, it was shown that this solution can lead to fast model convergence, reduced computational overhead, low energy expenditure, efficient communication, and model accuracy comparable to other solutions, all within mobile federated learning settings. Nevertheless, such a solution comes with some limitations in terms of optimization difficulty, reliance on dynamic network behavior, and performance inconsistency.

S Nadella et al. (2024) proposes the issues related to the integration of federated deep learning with edge computing for building intelligent systems with enhanced data privacy and decentralization features. Communication-efficient training, resource optimization techniques, model aggregation schemes, and security considerations for the distributed edge environment have been analyzed. Based on the results reported, federated deep learning can improve the level of data privacy, eliminate dependence on centralized data storage, and increase the scalability and efficiency of intelligent systems. Nevertheless, communication costs, scarce computing resources, data distribution issues, potential security risks, and non-convergence represent serious limitations in terms of large-scale implementation at the edge.

The recent studies regarding Federated Learning and DNN Compression have mostly considered the aspects such as pruning, quantization, knowledge distillation, and communication optimization that help in achieving efficiency, minimizing power utilization, and reducing communication cost in order to increase scalability, privacy, model convergence, and efficient deployment. However, some of the issues that still prevail in Federated Learning include the complexity involved in optimization techniques, dependence on hardware architecture, synchronization costs, non-IID heterogeneity, and instability during convergence, as illustrated in Table 1.

Table 1: Comparative Analysis of Federated Learning Compression Techniques

Author	Sector	Methods	Key Findings	Contribution	Limitations

K Balaskas et al. (2024)	Edge AI / DNN Compression	Diverse pruning with mixed-precision quantization	Reduced memory, latency, and power usage with minimal accuracy loss	Improved hardware-aware deployment efficiency for edge devices	High optimization complexity and hardware dependency
B Alhalabi et al. (2023)	Federated Learning / Edge Computing	Ensemble of pruned DNNs in federated learning	Lower communication overhead and faster training	Enhanced scalability and energy-efficient decentralized learning	Ensemble complexity and instability under non-IID data
NA Khan et al. (2025)	Deep Learning Optimization	Cluster-quantized knowledge distillation	Reduced model size and energy consumption with minimal accuracy degradation	Efficient lightweight model deployment in constrained environments	Increased training complexity and clustering sensitivity
X Lan et al. (2025)	Neural Network Compression	Counterclockwise block-by-block knowledge distillation	Improved inference efficiency and reduced computational complexity	Enhanced representation transfer for compact models	High optimization overhead and dependence on teacher quality
G Gad et al. (2024)	Wireless Federated Learning	Selective knowledge distillation	Reduced bandwidth usage and communication delay	Communication-efficient federated learning for wireless networks	Information loss and unstable convergence in heterogeneous environments
S Liu et al. (2025)	Cross-Organizational Federated Learning	Mutual knowledge distillation	Lower communication overhead and improved convergence	Scalable decentralized collaboration across organizations	Synchronization issues and knowledge inconsistency
U Bibi et al. (2024)	NLP Model Compression	Pruning and quantization techniques	Significant reduction in model size and energy consumption	Comprehensive analysis of transformer compression methods	Accuracy trade-offs and hardware dependency

P V Dantas et al. (2024)	Machine Learning Compression	Review of pruning, quantization, distillation, and factorization	Compression improves deployability and efficiency	Comprehensive survey of ML compression strategies	Performance degradation and poor generalization
W Villegas-Ch et al. (2024)	TinyML / IoT Federated Learning	Lightweight federated learning with communication optimization	Reduced energy and communication cost with privacy preservation	Efficient federated learning for TinyML-enabled IoT devices	Limited computational capability and communication instability
J P Jung et al. (2024)	Mobile Federated Learning	Pareto-optimal resource management	Faster convergence and lower energy consumption	Efficient client selection and communication optimization	Dependence on dynamic network conditions
G S Nadella et al. (2024)	Edge Computing / Federated Deep Learning	Communication-efficient federated deep learning strategies	Improved privacy, scalability, and decentralized intelligence	Analysis of federated deep learning integration in edge systems	Communication overhead and convergence instability

3.2 Feature Optimization Techniques

H Qin et al. (2026) proposes a feature selection approach that combines clustering and simulated annealing to improve both feature relevance and clustering effectiveness within the context of high-dimensional data. This approach relies on clustering-based data representation and optimization-based feature subset selection to increase learning effectiveness by minimizing irrelevant information. Tests have shown the approach to be superior in terms of improved classification performance, effective feature selection, and lower complexity than conventional approaches. Despite the fact that this new approach enhances scalability and efficiency in processing large data sets, it comes with the following limitations: optimization time, dependency on initial parameters, and sensitivity to noise and heterogeneity.

R Ananda et al. (2024) Proposes a more improved technique of feature selection by clustering, which includes the use of principal component analysis (PCA) for feature selection as well as reduction. The technique involves the use of clustering and PCA to select features that contain maximum information about the data. From experimentations, it is evident that the proposed technique offers improved performance in comparison to conventional feature selection techniques in terms of enhanced clustering results, effective representation of data, and low computing cost. Nevertheless, the technique is prone to loss of information during dimensionality reduction, parameter sensitivity, and handling of nonlinear data.

A Mahanipour et al. (2025) presents an embedded federated feature selection method and dynamic sparse training to achieve a trade-off between the accuracy of the model and the computational workload in federated learning environments. The technique includes feature selection and sparse parameter tuning in the training procedure, thus reducing communication and computational overheads while achieving desirable learning results. The proposed method is effective in improving the efficiency of training and minimizing memory usage and communication overheads while achieving accurate predictive performance. Conversely,

challenges associated with difficult optimization, sensitivity to sparsity configuration, and instability in heterogeneity non-IID datasets present some significant disadvantages.
W Cui et al. (2025) proposes a federated method for dimensionality reduction that uses high-dimensional sparse sliced inverse regression, which is capable of handling high-dimensional data in distributed environments while preserving the privacy of the data. In this approach, the technique of sparse inverse regression is incorporated into the framework of federated learning to obtain a relevant lower dimensional representation of features without exchanging any data among the clients. Results indicate better accuracy in dimensionality reduction, less communication cost, and better prediction performance in high-dimensional federated data. Nevertheless, the method faces challenges such as optimization difficulty, dependency on sparsity parameters, and poor performance in highly heterogeneous datasets.
Z Xing et al. (2024) introduces GOLFS – a novel approach to feature selection which makes use of both global and local data characteristics for improving the accuracy of clustering on high dimensional data. Through the use of global and local data information, GOLFS is able to rank the significance of features accurately while eliminating redundancy. Results show that, in addition to increasing clustering accuracy, GOLFS performs feature representation and reduction with a lower computational cost than traditional feature selection techniques. GOLFS is well suited for analysis of high dimensional data in clustering problems. Nevertheless, this technique might suffer from problems associated with parameter sensitivity and higher computational costs on big data.
M Alshinwan et al. (2025) proposes a model for unsupervised feature selection for texts using an improved Prairie Dog algorithm optimization framework to improve the performance of text clustering. This technique chooses the most relevant features from textual information based on optimization of feature relevance and reduction of redundancy in large dimensionality. Experiments show that the new model performs better than other traditional feature selection models in terms of clustering efficiency, feature selection efficiency, and computation efficiency. Nonetheless, this model will be affected by high optimization difficulty, higher parameter sensitivity, and inefficiency in dealing with highly noisy, sparse, and semantic texts.
M Sun et al. (2025) provides a Fractal Autoencoder model with Redundancy Regularization to perform feature selection without supervision on high dimensional data. This technique uses fractal-based autoencoder modeling techniques for hierarchical representation learning and redundancy regularization for removal of unwanted and redundant features. The effectiveness of this technique has been validated through experimental evaluation, which shows that the proposed technique has higher feature selection performance, better representation of data, and decreased dimensionality with minimum reconstruction error when compared to other unsupervised feature selection techniques. However, the proposed technique could face challenges such as computational complexity and low noise tolerance levels.
Shaikh et al. (2024) presents DIAFM, which is an advanced version of the incremental frequent itemset mining algorithm that is capable of effectively extracting the patterns that exist in dynamic transactional databases. Unlike other conventional techniques, this algorithm is capable of updating the patterns mined in an incremental manner without the need for continuous scanning of the whole dataset, hence saving on the required computational effort and processing time. Performance tests have proven that this algorithm is efficient and fast, uses less memory, and is more scalable than any other technique used to mine frequent itemsets. Nevertheless, the proposed algorithm is susceptible to deterioration when mining sparse datasets or complex item sets.
Y Zuo et al. (2025) proposes a novel feature selection technique using a sophisticated clustering algorithm, contributing to the development of a method to identify informative features effectively in the high dimensional space. Under this strategy, clustering will be used to group similar features and exclude irrelevant ones from the dataset, which makes the representation

of the data more realistic. According to experiments conducted, the developed feature selection technique proves superior in terms of better feature selection accuracy, improved clustering effectiveness, and reduced complexity when compared to conventional feature selection methods. The limitations of this technique can be sensitivity to parameters, increased overhead cost, and poor robustness to noise.

H von Linde et al. (2025) proposes a mechanism to assess the effectiveness of feature selection and clustering methods when dealing with specific project needs in industrial and information-oriented contexts. The proposed mechanism provides the basis for assessing the choice of feature selection and clustering methods, which is dependent upon the performance, scalability, interpretability, and limitations associated with the methods being considered. Based on the findings from these studies, the effectiveness of the selection of methods and analysis methodologies is improved compared to general-purpose methods. However, this framework of evaluation is difficult to apply based on the domain and the data set.

The recent research done on feature selection, clustering, and dimensionality reduction aims at enhancing the quality of representation, speed of computation, and effectiveness of learning in high-dimensional and distributed settings. Such algorithms as fuzzy clustering, principal component analysis, sparse training, optimization methods, autoencoder-based approaches, and association rule mining have shown impressive results in increasing the relevance of features, improving clustering precision, and ensuring computational efficiency while decreasing computation and memory usage. These approaches make it possible to perform efficient federated learning, text mining, and other unsupervised learning tasks. Nevertheless, the majority of the algorithms mentioned above have several drawbacks, as shown in Table 1.

Table 2: Comparative Analysis of Feature Selection Methods and Their Key Findings

Author	Sector	Methods	Key Findings
H Qin et al. (2026)	Feature Selection	Fuzzy C-means clustering with simulated annealing	Improved classification accuracy and feature relevance
R Ananda et al. (2024)	Feature Engineering	PCA-based clustering feature selection	Better clustering accuracy and reduced computation
A Mahanipour et al. (2025)	Federated Learning	Dynamic sparse federated feature selection	Lower communication and memory overhead
W Cui et al. (2025)	Federated Dimension Reduction	Sparse sliced inverse regression	Improved dimensionality reduction and prediction accuracy
Z Xing et al. (2024)	Clustering and Feature Selection	GOLFS using global and local information	Enhanced clustering performance with lower complexity
M Alshinwan et al. (2025)	Text Mining	Prairie Dog optimization-based feature selection	Improved text clustering and feature reduction
M Sun et al. (2025)	Unsupervised Feature Selection	Fractal autoencoder with redundancy regularization	Better feature representation and dimensionality reduction

M Shaikh et al. (2024)	Data Mining	Incremental frequent itemset mining (DIAFM)	Faster mining efficiency with lower memory usage
Y Zuo et al. (2025)	Feature Selection	Improved clustering-based feature selection	Higher feature selection precision and clustering efficiency
H von Linde et al. (2025)	Evaluation Frameworks	Project-specific clustering and feature selection evaluation	Improved method selection accuracy

3.3. Secure Federated Optimization

D Y Kim et al. (2024) introduces a federated learning algorithm design that uses a different representation space to map the gradients before transmitting the gradients to achieve lossless sparsification of the gradients. This helps reduce communication overheads while ensuring that no essential data is lost for the purposes of performing updates on the global model. It helps cut down on communication costs, improve transmission efficiency, and retain the ability of achieving proper convergence and maintaining accuracy levels in the resulting models, as proven in the experiments. However, the proposed technique adds overheads associated with the transformation process.

J Yan et al. (2025) suggests a mobility-aware asynchronous federated learning system with dynamic sparsification. In this technique, the degree of sparsification is dynamically determined based on client mobility and the characteristics of the network infrastructure, thereby facilitating efficient asynchronous updates of the model with minimal communication costs. Performance analysis shows better training performance, decreased latency, quicker convergence, and minimum use of bandwidth with high accuracy levels compared to typical federated learning approaches. While the algorithm offers scalability and flexibility in mobile federated learning systems, it faces challenges in terms of optimization problems, synchronization issues, and low performance levels due to high mobility or heterogeneity in data distribution.

P Wang et al. (2025) puts forth a federated learning architecture which makes use of model aggregation to boost performance in distributed learning while cutting down both communication and computation costs. The process involves the aggregation of lightweight base models from different clients, unlike federated learning, where there is direct exchange of global model parameters. Results show that the approach is more efficient in terms of communication, leads to faster convergence, uses fewer resources, and has good prediction accuracy when compared to traditional federated learning approaches. However, the approach faces some difficulties due to model heterogeneity, complexity in model aggregation, and synchronization challenges.

M H Narimani et al. (2025) proposes the FedRP, a federated learning framework for communication-efficiency by incorporating the use of random projection along with differential privacy to enhance efficiency while keeping data private. This is achieved by using random projection for client update compression before transmission and differential privacy to maintain data privacy during collaboration. Results from experiments show that this approach helps lower communication costs, enhance transmission efficiency, while providing accurate models and high privacy, outperforming the conventional federated learning framework. The proposed framework improves scalability and privacy preservation in a distributed setting but has some drawbacks, including increased information loss due to projection and decreased performance with heterogeneity.

L Cui et al. (2025) presents ALDP-FL as a framework that utilizes an adaptive local differential privacy scheme specifically tailored for federated learning. This framework aims at improving the degree of privacy protection while retaining the utility of models trained on distributed data. ALDP-FL employs privacy settings dynamically depending on sensitivity levels and training dynamics; hence allowing for the update of local models without exposing client data. Tests conducted using this scheme indicate effective privacy improvement, lower information leakage rates, and model accuracy similar to models trained using other differential privacy schemes in federated learning but with high communication efficiency. Although there is a positive side to the use of this technique, its use can lead to a trade-off between privacy and utility.

K Wei et al. (2024) presents a gradient sparsification technique for wireless federated learning in conjunction with differential privacy to optimize the communication process and enhance the security of the distributed learning paradigm. This technique focuses on transferring only those gradients that are crucial while using differential privacy methods to ensure that sensitive information is protected in wireless communication. Experiments reveal that the approach has managed to minimize the communication overhead, reduce bandwidth utilization, increase transmission efficiency, and perform at par with traditional federated learning techniques in terms of model accuracy. Nevertheless, the method may face the challenges of information loss owing to aggressive sparsification.

O Ibrahim Khalaf et al. (2024) develops a federated learning system that incorporates hybrid differential privacy schemes to facilitate safe and efficient knowledge sharing on heterogenous IoT platforms. By employing multiple privacy protection measures, the system aims to achieve effective learning collaboration while ensuring the safety of sensitive data from clients. Through empirical tests, it has been proven that the developed approach offers higher levels of privacy protection, decreases data leakage risk, achieves robust communication channels, and provides comparable performance in terms of prediction accuracy when compared to traditional federated learning methods. Nevertheless, the proposed solution faces challenges in terms of performance losses in the presence of heterogeneous non-IID data distributions.

A Alqazzaz et al. (2025) proposes federated learning in combination with homomorphic encryption to provide privacy-assured cooperative learning in the smart city domain. The technique facilitates encrypted model updates and secured sharing of information between different devices in a smart city environment, ensuring that no private data is revealed to central server systems. It has been observed that this technique provides higher privacy guarantees and learning effectiveness, with comparable accuracy compared to other traditional federated learning techniques. However, the technique suffers from heavy computational overheads and longer latency time.

D Rahbari et al. (2025) Proposes an efficient federated learning approach at the edge with the help of homomorphic encryption to achieve secure and privacy-preserving distributed learning at the edge. In this approach, the training of the models is carried out by encrypting the updates during the transfer of the data. This allows learning to be conducted while ensuring that there is no disclosure of any sensitive information of clients to any centralized server. Experimental analysis proves improvement in the terms of data privacy, secure communication, less information leakage, and effective performance of the models.

J Wang et al. (2026) proposes an optimal privacy protection scheme for cloud-based platforms using the combination of federated learning and homomorphic encryption. With this approach, clients can train their models in an encrypted environment while aggregating their models without revealing any sensitive information about themselves. The experiments conducted prove that the privacy of the clients is maintained, there is secure communication, increased confidentiality of data, and effective learning with less information leaking than conventional learning techniques in the cloud environment. Although the suggested system has its advantages, it is very costly in terms of encryption and computation time, along with communication delay.

K Peng et al. (2023) presents a scalable and privacy-preserving verifiable aggregation scheme for federated learning that provides reliable and safe model aggregation. The scheme integrates lightweight aggregation protocols with privacy-preserving verification processes to minimize the cost of communications while ensuring the correctness of the aggregated client data in collaboration. The experiments confirm the reduction in communication overhead, increased security in aggregation, better verification efficiency, and comparable model accuracies relative to those obtained using traditional federated learning schemes for model aggregation. Despite its benefits, the proposed scheme could increase verification overhead and compromise efficiency when implemented in federated learning with high heterogeneity.

A K Takele et al. (2025) Presents an effective method of clustered federated learning for IIoT systems that helps improve the prediction accuracy and decrease the training time. In this study, the proposed scheme clusters clients participating in the network based on their similarities in data and learning patterns. The experiments reveal that the suggested technique can help achieve better accuracy, converge faster, decrease the training time, and improve the communication efficiency in comparison with classical federated learning techniques. Despite its benefits, this method can be confronted with such difficulties as complexity in clustering, dynamic behavior of clients, communication costs, and low performance in heterogeneous non-IID environments.

K Borazjani et al. (2026) proposes a unique federated learning paradigm for computer vision-related tasks through an innovative data distribution scheme where the data distribution for federated learning is based on embeddings rather than labels. This approach makes use of feature embeddings to account for semantic similarity among data across different clients. This framework has shown promise as compared to the traditional non-IID label-based federated learning paradigm through better prediction accuracy, improved convergence behavior, and greater resistance to heterogeneity among distributed datasets. Although this method possesses many benefits to computer vision tasks, the disadvantages associated with this approach include high computational expense due to embedding learning, high communication cost, and appropriate representation learning.

M Seol et al. (2025) proposes a federated learning scheme that aims to enhance model performance through the resolution of class imbalance problems in non-IID data distribution settings. Imbalance mitigation is incorporated into the local training process by the clients to guarantee better class balance and global model aggregation in federated learning. The proposed architecture turns out to be superior to traditional federated learning approaches when dealing with classification challenges under the conditions of non-IID data and class imbalance. The proposed scheme, however, may present some new complexities, particularly in those situations when federated data distribution becomes more heterogeneous and dynamic.

K Zheng et al. (2025) proposes solutions involving artificial intelligence to effectively manage resources in the context of heterogeneous IIoT networks, focusing primarily on effective communication, computing, and energy consumption in distributed industrial networks. This study analyzes the role of machine learning and artificial intelligence in managing and allocating resources, task scheduling, and intelligent networking in heterogeneous IIoT architecture. The outcomes reveal that an increase in resource efficiency, minimal delays, scalability, and adaptability of the system has been observed. Although the proposed framework has shown some benefits, several problems still exist.

G Gad et al. (2024) introduces a federated learning system augmented with selective knowledge distillation to minimize the communication overhead associated with bandwidth-limited wireless networks. Through the transfer of only vital knowledge representations rather than full model parameters, it becomes possible for the system to conduct collaborative learning effectively, while minimizing communication expenses. It was shown through experiments that this system consumes less bandwidth, has less communication latency, is more training-efficient, and has comparable prediction accuracy in relation to conventional federated learning systems. On the other hand, there can be information losses, convergence problems, and decreased effectiveness with heterogeneously distributed non-IID data sets in unreliable wireless networks.

Modern federated learning research is primarily geared towards enhancing communication effectiveness, privacy preservation, resource optimization, and robustness to deal with heterogeneous non-IID data distributions. Methods like gradient pruning, knowledge distillation, clustering, differential privacy, homomorphic encryption, and adaptive aggregation methods have greatly minimized the communication expense, latency, and overhead while ensuring high model accuracy. The above methods have also contributed to the improvement of scalability, speed of convergence, and secure federated learning on various platforms. Nevertheless, problems like optimization challenge, synchronization issues, encryption cost, limitations in scalability, and lower accuracy with heterogeneous data distribution have not been solved yet, as seen in Table 3.

Table 3: Comparative Analysis of Privacy Preservation, Resource Optimization, and Non-IID Data Handling Techniques in Federated Learning

Author	Findings	Contribution	Limitation
D Y Kim et al. (2024)	Reduced communication overhead with preserved accuracy	Efficient gradient transmission in federated learning	Transformation and computation overhead
J Yan et al. (2025)	Faster convergence and lower latency	Efficient mobile federated learning communication	Synchronization instability and heterogeneity
P Wang et al. (2025)	Improved communication efficiency and convergence	Lightweight model aggregation for distributed learning	Aggregation complexity
M H Narimani et al. (2025)	Enhanced privacy with reduced communication cost	Communication-efficient privacy-preserving FL	Information loss due to projection
L Cui et al. (2025)	Improved privacy protection and communication efficiency	Adaptive privacy-aware federated learning	Privacy-utility tradeoff
K Wei et al. (2024)	Reduced bandwidth utilization and overhead	Secure wireless federated optimization	Information loss from sparsification
O Ibrahim Khalaf et al. (2024)	Improved secure knowledge sharing across IoT platforms	Hybrid privacy-preserving federated framework	Reduced performance in non-IID data
A Alqazzaz et al. (2025)	Enhanced privacy and secure model sharing	Secure smart city federated learning	High computational latency

D Rahbari et al. (2025)	Improved secure edge communication	Privacy-preserving edge AI federated learning	Encryption overhead
J Wang et al. (2026)	Increased confidentiality and secure cloud learning	Secure cloud federated framework	High computation and communication cost
K Peng et al. (2023)	Improved aggregation security and efficiency	Verifiable aggregation for federated learning	Verification overhead
A K Takele et al. (2025)	Better prediction accuracy and faster convergence	Clustered federated learning for IIoT	Clustering complexity
K Borazjani et al. (2026)	Improved robustness against non-IID distributions	Embedding-based federated learning	High embedding computation cost
M Seol et al. (2025)	Enhanced classification accuracy in imbalanced data	Better handling of non-IID imbalance	Increased preprocessing complexity
K Zheng et al. (2025)	Improved scalability and resource utilization	AI-driven IIoT resource management	Security and scalability issues
G Gad et al. (Gad et al., 2024)	Reduced bandwidth and communication latency	Selective knowledge distillation in FL	Information loss and convergence instability

4. Research Challenges and Open Issues

Even with many advances that have been made in federated learning and model compression, there remain a number of problems that still pose threats to the computational efficiency of distributed machine learning and data mining. First, the heterogeneity of non-IID data distribution among the client nodes impacts adversely the stability of convergence, unfairness, and predictive accuracy (Borazjani et al., 2026; S. Zhu et al., 2024). Second, the problem of communication cost still lingers as large-scale federated learning requires a continuous exchange of parameters in the face of limited network bandwidths (Narimani & Tavassolipour, 2025; Solat et al., 2025).This is due to the fact that techniques for data encryption, aggregation, and differential privacy add more computational load and delay to the process (L. Cui & Wu, 2025; J. Wang & Wang, 2026). Also, techniques such as communication-efficient aggregation and knowledge transfer are effective in scaling up, but can be affected by problems such as synchronization and optimization challenges in a heterogeneous environment (Gad et al., 2024; S. Liu et al., 2025). Moreover, IoT and edge devices have constraints in computation, memory, and energy efficiency, thus making their implementation difficult (Luzón et al., 2024; Villegas-Ch et al., 2024).Another critical challenge is scalable feature selection and dimensionality reduction for high-dimensional distributed datasets. Existing clustering-based and optimization-driven feature selection methods frequently suffer from parameter sensitivity, noise vulnerability, and increased optimization complexity (Qin et al., 2026; von Linde & Riedel, 2025). In heterogeneous Industrial IoT environments, intelligent resource allocation and adaptive scheduling frameworks must simultaneously optimize communication efficiency, latency, computational load, and energy utilization (Shen et al., 2025; Zheng et al., 2025). These limitations highlight the necessity for lightweight, adaptive, privacy-aware, and communication-efficient federated learning frameworks capable of supporting scalable and robust distributed intelligent systems.

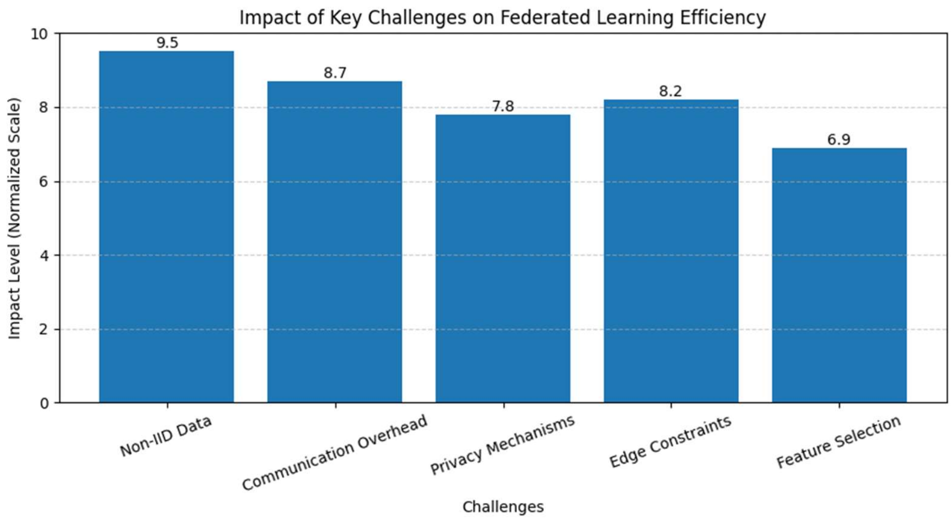

Figure 2: Challenges Influencing Computational Efficiency in Federated Learning

Figure 2 illustrates the relative impact of key challenges in Federated Learning efficiency. Non-IID data distribution has the highest impact, followed by communication overhead and edge device constraints. Privacy mechanisms and feature selection also contribute significantly (Salama et al., 2023). Overall, these factors collectively limit convergence speed, scalability, and model performance in distributed environments (Mai et al., 2023).

5. Comparative analysis of federated optimization and model compression methods

The latest studies in federated learning show that the problem of achieving both effective communication and a model's small size is increasingly recognized as an essential problem. The methods of federated optimization are oriented towards reducing communication costs and ensuring faster convergence in non-IID settings and for heterogeneous clients. Compression techniques were added to adaptive aggregation and client training techniques to minimize the amount of data to transmit by compressing gradient information. This allows us to see that communication problems still pose a serious limitation for federated learning frameworks (H. Liu et al., 2023).On the other hand, model compression methods like pruning, quantization, and lossy compression have been extensively employed in the context of federated learning models to cope with limitations associated with computation and data transmission. Studies have shown that through structured pruning and adaptive quantization, the cost associated with data transmission can be greatly minimized without compromising the stability of convergence in federated models. In this case, both layer-wise pruning and quantization techniques can result in efficient data compression without compromising on model accuracy, thus rendering them ideal for use in edge intelligence systems(Yang et al., 2023).Recent federated approaches have employed the combination of federated optimization with more sophisticated compression mechanisms to address both statistical heterogeneity and communication inefficiency. These systems, commonly known as efficient federated edge learning systems, utilize techniques like pruning, quantization, and compression with codebooks to minimize the cost of uplink and downlink communications within IoT and edge networks. However, there remain difficulties regarding the robustness of the system against extreme cases of non-IID distributions and evolving environments, which may lead to unstable convergence due to compression(Grativol et al., 2023).

6. Emerging Trends in Computationally Efficient Federated Learning

6.1 Communication-Efficient Federated Optimization

The recent research on federated learning addresses the problem of reducing the communication cost, as it is one of the main obstacles to efficient distributed training. Gradient sparsification, adaptive sampling of clients, quantization, and periodic synchronization are some of the methods to improve efficiency by sending small-sized messages without affecting convergence. In cases where communication costs are higher than the computing cost, these techniques prove useful. The results of recent experiments show great potential when applied to heterogeneous clients using quantization and sparse updating techniques (H. Liu et al., 2023; Z. Zhu et al., 2023).

6.2 Compression-Aware Federated Learning

Another important recent trend in federated learning is integrating model compression techniques directly into federated learning pipelines. Some recent approaches utilize structured pruning, quantization-aware training, and communication compression to save on both uplink and downlink bandwidth. For instance, layerwise pruning and quantization have proven effective in saving on communications costs without significantly affecting model performance. Lossy compression of updates has also been investigated as a means of minimizing bandwidth utilization without negatively impacting model convergence (Jiang et al., 2022; Wilkins et al., 2024).

6.3 Edge Intelligence and On-Device Learning

Federated learning approaches are often integrated with edge intelligence methodologies to facilitate online device-based learning. Through the use of lightweight models, optimized designs for hardware, and efficient model updates, machine learning training can take place directly on end-user devices, mobile phones, sensors, and embedded systems. Such an approach decreases the need for centralized cloud infrastructure while also providing increased speed and privacy protection. According to recent findings, efficient federated learning approaches can provide near-centralized performance levels within resource-limited scenarios (Li et al., 2024).

6.4 Heterogeneity-Aware Optimization

Learning from non-IID data distribution and heterogeneous systems is still a major issue for federated learning. Some recent techniques include adaptively adjusting the learning rate, personalization of federated learning algorithms, and using cluster-based techniques to address divergence due to statistical variations between clients. Such techniques have been found to offer better convergence and robustness in heterogeneous systems, especially edge learning scenarios with diverse computing and distribution capabilities.

6.5 Hybrid FL–Compression Frameworks

There is growing research on hybrid solutions that focus on optimizing federated learning as well as model compression. In such solutions, pruning, quantization, and gradient compression are considered within the context of federated optimization in order to minimize the computational and communication costs. Hybrid approaches can be useful in edge intelligence and IoT setups where many devices need to collaborate. Nevertheless, preserving accuracy while compressing becomes harder, particularly in highly non-IID scenarios (Yi et al., 2024).

6.6 Research Challenges and Future Directions

Despite this great progress, there are a number of issues that still require solution before computationally efficient federated learning can be realized. These include robustness in a highly non-IID regime, stability of convergence with aggressive compression, and adapting to changing network environments. In future research, we shall focus much attention to adaptive compression and hardware-aware federated learning, among others.

7. Research Gaps in Federated Learning for Machine Learning and Data Mining Applications

Even though federated learning has progressed considerably, there are still several research problems that restrict its application in the field of machine learning and data mining activities.

This applies especially to dealing with the problem associated with highly non-IID data, where models converge poorly and have sub-optimal results in practical applications. While personalization and clustering are proposed as possible solutions to the problem, no efforts have been made to create a universal solution that will ensure generalization and robustness. In addition, the balance between efficient communication and accuracy of the model in a distributed setting is crucial. While gradient compression and sparsification can be used to increase efficiency of the communications, it is also important to note that the former leads to loss of information, which destabilizes the convergence process. In addition, methods for compressing models to be computationally efficient may cause optimization errors in federated learning because of edge devices with resource constraints.Another drawback is that there is no standard framework for evaluating the performance of federated learning for data mining purposes. Most of the work in this regard is done based on individual data sets or simulated setups, which does not make it easy to compare and generalize different methods in terms of their efficiency. Furthermore, there are other challenges that still need to be addressed, including the risk of leaking information due to model updates, vulnerabilities to attacks, and inefficient systems in dynamic environments.

8. Proposed Research Directions for Computationally Efficient Federated Learning

Efforts in future studies in computationally efficient federated learning should concentrate on building a framework that optimizes not only communications but also computations and learning performance(Zhai et al., 2024), specifically in a highly heterogeneous environment with limited resources(Ren et al., 2023; Z. Zhu et al., 2023). One way to address the problem is through the formulation of an adaptive federated learning scheme, which adapts its operations by adjusting the level of communications, participation of clients, and training efforts in response to current conditions. Furthermore, the use of advanced methods of model compression such as structured pruning and knowledge distillation (O'Quinn et al., 2025), could help enhance the efficacy of learning and inference in edge devices. Finally, there is yet another important field of study which focuses on developing federated learning systems that can operate in heterogeneous environments as well as be personalized. This will make it possible to address issues related to the existence of non-IID data distributions, while at the same time maintaining global generalizability of the models. Use of methods from the realms of meta-learning and reinforcement learning could make the models even more adaptable in the face of dynamically changing networks. Robustness against adversarial attacks and gradient leakage and unreliability of clients continues to remain an important consideration. Figure. 3 illustrates proposed research directions for computationally efficient federated learning including communication-efficient optimization, compression-aware learning, edge intelligence(Cheikh et al., 2026; Salh et al., 2023), heterogeneity-aware optimization, resource-aware design, security and privacy preservation.

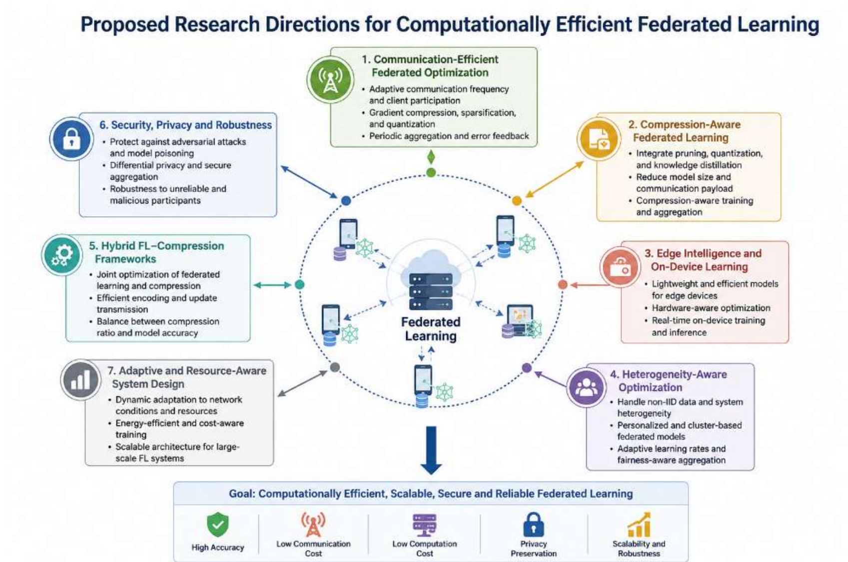

Figure 3: Computational Efficiency Strategies in Federated Learning Frameworks

9. Conclusion and Future Perspectives

The development of federated learning has brought about revolutionary transformation in the fields of distributed machine learning and data mining due to its ability to help numerous clients work together to train a shared model without using raw data. The technology helps mitigate the issues relating to data privacy, security, and regulatory compliances while supporting large intelligent applications in healthcare, finance, smart cities, and IoT-based environments. It provides notable benefits compared to centralized machine learning since it keeps data at the local device level. Thus, it is an essential tool for implementing AI models and solutions. However, there are a number of challenges that prevent the effective application of FL in real life scenarios. Communication overhead is among those obstacles because model parameters are repeatedly exchanged between servers and clients. Furthermore, non-IID data distributions, heterogeneity of devices used for federated learning, the limited availability of computational resources, and instability of connections affect the convergence process negatively. In order to overcome the mentioned issues, a wide array of federated optimization algorithms has been developed as well as methods of compressing models. These include pruning, quantization, knowledge distillation, sparsifying gradients, and adaptive aggregation. These methods have been proved to be very successful in lowering communication overheads, computational burden, memory usage, but still ensuring competitive learning outcomes.

For future work, it is necessary to consider the development of general and adaptive federated learning systems that would optimize communication overheads, computational complexity, learning accuracy, and security at the same time. New trends include hardware-aware federated learning, intelligent client sampling algorithms, dynamic compression, personalized federated learning models, and energy-aware optimization. At the same time, making learning more robust to adversarial attacks, preventing possible leaks of private information and providing greater convergence stability in heterogeneous non-IID environments are important topics. Federated learning in conjunction with edge intelligence, reinforcement learning, and the IoT of the next generation can serve as promising research directions.

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