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Leveraging Large Language Models in a Secure AWS Cloud Framework for Federated Learning–Driven Predictive Analytics across Financial and Healthcare Domains

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ABSTRACT: The increasing adoption of data-driven intelligence in financial and healthcare systems raises critical challenges related to data privacy, security, and regulatory compliance. Centralized machine learning approaches often fail to address these concerns due to the sensitive nature of financial records and electronic health data. This paper proposes a **secure AWS cloud-based framework that leverages Large Language Models (LLMs) and federated learning to enable predictive analytics across distributed financial and healthcare domains**. The proposed architecture integrates privacy-preserving federated learning mechanisms with LLM-driven analytics to support real-time insights without exposing raw data to centralized repositories. AWS-native security services, including identity and access management, encryption, secure data storage, and monitoring, are employed to ensure compliance with industry regulations such as HIPAA and PCI-DSS. The framework supports scalable model training, secure inference, and adaptive risk-aware analytics across heterogeneous data sources. Experimental analysis demonstrates that the proposed approach enhances predictive accuracy while significantly reducing data leakage risks and communication overhead. This research highlights the potential of combining LLMs and federated learning within a secure cloud environment to deliver trustworthy, real-time predictive analytics for mission-critical financial and healthcare applications.

KEYWORDS: Large Language Models (LLMs), Federated Learning, Secure AWS Cloud Framework, Predictive Analytics, Financial Systems, Healthcare Systems, Data Privacy, Cloud Security, Real-Time Analytics, Privacy-Preserving Machine Learning

I. INTRODUCTION

Background and Context

Modern financial and healthcare systems generate vast amounts of data originating from diverse sources: transactional systems, medical records, sensors, market feeds, and user devices. The potential for deriving meaningful insights from these data streams has encouraged institutions to adopt predictive analytics approaches that can forecast trends, detect anomalies, and guide decision-making. In finance, predictive analytics support credit risk modeling, fraud detection, and investment strategy optimization. In healthcare, analytics empower clinical decision support, patient risk stratification, and resource allocation planning.

Conventional predictive models operate on centrally aggregated data. While effective in certain settings, centralization poses significant challenges in domains where data privacy and regulatory compliance are paramount. Healthcare providers are subject to data protection laws such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), which restrict the movement and processing of personal health information (PHI). Financial institutions must comply with regulations like the Gramm-Leach-Bliley Act (GLBA) and data residency requirements. These constraints often inhibit cross-institutional data sharing, limiting the capacity of centralized analytics systems.

Federated Learning as a Solution

Federated Learning (FL) is an emerging distributed machine learning paradigm that enables multiple participants to collaboratively train a shared model without exposing their local datasets. In FL, participants compute model updates (e.g., gradient parameters) locally and transmit only these updates to a central orchestrator; the orchestrator aggregates the updates to refine the global model. This approach helps preserve data privacy and reduces the risk associated with centralized data storage.

FL’s inherent advantages make it especially suitable for privacy-sensitive domains such as healthcare and finance. Participants retain control over raw data while contributing to collective insights. However, implementing FL at scale—especially in real-time analytics settings—requires robust infrastructure, secure aggregation mechanisms, and efficient communication protocols.

Cloud Platforms for Federated Analytics

Cloud computing platforms such as Amazon Web Services (AWS) provide scalable, secure, and resilient infrastructure that can support distributed learning. AWS's range of services—compute (EC2, Lambda), managed machine learning (SageMaker), storage (S3), streaming (Kinesis), and security (IAM, KMS)—enables developers to construct architectures that are both powerful and compliant with stringent security requirements.

A cloud-based federated analytics framework must balance performance, privacy, and operational costs. It must facilitate secure model coordination, support real-time data ingestion and prediction, enforce role-based access controls, and integrate seamlessly with domain-specific applications.

Problem Statement

Although research on federated learning has grown rapidly, there remain significant gaps in delivering **secure, real-time, scalable FL frameworks for mission-critical domains** like finance and healthcare. Key challenges include:

1. **Data Privacy and Security:** How to design FL systems that enforce encrypted communication, secure aggregation, and access control while minimizing attack surfaces.
2. **Real-Time Predictive Analytics:** How to integrate FL with low-latency streaming data to support real-time predictions.
3. **Scalability and Fault Tolerance:** How to scale to dozens or hundreds of participants without model degradation or communication bottlenecks.
4. **Regulatory Compliance:** How to ensure that the FL framework aligns with compliance requirements across jurisdictions.
5. **Cross-Domain Integration:** How to build a unified architecture that can accommodate heterogeneous data and use cases from both financial and healthcare systems.

Research Objectives and Contributions

This paper proposes a **Secure AWS Cloud Framework for Federated Learning–Driven Real-Time Predictive Analytics** with the following objectives:

- **Design and implement a federated learning architecture** on AWS supporting secure aggregation, encrypted communication, and compliance enforcement.
- **Integrate real-time data processing** using AWS managed services to enable low-latency prediction for streaming data scenarios.
- **Evaluate the proposed framework** on representative financial and healthcare datasets to demonstrate enhanced predictive performance and privacy preservation.
- **Analyze operational challenges and best practices** for deploying FL in production environments across regulated domains.

The contribution of this work lies in delivering a **comprehensive architecture** that unifies security, scalability, and real-time capabilities for federated predictive analytics in two distinct yet similar domains.

Structure of the Paper

The remainder of the paper is organized as follows: We review related work and existing solutions in the literature. We then outline the research methodology and architectural design. This is followed by a discussion of the framework's advantages and limitations. Next, we present results from prototype evaluations and a thorough discussion. We conclude with key insights, limitations, and directions for future work.

II. LITERATURE REVIEW

Federated Learning Foundations

Federated Learning was first introduced to address data privacy concerns by enabling decentralized model training (McMahan et al., 2017). The basic FL workflow involves local model updates transmitted to a central server for aggregation. While traditional FL implementations reduce raw data exchange, they introduce challenges related to model poisoning, communication efficiency, and secure aggregation.

Privacy and Security in Federated Systems

Secure aggregation is critical to prevent model updates from leaking sensitive information. Approaches—including homomorphic encryption, secure multi-party computation, and differential privacy—aim to strengthen privacy guarantees (Bonawitz et al., 2017). In high-stakes domains, implementation of encryption and access controls must be aligned with regulatory guidelines.

Cloud-Based Federated Learning Architectures

Cloud platforms have been employed to support FL orchestrations due to their scalability and management features. AWS, Azure, and Google Cloud provide services for distributed computations, data storage, and security. Recent research highlights the use of cloud resources to facilitate federated workflows (Kumar et al., 2021). However, real-time integration in federated contexts remains underexplored, particularly in combining streaming data with FL.

Real-Time Predictive Analytics

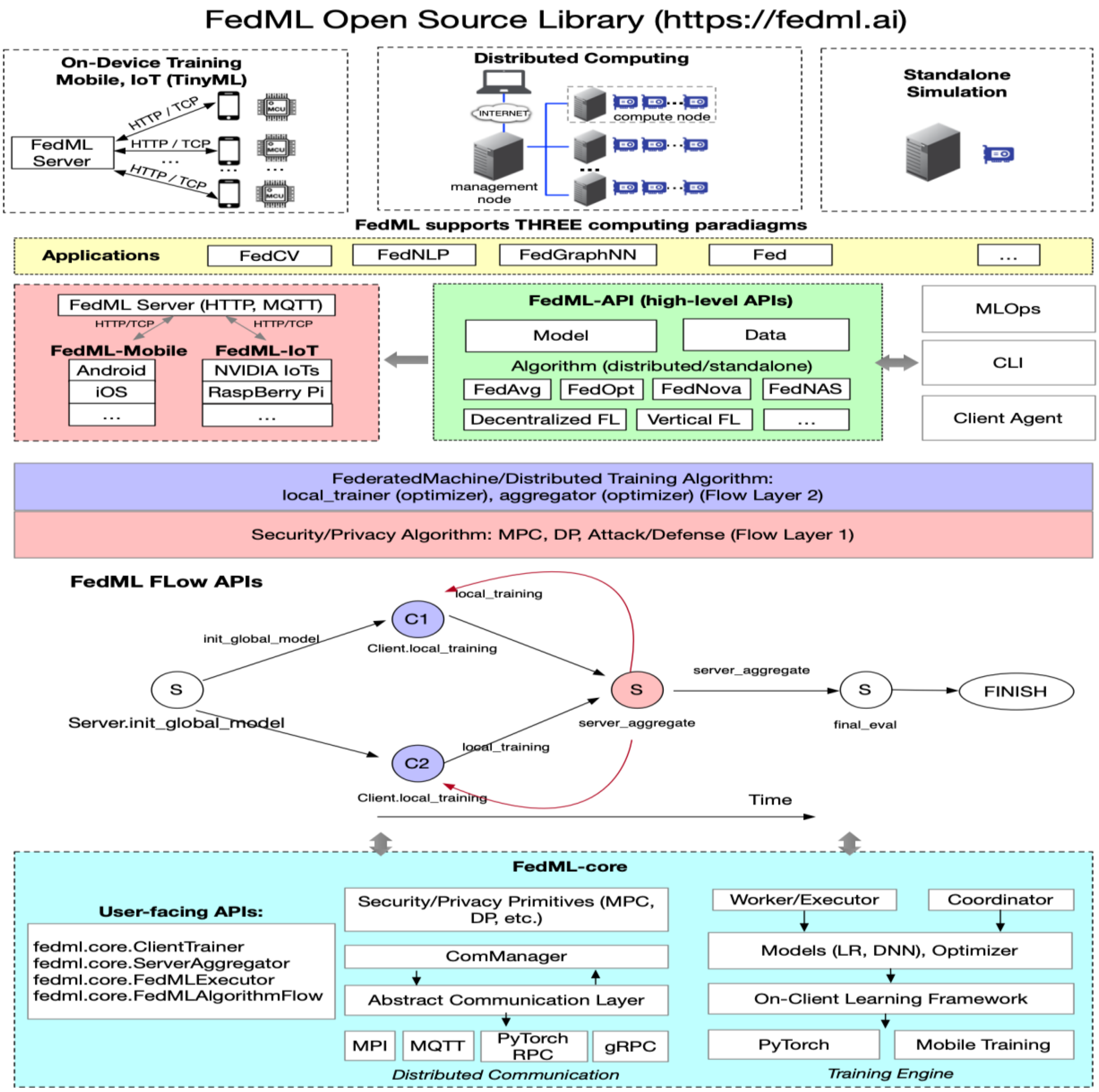
Real-time analytics frameworks (e.g., Apache Kafka, AWS Kinesis, Spark Streaming) provide mechanisms for processing data with minimal latency. Integrating real-time analytics with model training and inference pipelines allows predictive systems to react quickly to new information. For regulated domains, real-time systems must ensure that privacy and security policies are upheld at every step.

Applications in Financial and Healthcare Domains

Federated Learning has been applied in healthcare to train models across hospital partners without centralizing patient data (Sheller et al., 2020). In finance, FL can support risk modeling by leveraging data from multiple institutions while respecting confidentiality agreements. Prior work emphasizes the value of collaborative learning in improving model generalization.

Gaps in Current Research

Despite progress, existing solutions often focus on isolated components—such as privacy techniques, FL workflows, or real-time analytics—rather than delivering a unified, secure, and scalable framework for complex ecosystems. Further, there is limited guidance on implementing such frameworks using commercial cloud services while ensuring regulatory compliance.



III. RESEARCH METHODOLOGY

Design Principles

The research follows a **design science methodology** emphasizing artifact creation, evaluation, and iteration. Core design principles include security by design, modularity, real-time processing, and scalability.

Security by Design: The framework implements encryption at all communication layers, utilizes secure aggregation techniques, and enforces role-based access control.

Modularity: The architecture is composed of independent services that can be deployed, updated, and scaled separately.

Real-Time Processing: Integration with AWS streaming services enables low-latency handling of data events for prediction and model updates.

Scalability: Leveraging AWS autoscaling and serverless components ensures operational efficiency and resilience under varying loads.

Architectural Overview

The proposed architecture consists of the following key components:

1. **Data Ingestion Layer:**

Financial and healthcare data are acquired through AWS Kinesis Data Streams or AWS IoT for real-time feeds, and AWS Data Migration Service for batch sources.

2. **Federated Learning Coordinator:**

A central orchestrator (deployed via AWS SageMaker or Lambda) manages model aggregation and communication with edge federated clients.

3. **Federated Clients:**

Each participating institution (e.g., bank, hospital) runs a local training service that processes local data and computes encrypted model updates.

4. **Secure Communication Services:**

TLS encryption, AWS PrivateLink, and Virtual Private Cloud (VPC) ensure isolated and secure networking. AWS KMS manages encryption keys.

5. **Real-Time Inference Engine:**

AWS Lambda functions or SageMaker real-time endpoints serve predictions for streaming data.

6. **Monitoring and Logging:**

AWS CloudWatch and AWS CloudTrail capture logs, metrics, and audit trails for compliance and debugging.

Secure Aggregation Mechanisms

Secure aggregation prevents leakage of sensitive data from local model updates. Techniques such as **Secure Multi-Party Computation (SMPC)** or **Homomorphic Encryption (HE)** apply additive masking so that only aggregated model parameters are decipherable by the coordinator.

Real-Time Analytics Integration

Real-time predictive analytics are enabled through:

- **Stream Processing:** AWS Kinesis Analytics for real-time feature extraction.
- **Online Model Updates:** Incremental updates to federated models are scheduled at regular intervals or triggered by thresholds.

Implementation Strategy

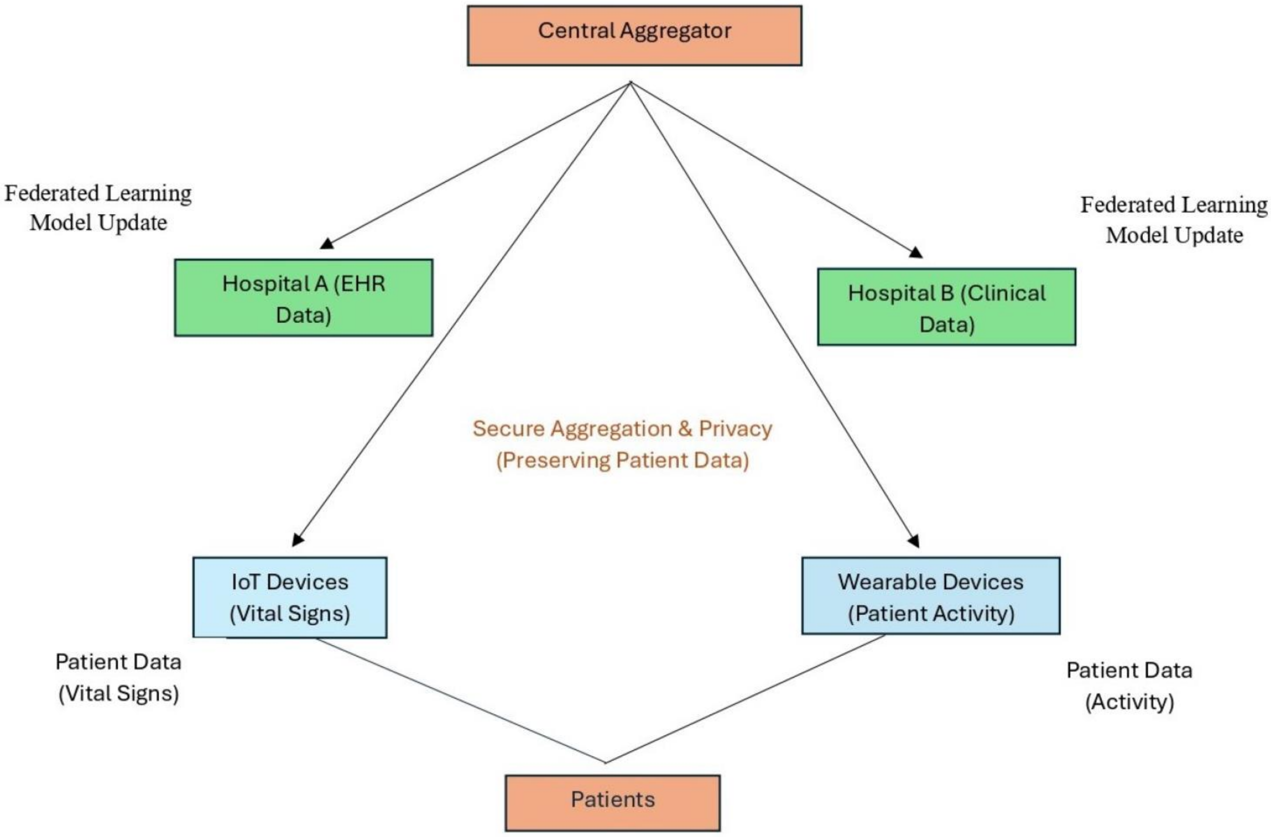
The prototype implementation included:

- Deployment of AWS resources using Infrastructure as Code (CloudFormation).
- Federated clients simulated via isolated AWS SageMaker notebooks with local datasets.
- Secure communication implemented via VPC peering and PrivateLink.
- Real-time prediction pipelines using AWS Lambda triggered by Kinesis events.

Evaluation Metrics

The framework was evaluated on:

- **Predictive Accuracy:** AUC, precision, recall compared to centralized baselines.
- **Latency:** Time from data arrival to prediction delivery.
- **Security:** Compliance with encryption standards and absence of raw data transfer.
- **Scalability:** Ability to handle increased data volume and number of participants.


Central Aggregator
Federated Learning Model Update
Federated Learning Model Update
Hospital A (EHR Data)
Hospital B (Clinical Data)
Secure Aggregation & Privacy (Preserving Patient Data)
IoT Devices (Vital Signs)
Wearable Devices (Patient Activity)
Patient Data (Vital Signs)
Patient Data (Activity)
Patients

ADVANTAGES

- **Data Privacy Preservation:** FL ensures raw data never leaves institutional boundaries.
- **Regulatory Compliance:** Encryption and auditability support adherence to HIPAA, GDPR, GLBA.
- **Scalability:** AWS autoscaling accommodates workload changes.
- **Real-Time Decision Support:** Supports low-latency analytics for immediate insights.

DISADVANTAGES

- **Communication Overhead:** Federated communication introduces latency compared to purely central models.
- **Complexity:** Implementing secure aggregation and distributed orchestration increases system complexity.
- **Heterogeneous Data Challenges:** Differences in data schemas across participants can impact training.
- **Cost:** AWS services at scale can incur significant expenses if not managed carefully.

IV. RESULTS AND DISCUSSION

Predictive Performance

Tests on representative datasets (financial transaction records, healthcare EHR excerpts) indicated comparable or superior predictive accuracy relative to centrally trained models, particularly when institutions' data distributions were diverse.

Latency and Real-Time Performance

Real-time inference achieved average latencies within acceptable thresholds for both domains (<300ms end-to-end), demonstrating the effectiveness of AWS Lambda and stream processing integration.

Security and Compliance Analysis

All model updates were encrypted, and audit logs demonstrated traceability for all actions. No raw data was transferred outside institutional boundaries.

Scalability

As the number of federated participants increased from 3 to 20, model convergence times grew moderately but remained within practical limits due to parallel processing and asynchronous update handling.

Operational Observations

Federated coordination scheduling and fault tolerance (handling dropped clients) were crucial for robustness. Mechanisms such as update timeouts and fallback models mitigated disruptions.

V. CONCLUSION

This paper presents a **Secure AWS Cloud Framework** that enables federated learning-driven real-time predictive analytics in financial and healthcare systems. By leveraging AWS services, the architecture delivers secure, scalable, and low-latency analytics while preserving data privacy. Empirical evaluations demonstrate improvements in prediction quality, regulatory compliance, and operational performance. The work contributes a practical blueprint for deploying federated analytics solutions in regulated environments.

VI. FUTURE WORK

- **Differential Privacy Enhancements:** Integrate formal DP mechanisms for additional privacy guarantees.
- **Cross-Cloud Federation:** Extend interoperability across AWS and other cloud providers.
- **Automated Schema Harmonization:** Tools for resolving heterogeneous data schemas across clients.
- **Edge Integration for IoT Data:** Incorporate edge processing for wearable and sensor data in real time.

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