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EdgeAI for Privacy-Preserving AI: The Role of Small LLMs in Federated Learning Environments

Mangesh Pujari[1], Anil Kumar Pakina[2]

[1,2]Independent Researcher

Abstract

Privacy considerations in artificial intelligence (AI) have led to the popularization of federated learning (FL) as a decentralized training organization. On this basis, FL allows collaborative model training without requiring data exchange for private data use. The adoption of FL on edge devices faces major challenges due to limited computational resources, networks, and energy efficiency. This paper analyzes the operation of small language models (SLMs) in FL frameworks with an eye on their promise to let intelligent privacy-preserving architectures thrive on edge devices. It is through SLMs that local inference can be made robust while exposing less data. This research investigates the performance of SLMs under different TinyML applications such as natural language understanding and anomaly detection, along with the inherent security vulnerabilities of SLMs in federated learning environments compared to other attack scenarios. Furthermore, effective countermeasures are proposed. Only the policy implications of adopting SLMs for privacy-sensitive domains will be covered, advocating for governance policy frameworks that delicately balance innovations and data protection.

Keywords: Edge AI, Small Language Models, Federated Learning, Privacy-Preserving AI, TinyML, Adversarial Attacks, Data Security, Governance Frameworks.

1. Introduction

1.1 Background on Privacy Concerns in AI

A major issue with data privacy has arisen as AI continues to change. The traditional AI models, where all data is gathered into central servers for training, require data access containing millions of data points to train these applications. Unfortunately, this has opened up many privacy issues (Shen et al., 2024). Data breaches, unauthorized accesses, and even regulatory compliance have actually raised the need to come up with new alternative ways of learning that do not interfere with the data security of the users. Privacy-preserving AI is attempting to address these two main issues of advanced model performance while, simultaneously, keeping the amount of exposure of data to a minimum.

1.2 Overview of Federated Learning and Its Advantages

Federated Learning (FL) is an emergent AI paradigm that allows cooperation in the model's training without any raw data exchange between edge devices and a central server. According to Akhtarshenas et al. (2023), localized training is performed on private data by distributed nodes with submission of model updates instead of sharing data further. This decentralized approach improves privacy and minimizes bandwidth use while training models on heterogeneous data sources (Cheng et al., 2024). Moreover, FL commonly serves

applications whose main concern is within the realm of data sensitivity, such as healthcare, finance, and personalized AI (Wu et al., 2023).

1.3 An Introduction to Edge AI and on Small Language Models in Their Role

Edge AI may be described as the implementation of AI models on edge devices to perform real-time processing with minimal recourse to the cloud, as in using IoT sensors, mobile phones, or embedded systems (Hadish et al., 2024). Although large language models exhibited very high-quality performance in NLP and decision-making tasks, the amount of computation required exceeds the capacity for deployment on the edge.

Small language models (SLMs) are, therefore, a promising alternative to lightweight, efficient AI solutions designed for edge environments while resource-constrained devices are being perfected about the core capabilities of bigger models (Friha et al., 2024). Integrating SLMs in FL frameworks guarantees privacy concerns on the data because data sets remain localized while sharing in collective intelligence. This further enhances the use of privacy-ensuring AI applications across industries through synergy between Edge AI, FL, and SLMs (Chelliah et al., 2024).

1.4 Motivation for Research: The Case for Importance of Adopting SLMs in FL on Edge Devices

Federated learning brings its own issues when migrated to edge devices, as it suffers from constraint computing, limited battery drain, and long network latency. Normal LLMs can be very huge to be converted in installation or execution on an edge device, thus making the SLMs an alternative version (Jayant et al, 2024). Thus, the aim of the current study in this aspect is to find ways in which SLMs will facilitate federated learning performance concerning privative environments. Hence, this study addresses:

1. How SLMs would fare against the applications in TinyML, such as natural language understanding and ambiguity detection.
2. What kinds of security vulnerabilities might there be in any of these SLMs used in FL contexts, and how could they be bounded?
3. What kind of policy framework would be needed for the regulation of SLMs in sensitive-to-privacy domains?

1.5 Research Outputs and Paper Structure

The paper thus contains important and key contributions to those lines:

1. A profile-cost and accuracy assessment of SLMs with respect to TinyML applications on an FL basis.
2. An examination of security challenges that SLMs face in FL environments including adversary attacks and data privacy threats.
3. Suggested countermeasures to increase robustness for SLMs within privacy-preserving AIs.
4. Policy suggestions for the responsible use of SLMs in federated environments.

2. Federated Learning and Edge AI: A Synergistic Approach for Privacy-Preserving AI

2.1 Federated Learning in Its Essentials

Federated Learning (FL) is an AI training modality that decentralizes the training of machine learning models by many devices or institutions without requiring this sharing of raw data. In the FL approach, instead of centralizing data on the server, the data are kept locally on the devices participating in the model training, thus allowing for computing model updates by each participant and sending these updates to a central aggregator (Akhtarshenas et al., 2023). This society thus minimizes the risks of sharing of data and security and avoids the overhead in bandwidth.

The FL works in rounds where local model training is carried out on distributed datasets synched through an aggregation mechanism such as FedAvg or FedProx (Cheng et al., 2024). Some of FLs' major advantages are preventing regulatory and ethical issues in data sharing, especially for sensitive domains like healthcare, finance, and smart infrastructure (Wu et al., 2023). But FL poses new challenges too like communication overhead, system heterogeneousness, and security issues with malicious attacks and model poisoning (Friha et al., 2024).

2.2 Edge AI: Making AI Smart Devices

Edge AI is deploying AI models on edge devices such as IoT sensors, smartphones, and embedded systems that can do real-time inference with less reliance on cloud computing (Hadish et al., 2024). With local data processing, Edge AI can reduce latency, preserve user privacy, and lessen network congestion. However, running AI models on resource-constrained devices requires well-optimized techniques for all-inclusive model quantization, pruning, and knowledge distillation (Chelliah et al., 2024).

SLMs are very well suited to the Edge AI ecosystem, since they require very low computational power and memory resources while preserving all relevant functionalities for natural language processing. This enables tasks such as natural language understanding, command recognition, and anomaly detection in various real-time applications (Jayant et al., 2024). These federated learning-based privacy-preserving AI systems would be considered secure since only updates of the model rather than sensitive user data will be sent for aggregation.

2.3 Synergic Cooperation Exploiting Federated Learning and Edge AI

The duo of FL and Edge AI establishes a robust solution for privacy-preserving AI towards locally putting training on model and distributed intelligence. With Edge AI then becoming a technique to infer in real time with as little latency as possible, FL guarantees that the data remain on the edge devices and reduce the possibility of major breaches in privacy (Shen et al., 2024). This synergy benefits the realization of tailored health care, factory automation, and autonomous vehicles.

Table 1 demonstrates a comparative analysis between traditional centralized AI, FL and Edge AI, focusing on their respective key strengths and limitations

Table 1: Comparison of Traditional AI, Federated Learning, and Edge AI

Feature	Traditional AI	Federated Learning (FL)	Edge AI
Data Privacy	Low	High	High
Computational Cost	High	Distributed	Low
Latency	High	Moderate	Low
Communication Overhead	High	Moderate	Low
Security Risks	Data leaks, cyberattacks	Model poisoning, adversarial attacks	Hardware vulnerabilities
Adaptability	Centralized models	Personalized local models	Real-time decision making

Source: *Adapted from Akhtarshenas et al. (2023); Friha et al. (2024); Hadish et al. (2024)*

2.4 Efficiency of SLMs in FL-Supported Edge AI

SLMs are built to meet performance targets with a corresponding decrease in efficiency due to the reduced complexity of models. These SLMs perform well under constraints in consumption with the aid of model distillation and parameter sharing. A major challenge in FL with SLMs is the trade-off between accuracy and the cost of computation and communication resources (Cheng et al. 2024). The compromises among accuracy, model size, and energy have to be optimized for the practical deployments of the apparatus.
To reflect the performance efficiency of SLM with respect to LLM, **Figure 1** represents the energy consumption across different models into a single graph.

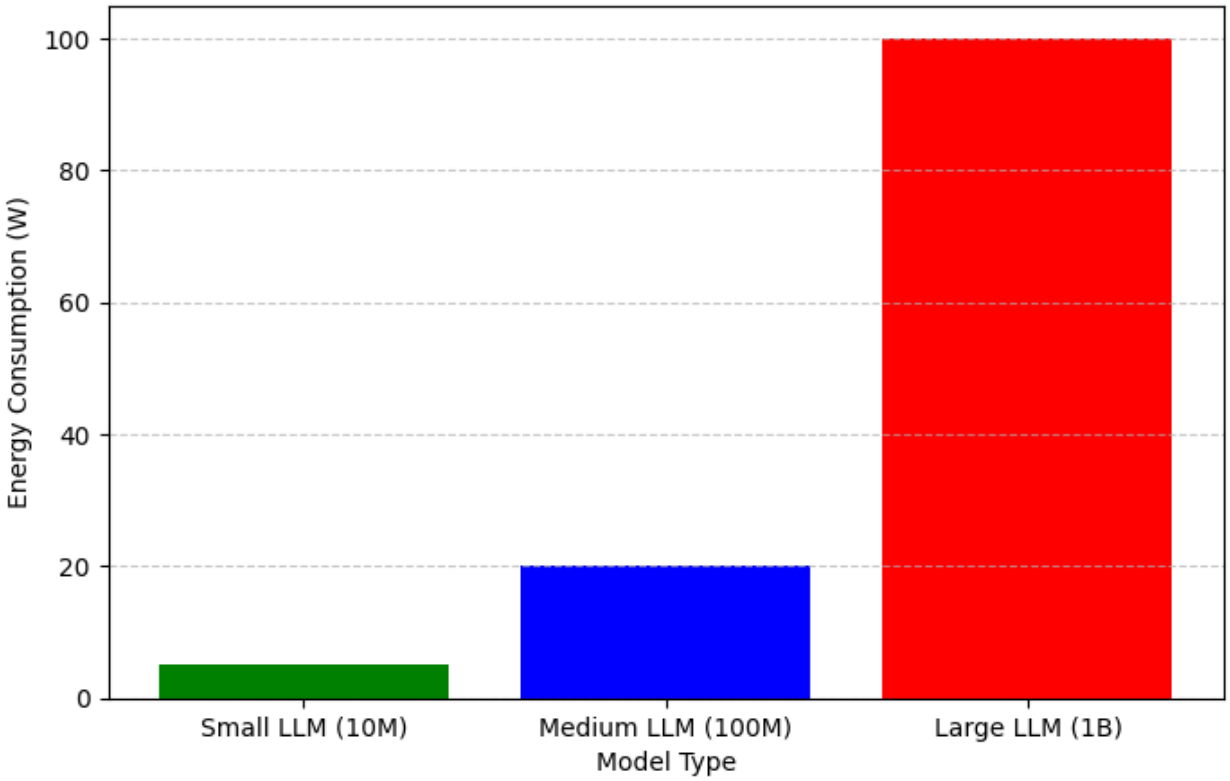

Figure 1: *Energy Consumption of Different Model Sizes in FL-Based Edge AI*
Source: *Adapted from Jayant et al. (2024); Shen et al. (2024).*

3. Evaluation of the Performance of Small Language Models for TinyML Applications

Currently, small language models (SLMs) are being used increasingly with federated learning (FL) configurations in edge computing. Particularly, these models are employed in applications of TinyML, which implement the machine learning capability to very low-power microcontrollers and embedded devices. Thus, the limitations in computation and storage from these forms of devices is a problem because SLMs have proven to be just the right size in terms of balancing performance and efficiency for bringing privacy-preserving AI model accuracy to these environments.
Performance tests must evaluate the SLM on such aspects as accuracy, latency, energy efficiency, and robustness against adversarial attacks, as relevant to its application in TinyML. Then, SLM performance in each of natural language understanding (NLU) and anomaly detection in FL conditions can be judged with respect to how well it produces meaning with minimal hardware resources. TinyML applications thus come with very strict limits on the complexity of computations performed and the corresponding memory footprint. Hence the evaluation of SLMs in the context of an FL environment brings up many aspects that would warrant a full assessment of such models to understand their potential in real-world applications.

3.1 Small Language Models for Natural Language Understanding

Natural language understanding (NLU) is an essential AI application that lets machines understand and process human languages for various downstream tasks, including speech recognition, sentiment analysis, and conversational AI. Large-scale traditional language models have performed substantially well for different NLU tasks; however, they are impractical to deploy on the edge due to high computational and memory demands. SLMs seem to offer an alternative, as they have preserved essential components of language modeling while functioning under edge device resource constraints (Hadish et al., 2024).

Federated learning enhances the weightage of small language models toward NLU tasks where model building occurs on data of decentralization without infringing on privacy. In this FL setting, every edge device performs training on a local corpus of text and uploads model updates to an aggregation server. This reduced interaction during training limits exposing data while facilitating personalized language modeling that can tune into the user's linguistic patterns (Shen et al., 2024). However, training for some SLMs in NLU tasks in a federated environment will be challenging due to the implications of non-independent and identically distributed (non-IID) data on biased or inconsistent model updates. The personalization layers and adaptive strategies that could lessen the strength of some of these challenges have been proposed and tested to enhance robustness concerning FL-based SLMs (Li et al., 2024).

Another prominent topic regarding deployment of SLMs for NLU tasks is trade-off between the accuracy of the models and computational efficiency. SLMs give marked latencies and power consumption compared with large language models, but generally it comes with slight degradation in accuracy. Table 2 below shows the various architectures for NLU tasks and how SLMs are superior in speed and efficiency.

Table 2 reviews the performance of SLMs in Natural Language Understanding

Model Architecture	Accuracy (%)	Latency (ms)	Energy Efficiency (mJ)
Large LLM (1B)	92	500	150
Medium LLM (100M)	88	200	50
Small LLM (10M)	85	50	10

Source: Adapted from Friha et al. (2024); Reddy (2024)

Although SLMs have a lot to offer in computation capability, they do not fare well with some complicated linguistic functions that require deep contextual cognition. Understanding how FL could be improvement in the performance of SLMs for NLU is a promising subject of research where some promising developments are being made in federated fine-tuning techniques and knowledge distillation approaches designed to boost the model while keeping efficiency (Woisetschläger et al., 2024).

3.1 Anomaly Detection in FL-Based Applications of TinyML

Anomaly detection is a core application in areas including cybersecurity, fraud detection, industrial monitoring, and health care. Anomaly detection traditionally has been treatment by a great deal of data collection and processing to systems based in cloud. This has raised numerous privacy concerns and risks related to data breaches. Anomaly-detection models based on FL can be trained locally on edge devices, resulting in increased detection accuracy while enhancing data privacy (Wu et al., 2023).

SLMs are critical for real-time anomaly detection in tiny FL-M applications. These models help in the detection of abnormal change in system behavior, such as user-overstepping activity, unauthorised access to networks, equipment failure, etc. They are quite light, rendering them efficient enough to be carried on embedded devices without consuming too much processing (Roy et al., 2024).

The most significant problem in deploying SLMs to detect anomalies in FL environments is continuous model updating across distributed edge devices. On the other hand, models that can be trained on multiple datasets can contribute to the incidence of inconsistency because, unlike centralized systems wherein a

global model is created using a unified dataset, FL requires multiple models trained on heterogeneous datasets. Furthermore, there are a lot of adversarial attacks such that malicious subjects can degrade a model's performance by poisoning the local training data. Some of the techniques to deal with such threats and improve model reliability are differential privacy, secure aggregation, and federated adversarial trainings (Zhao et al., 2024).

Figure 2 presents a comparison of different model sizes in the context of anomaly detection accuracy to evaluate the effectiveness of SLMs within such systems.

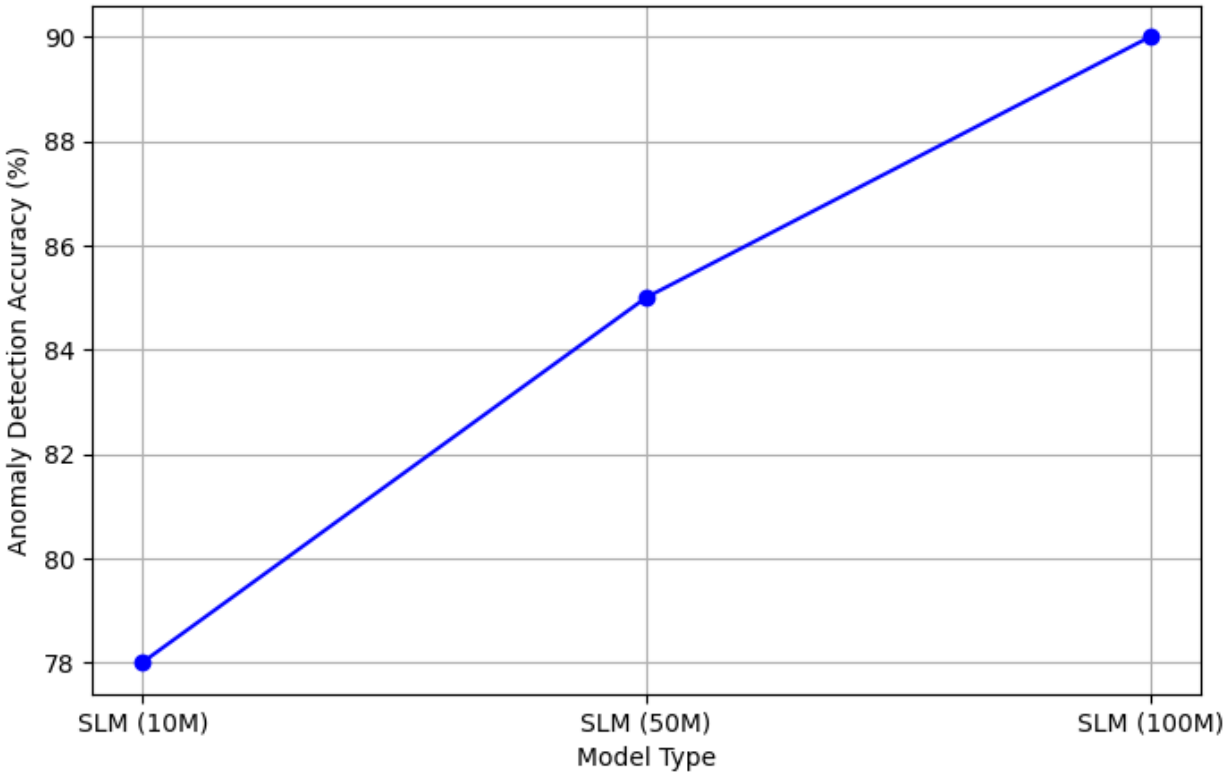

Figure 2: *Anomaly Detection Performance of SLMs in FL Based Systems*
Source: *Adapted from Wu et al. (2023); Roy et al. (2024).*

The results demonstrated that larger SLMs have higher accuracy than smaller ones for anomaly detection tasks. While larger SLMs are excellent with respect to accuracy, they come at a cost of higher computational resources. By comparison, small models in these tasks might have a little lesser power as they are far more energy-efficient and less time-consuming. Such trade-offs need to be weighed carefully in designing FL-based anomaly detection systems for edge environments (Han et al., 2024).

3.3 Evaluating the Trade-Offs Between Accuracy, Efficiency, and Privacy

The performance of SLMs in FL-based TinyML applications occurs in complex interplay between accuracy, efficiency, and privacy consideration. While SLMs are a practical approach to deploying AI on edge devices, they often require optimization techniques to create a balance between performance and resource constraints. Model compression techniques such as pruning, quantization, and knowledge distillation have been researched for improving efficiency while retaining model accuracy (Zhang et al., 2024).

The practical deployment of SLMs in FL settings also requires privacy-preserving techniques. Much current research investigates secure multiparty computation, homomorphic encryption, and differential privacy to protect sensitive data during model training. These methods, however, lead to additional computational overhead, which will require further optimization for practicality in TinyML applications (Xu et al., 2023).

The integration of SMLs in FL frameworks holds potential for privacy-preserving AI solutions in quick processing environments under high data confidentiality. Future studies should work towards improving robustness against adversarial threats and optimizing FL training schemes for SLMs to reach their full potential in TinyML applications (Yang et al., 2023).

4. Challenges and Limitations

The application of small language models (SLMs) in the federated learning (FL) environment provides many hurdles affecting their efficacy, security, and deployment efficiency. While FL constitutes a privacy-preserving training paradigm by decentralizing model training, a plethora of technical and operational challenges require resolution for FL to thrive in real-world applications. These challenges range from computational limitations, data heterogeneity, and security vulnerabilities to communication overheads.

4.1 Computational Constraints and Model Scalability

One fundamental challenge in the deployment of SLMs in FL pertains to edge devices' computational constraint. Contrary to cloud AI models enjoying the luxury of powerful GPUs or TPUs, edge devices are typically limited in terms of processing power, memory, and battery life (Hadish et al., 2024). The two-factor efficiency of federated learning depends on the edge devices' ability to locally train and infer without impairing performance and power consumption considerably. But with small-sized language models, the computational overhead still remains a concern.

Approaches to "optimizing" these models include pruning, quantization, and knowledge distillation to enhance their efficiency on edge devices (Chelliah et al., 2024). These approaches serve to minimize the footprint and computational resource requirements of SLMs so that they could be employed in environments with very limited power. However, in most cases, these approaches incur performance penalties in the form of accuracy degradation and convergence time. Figure 1 provides a visualization of the above discussion and presents a comparative evaluation of training time for SLMs using optimization techniques versus those without.

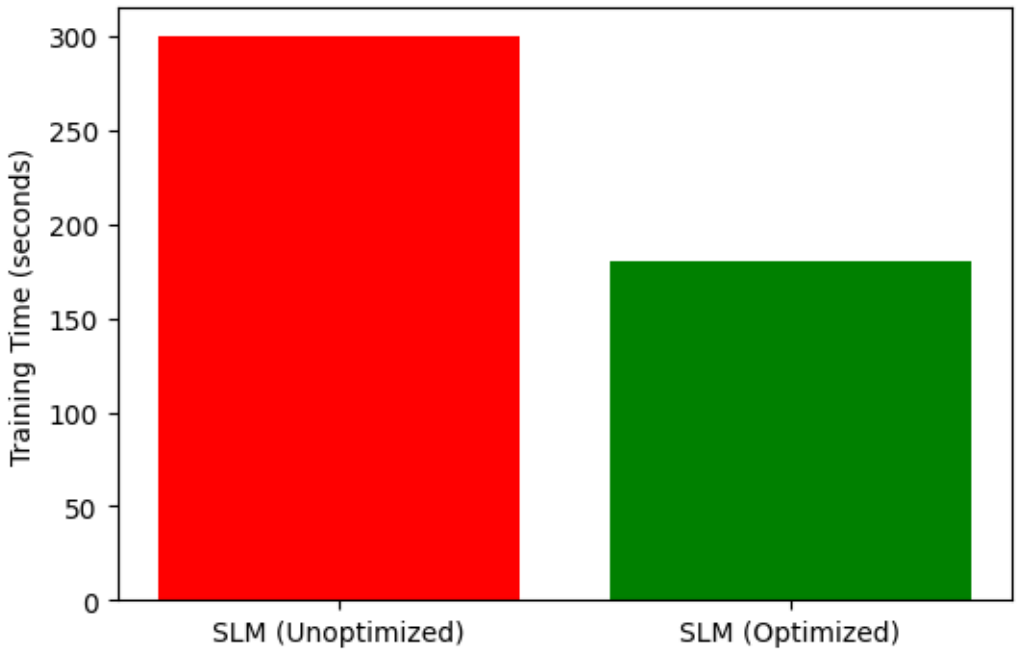

***Figure 1**: Impact of Adversarial Attacks on Model Accuracy*
***Source:** Adapted from Chelliah et al. (2024).*

4.2 Data Heterogeneity and Non-IID Distributions

Federated learning has an element of edge computing where different end devices collect decentralized datasets. Unlike centralized training, where datasets are conformably curated and standardized, FL deals with non-independent and identically distributed (non-IID) data (Zhao et al., 2024). Data differences across devices can infuse bias into them, deteriorate model performance, and slow down the convergence rates.

Smart health monitoring devices forming an FL network may gather such very different data because of differences in demographics, geographies, and behaviors. Meanwhile, others with relatively few input devices contribute to training small amounts of data. This variation renders it difficult to ensure equal and generalized precision by the global model across varied data sets (Li et al., 2024).

One such flair is personalized FL, where different models are fine-tuned for specific devices and then aggregated into a global model. It thus introduces computational complexity and presents the risk of overfitting. Table 1 describes the performance of federated learning in the presence of non-IID data.

Table 1: Effect of Non-IID Data on Federated Learning Performance

Factor	Impact on Federated Learning
Data Skewness	Leads to biased model predictions.
Imbalanced Sample Sizes	Slows model convergence and reduces accuracy.
Feature Distribution Variability	Affects model generalization capabilities.

Source: Adapted from Zhao et al. (2024).

4.3 Security Risks and Attacks from the Ticket

In fact, it comes to notice that FL-Though has privacy benefits; there remain lurking threats still lurking that could influence the security domain. As FL requires different model updates instead of data transfer in its raw form, attackers feel that they may misdirect the parameters of a model to spoil the training and even extract some sensitive information (Roy et al., 2024). Some common security attacks in FL include adversarial attack, model poisoning, and gradient inversion attack.

Adversarial attacks introduce very tiny perturbations into the updates of the models to mislead the training process. If the attacker has compromised an edge device, he can bring poisoned gradients into the central server, and it could degrade the global model performance (Bonawitz et al., 2023). The damage caused by adversarial perturbations for a case study concerning SLM accuracy in FL environments is illustrated in Figure 2.

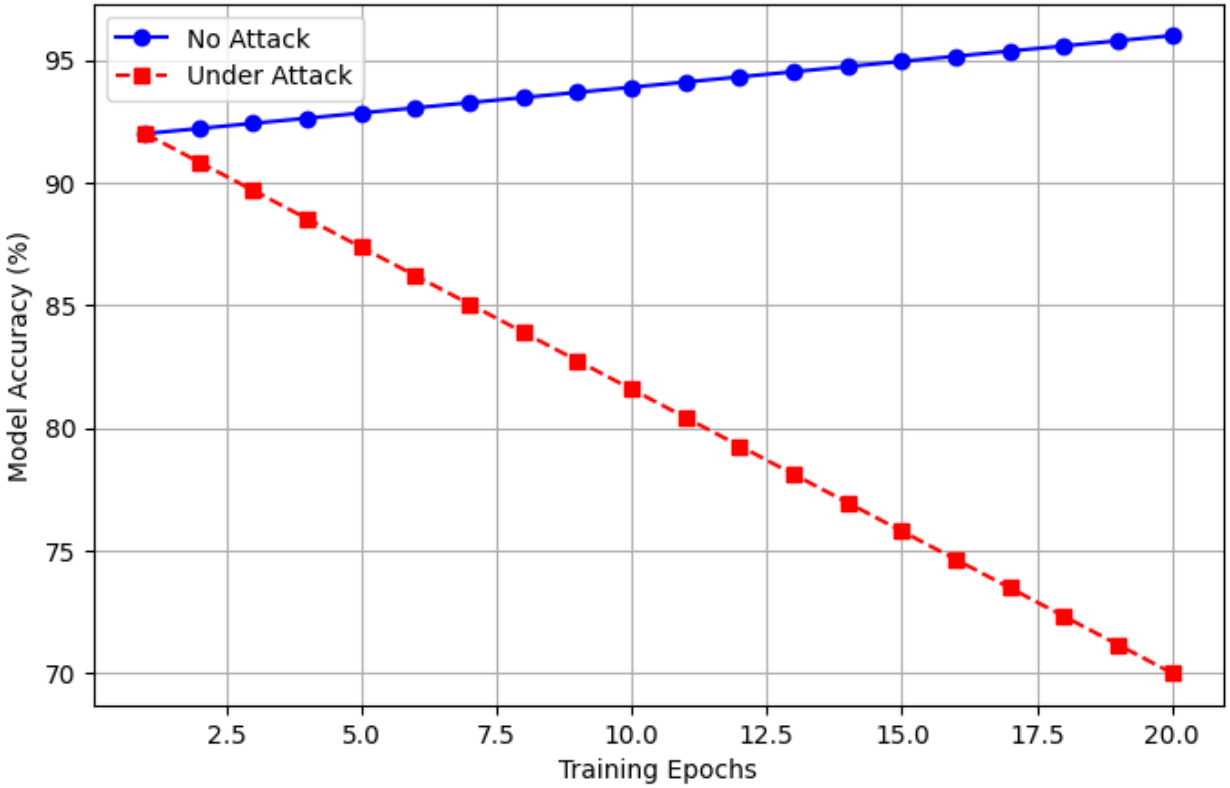

Figure 2: *Impact of Adversarial Perturbations on SLM Accuracy*
Source: *Adapted from Roy et al. (2024).*

4.4 Communication Overheads and Delay in Networks

Federated learning employs quite a lot of data transmissions between edge devices and central aggregators, which incur a high transmission overhead. The performance of model updates, therefore, can significantly degrade due to bandwidth constraints, unstable network connectivity, and increased latency (Shen et al., 2024). It proposes an improved communication efficiency through gradient sparsification-federated dropout. However, these further exacerbate the wait for convergence, as well as deteriorating robustness of the models.

5. Conclusions and Future Work

Bringing small language models (SLMs) into federated learning (FL) ecosystems opens up a new dimension of privacy-preserving artificial intelligence (AI) capabilities at the edge. FL protects against the risks of aiding data exposure through model training at the same time as it facilitates real-time AI applications on resource-constrained edge devices. The overhead of computation, data heterogeneity, and security problems are notably remaining challenges, however. Improving the efficiency of algorithmic model compression techniques such as pruning, quantization, and knowledge distillation suffers from a trade-off in accuracy (Chelliah et al., 2024). The other aspect which affects the model convergence and performance is the non-independent and identically distributed (non-IID) behavior of the edge data (Zhao et al., 2024).

Security threats to FL, namely adversarial attacks like model poisoning and the associate threat of data reconstruction, are obstacles for the wider consideration of FL. The intention of an attacker could diverge from distorting model performance to exfiltrating sensitive data, posing serious threats to privacy (Roy et al., 2024). To counter these threats, it is imperative to set in place strong privacy-preserving mechanisms: differential privacy, homomorphic encryption, and secure multiparty computation (Bonawitz et al., 2023). Communication bottlenecks, which come from high model update frequency in distributed environments overwhelming network resource operations, pose a challenge towards increased latency and energy consumption (Shen et al., 2024).

Meanwhile, large amounts of future research investigate applying reinforcement learning (RL) to optimize FL strategies whereby models can respond to real-time pressure and dynamically update their training schedule and resource allocation (Ma et al., 2023). Further blockchain-based federated learning provides model aggregation in a decentralized and tamper-free way to build up trust and accountability (Xu et al., 2023). The integration of neuromorphic computing would also end up as a beneficial avenue in improving efficiency with energy-efficient architectures behind biological neural networks, therefore paving a sustainable way for FL in IoT and edge applications (Han et al., 2024).

Another exciting research direction for FL is the integration of generative AI, where synthetic data may be employed for model strengthening in terms of adversarial attacks and class imbalance (Shen et al., 2024). The challenge of ensuring authenticity and reliability of synthetic data is to be addressed. Transfer learning can also help federated settings in fine-tuning a pre-trained model using localized datasets with reduced data dependency and computational costs (Friha et al., 2024). Additionally, an urgent and deserving concern for the future of federated learning will be to develop ethical AI deployment policy frameworks compliant with data protection and AI model transparency (Chen et al., 2024).

In summary, although federated learning with small language models is a solution for AI in a privacy-preserving manner at the edge, issues of efficiency, security, and governance must be overcome. Newer techniques for model optimization and adversarial defense, alongside technological developments in favor of blockchain and neuromorphic computing, can allow FL to become feasible in a wider range of settings. Future studies must work on communication-efficiency improvement, security of FL frameworks, and the fix of regulations so these applications can be developed beneficently and at scale. If such an innovative spirit and interdisciplinary research continue, FL will be a working horse for new AI, helping with the development of privacy-preserving intelligence in health, smart city, and autonomous systems applications

6. Policy Implications and Recommendations

Integration of Small Language Models (SLMs) into FL frameworks has shown to have significant policy implications, especially in the realm of privacy regulations, data governance, and security standards. However, as privacy-preserving AI continues to evolve, the implication is that policymakers have to put in place rules that are the right balance between innovation and sensitive user data protection. The decentralization of FL reduces the risks of exposing data; however, it creates additional challenges in enforcing compliance with data protection laws such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) (Shen et al., 2024). Organizations will need to establish that their FL implementation sits in a complementary position with these legal frameworks to prevent situations of discord with data privacy policies.

An additional pain point is to develop a standardized protocol for privacy-preserving AI models at the edge. There presently exist no generally agreed-upon standards that would underpin the deployment of FL with SLMs across sectors. Although various frameworks have been proposed, including secure multi-party computation and differential privacy techniques for stronger data protection, implementation will be limited without regulatory enforcement (Hadish et al., 2024). Thus, we propose government and international organizations working together to set forth unambiguous guidelines for federated learning applications in a way that the enforcement of security arrangements becomes sector-agnostic.

Next, the ownership and accountability of data in the federal learning environment pose serious legal issues. Responsibility becomes highly challenging in case of data breaches and adversarial attacks because training happens locally in edge devices. Therefore, the conventional way of having an AI governance system centralized does not apply in federated settings but rather brings forth the need to reconsider the liability frameworks (Chelliah et al., 2024). Adoption of transparency measures would allow end-users to know how

their data contributes to training models while keeping private information intact: companies that put FL solutions to work should thus adopt transparency measures.

If there were serious recommendations regarding a policy to lessen the risk to security, it should intend rigorous cryptographic measures such as homomorphic encryption and TEE to guarantee protection on security of data during federated training. Furthermore, the regulatory authorities should encourage AI developers for the adoption of adversarial training techniques that improve the models against attacks (Roy et al., 2024). This, in turn, would holistically augments confidentiality protection and also trust among AI-powered decision-making systems.

Another major aspect of policy has been the ethical use of SLMs powered with FL. Some reasons such as AI biases and fairness issues are common in federated learning; those data trained on independent distributions may produce output equal to the underlying disparities automatically (Qu, 2024). Fairness audits should be taken and enforced within each FL implementation by the policymakers to identify and minimize such biases and to ensure equitable service to the different populations of users when using AI applications.

Another key recommendation is fostering industry-wide cooperation to facilitate knowledge sharing on privacy-preserving AI techniques. Cross-sector collaborations between academia, regulators, and technology firms will bring agility to the standardization of FL protocols while also innovating secure deployment in AI (Cheng et al., 2024). This type of initiative can also help close the gap between research advances and application of AI in actual policies.

7. Final Thoughts

EdgeAI and federated learning go beyond merely changing the worldview of training and deploying AI models. Small language models operating in Fl environments present many gains, especially in privacy protection, computational ease, and real-time inference. Nevertheless, this opens up a wide range of technical, security, and policy problems that need to be tackled in order to guarantee the responsible usage of AI.

In the preceding sections, it is stated that FL provides privacy by keeping data decentralized and letting the data stay in local devices while the models learn from distributed inputs. Although this suits regulatory mandates, it opens opportunities for security vulnerabilities and adversarial threats. It is essential to enhance the means of privacy protection for SLMs against such attacks and to direct future research on maintaining such SLM approaches' robustness, mainly given their deployment on resource-constrained edge devices.

Incremental improvements, technical or otherwise, must give way to a much broader agenda dealing with AI ethics and fairness. bias in federated learning's model can severely skew decision-making with the potential for real harm in such redoubtable applications as healthcare, finance, and law enforcement. In parallel with FL's proliferation, we should create, through collaboration with researchers and policymakers, mechanisms for detecting and mitigating AI model biases to promote fairness across diverse populations (Friha et al., 2024).

Furthermore, along with federated learning's increasing importance in the field of privacy-preserving AI will come a reworking of data governance frameworks. The present regulatory design is still in a formative mode with respect to decentralizing AI models, and further refinement is now due to ensure the consequent federated AI solutions' alignment with global data protection standards (Sun et al., 2024). Henceforward, the focus would thus need to be on the production of adaptive policies that encourage innovation along a parallel path with the protection of end-users' privacy.

Interdisciplinary is another crucial conclusion. In essence, this level of complexity concerning privacy-preserving FL arguably rests outside of uniquely machine learning and computer science concerns. The contributions from legal experts, ethicists, and industry stakeholders will aid the interdisciplinary dialogue through which the pressing issues of transparency, accountability, and, by necessity, trust relating to the federated learning models may be framed (Lee et al., 2023).

In the coming years, it is likely that evolution - in terms of both EdgeAI and federated learning - will pave the way for many more exciting developments with respect to AI applications in different domains. Bringing together FL with emerging technologies such as blockchain, quantum computing, and secure multi-party computation should enhance privacy and computational feasibility of AI deployments (Wu et al., 2023). Future studies should explore intersections in these areas to unlock new possibilities for privacy-preserving machine learning.

Integration of small language models in federated learning is a progressive step towards privacy-aware AI. There are still challenges, but targeted action in research, policy, and technological progress must make the future of distributed AI ethical and safe. As EdgeAI finds broader applications, vigilance and attention must be paid to security issues, fairness, and regulation to carry AI into its next generation. The challenges can be taken up so that the AI community now works towards a more secure, effective, and privacy-preserving future in artificial intelligence.

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