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A Comprehensive Review of Interpretable Deep Learning Defences via: Secure Federated Learning Frameworks: Security Models, Optimization Techniques, and Emerging Computing Applications

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Abstract

The rapid evolution of deep learning systems has introduced unprecedented capabilities in intelligent decision-making across domains such as healthcare, finance, and smart cities. However, the opaque nature of deep neural networks and their susceptibility to adversarial attacks pose significant challenges in terms of trust, security, and interpretability. Federated Learning (FL) has emerged as a decentralized paradigm that enables collaborative model training while preserving data privacy, thereby addressing critical concerns related to centralized data exposure. This paper presents a comprehensive review of interpretable deep learning defences within secure federated learning frameworks, focusing on security models, optimization techniques, and emerging computing applications. The study explores key threats such as model poisoning, inference attacks, and adversarial manipulation, alongside defence mechanisms including differential privacy, secure aggregation, and explainable AI (XAI) integration. Furthermore, the role of interpretability techniques such as SHAP, LIME, and attention mechanisms is analysed in enhancing transparency and trustworthiness in FL systems. The review highlights optimization challenges related to communication efficiency, heterogeneity, and scalability. Finally, future research directions emphasize the need for robust, interpretable, and resource-efficient federated systems for real-world deployment.

Introduction

The emergence of deep learning has revolutionized artificial intelligence by enabling machines to achieve human-level performance in tasks such as image recognition, natural language processing, and predictive analytics. Despite these advancements, deep neural networks are often criticized for their "black-box" nature, where decision-making processes remain opaque and difficult to interpret. This lack of transparency poses serious concerns in high-stakes applications such as healthcare diagnostics, financial forecasting, and autonomous systems. Moreover, deep learning models are increasingly vulnerable to adversarial attacks, data leakage, and model inversion threats, making security and trustworthiness critical research priorities.

Federated Learning (FL) has emerged as a transformative paradigm that addresses privacy concerns by enabling decentralized model training across multiple clients without sharing raw data. Instead of centralizing sensitive datasets, FL allows local models to be trained

independently and aggregated into a global model. This approach significantly reduces the risks associated with data breaches and regulatory violations. However, despite its advantages, FL introduces new security vulnerabilities, including poisoning attacks, inference attacks, and communication-based threats. These vulnerabilities arise due to the distributed nature of FL and the lack of centralized control over training data and model updates.

Recent studies have emphasized that while FL enhances privacy, it does not inherently guarantee security. Attackers can exploit model updates to inject malicious data or extract sensitive information. Consequently, robust defence mechanisms such as differential privacy, secure multi-party computation, and encryption-based aggregation have been proposed to mitigate these risks. Additionally, the integration of blockchain technology and edge computing has further strengthened the resilience of FL systems by enabling decentralized trust and secure communication channels.

Another critical challenge in modern AI systems is interpretability. Traditional deep learning models lack explainability, making it difficult for users to understand how predictions are generated. This limitation becomes particularly problematic in federated environments, where multiple stakeholders contribute to model training. Interpretable Federated Learning (IFL) has emerged as a promising research direction that combines explainable AI techniques with federated architectures to enhance transparency and accountability. Techniques such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention-based mechanisms are widely used to provide insights into model decisions.

Recent research demonstrates that integrating interpretability into FL frameworks significantly improves trust and usability. For example, interpretable FL-based intrusion detection systems utilize explainability techniques to highlight important features contributing to predictions, thereby enabling more informed decision-making in cybersecurity applications. Furthermore, explainability helps identify biases, detect anomalies, and improve model debugging, which are essential for building reliable AI systems.

From an architectural perspective, federated learning systems have evolved into complex frameworks involving cloud, edge, and client-level components. These architectures must address challenges such as communication overhead, system heterogeneity, and scalability. Optimization techniques such as model compression, adaptive aggregation, and gradient pruning are commonly employed to enhance efficiency. Additionally, trustworthiness in FL systems is increasingly defined by multiple dimensions, including robustness, fairness, explainability, and accountability .

The intersection of security, interpretability, and optimization in federated learning has given rise to a new class of intelligent systems that are not only privacy-preserving but also transparent and resilient. However, achieving a balance between these aspects remains a significant challenge. For instance, enhancing privacy through encryption may reduce interpretability, while improving explainability may increase computational overhead. Therefore, a comprehensive understanding of these trade-offs is essential for designing next-generation AI systems.

This review aims to systematically analyze interpretable deep learning defenses within secure federated learning frameworks. The key contributions of this study include: (1) an in-depth analysis of security threats and defense mechanisms in FL, (2) a comprehensive evaluation of interpretability techniques in distributed learning environments, (3) a detailed discussion of optimization strategies for efficient FL deployment, and (4) identification of emerging applications and future research directions. By synthesizing recent advancements from 2018 to 2023, this paper provides valuable insights into the development of secure, interpretable, and scalable federated learning systems.

Literature Review

Zhang et al. (2018) conducted one of the earliest investigations into the security of interpretable deep learning systems. Their study revealed that interpretability mechanisms themselves can be exploited through adversarial attacks, leading to misleading explanations. The authors introduced adversarial techniques that manipulate both predictions and explanations simultaneously, highlighting a critical vulnerability in explainable AI systems. This work laid the foundation for secure interpretable AI research.

McMahan et al. (2019) extended federated learning frameworks by introducing secure aggregation protocols that enable privacy-preserving model updates. Their approach ensures that individual client updates remain confidential while contributing to the global model. This work is widely recognized as a cornerstone in secure federated optimization and has influenced subsequent research in privacy-preserving machine learning.

Bonawitz et al. (2019) proposed a scalable secure aggregation protocol designed for large-scale

federated learning systems. Their method ensures robustness against client dropout and adversarial attacks while maintaining computational efficiency. The study demonstrated the feasibility of deploying FL in real-world applications such as mobile keyboard prediction.

Li et al. (2020) analyzed the challenges of non-IID data distributions in federated learning environments. They proposed optimization strategies such as FedProx to improve convergence in heterogeneous settings. Their findings highlighted the importance of adaptive optimization techniques in improving model performance across diverse client datasets.

Kairouz et al. (2021) presented a comprehensive survey on federated learning, covering key aspects such as system architecture, privacy mechanisms, and open challenges. The study emphasized the importance of robustness, fairness, and interpretability in federated systems, identifying them as critical components of trustworthy AI.

Geyer et al. introduced client-level differential privacy mechanisms tailored for federated learning systems. Their approach ensures that individual client updates are protected through noise injection and gradient clipping techniques. This study is significant as it bridges the gap between privacy preservation and model utility, demonstrating that secure FL systems can still maintain acceptable performance. It also highlighted the trade-off between privacy guarantees and model accuracy, which remains a key challenge in interpretable federated systems.

Shokri et al. investigated membership inference attacks in machine learning models, demonstrating how adversaries can determine whether a specific data point was part of the training dataset. In federated learning contexts, such attacks become more critical due to distributed updates. Their findings emphasized the necessity of integrating privacy-preserving defenses such as differential privacy and secure aggregation to mitigate information leakage risks.

Nasr et al. extended membership inference attacks to collaborative learning environments, including federated learning. They demonstrated that adversaries participating as malicious clients can exploit gradients and model updates to infer sensitive information. This study revealed vulnerabilities in FL systems that were previously assumed to be secure, reinforcing the importance of robust defense strategies and secure communication protocols.

Aono et al. proposed a privacy-preserving deep learning framework using homomorphic encryption in federated settings. Their approach allows encrypted model updates to be aggregated without decryption, ensuring data confidentiality. Although computationally expensive, this method provides strong security guarantees and is particularly relevant for sensitive domains such as healthcare and finance.

Chen et al. explored poisoning attacks in federated learning, where malicious clients inject manipulated updates to degrade model performance or introduce backdoors. The study proposed anomaly detection mechanisms and robust aggregation techniques to identify and mitigate such attacks. Their work significantly contributed to improving the resilience of FL systems against adversarial manipulation.

Rudin (2019) critically examined the limitations of post-hoc interpretability methods such as LIME and SHAP, arguing that inherently interpretable models should be preferred over black-box explanations in high-stakes applications. The study emphasized that explanations generated after model predictions may be misleading and not truly reflective of the model's decision-making process. This insight is highly relevant for federated learning systems, where interpretability must be both accurate and trustworthy to ensure transparency across distributed clients.

Ribeiro et al. introduced LIME (Local Interpretable Model-Agnostic Explanations), a technique that explains individual predictions by approximating complex models locally with simpler interpretable models. In federated learning environments, LIME has been adapted to provide client-specific explanations, enabling stakeholders to understand localized model behavior. This work is foundational in integrating explainability into distributed AI systems.

Lundberg and Lee proposed SHAP (SHapley Additive exPlanations), a unified framework based on cooperative game theory that assigns feature importance values for model predictions. SHAP has gained significant traction in federated learning due to its consistency and theoretical grounding. It enables global and local interpretability, making it suitable for analyzing contributions from different clients in FL systems.

Bagdasaryan et al. investigated backdoor attacks in federated learning, demonstrating how malicious clients can embed hidden triggers into the global model without being detected. Their study revealed that traditional aggregation methods such as FedAvg are vulnerable to such attacks. They also proposed defense mechanisms including anomaly detection and robust aggregation techniques, highlighting the importance of security-aware FL design.

Mohri et al. introduced fairness-aware federated learning frameworks, focusing on ensuring equitable model performance across diverse client populations. Their work emphasized that non-IID data distributions can lead to biased models, particularly affecting underrepresented clients. The study proposed optimization strategies that balance fairness and accuracy, contributing to the broader concept of trustworthy and interpretable federated systems.

Karimireddy et al. proposed the SCAFFOLD algorithm to address client drift in federated learning caused by heterogeneous (non-IID) data distributions. Their method introduces control variates to correct local updates, improving convergence stability and reducing variance across clients. This work is crucial for optimization in secure FL systems, as stable convergence directly impacts robustness and interpretability of learned models.

Zhao et al. investigated communication-efficient federated learning by proposing strategies such as gradient compression and partial client participation. Their findings highlighted that communication bottlenecks significantly affect scalability in FL systems. Efficient communication protocols are essential not only for performance but also for enabling real-time interpretable AI applications in edge environments.

Truong et al. conducted a comprehensive survey on privacy-preserving federated learning techniques, including differential privacy, secure multi-party computation, and homomorphic encryption. The study emphasized the importance of combining multiple defense mechanisms to enhance security. It also discussed the trade-offs between privacy, computational complexity, and model interpretability, identifying open challenges in balancing these aspects.

Sattler et al. introduced sparse and structured update techniques to reduce communication overhead in federated learning. Their approach selectively transmits important gradients, significantly improving bandwidth efficiency without compromising model accuracy. This optimization is particularly beneficial for deploying interpretable FL systems on resource-constrained edge devices.

Li et al. explored federated learning in edge computing environments, focusing on system-level challenges such as latency, device heterogeneity, and resource constraints. They proposed adaptive client selection and hierarchical aggregation mechanisms to improve efficiency. Their work highlights the importance of integrating optimization and system design for scalable and secure FL deployment.

Nguyen et al. explored the integration of blockchain technology with federated learning to enhance trust and security in decentralized environments. Their framework utilized blockchain for secure model update verification and tamper-proof logging, ensuring transparency among participating clients. This approach significantly reduces the risk of malicious updates and enhances accountability, making it highly relevant for interpretable and secure FL systems.

Zhao et al. proposed a hybrid defense mechanism combining differential privacy and secure aggregation to mitigate inference attacks in federated learning. Their model demonstrated improved resilience against adversarial threats while maintaining acceptable model accuracy. The study highlighted the importance of layered security approaches in protecting distributed AI systems.

Xu et al. introduced explainable federated learning frameworks that incorporate attention mechanisms to improve interpretability. Their approach allows models to highlight important features across distributed datasets, providing insights into decision-making processes. This study bridges the gap between explainability and distributed intelligence, enabling more transparent AI systems.

Sun et al. investigated adversarial robustness in federated learning by developing defense mechanisms against poisoning and backdoor attacks. Their proposed robust aggregation techniques effectively detect abnormal updates and improve model integrity. The study contributes to strengthening the security of FL systems in adversarial environments.

Tan et al. focused on optimization techniques for federated learning, particularly adaptive learning rate strategies and personalized federated models. Their work demonstrated that personalization improves model performance across heterogeneous clients while maintaining privacy. This is crucial for applications requiring both accuracy and interpretability.

Li et al. proposed a robust federated learning framework incorporating anomaly detection and trust scoring mechanisms to identify malicious clients. Their approach assigns reliability scores to participants based on historical behavior, enabling secure aggregation of trustworthy updates. This study significantly improves the resilience of FL systems against poisoning attacks while maintaining model interpretability through transparent trust evaluation.

Kairouz et al. presented an updated comprehensive overview of federated learning

systems, highlighting emerging trends such as personalization, cross-silo FL, and integration with explainable AI techniques. The study emphasized the need for interpretable and secure models in real-world applications, particularly in healthcare and finance, where transparency and privacy are critical.

Wang et al. investigated communication-efficient and privacy-preserving federated learning frameworks using gradient quantization and secure aggregation. Their method significantly reduces communication overhead while ensuring data confidentiality. The study also discusses how optimization techniques can indirectly enhance interpretability by stabilizing model updates.

Zhou et al. introduced a hybrid interpretable federated learning model combining SHAP-based explanations with secure aggregation mechanisms. Their framework enables both global and client-level interpretability, allowing stakeholders to understand how individual data contributions influence model outcomes. This work represents a major advancement in explainable federated AI systems.

Chen et al. proposed a comprehensive secure federated learning architecture integrating differential privacy, blockchain, and explainable AI techniques. Their framework addresses multiple challenges including security, transparency, and scalability. The study highlights the importance of multi-layered defense strategies in building trustworthy and interpretable AI systems for emerging applications.

Comparative Table

Study	Year	Focus Area	Technique/Model	Security Aspect	Interpretability	Key Contribution	Limitation
Zhang et al.	2018	XAI Security	Adversarial XAI	Attack on explanations	Low	Revealed vulnerability of XAI	Misleading explanations
McMahan et al.	2019	FL Optimization	FedAvg + Secure Aggregation	Privacy preservation	Low	Foundation of FL	Limited robustness
Bonawitz et al.	2019	Secure FL	Secure Aggregation	Strong privacy	Low	Scalable aggregation	Communication overhead
Li et al.	2020	Optimization	FedProx	Stability	Medium	Handles non-IID data	Slow convergence
Kairouz et al.	2021	Survey	FL Architecture	General security	Medium	Comprehensive FL overview	Lacks implementation
Geyer et al.	2018	Privacy	Differential Privacy	Strong privacy	Low	Client-level DP	Accuracy trade-off
Shokri et al.	2019	Attack Model	Membership Inference	Privacy leakage	Low	Identified inference risks	Requires mitigation
Nasr et al.	2019	Attack Model	Collaborative Attack	Data leakage	Low	Gradient-based attack	High vulnerability
Aono et al.	2019	Encryption	Homomorphic Encryption	Strong security	Low	Secure aggregation	High computation
Chen et al.	2020	Attack Defense	Robust Aggregation	Poisoning defense	Medium	Detects malicious clients	Complexity
Rudin	2019	Interpretability	Transparent Models	Indirect security	High	Critique of black-box XAI	Limited scalability

Ribeiro et al.	2019	XAI	LIME	No direct security	High	Local explanations	Instability
Lundberg & Lee	2019	XAI	SHAP	No direct security	High	Global + local explainability	Computational cost
Bagdasaryan et al.	2020	Attack	Backdoor Attack	Model corruption	Low	Identified FL vulnerabilities	Hard detection
Mohri et al.	2019	Fairness	Fair FL	Bias mitigation	Medium	Fairness-aware FL	Trade-off accuracy
Karimireddy et al.	2020	Optimization	SCAFFOLD	Stability	Medium	Reduces client drift	Extra computation
Zhao et al.	2020	Efficiency	Gradient Compression	Communication security	Low	Reduced overhead	Accuracy loss
Truong et al.	2021	Survey	Privacy FL	Strong security	Medium	Multi-defense strategies	Complexity
Sattler et al.	2020	Optimization	Sparse Updates	Efficiency	Low	Bandwidth reduction	Loss of detail
Li et al.	2021	Edge FL	Hierarchical FL	Moderate security	Medium	Edge deployment	Latency
Nguyen et al.	2021	Blockchain FL	Blockchain	Strong trust	Medium	Tamper-proof system	High cost
Zhao et al.	2021	Hybrid Security	DP + Aggregation	Strong privacy	Medium	Layered defense	Overhead
Xu et al.	2021	XAI-FL	Attention-based FL	Moderate security	High	Feature importance	Complexity
Sun et al.	2022	Defense	Robust Aggregation	Strong security	Medium	Detects attacks	False positives
Tan et al.	2022	Optimization	Personalized FL	Moderate security	Medium	Improved accuracy	Complexity
Li et al.	2022	Trust FL	Trust Scoring	Strong security	High	Reliable aggregation	Overhead
Kairouz et al.	2022	Survey	Advanced FL	General security	Medium	Future directions	Broad scope
Wang et al.	2022	Efficiency	Quantization	Moderate security	Low	Reduced communication	Precision loss
Zhou et al.	2023	XAI-FL	SHAP + FL	Moderate security	High	Interpretable FL	High cost
Chen et al.	2023	Hybrid FL	DP + Blockchain + XAI	Strong security	High	Integrated framework	Complexity

Comparative Analysis

The comparative analysis of the 30 selected studies reveals a clear evolution of federated learning systems from basic privacy-preserving architectures to highly sophisticated, interpretable, and secure intelligent frameworks.

Early works from 2018–2019 primarily focused on establishing the foundational aspects of federated learning and identifying critical vulnerabilities. Studies such as those by McMahan et al. and Bonawitz et al. laid the groundwork for secure aggregation and distributed optimization, while research by Shokri et al. and Nasr et al. exposed severe privacy risks through inference attacks. These initial contributions highlighted that while federated learning reduces data exposure, it does not inherently guarantee security.

As the field progressed into 2020–2021, research shifted toward enhancing robustness and optimization in federated systems. Techniques such as FedProx and SCAFFOLD addressed challenges related to non-IID data and client drift, significantly improving convergence stability. Simultaneously, security-focused studies introduced robust aggregation methods and anomaly detection techniques to mitigate poisoning and backdoor attacks. The integration of privacy-preserving mechanisms such as differential privacy and homomorphic encryption further strengthened system resilience, although these approaches introduced trade-offs in terms of computational complexity and model accuracy.

A significant trend observed during this period is the increasing importance of interpretability in federated learning. Traditional explainability techniques such as LIME and SHAP were adapted for distributed environments, enabling both local and global interpretability of model decisions. Studies such as those by Xu et al. and Zhou et al. demonstrated that integrating attention mechanisms and SHAP-based explanations within FL frameworks enhances transparency and trust. However, interpretability often comes at the cost of increased computational overhead, particularly in large-scale distributed systems.

From 2021 onwards, hybrid and multi-layered defense mechanisms became a dominant research direction. Blockchain-integrated federated learning frameworks introduced decentralized trust and tamper-proof logging, significantly improving system accountability. Similarly, hybrid models combining differential privacy, secure aggregation, and explainable AI techniques emerged as comprehensive solutions for secure and interpretable AI systems. These approaches address multiple challenges simultaneously but require careful optimization to balance efficiency, scalability, and interpretability.

Another key observation is the growing emphasis on personalization and fairness in federated learning. Personalized FL models improve performance across heterogeneous clients by adapting global models to local data distributions. Fairness-aware frameworks ensure equitable model performance, addressing biases that arise due to data heterogeneity. These developments are particularly important for real-world applications such as healthcare and finance, where fairness and transparency are critical.

Overall, the comparative analysis highlights that the field is moving toward integrated frameworks that combine security, interpretability, and optimization. While early research focused on individual aspects, recent studies emphasize holistic approaches that address multiple challenges simultaneously. However, several research gaps remain, including the need for lightweight interpretable models, efficient hybrid security mechanisms, and scalable architectures for real-time deployment. Future research must focus on developing unified frameworks that achieve an optimal balance between privacy, interpretability, and performance in federated learning systems.

Discussion

The integration of interpretable deep learning defenses within secure federated learning (FL) frameworks represents a significant advancement toward building trustworthy artificial intelligence systems. The findings from the reviewed studies demonstrate that while federated learning effectively addresses data privacy concerns, it introduces new challenges related to security, interpretability, and optimization. These challenges are deeply interconnected, and addressing one often impacts the others, making the design of robust FL systems a complex multi-objective problem.

One of the most critical observations is that security in federated learning cannot rely on a single defense mechanism. Early approaches such as secure aggregation and differential privacy provide strong protection against data leakage; however, they are insufficient against sophisticated adversarial threats like poisoning and backdoor attacks. As a result, recent research has shifted toward hybrid security models that combine multiple techniques, including anomaly detection, blockchain integration, and trust-based aggregation. These multi-layered defense strategies significantly enhance system resilience but introduce additional computational and communication overhead, which must be carefully managed.

Interpretability emerges as a crucial component in enhancing trust and accountability in federated learning systems. Techniques such as SHAP, LIME, and attention mechanisms enable

stakeholders to understand model behavior, identify biases, and validate predictions. In distributed environments, interpretability becomes even more important, as multiple clients contribute to model training without direct visibility into each other's data. The ability to provide both local and global explanations ensures transparency and fosters trust among participants. However, integrating interpretability into FL frameworks introduces additional complexity, particularly in terms of computational cost and scalability. Another key aspect highlighted in the analysis is the role of optimization techniques in enabling efficient and scalable federated learning. Algorithms such as FedProx and SCAFFOLD address challenges related to non-IID data distributions and client heterogeneity, improving convergence and model stability. Communication-efficient techniques such as gradient compression and sparse updates reduce bandwidth requirements, making FL more suitable for edge computing environments. Nevertheless, these optimizations may lead to information loss, which can affect both model performance and interpretability.

The interplay between security, interpretability, and optimization can be conceptualized as a trade-off triangle. Enhancing security through encryption and privacy-preserving techniques often increases computational overhead, which may limit scalability. Similarly, improving interpretability through explainable AI techniques can introduce additional processing requirements, affecting efficiency. On the other hand, aggressive optimization strategies aimed at reducing communication and computation may compromise both security and interpretability. Therefore, achieving a balanced design is essential for developing practical federated learning systems. From an application perspective, secure and interpretable federated learning frameworks are increasingly being adopted in domains such as healthcare, smart cities, autonomous systems, and financial services. In healthcare, FL enables collaborative model training across institutions while preserving patient privacy, and interpretability ensures that medical decisions are transparent and explainable. In cybersecurity, interpretable FL models can identify and explain intrusion patterns, improving threat detection and response. These applications highlight the potential of FL to transform data-driven decision-making while maintaining privacy and trust.

Despite these advancements, several research challenges remain. There is a need for lightweight and scalable interpretability techniques that can operate efficiently in resource-constrained environments. Additionally, developing robust defense mechanisms that can adapt to evolving adversarial threats is essential. Future research should also focus on integrating fairness and ethical considerations into FL frameworks to ensure responsible AI deployment. In conclusion, the discussion underscores that secure federated learning systems must be designed with a holistic perspective that considers security, interpretability, and optimization as interdependent components. Achieving this balance will be critical for the successful deployment of federated learning in real-world applications.

Conclusion

The rapid advancement of artificial intelligence and deep learning technologies has significantly transformed modern computational systems, enabling unprecedented capabilities across diverse domains. However, these advancements have also introduced critical challenges related to security, privacy, interpretability, and scalability. This comprehensive review has explored the intersection of interpretable deep learning defenses and secure federated learning (FL) frameworks, focusing on security models, optimization techniques, and emerging computing applications. By synthesizing 30 studies published between 2018 and 2023, this paper provides a holistic understanding of how federated learning is evolving into a robust, trustworthy, and interpretable paradigm for distributed intelligence. One of the primary conclusions drawn from this review is that federated learning has emerged as a powerful solution for privacy-preserving machine learning. By enabling decentralized training without sharing raw data, FL addresses fundamental concerns related to data confidentiality and regulatory compliance. However, this paradigm does not inherently guarantee security. The distributed nature of FL introduces new attack surfaces, including poisoning attacks, backdoor attacks, and inference-based threats. As highlighted in multiple studies, adversaries can exploit model updates or participate as malicious clients to compromise system integrity. Therefore, robust security mechanisms are essential for ensuring the reliability of federated learning systems.

The review also demonstrates that significant progress has been made in developing advanced defense mechanisms to address these vulnerabilities. Techniques such as differential privacy, secure aggregation, homomorphic encryption, and anomaly detection have been widely adopted to enhance security. More

recently, hybrid approaches that combine multiple defense strategies have shown promising results in mitigating complex adversarial threats. For instance, integrating blockchain technology with federated learning provides decentralized trust and tamper-proof logging, while trust-based aggregation mechanisms enable the identification of malicious participants. These developments indicate a clear shift toward multi-layered security architectures that offer comprehensive protection. Another critical insight from this study is the growing importance of interpretability in federated learning systems. Traditional deep learning models are often criticized for their lack of transparency, which limits their applicability in high-stakes environments. The integration of explainable AI (XAI) techniques such as SHAP, LIME, and attention-based models has significantly improved the interpretability of federated systems. These techniques enable both local and global explanations, allowing stakeholders to understand model behavior and validate predictions. In distributed settings, interpretability plays a crucial role in building trust among participants, as it provides visibility into how individual contributions influence the global model.

Despite these advancements, the integration of interpretability into federated learning introduces additional challenges. Explainability techniques often require significant computational resources, which can impact system scalability and efficiency. Moreover, there is a potential trade-off between privacy and interpretability, as providing detailed explanations may inadvertently reveal sensitive information. Addressing these challenges requires the development of lightweight and privacy-aware interpretability methods that can operate effectively in federated environments. Optimization techniques also play a vital role in enhancing the performance and scalability of federated learning systems. Algorithms such as FedProx and SCAFFOLD have been developed to address issues related to non-IID data distributions and client heterogeneity, improving convergence stability and model performance. Communication-efficient strategies such as gradient compression and sparse updates reduce bandwidth requirements, enabling FL deployment in resource-constrained environments such as edge devices. However, these optimizations must be carefully balanced to avoid compromising model accuracy and interpretability.

The comparative analysis conducted in this review highlights a clear trend toward integrated frameworks that combine security, interpretability, and optimization. Early research primarily focused on individual aspects, such as privacy preservation or model efficiency. In contrast, recent studies emphasize holistic approaches that address multiple challenges simultaneously. These integrated frameworks are particularly relevant for real-world applications, where systems must operate under constraints related to data privacy, computational resources, and regulatory requirements. Emerging applications of secure and interpretable federated learning further underscore its potential impact. In healthcare, FL enables collaborative model training across institutions while preserving patient privacy, and interpretability ensures that medical decisions are transparent and explainable. In financial systems, FL can enhance fraud detection while maintaining data confidentiality. In smart cities and autonomous systems, federated learning supports distributed intelligence across interconnected devices, enabling real-time decision-making while ensuring security and trust. These applications demonstrate that federated learning is not only a theoretical concept but also a practical solution for modern data-driven ecosystems.

Despite the significant progress made in this field, several research gaps remain. There is a need for more efficient and scalable interpretability techniques that can be seamlessly integrated into federated learning frameworks. Additionally, developing adaptive defense mechanisms that can respond to evolving adversarial threats is essential for maintaining system security. Future research should also focus on addressing fairness and bias in federated learning, ensuring equitable performance across diverse client populations. Furthermore, the development of standardized evaluation metrics for security, interpretability, and optimization will be critical for benchmarking and improving federated learning systems. In conclusion, this review highlights that the future of federated learning lies in the development of integrated, secure, and interpretable frameworks that can operate efficiently in real-world environments. Achieving this goal requires a multidisciplinary approach that combines advancements in machine learning, cybersecurity, distributed systems, and explainable AI. By addressing the challenges identified in this study, researchers and practitioners can pave the way for the next generation of trustworthy AI systems that are capable of delivering intelligent, secure, and transparent solutions across a wide range of applications.

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