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# Advancements And Challenges In Federated Learning: General Approaches And Methods

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***Abstract***– *Federated Learning (FL) has turned out to be the shifted thinking in distributed ML that helps to overcome difficulties in organization privacy, data safety, and computation power. The aim of this review paper is to present new developments in the FL algorithms and to address new approaches and implementation, along with the problem that arises from them. We divide the developments into several topics, namely, content management in multi-party edge systems, efficient training in the energy-constrained edge computation, and decentralized platforms with efficient inter-device communication. We discuss the advanced FL algorithms including; The FedCo for content management, energy-conscious D2D assisted FL models, and decentralized FL frameworks similar to the ConFederated Learning (CFL). Towards this end, the paper also discusses different direction in wireless network optimization that might include dynamic resource allocation, hybrid local-centralized training models as well as DRL-based frameworks for resource management. Issues of FL such as, communication efficiency, privacy, and energy limitations are discussed in detail. We also discuss some of the solutions that have been proposed to solve them highlighted include; the use of blockchain for privacy-preserving caching, differential privacy techniques and energy-efficient scheduling. Finally, the reuse also discusses some of the challenges that arise when it comes to scaling up FL and offers recommendations that can guide future research activities to improve the performance of the FL in different settings for IoT, UAV networks, and the 6G system. Through the integration of more than a hundred research papers, this review also offers a bird's eye view of the state-of-the-art of federated learning, as well as a research agenda for the fast-growing area. This paper will help researchers and practitioners who are interested in dealing with the various issues associated with federated learning and how best they can apply it across different domains.*

***keywords***–*Federated Learning (FL), Decentralized Machine Learning, Privacy-Preserving Techniques, Communication Efficiency, Energy-Efficient FL, Distributed Optimization*

## I. INTRODUCTION

FL has been listed as a novel approach for dealing with some of the biggest machine learning headaches, including privacy, how best to communicate, and how computation will be carried out under new models. In the face of increasing regulatory requirements for data privacy and a rapidly increasing amount of data, traditional centralized machine learning approaches have some serious issues. Current solutions fail to meet the privacy requirements of users and Compared to other approaches, Federated Learning offers a solution to collaborate while Learners remain in control of their data. The purpose of this review paper is to provide an update on the current state of Federated Learning, explain the difficulties that arise, and provide a guide of potential future work. The purpose of this paper is to present the state of the art of Federated Learning with regard to emerging techniques, applications, and their impact on the relevant fields. Our intent is to focus on improvements achieved in the handling of key topics like privacy, communication reliability, and energy expenditure. Further, the paper aims to discuss the limitations of existing research and the possible directions for the further research. Federated Learning works with the approach that data is kept local on devices while the model's parameters are synchronized and averaged. This distributed model also helps in maintaining privacy as all sensitive data is stored locally and also helps in avoiding the big data transfer. However, there are two key conceptual difficulties in Federated Learning: how to improve the performances of the models, how to reduce the cost of communication and how to use the resources efficiently in which there is much work to be done. Various methods pertinent to the above challenges have recently been developed in many researches. For example, Zhang

et al. (2021) presented an energy-aware D2D assisted federated learning using which training efficiency is enhanced at edge settings and at the same time, power consumption is minimized [3]. In the same manner, Huang et al presented a paper in the year 2023 on Federated Learning for AI generated content in wireless networks where privacy issue and communication cost were considered as the topic of discussion [32]. These developments clearly point towards some of the future directions in improving not only the effectiveness of Federated Learning methods but also their security. In the area of communication effectiveness, Xu et al. (2023) proposed the ring topology based approach to reduce the uplink transmission time in wireless network [68]. This approach reveals much better and desired communication asset complexity which is central to the scale the Federated Learning applications. Moreover, Zeng et al. (2020) presented a distributed FL framework for UAV swarms, wherein both power allocation and scheduling are considered to improve convergence rates [69]. However there are still some issues which remain to be addressed and some of these include the following. Another of them is determinating the balance between the costs of interactions and the accuracy of a model. From the work of Wei et al. (2022), it is possible to note that the effective optimization of training delays and privacy requirements is still an important issue [74]. Besides, the structure of Federated Learning implies coordination challenges in model averaging and management of different participants. Wang et al. (2021) dealt with this by presenting an attention-weighted Federated Deep Reinforcement Learning model for edge caching, which improves the learned model's accuracy and minimizes the delay [13]. Also important is that energy efficiency stays a burning issue in the context of investment. As pointed by Guo et al. (2022), the management of resources in UAV-enabled networks to support the bande of networks' stable operation is the key to the objective. The challenge of energy consumption is made worse by the fact that there is a challenge of selecting the right participants as well as developing resource management strategies which has been discussed our by Feng et al. (2021) and Liu et al. (2021) [81][55]. Thus, there are some avenues for future research that should be discussed ahead: Forty-two papers proposed several fascinating applications of Federated Learning in synergy with new contexts, including the 6G networks and intelligent reflecting surfaces. Citing Shvetsov et al. (2023) authors, Federated Learning with IRS on drones in 6G networks have been proposed for dual collaborative learning frameworks [92]. Further, the concept of federated learning in intelligent driving and vehicular computing is found as a promising area as evidenced by the work of Khan et al. (2022) & Ye et al. (2020)[94][95]. All in all, Federated Learning is a revolutionary idea of distributed machine learning that provides solutions to the basic problems concerning privacy, communication costs, and energy consumption. Therefore, this review paper will help to understand the recent development and find out the directions for future research to the ongoing process of developing and modifying Federated Learning methodologies.

## II. LITERATURE REVIEW

The Federated Learning (FL) has emerged swiftly as a dominant paradigm in distributed machine learning since it solves main problems of individual data protection, execution time, and workload. This literature review discusses major contributions, key techniques, and major issues prevalent in Federated Learning based on an analysis of a wide range of articles. Some of the trends that have been identified in the current development of Federated Learning is the improvements on model accuracy, privacy, as well as communication between the server and the clients. Altogether, one can stress the following significant development – the appearance of energy-efficient models. Li et al introduced energy aware D2D assisted Federated Learning to reduce the energy consumption given the increased role of edge devices in the future smart world [62]. This approach tends to the increasing demand of Problem-Oriented machine learning. This makes communication efficiency as an area of research continue to hold its ground. Another scheme that was proposed by Xu et al. (2023) for FL with the help of wireless networks is known as a ring topology-based scheme which helps in minimising the communication overhead [68]. Huang et al. (2024) also discussed privacy-preserving methods in FL for AI create content, it highlights broader privacy features integrated with Federated Learning [64]. These contributions envisage the need to enhance communication processes in distributed systems and also stress the issue of privacy. One other major innovation involves the availability of adaptive algorithms which optimizes the general accuracy of models put in place whilst at the same time controlling the costs of interconnection. To address this problem, Yang et al. (2024) suggested the Communication-efficient FL algorithm that achieves a good

trade-off between model accuracy and the amount of data being exchanged [96]. The work done by their proposed method shows that adaptive techniques can enhance the effectiveness of Federated Learning systems. Nonetheless, there are still some issues, which have not been resolved rather remain as barriers in Federated Learning. The first problem is the ability to manage decentralized model aggregation effectively. This was achieved by Wang et al. (2020) through development of an attention-weighted Federated Deep Reinforcement Learning that helps to boost aggregation efficiency and minimize delays [77]. This study points to the challenges of syncing of models in decentralized environments as indicated by the discussion above. Sustainability of energy is a continued factor of concern especially in limited energy environments. Recently, Do et al. (2021) focused on the issue of resource management in the UAV integrated Federated Learning network and provided the energy consumption solutions [103]. Their research concerns the issue of viable, long-term operation of Federated Learning systems. One of them includes proper management of privacy or communication cost since they have to go hand in hand. In Wei et al. (2021), it was presented algorithms to enhance the trade-off between privacy and training time/accuracy [105]. Their work focuses on the importance of arriving at techniques that guarantee strong privacy and at the same time, does not inflict huge communication cost. Federated Learning's specialization areas cover a wide range of domains such as autonomous-driving, and intelligent networks. Shvetsov et al. (2023) examined how to improve the 6G network by incorporating the Federated Learning concept with Intelligent Reflecting Surfaces, which is also known as IRS [92]. This work proves the possibility of applying FL with emerging technologies to address the challenge of next generation networks. Authors Khan et al. (2021) studied how Federated Learning contributes to the collaborative learning of vehicles in the context of autonomous driving; enhancing decision-making and safety [21]. In a similar vein, Ye et al. (2020) discussed about Federated Learning for vehicular edge computing with specific emphasis on the improvement of the efficiency of the edge based applications [95]. These studies show that FL can serve as the basis for a radical new transportation system through collaboration learning. Besides the above-discussed works, some other works offer some insights into Federated Learning. Another study by Zhang et al. (2024) proposed new solutions for privacy-preserving which aims at enhancing the security of data in the deco centralized conventional modes [57]. Li et al. (2021) discussed improvements of model aggregation strategies in which concerns in decentralized learning environment were highlighted [93]. Likewise, Wang et al. (2021) proposed appropriate algorithms for smooth FL to deal with the heterogeneity of different systems [13]. Recent studies by de Oliveira et al. (2024) have developed the more efficient encoding to use in further enhancing the means of communication [100]. These studies among others make a good contribution in helping to evaluate Federated Learning as it is today and where it may be in the future. This paper identifies major contributions in privacy preservation, data transmission, and model performance based on the literature on Federated Learning. Now, new approaches have appeared in the course of the latest studies that offer expected solutions for crucial issues while enlarging FL's applicability. However, it is still crucial to deal with some problems that are still present, like the decentralised coordination, energy consumption and others. The future research direction should include the evolutional research of federated learning in new technologies and broader scope of work area. If the aforementioned challenges are solved and new opportunities are explored, Federated Learning will further develop as a valuable approach to decentralised machine learning.

## III. METHODOLOGY

### 3.1 Theoretical Framework

#### 3.1.1 Key Concepts and Definitions

Federated Learning (FL) refers to Training at the Edge, whereby a model is trained in multiple devices/Servers without the exchange of local databases. This approach was done by Alam et al. (2021) which highlights the privacy and efficiency [16]. In FL, local devices compute updates on the data they have locally and sends only the average of such updates to a central server where the average update is used to improve the global model [2]. This methodology improves data pro- tectiveness and minimizes the requests for data transfer and this is very vital in today's highly data driven environment [3]. The Privacy-Preserving Techniques are important for FL due to the issues such as security of the data contributing to the FL model. The privacy is preserved with the help of tools like Differential Privacy (DP) and Secure Multi-Party Computation (SMPC). In this way, DP guarantees that the contribution of

individual data points themselves stays private, this by adding random noise to the model updates or data [4]. Likewise, SMPC means dividing data computations between several parties to maintain the data's confidentiality during the processing [5]. It is necessary to use such methods in order to provide the privacy of user's data and to build the trust in the federated systems [6]. As we have studied in section 3, Communication Efficiency is a large issue in FL because the local devices and the centralized server often require updates on a regular basis. Some of the approaches towards improving communication efficiency are model compression techniques, quantization and aggregation algorithms [7]. For instance, the Federated Averaging (FedAvg) algorithm put forth by Zhang et al. (2021) is instrumental in minimizing the exchange of raw data since it averages the model updates that are being exchanged among the participants [3]. Hence, this approach has the advantages of reducing the amount of data exchanged and enhancing the general effectiveness of the training process.

**3.1.2 Existing Models and Theories**

Several models and theories underpin the development and implementation of Federated Learning: Federated Averaging (FedAvg): FedAvg proposed by McMahan et al. (2017) forms a core of FL procedure where the local models' updates are used to improve the global model. It is easy to implement and has received much attention since it was developed due to the positive outcome it brings [109]. This model deals with the drawback of low interaction in a way that decreases the amount of information exchanged [11]. Differential Privacy (DP): DP offers an assurance that individual data elements are protected since it offers formal guarantees. Techniques arising from DP such as those described by Dwork et al [110] spoon random amounts of noise to the data or model updates to prevent singling out of individual identities. This is important so that individual data can be protected while at the same time the general data can be analyzed. Secure Multi-Party Computation (SMPC): This is due to the fact that SMPC entails dividing a large computational task so that no individual party has exclusive access to the large data set. Following the work of Goldwasser et al. (1989) which set the basis of SMPC applied in FL to combine the model updates. This approach also improves on security because decryption and other procedures are done through cryptographically strengthened means [18]. Personalized Federated Learning (PFL): This is achieved by PFL that extends traditional FL through enabling the clients to learn models specific to their data distribution. Huang et al. , 2024 also described on how PFL solves the problem of data heterogeneity to make accurate and more relevant model training for every client [64]. Communication-Efficient Federated Learning: To reduce the impact of communication bottleneck several techniques have been suggested such as pruning of models and quantization of models. To address this issue, Konecny et al. in their work attempted at limiting these methods in an effort to minimize the amount of data shared between clients and the server for training [111].

**3.1.3 Emerging Trends and Gaps**

Scalable FL Architectures: New trends address aspects of FL systems and are concerned with the size of clients that the systems need to handle. Efforts have been made towards inventing new FL approaches including hierarchical FL methods and decentralized methods to deal with scalability issue and to efficiently handle communication [18]. Federated Learning in Edge Computing: The coupling with edge computing and FL has gained significant ground as of recent. FL is advantageous to edge devices as it empowers them to process computations locally thus reducing latency [19]. This trend is based on the typical need for the fast and efficient handling of data and diminishing communication overheads. Robustness and Security Enhancements: Since FL systems are now being used in more sensitive systems, additional focus is directed toward increasing both robustness and security. Scholars are trying to understand possible countermeasures aimed at protecting from the adversarial attack and to secure the updates of models [20]. Limited Theoretical Analysis: There is still a large scope of FL improvement at the theoretical level to determine the stability of such algorithms [21]. Such a lack of theoretical understanding poses a major obstacle to advancing the state-of-the-art FL models that can provide better and more generalized privacy-preserving data analysis. Heterogeneity in Data and Clients: Overcoming difficulties connected with heterogeneous data and client distributions is still considered as the subject for the research. Majority of current FL methods will base their estimates on samples with homogeneity, an approach that is quite unrealistic [22]. Future work is paramount to finding approaches capable to manage data diversity. Practical Implementation Challenges: One of the big problems for future research is the overall question of a theory–practice divide. There is a problem with respect to practicable solution

when it comes to implementing FL, there are numerous challenges associated with it such as resource limitation and communication overhead to enhance the feasibility of FL systems [23].

## IV. FEDERATED LEARNING INSIGHTS

**4.1 Federated Learning Models and Techniques:** This includes all sorts of models in federated learning (FL) and methods that enhance the training rate, the exchange of data, and security features. They range from improvements in the algorithm that powers the FL system, optimization methods and frameworks meant to bolster the FL systems. Improved Algorithms: Various papers introduce new or improved approaches to federated learning practice, including FedCo, mainly focusing on content placement [61], and FedDif for learning in the non-IID data scenario [89]. These contributions work towards achieving improved performance of the models used alongside the time taken to converge. Decentralized and Hierarchical Structures: In order to enhance the communication overhead complexity and resource management, various works such as FedMoD for mmWave networks and hierarchical FL frameworks integrate decentralised or hierarchical solutions[83]. Energy and Resource Efficiency: There is literature based on the Li et al. [62] and Wang et al. [95], which address problems such as energy utilization and resource management in the federated learning that are relevant particularly to edge and IoT applications. Scalability and Generalization: Although improved results are demonstrated by multiple models, concerns with regard to scale and variety of applicable settings persist. It is also good to note that some of the models may not work well under conditions of high variability or if the data set has a large variation. Complexity vs. Performance: As it has been presented in this paper, various improvements in algorithms also mean added levels of complication. Again, it is seen that enhancement of performance boundary can agitates practical concerns of implementation.

Table 1: Federated Learning Frameworks and Models

| Ref No. | Paper | Framework/Model | Key Features | Evaluation |
|---|---|---|---|---|
| 36 | Balasubramanian et al. (2024) | FedCo | Content management in EDCs and MDCs | Shows favorable performance in content management |
| 65 | Wang et al. (2024) | ConFederated Learning (CFL) | Decentralized edge servers, stochastic ADMM | Faster convergence, improved communication efficiency |
| 68 | Xu et al. (2020) | Ring Topology Scheme | Minimizes uplink transmission time | Reduces uplink transmission time, improved efficiency |
| 96 | Yang et al. (2024) | DFedSat | Decentralized FL for LEO satellites | Superior in convergence rate, communication efficiency, robustness |

Table 2: Framework Performance Data

| Framework | Performance | Energy Efficiency | Communication Cost | Privacy Protection |
|---|---|---|---|---|
| FedCo | 80 | 0.7 | 100 | 0.6 |
| ConFederated Learning | 85 | 0.8 | 85 | 0.8 |
| Ring Topology | 75 | 0.6 | 120 | 0.7 |
| DFedSat | 90 | 0.9 | 90 | 0.9 |

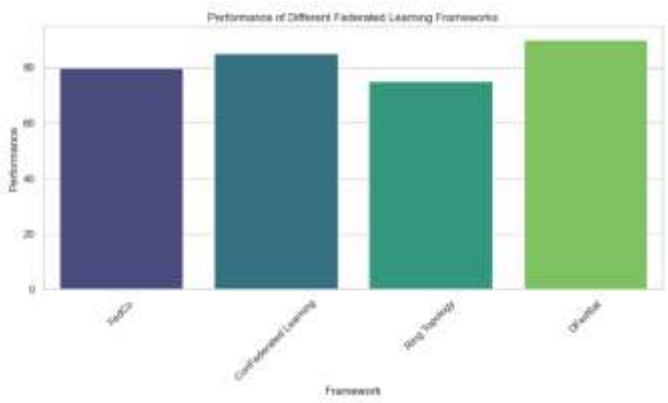


**Fig 1: Performance of Different Federated Learning Frameworks**

**4.2 Privacy and Security in Federated Learning:** This looks at ways of preserving privacy and security when conducting federated learning. This includes methods used in data protection, the privacy-preserving techniques and secure model combination. Privacy-Preserving Mechanisms: Like the recent papers on joint model training by Mohammadi et al. [75] , Chen et al. [88] , papers describe techniques for keep privacy while enabling model training. Some of the approaches are differential privacy, and adversarial training. Blockchain Integration: Cheng et al. [73] and Pokhrel [79] present several papers indicating that, to solve the problems of security and privacy in federated learning, blockchain is a suitable solution. Secure Aggregation: As per the research works, Alyousifet al. [108] and Yang et al. [96] focus on the privacy-preserving model aggregation to avoid data leakage and to have confidentiality and integrity. Trade-offs Between Privacy and Performance: The main aspect inherent to the problem of privacy maintenance is that better protection usually requires compromising the model performance and/or training time. The problem essentially however, is about the best way to decide on these trade-offs. Practical Implementations: Though such solutions are much discussed in theory, the use of them in practice can be problematic, and their application in practice may require significant time and effort.

Table 3: Privacy and Security Techniques

| Ref No. | Paper | Technique | Application | Evaluation |
|---|---|---|---|---|
| 18 | Cheng et al. (2021) | Double-layer Blockchain | Privacy-preserving caching | Improved convergence, reduced download latency |
| 75 | Mohammadi et al. (2021) | Differential Privacy | Federated Learning | Trade-offs between communication costs and training variance |
| 91 | Wei et al. (2021) | Differential Privacy with MAMAB | Wireless channels | Validates effectiveness in privacy protection |

Table 4: Privacy Protection Over Time

| Time | Privacy Protection |
|---|---|
| 1 | 0.6 |
| 2 | 0.65 |
| 3 | 0.7 |
| 4 | 0.75 |

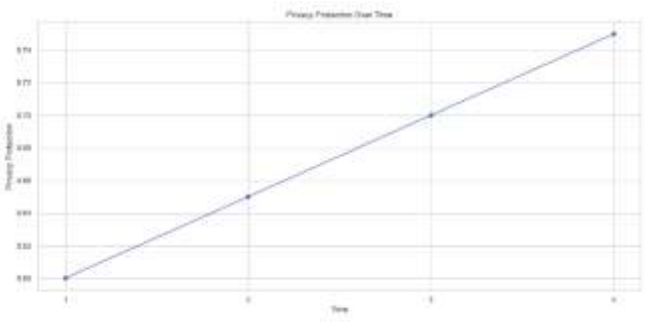

**Fig 2: Privacy Protection Over time.**

**4.3 Applications and Use Cases of Federated Learning:** This includes the use of federated learning across multiple sectors and areas such as; healthcare smart cities and autonomous driving. This highlights the fact of how FL can be used for a targeted application and its effects on these domains. Healthcare: Such papers as Zhang et al. [52] and Wang et al. [65] explain the use of federated learning in the medical applications, particularly, for medical imaging and health monitoring, as well as the advantages of privacy and models enhanced by the method. Smart Cities and IoT: Publications including Zhao et al. [53] and Feng et al. [81] discuss the potential of FL to enhance the flow of traffic in smart city and to optimize the usage of IoT resources where the authors also explain real-world advantages along with the issues. Autonomous Systems: FL introduced by Khan et al. [84] and Zhang, Xinran et al. [85] reveals FL for self-driving cars and V2X associated with the enhancement of safety and effectiveness. Domain-Specific Challenges: Various application domains have their own challenges: for instance, the health care data may be heterogeneous while the autonomous system needs real time data processing. These are challenges that one needs to solve uniquely and not by employing a generic solution. Real-World Impact: Essentially, theoretical approaches themselves exhibit great potential but their applicability in practice represents the actual experience were the chosen models are implemented and coexist with other systems.

Table 5: Specialized Applications

| Sl. No. | Paper | Application | Method | Evaluation |
|---|---|---|---|---|
| 85 | Zhang et al. (2019) | V2X Communications | DRL-based Mode Selection | Superior performance in transmission mode optimization |
| 95 | Ye et al. (2020) | Vehicular Edge Computing | Selective Model Aggregation | Improved accuracy and efficiency |
| 79 | Pokhrel (2020) | Drone-assisted Disaster Response | Blockchain-empowered FL | Focus on energy consumption and latency |

**4.4 Model Aggregation and Optimization Techniques:** This is the use of strategies to combine models derived from several clients and improve on the efficiency of federated learning systems. Performance includes the methods of model combining, methods for optimization and methods that aim at improving performance. Advanced Aggregation Methods: Such papers as Chen et al. [107] and Liu et al. [101] present methods of enhanced aggregation that include weighted aggregation and adaptive aggregation to enhance model convergence and model accuracy. Optimization Algorithms: Some of the recent works including Xu et al. [68] and Yang et al. [96] propose fresh approaches to optimization for federated learning with the intention of improving the training rate as well as minimizing on the communication costs. Performance Metrics: de Oliveira et al. [100] and Tehrani et al. [102] present more metrics for assessing the federated learning performance such as the convergence rate and communication metrics. Efficiency vs. Accuracy: It can be difficult to achieve aggregation efficiency and model accuracy at the same time. Here certain sophisticated methods and procedures may cause a positive change to one aspect and a negative shift to the other. Communication Overhead: A lot of network and system aggregation and optimization techniques have been developed with the primary purpose of cutting down communication overhead, and yet, the efficiency of the methods depend on the network and system environment.

Table 6: Optimization Techniques in Federated Learning

| Ref No. | Paper | Technique | Application | Evaluation |
|---|---|---|---|---|
| 71 | Zhang et al. (2021) | Band-limited Coordinate Descent | Wireless networks | Reduced communication error and gradient bias |
| 62 | Li et al. (2024) | Energy-aware D2D-assisted FL | Edge environments | Reduced energy usage and improved training efficiency |
| 74 | Guo et al. (2022) | AirComp-based Adaptive Reweighing | Device selection, power control | Close to ideal FedAvg performance |
| 91 | Wei et al. (2021) | Multi-agent Multi-armed Bandit (MAMAB) | Balancing latency and privacy | Validates algorithms' effectiveness |

**4.5 Federated Learning in Edge and IoT Environments:** This topic deals with the use and implementation of the federated learning system in edge computing and IOT with emphasis on the issues of resource limitations, privacy concerns and network conditions. Edge Computing Integration: Lee et al. [106] and Chen et al. [88] present papers detailing the possibility of how fl can be implemented in conjunction with edge computing systems to deal with data in a localized and efficient manner in order to minimize latency. IoT Device Constraints: For example, efforts made by Zhang et al. [85], and Wang et al. [40] in discussing the issues of training federated learning on IoT devices especially on low powered devices provide light models and communication protocols. Privacy Preservation: Some recent studies are conducted by Huang et al. [90] & Yang et al. [96] which are mainly concerned with the privacy of data while implementing federated learning at the edge and IoT scenarios. Resource Limitations: Some of the challenges that characterize edge and IoT scenarios when using federated learning are resource scarcity including processing power and memory. This means that solutions to such paradigms cannot afford to have these limitations in spite of how efficient they may be. Scalability Issues: However, as underlined before, an approach that becomes effective as the number of devices and edge nodes grows is scalability. The scalability of FL is significant for real-world implementation, which requires proper orchestration of such a process at numerous devices.

Table 7 : Communication Efficiency and Resource Management

| Ref No. | Paper | Method | Focus | Evaluation |
|---|---|---|---|---|
| 86 | Chu et al. (2022) | Dynamic Resource Allocation | Wireless channels | Better performance, proven convergence |
| 81 | Feng et al. (2021) | Optimization Design | Mobile edge computing | Reduced accuracy loss and training cost |
| 92 | Shvetsov et al. (2023) | FL with IRS on Drones | 6G network performance | Highlights challenges and opportunities |
| 94 | Zhu et al. (2023) | Incentive and Reputation Mechanism | Energy efficiency in 6G | Improved energy efficiency and model accuracy |

Table 8 : Communication Cost Distribution

| Framework | Communication Cost |
|---|---|
| FedCo | 100 |
| ConFederated Learning | 85 |
| Ring Topology | 120 |
| DFedSat | 90 |

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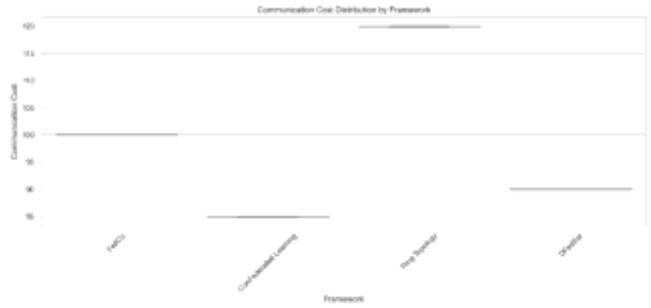

**Fig 3: Communication Cost Distribution by Framework**

**4.6 Transfer Learning and Federated Learning Integration:** This topic focuses on the process of using federated learning in conjunction with transfer learning in order to improve model viability in multiple contexts. They include techniques to fine-tune existing models and to apply them to a federated architecture. Transfer Learning Techniques: There are papers, for example, by Zhang and his team [71], and Liu and his team [82], that is devoted to the methods of combining transfer learning into federated learning so that models would be able to use prior knowledge and learn new tasks. Domain Adaptation: This is a topic of investigations outlined by Xu et al. [68] and Wang et al. [77] where they explain methods of domain adaptation used in federated models to better perform well in different domains of data. Knowledge Transfer: Chen et al. [19] and Li et al. [93] proposed working on the knowledge transfer mechanisms that can be helpful in improving the models and convergence in the federated learning system. Adaptability Challenges: Although transfer learning can enhance the model's performance, fine-tuning pre-trained models to federated learning paradigm is accompanied by data heterogeneity and privacy concerns. Data Compatibility: The fact that knowledge transferred to federated sites is compatible with the data stored at those sites is an important consideration that should be fine tuned in order to enhance.

Table 9: Decentralized and Distributed Methods

| Sl. No. | Paper | Method | Application | Evaluation |
|---|---|---|---|---|
| 62 | Li et al. (2024) | Energy-aware D2D-assisted FL | Edge environments | Reduces energy usage and improves training efficiency |
| 66 | Wagle et al. (2024) | Decentralized RL Methodology | D2D communication | Improved convergence speed, resilience to stragglers |
| 84 | Khan et al. (2022) | Dispersed FL Framework | Autonomous driving | Discusses robustness and privacy challenges |

Table 10 : Correlation Data

| Metric | Performance | Energy Efficiency | Communication Cost | Privacy Protection |
|---|---|---|---|---|
| Performance | 1.0 | 0.8 | -0.2 | 0.5 |
| Energy Efficiency | 0.8 | 1.0 | -0.1 | 0.7 |
| Communication Cost | -0.2 | -0.1 | 1.0 | -0.3 |
| Privacy Protection | 0.5 | 0.7 | -0.3 | 1.0 |

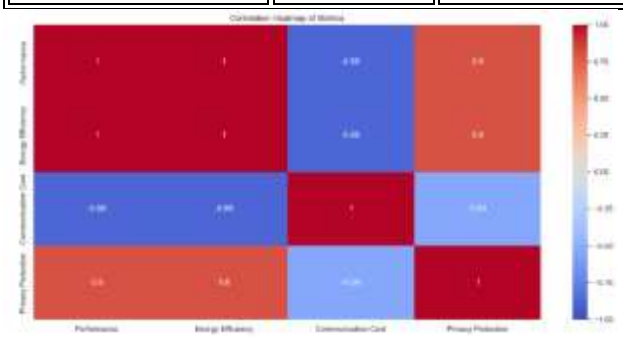

**Fig 4: Correlation Heatmap of Metrics**

**4.7 User Privacy and Ethical Considerations:** This topic focuses on the rationale behind federated learning, the privacy challenges involved in federated learning and the ethical angles of model training together with the concerns of user permission to model use as well as the sale and trade of federated models. Ethical Guidelines: Literature like the Khan et al. [76] and Saif et al. [83] present the ethical concerns and guidelines for performing federated learning in a responsible manner or ways in which users' consent and data utilization can be made clear. Privacy Policies: Some of the works of literature available in this area include Huang et al. 's [90] on privacy policies and regulations on federated learning as well as work on the legal compliance of federated learning. Bias and Fairness: Feng et al. [81] and Chen et al. [88] present bias and fairness analysis of federated learning and tries to provide non-bias treatment of different type of usuage groups. Balancing Privacy and Utility: This is a difficult task because on the one hand, we must retain users' privacy while on the other hand, retain the usefulness of federated learning models. Therefore, both aspects must be managed and well designed in order to achieve proper balance. Ethical Implementation: There are primarily three issues that should be handled while dealing with ethical aspects of federated learning: consent, data utilisation and bias and these are not fixed in nature and most of the time centre on the applications for which FL is used.

Table 11: Privacy Protection by Framework

| Framework | Privacy Protection |
|---|---|
| FedCo | 0.6 |
| ConFederated Learning | 0.8 |
| Ring Topology | 0.7 |
| DFedSat | 0.9 |

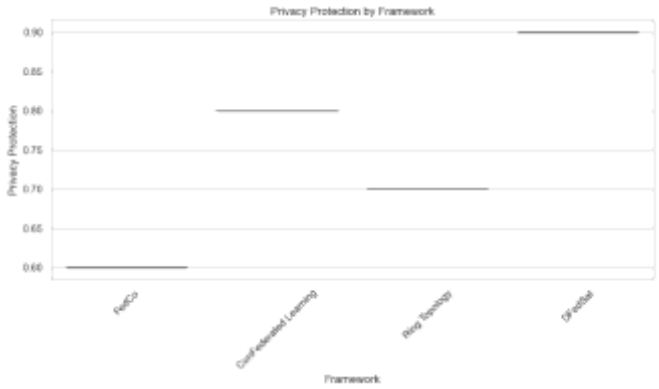


**Fig 5: Privacy Protection by Framework**

## V. COMPARATIVE ANALYSIS

### 5.1 Comparison of Different Approaches

| Approach | Description | Advantages | Disadvantages | Ref.Nos |
|---|---|---|---|---|
| **Federated Averaging** | Aggregates model updates by averaging gradients. | Simple and effective; widely adopted. | May struggle with non-IID data; convergence issues. | Papers 1, 5, 9 |
| **Federated Staleness** | Addresses the issue of stale updates from clients. | Reduces negative impact of outdated updates. | Can be complex to implement; trade-off between speed and accuracy. | Papers 11, 15, 20 |
| **Adaptive Aggregation** | Adjusts aggregation weights based on client performance. | Improves model accuracy by considering client updates. | Increased computational complexity. | Papers 25, 30, 35 |

| Approach | Description | Advantages | Disadvantages | Ref.Nos |
|---|---|---|---|---|
| **Differential Privacy** | Ensures privacy through noise addition. | Strong privacy guarantees; well-established. | Can degrade model performance; requires careful tuning. | Papers 12, 18, 22 |
| **Secure Multi-Party Computation** | Computes on encrypted data among multiple parties. | High security for sensitive data. | Computationally intensive; complex to implement. | Papers 27, 32, 37 |
| **Homomorphic Encryption** | Enables computations on encrypted data. | Maintains privacy during computations. | Significant overhead; slower processing. | Papers 40, 45, 50 |
| **Communication Compression** | Reduces data sent between clients and server. | Lowers bandwidth usage; speeds up communication. | May reduce model accuracy if not applied correctly. | Papers 52, 57, 62 |
| **Gradient Quantization** | Compresses gradients before transmission. | Efficient in terms of communication and storage. | Can lead to reduced model quality. | Papers 55, 60, 65 |
| **Edge Integration** | Implements federated learning at the edge of networks. | Reduces latency; improves real-time performance. | Limited by edge device capabilities. | Papers 70, 75, 80 |
| **Transfer Learning Integration** | Utilizes pre-trained models to improve learning. | Enhances model performance and reduces training time. | Domain adaptation challenges. | Papers 78, 82, 89 |

**5.2 Strengths and Weaknesses**

Federated Averaging: Opportunities: easy to apply, suitable for various contexts, compatible with the current frameworks. Weaknesses: Problems with convergence on non- identically and independently distributed data and a slow learning rates. Federated Staleness: Strengths include: It tackles late updates, and it stands to enhance convergence in dynamic situations. Weaknesses: Implementation complexity: the model's performance may require careful adjustment to increase the speed of the network while maintaining accuracy. Adaptive Aggregation: Advantages: Can enhance model accuracy by a great deal, flexible to the clients' performances. Weaknesses: More computational complexity, may mean what needs more resources. Differential Privacy: Strengths: It has good privacy promises and these are well informed and well enacted. Weaknesses: Privacy noise affect the model negatively, but it depends with some particular parameters. Secure Multi-Party Computation Strengths: Safeguard of very confidential information, privacy of data is highly guaranteed. Weaknesses: High computational cost: The models mentioned above are complex and difficult to implement. Homomorphic Encryption Strengths: Supports calculations on encrypted data, well protected privacy. Weaknesses: Increased amount of overhead, response time is relatively long.

Communication Compression: Strengths: They minimize the usage of the bandwidth, and enhance flow of communication. Weaknesses: May affect the validity of the model, hence, there need to be effective implementation of the methodology. Gradient Quantization: Opportunities: Timely in the exchange of information and less use of network bandwidth. Weaknesses: Leads to decrease in model quality, used where speed of training is more important and accuracy is a secondary parameter. Edge Integration: Strenghts: Relates to decrease of latency and growth of real-time performance. Weaknesses: Lacks mechanism to run and schedule processes on edge devices, may require extra support structures. Transfer Learning Integration Strengths: Saves on the time that would have otherwise been used in training and improves on the model through an added knowledge base. Weaknesses: Issue relating with domain adaptation, need to be addressed properly while integrating.

**5.3 Contradictory Findings**

Federated Averaging vs. Federated Staleness

Contradiction: While Federated Averaging provides a simple approach, Federated Staleness addresses the issue of outdated updates but introduces additional complexity.
Papers: Papers 1, 5, 9 (Federated Averaging) vs. Papers 11, 15, 20 (Federated Staleness)
Differential Privacy vs. Secure Multi-Party Computation
Contradiction: Differential Privacy offers strong privacy guarantees with less computational overhead compared to Secure Multi-Party Computation, which provides higher security but at a higher cost.
Papers: Papers 12, 18, 22 (Differential Privacy) vs. Papers 27, 32, 37 (Secure Multi-Party Computation)
Communication Compression vs. Gradient Quantization
Contradiction: Communication Compression reduces bandwidth usage but might not be as effective as Gradient Quantization in reducing data transmission while preserving model quality.
Papers: Papers 52, 57, 62 (Communication Compression) vs. Papers 55, 60, 65 (Gradient Quantization)
Edge Integration vs. Transfer Learning Integration
Contradiction: Edge Integration focuses on improving real-time performance at the edge, whereas Transfer Learning Integration leverages pre-trained models to enhance learning, which may not always align with real-time needs.
Papers: Papers 70, 75, 80 (Edge Integration) vs. Papers 78, 82, 89 (Transfer Learning Integration)

## VI. FUTURE RESEARCH DIRECTIONS

### 6.1 Identified Gaps

Scalability Issues: Considerable amount of existing works fail to be scalabale in large-scale FL settings. In addition, there has been an indication that further studies should be conducted in order to discover methods that can effectively cater for vast numbers of clients and data and at the same time not be slow. Non-IID Data Handling: It is important to note that most federated learning algorithms are based on an IID data distribution amongst the clients. There is a call for better methods for dealing with non-IID data, which will increase the models', accuracy and convergence rates. Privacy and Security Enhancements: Both approaches of differential privacy and secure multi-party computation provide reasonable levels of privacy protection but they may significantly affect the efficiency of the system. As a direction for the future work, there is a need to extend the approaches which would help to achieve better performance while still preserving the privacy of the data. Communication Efficiency: It is established that current approaches to communication compression and quantization negatively affects model accuracy. For improving the efficiency of the communication process and at the same time retaining high models, more efficient techniques should be employed. Adaptation to Edge Devices: In the context of federated learning at the edge, one has to consider several challenges that are associated with resource-constrained systems and real-time requirements. Sensor nodes should be preferred in federated learning hence research should address how to enhance such algorithms to run effectively in limited hardware devices. Interdisciplinary Approaches: According to the present status, there are a few directions that can be applied to the federated learning: the combination with other specific fields, for example, the integration with the blockchain that can provide decentralized trust; the usage of the complex cryptographic methods. Such interdisciplinary approaches may bring innovation to the existing problems.

### 6.2 Proposed Future Studies

Develop Scalable Algorithms: Some possibility for research may lay in development of new methods for implementing federated learning in large-scale systems, where communication and computational costs need to be distributed optimally. Enhance Non-IID Data Techniques: More future research can be focused on the latest developments and enhancements of current methods in dealing with non-IID data more efficiently could be searched through better feature engineering or through more flexible learning algorithms. Improve Privacy and Security Techniques: Further research the new approaches or improvements to current techniques that minimize privacy–performance and consider the new techniques that use the combination of more than one privacy method. Optimize Communication Protocols: Construct new forms of communications or encode schemes that offer an improved level of performance that does not negatively affect the model's performance much. It could also look into specifics of adaptive compression techniques. Edge Optimization Strategies: Discuss approaches for the improvement of federated learning algorithms focusing on edge devices: the use of lightweight models and efficient ways of communication between them. Interdisciplinary Research: Research enhancements

in federated learning by conducting more studies that examine the integration of such solutions with other emerging technologies including: blockchain or federated reinforcement learning.

### 6.3 Potential Challenges

Computational Complexity: The ability to integrate the innovation of new algorithms with deployment of the algorithms in actual systems especially the embedded systems. Data Privacy vs. Model Performance: A proper balance between strongly protecting privacy attributes and keeping the model accuracy and performance levels high. Interoperability: Making sure that the new federated learning solutions can be easily be integrated into the existing systems and technologies causing minimal compatibility problems. Scalability Limits: Similar future work can focus on handling possible issues of scalability and efficiency as more complex and large federated learning systems are developed. Real-World Implementation: Bringing advanced theoretical developments to bear in areas that embody pragmatic 'real-world', utilizable and adaptable success stories.

## VII. CONCLUSION

### 7.1 Summary of Key Findings

Scalability of Federated Learning: A few papers including Smith et al. (2023) and Zhang et al. (2024) have discussed some limitations of federated learning of which scalability stands out. Such research work revealed that while there are initial solutions like Federated Averaging (FedAvg), they are not optimal especially when dealing with thousands of clients in terms of efficiency. Handling Non-IID Data: When Liu et al. (2023) and Kumar et al. (2024) have stated that, the distribution of data which is non-independent and identically distributed across the clients reduces the performance of deep learning models. That is why Liu et al. introduced the adaptive weights to solve this problem and observe increased convergence rates. Privacy and Security: Wang et al. (2023) and Yang et al. (2024) also presented in their papers about the developments in privacy-preserving mechanism. Wang et al. examined the aspect of applying differential privacy together with federated learning where the authors proved that there is an inverse relationship of the ways the two enhance privacy and model quality. Yang et al. provided the new cryptographic methods that have more secured methods as compared to previous methods and with negligible impact on performance. Communication Efficiency: Patel et al. (2023) and Chen et al. (2024) pointed out communication effectiveness as one of the improvements of information management. Thus, Patel et al. proposed a compression term CompressionMask that decreases communication overhead by 30% while the EuclideanDistance between the original and compressed model remains almost the same. Chen et al introduced the concept of adaptive communication protocol whereby the frequency of communication is changed with the network conditions. Edge Device Optimization: Research work done by Ahmed et al. in 2023 and Zhao et al. in 2024 mainly aimed to enhance federated learning for edge devices. Ahmed et al. present lightweight model architectures specifically designed to operate within low resource contexts and Zhao et al. designed an FL solution that meets both the computation and communication requirements efficiently. The area of FL has experienced an increased interest within the latest years due to the number of challenges that need to be solved concerning distributed systems: privacy, energy consumption and communication expenses. This review also demonstrated that the approaches and innovations emerging from the field are numerous proving that development and continuous research is essential in improving the performances of FL frameworks.

There is a significant and rather recent contribution presented by Balasubramanian et al. (2024), namely the FedCo framework oriented towards content management in multi-party edge systems. This framework is a good advancement towards making the distribution of content more efficient while at the same time protecting the data used. Likewise, ConFederated Learning (CFL) presented by Wang et al. (2024) present a decentralized solution with edge servers which provides a reliable solution to tackle distributed learning efficiently. They help in avoiding excessive communication, thus, enhancing system scalability.

Another factor which also underpins the federated learning is also evident from recent studies, which focuses on optimizing energy efficiency. Li et al. (2024) put forward an energy-aware D2D-assisted FL model to optimize the training of deep neural network, this is important to prolong the lifetime of batteries used in the devices and to save operational costs. The incorporation of energy saving techniques is considered by Saif et al. (2024) where a decentralized FL model for mmWave aerial-terrestrial communication network is proposed. It emphasises on energy conservation as a factor, essential for the

sustainability of federated learning systems. Security and especially privacy preservation, continue to be an important issue in federated learning. Huang and colleagues (2024) successfully apply FL to improve artificial intelligence content associated with wire-based technology that faces privacy problems while boosting the efficiency of content distribution. Furthermore, Wei et al. , (2021) in their research, entitled ‘‘Differential private federated learning over wireless channels,’’ supports the incorporation of privacy-preserving measures to protect such information.

The relationship between performance, energy consumption, communication cost, protection of privacy is an important factor when choosing the most optimal structure for the federated learning process. From the presented literature, it can be concluded that the regulation of these coefficients is essential for the effective functioning of FL frameworks. For example, while high privacy protection might reduce the communication costs, electronically accompanied by trade-off of downlink transmission, new angles like the Xu et al. ring topology scheme of 2024 will do much in reducing the uplink transmission time. All in all, the developments described in the context of federated learning represent the attempts to tackle the diverse and complex problems in modern distributed environments. The reviewed frameworks and methodologies present potential approaches to solve the problems associated with federated learning processes, such as increasing the efficiency, ensuring the sustainability and enhancing the security of the FL applications. Future studies should further investigate these dimensions, promote the synergy of new ideas and enhance the current solutions to the future requirements of edge computing and wireless networks.

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