Intesab Aalami
ISSN: 2348-5035
Vol. 12/ No. 5/ September 2024

Federated Learning for Privacy-Preserving Machine Learning

Dr. Sneha Patel

Abstract

Federated Learning (FL) enables multiple devices or organizations to collaboratively train machine learning models without sharing raw data. Instead of centralizing sensitive information, only model updates are exchanged, improving privacy, reducing communication risks, and supporting regulatory compliance. Federated learning is increasingly applied in healthcare, finance, IoT, mobile applications, and smart manufacturing. This paper discusses its principles, applications, challenges, and future directions.

Keywords

Federated Learning, Privacy-Preserving Machine Learning, Artificial Intelligence, Distributed Learning, Data Privacy, Edge Computing, Secure Aggregation, Internet of Things, Machine Learning.

Introduction

The increasing demand for artificial intelligence has led to the collection of massive datasets. Traditional centralized machine learning requires data to be transferred to a central server, creating privacy, security, and compliance concerns.

Federated Learning addresses these issues by training models locally on user devices or organizational servers. Only model parameters are shared with a central coordinator, ensuring that sensitive data never leaves its original location.

Federated learning is widely used in healthcare for collaborative diagnosis, banking for fraud detection, smartphones for personalized services, and industrial IoT for predictive maintenance. It combines privacy preservation with high-quality model development.

The integration of federated learning with edge computing, cloud computing, 5G, and artificial intelligence enables scalable, low-latency, and secure intelligent systems suitable for modern digital ecosystems.

Despite its benefits, federated learning faces challenges including communication overhead, heterogeneous data, adversarial attacks, privacy leakage, and limited computing resources. Secure aggregation, differential privacy, and homomorphic encryption improve protection.

Future research focuses on explainable federated AI, cross-silo collaboration, federated foundation models, adaptive optimization, and privacy-enhancing technologies to enable trustworthy and scalable machine learning.

Conclusion

Federated Learning is transforming privacy-preserving AI by allowing collaborative model training without exposing sensitive information. Continued advances in secure aggregation, explainability, and distributed optimization will expand its adoption across healthcare, finance, manufacturing, and smart connected systems.

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