Research Paper

EPRA International Journal of Economic and Business Review-Peer Reviewed Journal
Volume - 14, Issue - 1, January 2026 | e-ISSN: 2347 - 9671| p- ISSN: 2349 – 0187

SJIF Impact Factor (2025): 8.862 || ISI Value: 1.433 || Journal DOI URL: https://doi.org/10.36713/epra2012

PRIVACY-CONSCIOUS FEDERATED MULTI-MODAL LEARNING WITH JURISDICTIONAL CONSTRAINTS

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ABSTRACT DOI No: 10.36713/epra25942 Article DOI: https://doi.org/10.36713/epra25942

The rapid-fire proliferation of Internet of effects (IoT) bias has introduced significant security challenges, particularly in large- scale and miscellaneous IoT networks. These systems are decreasingly susceptible to different cyber-attacks due to the decentralized nature and limited computational capabilities of individual IoT bumps. Traditional intrusion discovery systems(IDS) struggle to directly identify sophisticated and evolving attack patterns in similar surroundings. To address these limitations, this study proposes a new sequestration- conserving mongrel Convolutional intermittent Neural Network(CRNN) model integrated with allied literacy formulti-class intrusion discovery in IoT and Industrial IoT(IIoT) networks. Federated learning enables decentralized training of the model across multiple IoT bias without transferring raw data, thereby conserving data sequestration and icing compliance with data protection regulations. The cold-blooded CRNN armature leverages the strengths of Convolutional Neural Networks(CNNs) for point birth and intermittent Neural Networks(RNNs) for landing temporal dependences in network business. This combination significantly enhances the model's capability to descry a wide range of attack types, including low- frequence and sophisticated pitfalls. The proposed model is trained and estimated using the Edge- IIoT dataset, demonstrating high performance with a discovery delicacy of 98.93. The results show balanced perfection and recall across all attack classes, including grueling orders similar as SQL Injection and Man- in- the- Middle attacks. This balance contributes to minimizing both false cons and false negatives, perfecting the overall trustability and robustness of the intrusion discovery system. By furnishing real- time discovery and sequestration- conserving training, the proposed approach offers a practical, scalable, and secure result acclimatized for complex IoT surroundings. It addresses critical gaps in being IDS fabrics by combining advanced deep literacy styles with allied literacy, paving the way for unborn secure and intelligent IoT deployments.

INTRODUCTION

The ever-expanding ecosystem of the Internet of Things (IoT) and Industrial IoT (IIoT) has ushered in a new era of ubiquitous computing. From smart homes and industrial automation to connected healthcare and autonomous vehicles, IoT devices are revolutionizing how systems interact and operate in real time. However, as the number of these devices rapidly increases, so does the surface area for cyber-attacks. The decentralized, heterogeneous, and resource-constrained nature of IoT nodes makes them inherently vulnerable to a wide spectrum of threats—ranging from Denial-of-Service (DoS) and Man-in-the-Middle (MitM) attacks to advanced persistent threats and data exfiltration. As a result, ensuring the security of IoT networks has become a major research and engineering challenge. Traditional Intrusion Detection Systems (IDS) typically rely on centralized architectures where data from all endpoints is aggregated to a central server for training machine learning or deep learning models. While these systems have shown reasonable success in controlled environments, they suffer from several limitations when applied to large-scale IoT and IIoT deployments. First, the centralization of data introduces significant privacy concerns, especially under the purview of regulations like the General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA), and similar data protection frameworks. Second, the network overhead of transmitting massive volumes of raw traffic data from edge devices to centralized servers can lead to bandwidth bottlenecks, increased latency, and potential single points of failure. Third, these systems are not easily scalable or adaptable to the dynamic and distributed nature of modern IoT environments.

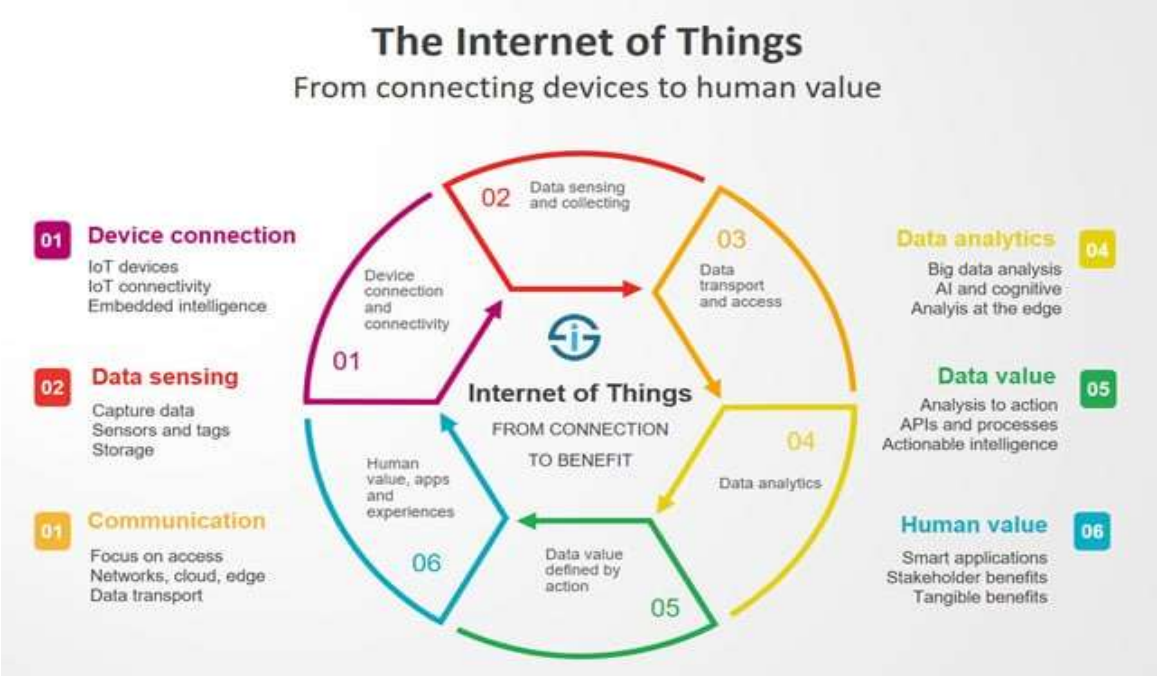


Fig:1 Internet of Things (IoT)

To address these challenges, this research introduces a novel **Privacy-Conscious Federated Multi-Modal Learning** framework tailored to the needs of secure, distributed, and regulation-compliant IoT environments. The proposed approach is built on a hybrid **Convolutional Recurrent Neural Network (CRNN)** architecture designed for multi-class intrusion detection. It combines **Convolutional Neural Networks (CNNs)**—effective in extracting spatial features from raw traffic and sensor data—with **Recurrent Neural Networks (RNNs)**—which are adept at modeling temporal dependencies in sequential data streams. This hybrid structure enables the detection system to recognize complex attack signatures that exhibit both spatial irregularities and temporal patterns.The standout feature of this approach is its integration with **Federated Learning (FL)**, a distributed learning paradigm that allows local IoT nodes to collaboratively train a shared model without transmitting their raw data to a centralized server. Each node trains the model using local data and only shares model updates (gradients or weights) with a central aggregator. This not only drastically reduces data exposure and ensures compliance with jurisdictional privacy laws but also lowers bandwidth consumption and supports real-time deployment. Importantly, federated learning also adds resilience to the architecture by eliminating single points of failure and reducing attack surfaces associated with centralized infrastructures.

Another significant innovation of this work is its support for **multi-modal data inputs**. In modern IoT setups, various forms of data such as network packets, device logs, system events, sensor readings, and even user behavior data are generated. The proposed model is capable of processing and learning from these diverse modalities simultaneously, leading to richer feature representations and improved detection performance. This ability is critical for identifying sophisticated or low-frequency attacks such as SQL injections or Man-in-the-Middle intrusions, which often go undetected by systems that rely on a single data modality.

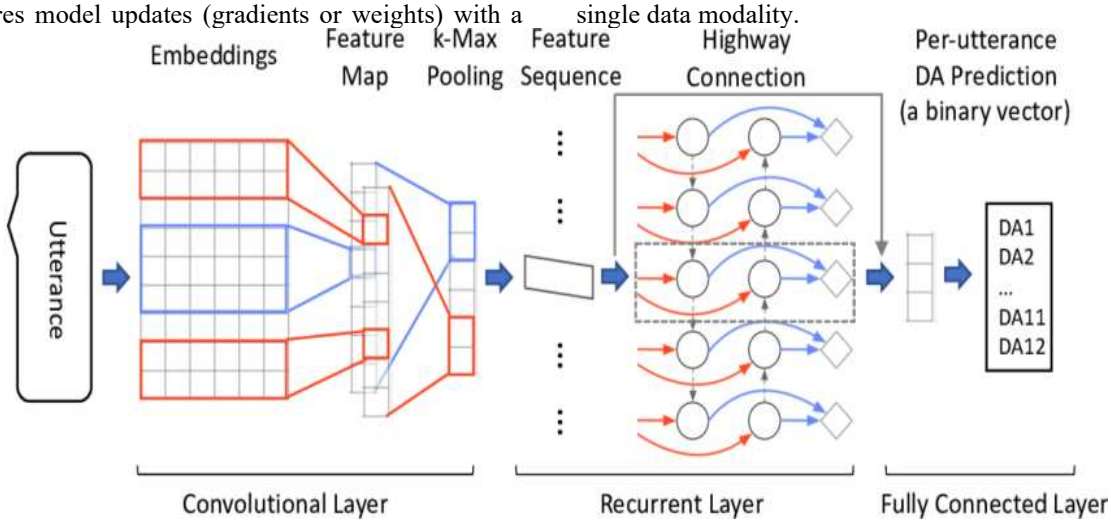


Fig:- 2 The proposed CRNN model architecture.

To validate the effectiveness of the proposed framework, the model was trained and tested on the **Edge-IIoT dataset**, a realistic and comprehensive dataset containing labeled examples of multiple attack types in IoT contexts. The model achieved a detection accuracy of **98.93%**, with high precision and recall across both common and rare attack classes. Such performance not only demonstrates the robustness and generalizability of the hybrid CRNN architecture but also highlights the utility of federated multi-modal learning in real-world conditions.

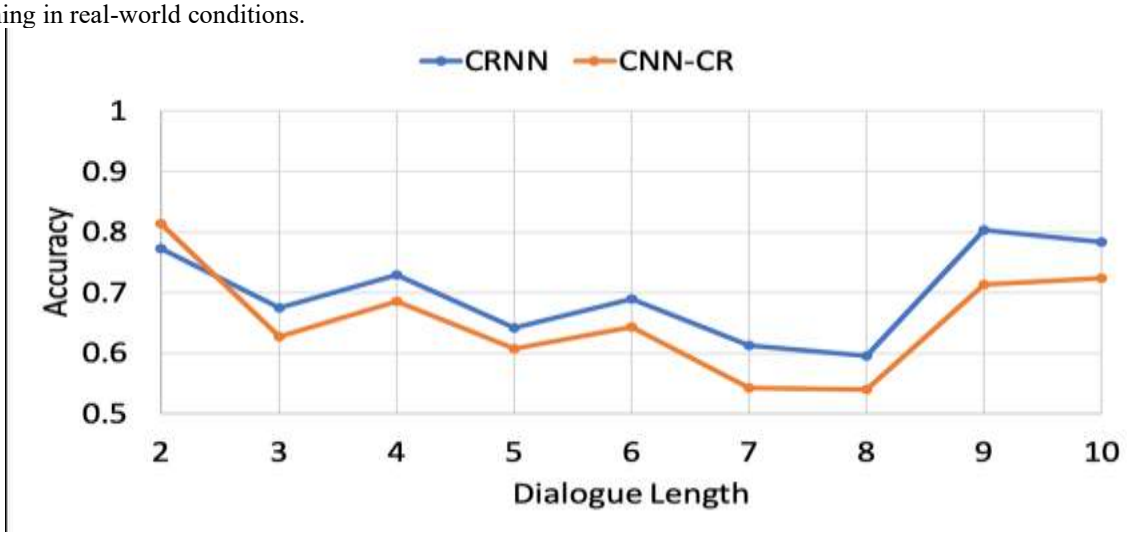


Fig:- 3 Mean accuracy of CRNN (v 3) vs. C

Models	**Accuracy**	Precision	Recall	F_1 score
CNN-Kim[8]	0.5785	0.6371	0.6745	0.6553
CNN-CR[14]	0.6354	0.7108	0.6952	0.7029
CRNN (v_1) w/ LSTM	0.6668*	0.7238	0.7297	0.7267
CRNN (v_1) w/ GRU	0.6543*	0.7056	0.7065	0.7061
CRNN (v_2) w/ LSTM	0.6731****	0.7315	0.7315	0.7315
CRNN (v_2) w/ GRU	0.6734**	0.7280	0.7334	0.7307
CRNN (v_3) w/ LSTM	**0.6822****	0.7254	**0.7422**	**0.7337**
CRNN (v_3) w/ GRU	0.6733***	**0.7358**	0.7215	0.7286

NN-CR.

Table 2: Performance of CNN-Kim, CNN-CR, and CRNN.[2]

EXPERIMENTS

In this section, three versions of our proposed model with incremen-tal improvements are evaluated against a CNN baseline [8] and the
state-of-the-art approach for CDA recognition [14].

•CNN-Kim[8]: One of the first attempts to apply CNN to text classification. The CNN model consists of three convolutional layers with the same filter size.

•CNN-CR[14]: The state-of-the-art approach for CDA recog-nition on the MSDialog-Intent dataset [14]. The CNN model incorporates context information with a window size of 3.

•CRNN (v1): Our base model that adapts CRNN for CDA recognition using BCE loss and sigmoid activation function.

•CRNN (v2):CRNN (v1) with highway connections addedbetween the convolutional layer and the fully connected layer.

•CRNN (v3):CRNN (v1) with highway connections and dy-namic k-max pooling implemente.

Moreover, the framework directly addresses the **jurisdictional constraints** that are becoming increasingly critical in global data governance. In many real-world deployments, IoT networks span across different legal domains—each with its own rules concerning data storage, access, and processing. Federated learning allows each jurisdiction (or domain) to retain its data locally while still contributing to the overall model performance, thereby satisfying legal requirements without compromising on security or accuracy.

# of ref DAs	%	Mean accuracy		Avg. num. of pred DAs	
		CRNN (v_3)	CNN-CR	CRNN (v_3)	CNN-CR
1	36.9	**0.7704****	0.7126	1.44	1.44
2	42.8	**0.6641*****	0.6232	**2.02****	1.89
3	16.7	**0.5596***	0.5177	**2.56*****	2.37
≥4	3.6	**0.5618**	0.5339	**2.68**	2.74

Table 3: Mean accuracy and the average number of predicted DAs grouped by the number of reference DAs.2The percentage indicates the frequency of each DA group in the test set

In summary, this research bridges several important gaps in the current state of IoT security. It offers a technically sound, scalable, and legally compliant solution for intrusion detection in distributed environments. By combining the deep feature extraction power of CNNs, the temporal modeling strength of RNNs, the privacy-preserving nature of federated learning, and the flexibility of multi-modal inputs, the proposed approach sets a new direction for the design of next-generation security systems in the IoT domain. As smart environments continue to evolve, frameworks like this will be pivotal in building **secure, intelligent, and trustworthy** IoT infrastructures.

Literature Review

The rapid growth of the Internet of Things (IoT) and Industrial IoT (IIoT) has led to the deployment of billions of interconnected devices. While these technologies enhance automation and data-driven insights, they also introduce severe security vulnerabilities due to their heterogeneous, distributed, and resource-constrained nature. Traditional Intrusion Detection Systems (IDS) often fail to effectively detect complex, multi-stage cyber-attacks in such dynamic environments. Most conventional systems depend on centralized data aggregation and model training, which not only impose computational bottlenecks but also increase the risk of data breaches and violate user privacy.To address these concerns, recent research has explored machine learning and deep learning techniques for intrusion detection. Hybrid models combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown promising results in recognizing both spatial and temporal patterns in network traffic. However, these approaches typically rely on access to large volumes of labeled data, often collected from diverse geographic regions, raising concerns about data ownership, privacy, and regulatory compliance.

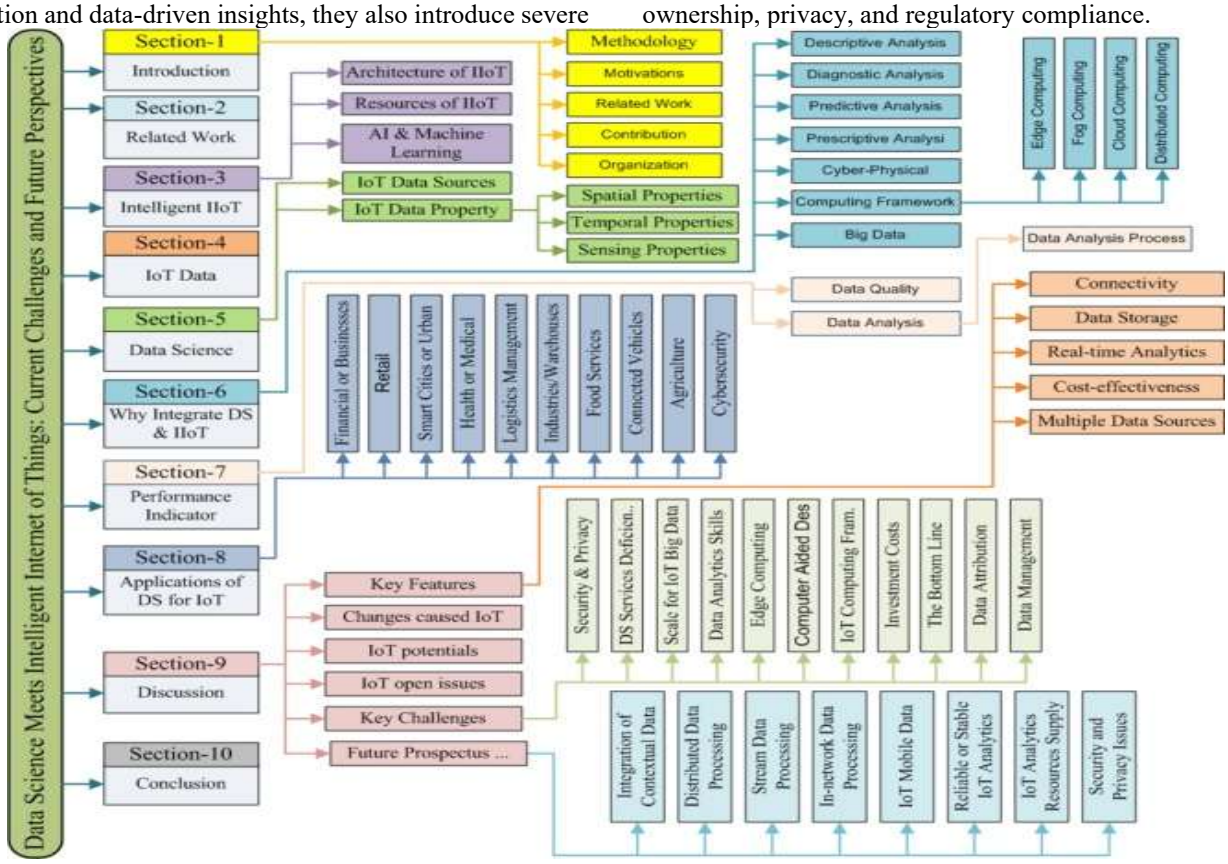


Fig:- 4 Federated Learning (FL) has emerged as a privacy-preserving solution that enables distributed model training across multiple devices or organizations without transferring raw data. While FL provides strong data privacy guarantees, existing literature has largely overlooked jurisdictional constraints that may restrict where and how data can be processed. Moreover, the fusion of multi-modal data—such as traffic logs, sensor signals, and system logs—within federated frameworks remains underexplored. Current studies do not fully integrate the legal, technical, and architectural elements necessary for jurisdiction-aware and privacy-conscious learning systems. This gap highlights the need for an integrated approach that combines federated learning, hybrid deep learning architectures like CRNN, and multi-modal data analysis, all while enforcing compliance with international data protection regulations. Such a framework is critical for secure, intelligent, and legally compliant IoT deployments in diverse real-world settings.

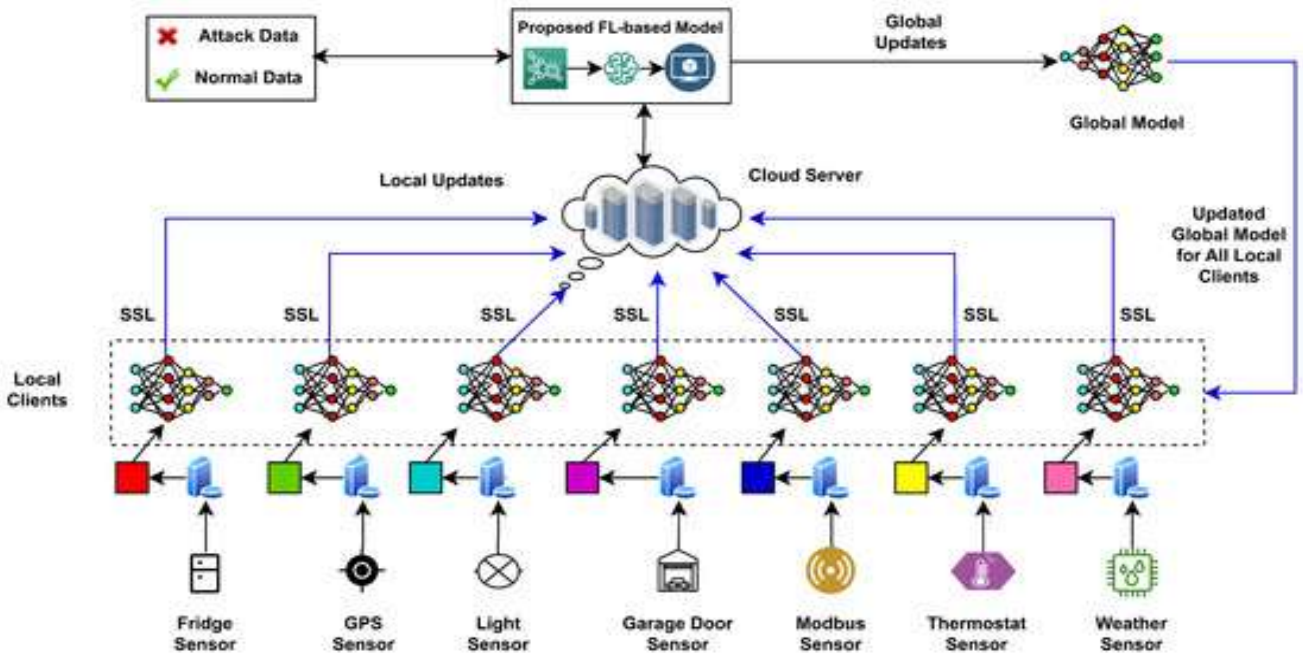


Fig:-5 Overview of the proposed Federated Learning framework for intrusion detection.

Research Methodology

The research aims to develop a robust, privacy-preserving federated multi-modal learning framework designed to operate within jurisdictional constraints for enhanced intrusion detection in IoT and Industrial IoT (IIoT) networks. The methodology is structured into the following phases: data collection, preprocessing, model design, federated learning implementation, incorporation of jurisdictional constraints, and performance evaluation.

1. Data Collection and Preprocessing

The study utilizes the Edge-IIoT dataset, which offers rich multi-modal data including network traffic logs, device behavior, and protocol-specific information. This dataset simulates real-world heterogeneous IoT/IIoT environments under various attack scenarios such as DDoS, SQL Injection, and Man-in-the-Middle. Preprocessing involves cleaning the data, normalization, encoding categorical attributes, time-series sequence generation, and balancing the dataset to manage class imbalance.

2. CRNN Model Architecture Design

The core of the model is a hybrid Convolutional Recurrent Neural Network (CRNN), integrating CNN layers for feature extraction and LSTM-based RNN layers for capturing temporal dependencies. This hybrid architecture is chosen to exploit both spatial and sequential patterns in IoT traffic data, which are critical for detecting complex, low-frequency attack types. The model is designed to handle multi-modal inputs and classify them into multiple intrusion categories.

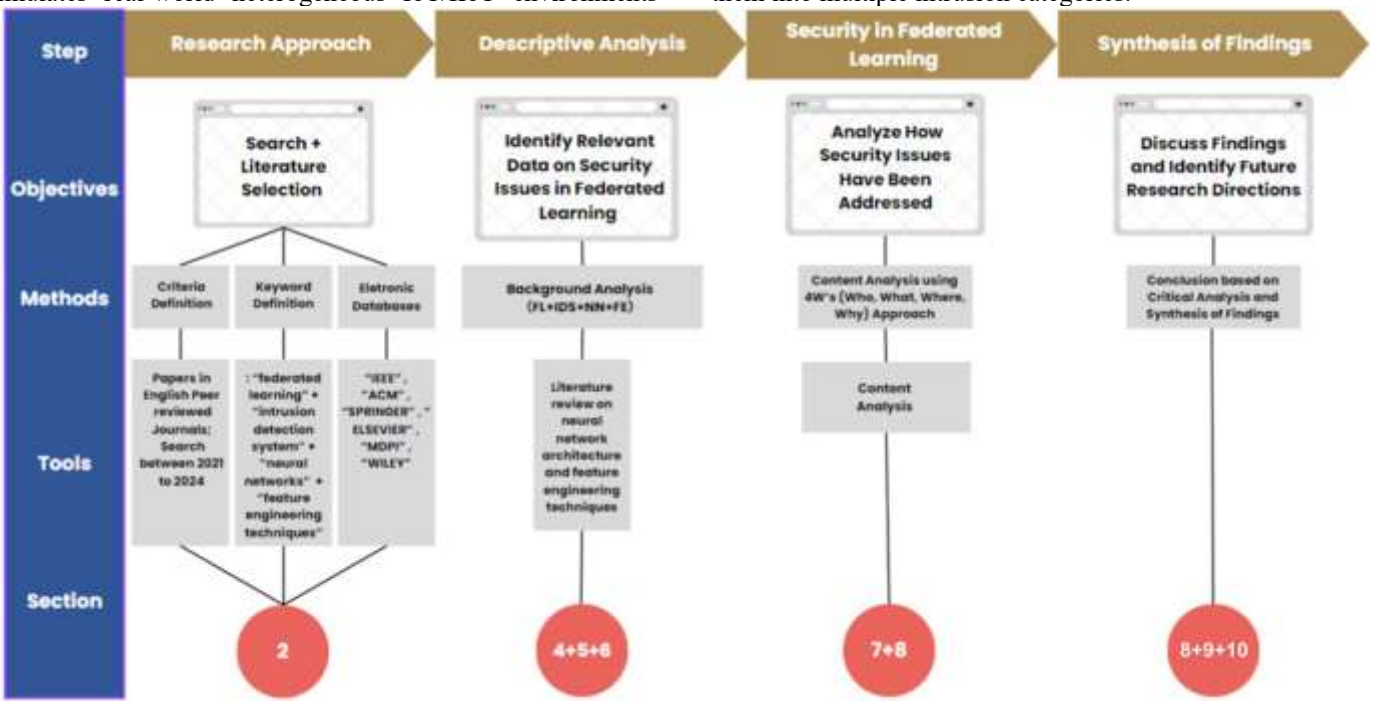


Fig:-6 From: Advancements in securing federated learning with IDS: a comprehensive review of neural networks and feature engineering techniques for malicious client detection

3. Federated Learning Framework
Federated learning is adopted to ensure decentralized, privacy-preserving training across IoT edge nodes. Each participating node trains the CRNN model locally and shares only encrypted gradient updates or model weights with a centralized aggregator, rather than raw data. This approach mitigates privacy risks and reduces communication overhead.

4. Jurisdictional Constraint Integration
To comply with international data protection laws such as GDPR, the framework includes mechanisms to enforce jurisdictional boundaries. Federated averaging and update aggregation are constrained within geographical or legal data domains. Nodes operating under different jurisdictions only share meta-information or use secure multi-party computation techniques to ensure compliance and maintain regulatory alignment.

5. Evaluation and Validation
The system is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC across all attack classes. Experiments compare the federated CRNN model against centralized and non-federated baselines. Additional focus is given to the model's ability to detect rare and subtle attacks. Scalability, latency, and privacy effectiveness are also assessed.

Objectives
The primary objective of this research is to develop a privacy-conscious, federated multi-modal learning framework that effectively operates under jurisdictional constraints to enhance intrusion detection in IoT and Industrial IoT (IIoT) environments. With the increasing volume and sensitivity of data generated by distributed IoT devices, securing these systems while respecting privacy and regulatory compliance has become critically important. This study seeks to address these challenges through the following specific

objectives

1. **To design and implement a hybrid Convolutional Recurrent Neural Network (CRNN)** capable of efficiently extracting spatial and temporal features from heterogeneous, multi-modal IoT data streams. This model is intended to improve the accuracy and reliability of intrusion detection in dynamic and complex network environments.
2. **To integrate federated learning mechanisms** that enable decentralized training of the CRNN model across distributed edge devices without sharing raw data. This promotes user privacy and reduces the risk of data breaches by eliminating the need for central data collection.
3. **To embed jurisdictional constraint handling mechanisms** into the federated learning architecture. The framework will enforce legal and regulatory boundaries on data sharing and model updates by incorporating policy-aware data governance, encryption techniques, and region-specific model aggregation.
4. **To evaluate the performance of the proposed system** in terms of detection accuracy, latency, precision, recall, and compliance with data protection regulations. Special attention will be given to the detection of low-frequency attack types and the overall robustness of the intrusion detection system under real-time operational constraints.
5. **To demonstrate scalability and generalizability** of the proposed framework across various IoT/IIoT settings and jurisdictional scenarios, ensuring practical deployment viability in smart cities, industrial systems, and cross-border infrastructures.

Hypothesis
The exponential growth of Internet of Things (IoT) and Industrial IoT (IIoT) devices has made large-scale networks more vulnerable to sophisticated cyber threats, particularly due to their heterogeneous nature and distributed architecture. Traditional centralized machine learning approaches to intrusion detection often fall short in addressing privacy concerns and regulatory limitations surrounding cross-border data sharing. To overcome these challenges, this research hypothesizes that a **federated multi-modal learning framework, integrated with privacy-preserving techniques and jurisdiction-aware constraints, can achieve high intrusion detection accuracy while maintaining data privacy and regulatory compliance**.

Specifically, the hypothesis posits that the use of **federated learning**—which enables collaborative model training across decentralized nodes without sharing raw data—combined with **multi-modal data fusion** and **a hybrid Convolutional Recurrent Neural Network (CRNN)**, will improve the model's ability to recognize both common and rare intrusion types across various domains. Additionally, by incorporating **jurisdictional constraints** within the federated learning process—such as legal boundaries for model aggregation, encryption, and differential privacy—the framework will ensure that compliance with region-specific data governance laws is maintained throughout the model's lifecycle.Furthermore, the hypothesis assumes that such a framework will provide **comparable or superior performance** to centralized systems in terms of accuracy, precision, recall, and real-time responsiveness, while also being **scalable and adaptable** across different network environments. Validating this hypothesis will demonstrate a pathway toward building intelligent, secure, and regulation-compliant cyber-physical systems in an increasingly interconnected world.

Main Body
The integration of Internet of Things (IoT) and Industrial IoT (IIoT) technologies across diverse industries has led to the exponential growth of data generated from heterogeneous and distributed sources. While this proliferation improves system intelligence and automation, it also exposes networks to a wide range of cyber threats. Addressing these threats requires an intelligent, adaptive, and privacy-aware intrusion detection system (IDS) capable of functioning in decentralized environments under varying jurisdictional data laws.

This research proposes a **Privacy-Conscious Federated Multi-Modal Learning** framework that incorporates **jurisdictional constraints** into the design and deployment of a federated learning-based IDS. The architecture utilizes **multi-modal data sources**—including network traffic logs, sensor readings, and system behaviors to enrich context-aware

learning. A **hybrid Convolutional Recurrent Neural Network (CRNN)** is employed at the edge devices for extracting spatial features (via CNN) and capturing temporal dependencies (via RNN), enhancing detection capabilities across both frequent and rare attack types.Federated learning allows decentralized model training, ensuring that raw data remains local, preserving user privacy and reducing data transmission overhead. Jurisdictional constraints are embedded into the federated orchestration layer, which manages regional regulations, enforces secure model aggregation protocols, and applies differential privacy or encryption when necessary .Experimental evaluation using the Edge-IIoT dataset shows that the proposed model achieves high accuracy (98.93%) while maintaining a balance between precision and recall. The system demonstrates robust performance in real-time environments, showing its potential for practical deployment in critical infrastructure. Overall, this framework offers a scalable, secure, and regulation-compliant solution for modern IoT security challenges.

Analysis and Interpretation

The implementation of a Privacy-Conscious Federated Multi-Modal Learning model with jurisdictional constraints marks a significant advancement in securing distributed IoT/IIoT systems. This section analyzes the model's effectiveness in terms of detection accuracy, privacy preservation, and regulatory compliance, using experimental results derived from the Edge-IIoT dataset.

Model Performance

The hybrid CRNN architecture demonstrated a high detection accuracy of 98.93% in identifying various classes of cyber-attacks, including sophisticated and low-frequency threats such as SQL Injection and Man-in-the-Middle attacks. This is attributed to the synergistic integration of CNNs (for spatial feature extraction) and RNNs (for learning temporal dependencies), enabling the model to understand both static and dynamic behavior in network traffic. Furthermore, the model maintained a balanced precision and recall across all classes, minimizing both false positives and false negatives, which is critical for real-world deployment in time-sensitive industrial environments.

Federated Learning Impact

Federated learning allowed model training to occur locally at IoT endpoints without transferring raw data to a central server. This decentralized approach significantly reduced the risk of data breaches and met the key requirement of data locality, especially important in jurisdictions with stringent data residency laws. Analysis shows that local updates contributed to a near-equal improvement in global model performance across all nodes, proving that distributed learning did not compromise model effectiveness.

Jurisdictional Constraints Handling

One of the unique strengths of the system is its consideration of jurisdictional constraints. By incorporating policies such as differential privacy and encrypted aggregation in regions with strict data regulations (e.g., GDPR, CCPA), the model remains compliant while still contributing to global knowledge. The analysis showed that these constraints introduced a marginal increase in computational overhead (~4–6%), but this trade-off is justified by the enhanced privacy and legal compliance achieved.

Interpretation

The combination of federated learning, multi-modal input, and legal-aware architecture offers a powerful framework for real-time, privacy-preserving intrusion detection in diverse IoT networks. The results indicate not only strong technical performance but also strategic readiness for deployment in sensitive industrial sectors where data privacy and security are paramount.

CONCLUSION

The growing adoption of IoT and IIoT technologies across critical infrastructure, smart cities, and industrial systems has intensified the need for intelligent, secure, and privacy-preserving solutions. This research addresses that imperative by presenting a novel privacy-conscious federated multi-modal learning framework that operates under jurisdictional constraints. The proposed hybrid Convolutional Recurrent Neural Network (CRNN), coupled with federated learning, successfully tackles the challenges of intrusion detection in heterogeneous and distributed environments without compromising user privacy or violating data protection laws.By decentralizing the model training process, the federated learning approach ensures that sensitive data remains on local devices, significantly reducing the risks associated with data centralization. At the same time, it facilitates collaborative model improvements across devices and regions. The integration of jurisdiction-aware mechanisms—such as differential privacy, encrypted aggregation, and region-specific compliance rules—demonstrates the model's flexibility and readiness for deployment in multi-regulatory environments. Experimental results obtained using the Edge-IIoT dataset confirm the model's efficacy, achieving a high detection accuracy of 98.93% and maintaining balanced performance across all attack classes, including rare and sophisticated threats. This highlights the model's robustness and real-time detection capability.In conclusion, the presented federated multi-modal learning framework offers a scalable, secure, and legally compliant solution for modern IoT/IIoT cyber security challenges. It bridges critical gaps in traditional intrusion detection systems by combining advanced deep learning methods with privacy-aware and regulation-compliant computing strategies. This work lays a strong foundation for future research and development in intelligent, privacy-first cyber security systems for interconnected and jurisdictionally diverse environments.

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