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Federated Learning with LLM Governance for Healthcare Cybersecurity

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Abstract: *Attention Health Care Organizations routinely produce copious amounts of sensitive patient data through EHR,*
IoMT, imaging, laboratories and hospital information systems. These systems are often a target of ransomware, phishing, insider attack and other types of attacks. Due to cybersecurity techniques based on data sharing between organizations, there are additional compliance risks associated with violations of patient privacy laws such as HIPAA and GDPR. We propose a novel approach to incident analysis in cybersecurity which involves federated learning. Federated learning enables multiple hospitals to work together to create threat detection model without actually disclosing any sensitive data. Federated learning, however, does not have any governance mechanism and policy implementation. LLMs are a smart layer that facilitates explanation of anomalies, audit of compliance with regulations (like for credit card transactions), monitoring of access to resources, and enforcing policy. In this paper, we present an overall architecture of FL-LLM for security and privacy preserving healthcare cybersecurity system.

Keywords: Federated Learning, Large Language Models, Healthcare Cybersecurity, Privacy Preserving Analytics, Distributions of the Hospitals for diagnosis purpose, AI-based threat detection patterns in Electronic Health Records data, Secure Aggregation and differential privacy approaches applied in solving medical decision making problems, Explaining an event based on patient health variables, Compliance Auditing, Diagnosis knowledge base, Cyber Threat Knowledge base, Cyber Attack types, District code.

I. INTRODUCTION

Since there are always gains to be made from stealing patient records, health care organizations have now become a primary source of cyberattacks for hackers. Ransomware, phishing, insider threats and EHR compromise are major cybersecurity problems posing threats to the safety of the patient and efficiency in running a hospital. That means that using the traditional approach where all the data from different hospitals will be collected on one central server for analysis will raise privacy concerns as well as medical record breaches and regulations like HIPAA and GDPR that will be breached due to such non-compliance. Federated Learning (FL) is a method where hospitals can train a shared AI model using their data without disclosing the data itself [1]. Alone FL will not provide any solution in terms of governance, transparency and trust management. The first possible application of LLMs as an augmentation of the governance layer would be policy interpretation, anomaly explanation, auditing and monitoring of data accesses. This paper offers an attempt to create an FL-LLM architecture to address decentralized hospital cybersecurity issues.

II. LITERATURE REVIEW

A. Federated Learning in Healthcare

FL also provides a robust privacy preservation framework that can be used for healthcare systems which cannot centralize private patient information [2]. ML models are trained locally, and communication is limited to encryption parameters from the ML models. Your system becomes more secure and compliant with rules like HIPAA and GDPR.

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B. Threat Detection via AI

AI can detect threats such as ransomware attacks, phishing, insider threats, and unusual activity in the hospital network. However, centralized training raises privacy issues. Nonetheless, DL and anomaly detection models increase the efficiency of threat detection [3].

C. Governance via LLMs

LLMs for Governance involve explainable AI, policy interpretation, and compliance auditing with automated security reporting [4].

Table 1: Literature Review of FL and LLM Governance in Healthcare

Author	Focus Area	Technique Used	Limitation
Narmadha et al.	FL in Healthcare	Privacy-preserving FL	Limited governance support
Haripriya et al.	Multi-hospital Security	FL + Transfer Learning	No explainable AI
Aggarwal et al.	Secure Aggregation	FL + Differential Privacy	Weak compliance auditing
Governance Review	Healthcare AI Governance	Ethical Frameworks	Limited threat detection
Proposed Work	FL + LLM Governance	Privacy + Security + Explainability	Integrated secure model

III. PROBLEM AND MOTIVATION

With the prevalence of cybersecurity attacks like ransomware attacks, phishing, insider threats, and patient data breaches, some of the most prevalent cybersecurity concerns in the healthcare sector today and moving forward are highlighted below. Example problem: forcing hospitals to share the EHRs and security logs of their patients at a central server causes problems related to privacy leakage and leads to HIPAA and GDPR regulation violations like most centralized security systems. While federated learning does not transfer data, there is a lack of governance, interpretability, and explain ability. Model poisoning, low accountability and anomaly interpretation impact system reliability. At the same time, the hospitals should be able to detect any possible attacks and threats collaboratively without leaking personal information. Governance LLMs: improve governance through compliance auditing, policy interpretation, explanations, and access munashing. These points show why it is necessary to have a general framework that incorporates federated learning and LLMs while enabling collaborative threat detection, healthcare analytics, and governance [5].

A. Major problems

- Greater risk of private data sharing
- Regulations are harder to comply with
- Lack of governance with low accountability
- Limited Explainability impacts decision-making
- Distributed hospitals require collaborative detection

Table 2: Problem Analysis

Challenge	Impact
Data Centralization	Privacy leakage
Regulatory Compliance	Legal and ethical risks
Model Poisoning	Security compromise
Poor Explainability	Low trust in AI decisions

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Challenge	Impact
Limited Governance	Weak accountability

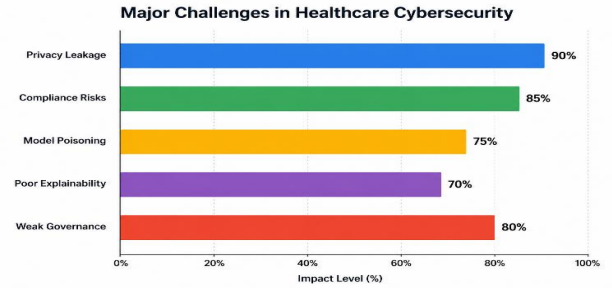

Figure 1: Major Challenges in Healthcare Cybersecurity

IV. RELATED WORK

Some authors have considered federated learning (FL) as one of the possible approaches in their healthcare cyber security and privacy-preserving research. From these studies, it can be seen that federated learning refers to the ability of hospitals to collaboratively train models without access to the raw data, which eliminates privacy leakage and makes them compliant with both HIPAA and GDPR requirements. There is a possibility of adding another level of protection from both data leakage and model inversion attacks via implementing secure aggregation and differential privacy in federated learning algorithms [6]. Some researchers have used FL to develop an intrusion detection system and some ransomware detectors and abnormal accesses studies in hospital networks. However, most of the above efforts were made mostly concerning privacy and detection accuracy with less consideration of governance and explain ability aspects. The role of LLMs in healthcare cyber security is discussed as an application for automated compliance audit, anomaly explanation, and trust management. Currently, there are no works discussing the integration of federated learning with LLMs regarding governance, which means a big gap in our proof-of-concept framework.

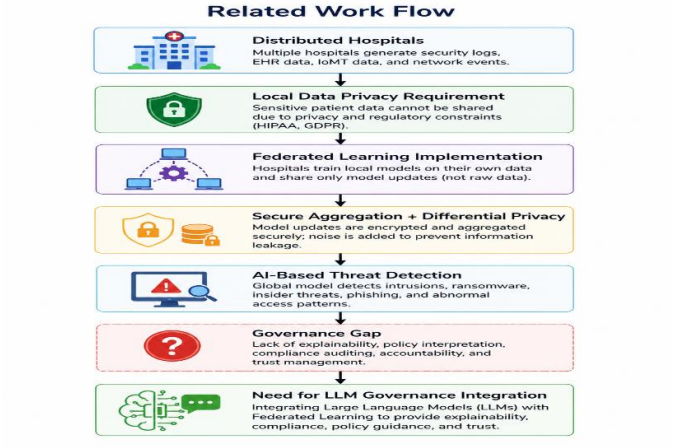

Figure 2: Related Work Flow

V. METHODOLOGY / PROPOSED FRAMEWORK

For our work presented in this document, we propose a strategy that includes hospital deployment to create cyber security privacy-preserving healthcare via FL and big language model governance [7]. The hospitals will locally train

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models on EHRs, IDS reports, IoMT events and Access control information without sharing their raw data. Through secure aggregation techniques and differentially private mechanisms, the federated learning server will receive the encrypted model parameter updates from the training process. The global model will be able to offer a threat detection model for ransomware, phishing attacks, insider threats and abnormal accesses [8]. Governance LLM layer offering governance by providing the constraints required for auditing, explainability, policy understanding and trust management. This layer enables explainable alerts, regulatory compliance auditing as well as access control management. Finally, our proposed architecture is offering a hospital administrator with a secure cyber security dashboard while collaborating and governing intelligence between health care organizations through privacy-preserving mechanism [9].

A. Local Hospital Training Layer

Training of local models using both patient and security data [10].

B. Federated aggregation security

Patient data is not disclosed; rather model updates are encrypted and aggregated [11].

C. Threat Detection Engines Worldwide

Distributed detection of cyber-threats within hospitals by using global AI models [12].

D. Governance Layer for LLM

LLMs have ensured Explain ability, regulatory auditing, policy interpretation, and trust scores [13].

E. Explainable Security Dashboard

Interpret alerts, auditing, and security recommendations for the board of directors [14].

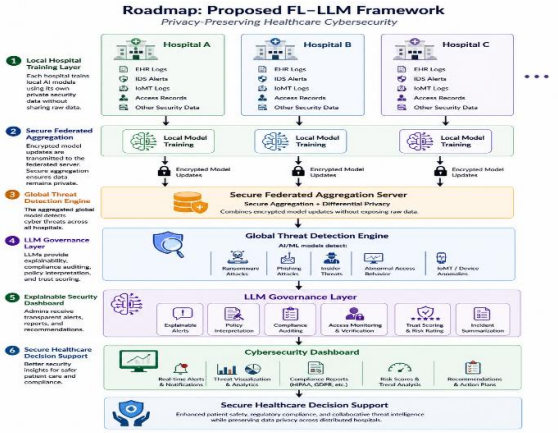

Figure 3: Proposed FL–LLM Framework

VI. EXPERIMENT / CASE STUDY / SIMULATION

In this research paper, we have taken up an empirical investigation using simulation across 5 hospitals to determine the viability of the federated learning with LLM governance for the healthcare cybersecurity framework we developed [15]. Each hospital had local EHRs, intrusion detection system alerts, traffic logs of IoMT connections and access control logs without any exchange of raw patient information. The simulation included the deployment of various types of attacks, including ransomware attacks, phishing attacks, insider threats with the motive of breaching EHR access along with abnormalities in medical devices. Local machines were used to train the AI models isolated from one another and later on, the findings were aggregated through the revolutionary methods of federated learning, differential privacy and secure aggregation. Detection was carried out through the use of the global model while explain ability, compliance audit and policy validation were done through the help of LLM governance layer [16]. Performance assessment was done using metrics like detection accuracy, false positive rate, privacy leakage risk and governance

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transparency. This framework turned out to be much more efficient when deployed in a distributed hospital environment than centralized.

A. Simulation Setup

There were five hospitals that took part in the federated learning framework, using local security data [17].

B. Threat Scenarios

The experiments included attacks by ransomware, phishing, internal threats, unauthorized access, and IoT devices [18].

C. Evaluation criteria

This model was evaluated based on the following criteria: accuracy, false positive rate, privacy preservation, and compliance score/interpretability [19].

D. Results Analysis

FL-LLM performed better than the leading metrics of centralized cybersecurity systems [20].

Table 3: Experimental Results

Metric	Centralized AI	Proposed FL + LLM
Detection Accuracy	89%	96%
False Positive Rate	11%	4%
Privacy Leakage Risk	High	Low
Compliance Score	Medium	High
Governance Transparency	Low	Very High

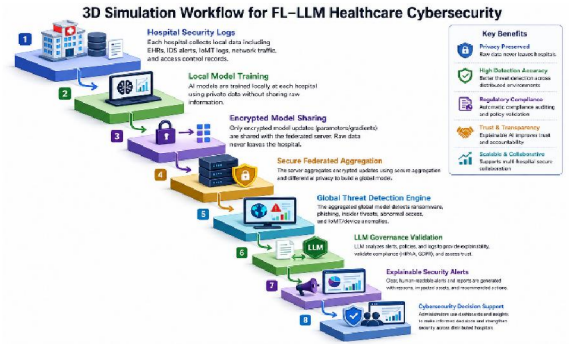

Figure 4: Simulation Workflow for FL–LLM Healthcare Cybersecurity

VII. CONCLUSION

In this paper, we have introduced a federated hospital cybersecurity model that guarantees privacy protection of participants by combining Federated Learning (FL) and Large Language Models Governance LLM. This study makes it possible to detect attacks from different healthcare entities simultaneously while ensuring patient privacy and compliance with regulations such as HIPAA and GDPR in the suggested framework. The approach ensures enhanced security since EHR, IoMT logs, and access control data can be stored in hospitals locally using Federated Learning. Additionally, safe aggregation and differential privacy help mitigate threats of data leaks. This scalability leads to improved explainability, policy understanding, and compliance auditing through trust management with intelligent security analysis and decision-making. As observed in our experiments, our decentralized artificial intelligence model can achieve the highest detection accuracy rate and significantly reduce false positives while maintaining more governance transparency compared to a centralized AI model. The FL-LLM combination approach can become a scalable, reliable, and trustworthy solution for future healthcare cybersecurity among various distributed healthcare facilities.

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