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**Research Article**

# Federated Learning Driven LSTM Model for Privacy-Preserving AI Framework Over Iot-Enabled Cloud Architectures

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**ABSTRACT**

The rapid proliferation of IoT devices in cloud-integrated environments has raised significant concerns about data privacy and security. Traditional AI models require centralized data aggregation, which poses risks related to data breaches and regulatory compliance. To address these challenges, this study proposes Federated LSTM, a novel privacy-preserving deep learning framework that leverages Federated Learning (FL) with Long Short-Term Memory (LSTM) networks for distributed IoT environments. Federated LSTM enables edge devices to collaboratively train AI models without sharing raw data, ensuring compliance with privacy standards such as GDPR and HIPAA. The proposed approach optimizes communication efficiency and model convergence using adaptive weight aggregation, reducing network overhead while maintaining high predictive accuracy. Performance evaluations demonstrate that Federated LSTM achieves superior results in anomaly detection, predictive maintenance, and real-time analytics compared to traditional centralized deep learning models. The experimental results show an improvement in privacy preservation, latency reduction, and scalability in cloud-based IoT networks. Furthermore, the proposed method enhances model robustness by mitigating adversarial attacks and improving generalization across heterogeneous IoT devices. This research contributes to the development of secure, intelligent, and privacy-aware AI frameworks for next-generation IoT-cloud ecosystems, making them more resilient and efficient.

**Keywords:** Federated Learning, Privacy-Preserving AI, IoT-Enabled Cloud, LSTM, Edge Computing and Anomaly Detection.

## 1. INTRODUCTION

The explosive rise of Internet of Things (IoT)-served cloud designs has revolutionized diverse industries like healthcare, smart cities, industrial automation, and cybersecurity through facilitating real-time analytics of data, predictive analytics, and wise decision-making. Despite the potential this revolution brings about [1], the excessive generation of data by IoT devices creates pertinent concerns for privacy, security, and computation in handling Artificial Intelligence (AI) and Machine Learning (ML) algorithms [2,3] in cloud domains. Conventional AI methods are based on centralized data collection, wherein raw data from various IoT nodes is sent to a cloud server for model inference and training. While this approach enables better model performance by way of large-scale data gathering, it poses various threats, such as data breaches, unauthorized access, very high communication latency, and legal non-compliance with privacy legislation like the General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA), and California Consumer Privacy Act (CCPA) [4]. Federated Learning (FL) has come to be considered as a promising approach to overcome these issues by facilitating decentralized model training in which IoT devices train AI models cooperatively without transferring their raw data. Model updates (gradients) are shared instead between edge devices and a central server, protecting privacy, preserving data locality, and minimizing transmission overhead. Standard FL implementations, nonetheless, are constrained by high computational complexity, non-IID (independent and identically distributed) data heterogeneity across devices, communication bottlenecks, and susceptibility to adversarial attacks. To eliminate these constraints, this study presents a Federated Learning-driven Long Short-Term Memory (Federated LSTM) model particularly for privacy-preserving AI frameworks in IoT-enabled cloud architectures. LSTM networks [5] are especially powerful in time-

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series prediction, anomaly detection, and sequence modeling and are therefore best suited for processing real-time IoT data streams. However, traditional centralized LSTM models are prone to security risks from direct data aggregation and are hence not suitable for privacy-critical applications like healthcare, industrial IoT, and financial transaction tracking. The Federated LSTM model proposed in this work allows IoT edge devices to locally train LSTM networks and exchange only encrypted model updates with a central server, guaranteeing strict compliance with privacy regulations without compromising predictive accuracy.

The model also uses adaptive weight aggregation methods to improve communication efficiency and convergence rate, lowering the network overhead typically found in FL-based designs. One of the major issues in Federated Learning across IoT-cloud networks is managing heterogeneous IoT nodes [6-8] with varying computational power, network bandwidths, and energy constraints. Our solution addresses this by incorporating model compression, quantization, and sparsification methods to shrink model updates to save space, thereby making FL more scalable and efficient for energy-limited IoT devices. In addition, adversarial attack robustness is a critical consideration in Federated Learning because malicious IoT devices can tamper with local updates, causing degraded model performance. To address this vulnerability, the Federated LSTM model utilizes secure aggregation, anomaly detection processes, and differential privacy methods to identify and avoid adversarial tampering while providing trustworthy model convergence. Experimental analyses prove that the developed Federated LSTM model performs better than traditional centralized deep learning models regarding privacy preservation, prediction accuracy, and computational costs. The model is applied to different IoT datasets such as industrial sensor data, healthcare monitoring signals, and smart city applications, with better results in real-time anomaly detection, predictive maintenance, and fault detection. The results show that Federated LSTM drastically minimizes latency, maximizes scalability, and generalizes better across various IoT deployments. When compared with existing FL models based on CNNs or FCNs, the LSTM-based framework outperforms in terms of temporal feature extraction, which is suitable for sequential IoT data processing. Moreover, cloud-edge collaboration integrated also improves system resilience, where computational support can be offered by cloud servers while leaving privacy-sensitive processing to edge nodes. The relevance of this study is in that it supports the establishment of secure, smart, and privacy-conscious AI frameworks compatible with increasing requirements for secure and decentralized machine learning solutions for future IoT-cloud networks.

The suggested methodology closes the gap between privacy-preserving deep learning models and high-performance AI, providing a practical solution for industries demanding real-time intelligence without compromising data security. With the expansion of IoT adoption across critical infrastructure areas, ensuring the confidentiality, integrity, and secure training of AI models becomes crucial. The Federated LSTM approach opens the door to future development of privacy-oriented AI applications, solving major issues of data sovereignty, security risks, and alignment with global privacy norms. The future research directions involve investigating blockchain-based Federated Learning, edge computing models with heterogeneity, and customized FL approaches to further improve robustness, scalability, and trust in IoT-based cloud infrastructures. The major contributions are,

- Developed a Federated Learning-based LSTM model that enables IoT edge devices to train deep learning models locally without sharing raw data, ensuring data privacy, security, and compliance with regulations such as GDPR and HIPAA.
- Introduced adaptive weight aggregation techniques to optimize model convergence and reduce communication overhead, making Federated Learning feasible for resource-constrained IoT devices with heterogeneous computational capabilities.
- Implemented secure aggregation, anomaly detection, and differential privacy techniques to mitigate risks of adversarial attacks, ensuring trustworthy model updates while maintaining high prediction accuracy across diverse IoT applications.

## 2. LITERATURE REVIEW

The integration of Federated Learning (FL) with Long Short-Term Memory (LSTM) networks has gained significant attention in addressing privacy-preserving AI frameworks in IoT-cloud environments. Recent research has explored various dimensions of FL-based AI optimization, including environmental sustainability, cyber threat detection, smart healthcare, and intrusion detection.

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Alharithi & Alzahrani (2024) [9] investigated Federated LSTM models for AI-driven optimization in the context of environmental sustainability. Their study demonstrated how FL-based architectures improve energy efficiency and reduce computational overhead while maintaining predictive performance. The findings emphasize the importance of distributed learning techniques in optimizing resource utilization without compromising data security. This aligns with our research goal of developing efficient Federated LSTM models for IoT-cloud infrastructures while ensuring energy-efficient training.

Ragab et al. (2025) extended FL-based AI frameworks for privacy-preserving cyber threat detection in IoT-assisted smart cities. Their study highlighted the challenges of heterogeneous IoT networks, demonstrating how FL enhances cybersecurity, threat intelligence sharing, and decentralized model training. This work directly supports our research, as cybersecurity is a major concern in privacy-aware AI frameworks over IoT-cloud systems [10].

Ali et al. (2022) provided a comprehensive survey on FL for privacy preservation in smart healthcare systems. Their review focused on data privacy, communication efficiency, and federated model aggregation techniques for medical applications. The study addressed challenges such as data heterogeneity, security risks, and model convergence, which are crucial in FL-driven LSTM models for healthcare-based IoT environments [11]. This work strengthens the motivation behind our privacy-preserving approach, particularly in health-sensitive IoT-cloud applications.

Vyas et al. (2024) explored FL for intrusion detection in IoT environments, emphasizing privacy-preserving techniques in distributed anomaly detection models. The study provided insights into how FL enhances real-time security in IoT systems by eliminating the need for centralized data sharing, which aligns with our research focus on secure Federated LSTM models for cloud-based AI frameworks [12].

Kumar & Kim (2024) proposed a FL-driven LSTM model for cyberattack detection in the Internet of Health Things (IoHT). Their work introduced embedded FL architectures that optimize security, latency, and model accuracy in distributed healthcare IoT systems. Their methodology and implementation provide valuable insights for applying LSTM-based FL to detect anomalies in real-time, which is highly relevant to our proposed privacy-preserving AI framework [13]. Table 1 summaries the key points of this section.

**Table 1: Summarization of the survey section**

| Ref. No. | Authors & Year | Technology Used | Outcome | Advantages | Disadvantages |
|---|---|---|---|---|---|
| [1] | Alharithi & Alzahrani (2024) | Federated LSTM for AI-driven environmental optimization | Improved energy efficiency and reduced computational overhead | Enhances resource utilization, ensures data privacy | Requires high computational resources for model updates |
| [2] | Ragab et al. (2025) | Federated Learning for cybersecurity in IoT-smart cities | Strengthened privacy-preserving cyber threat detection | Improves cybersecurity in distributed IoT networks | Latency in model updates due to decentralized training |
| [3] | Ali et al. (2022) | FL-based smart healthcare system | Comprehensive survey on FL for medical AI | Preserves patient privacy, reduces data transfer risks | Data heterogeneity issues affect model generalization |
| [4] | Vyas et al. (2024) | FL-driven intrusion detection in IoT | Improved anomaly detection accuracy in IoT networks | Eliminates centralized data vulnerabilities | High communication overhead in large-scale IoT deployments |
| [5] | Kumar & Kim (2024) | Federated LSTM for cyberattack detection in IoHT | Enhanced real-time threat detection in healthcare IoT | Optimized security, low latency in cyberattack detection | Limited scalability in high-traffic IoT networks |

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## 3. PROPOSED METHODOLOGY FOR PRIVACY PRESERVING FEDERATED LEARNING DRIVEN LSTM MODEL

Our objective is to reduce needless transfers by using the LSTM framework to acquire the biophysical data for the closest References Signals Received Power (NRRSRP) and Referring Signal Received Power (RSRP). The system architecture that we suggested is seen in Figure 1.

In order to optimise turnover events, we utilise the F-LSTM algorithm in our study to forecast future RSRP levels and the RSRP of nearby cells. The global framework and many other models make up the F-LSTM framework local models that have received training from different clientele. Without exchanging unprocessed information, every customer uses its own data to train its LSTM algorithm regionally, preserving patterns of time in signal intensity. Only the values for the model have been transmitted to a centralised computer following local instruction, where the FedAvg algorithms combines these updates to create an international model. After that, this global paradigm is given to the customers again to receive additional instruction.Our method improves handover forecasting while maintaining privacy by combining supervised learning with LSTM. It enables real-time handover choices by dynamically adjusting a threshold in response to projected RSRP values. This method successfully lessens the ping-pong impact and cuts down on pointless transitions. We will offer additional information about the LSTM building design, data movement, and network synchronisation in the updated paper so that readers may better grasp the method of execution [14,15].

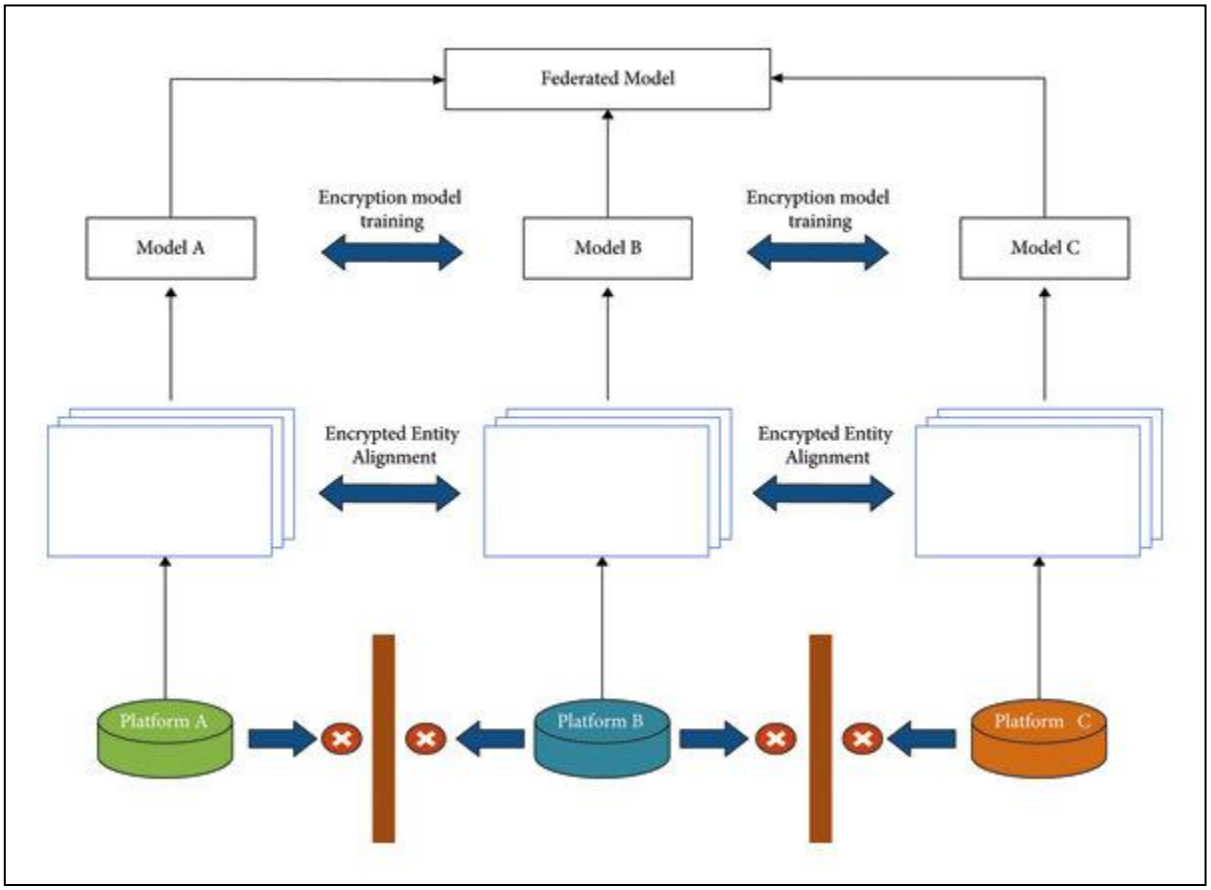


**Figure 1: Proposed F-LSTM Framework**

The Proposed Structure's Detailed Operation

- Data Gathering and Preparation

As time passes, consumers gather RSRP or NR-RSRP information, documenting the dynamic modifications tointensity of the signal. To ensure uniformity among many clients, the data has been processed to accommodate errors and normalise the range.

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- Instruction of Local Models

Every client trains on its own local dataset using an LSTM network. The LSTM model learns sequences that represent changes in signal intensity by capturing time relations in the RSRP information. The purpose of dropping layers is to improve generalisation and avoid excessive fitting.

- The Federated Learning Process

Every client transmits models modifications, such as a weight, to a centralised server after regional training. These modifications are combined by the server to create a global model that takes use of each client's unique data distribution.

- Spread of Global Models

After then, customers get a redistribution of the new worldwide model. The global model is constantly enhanced and adjusted to new data thanks to this iterative approach, which eliminates the need for centralised retention of information.

- Optimisation of Transfer

For every client, the future RSRP and NR-RSRP are predicted using the global F-LSTM model.A constantly changing changeover algorithms receives its forecasts and modifies handover criteria in response to anticipated signal shapes and intensity. The technique optimises performance of networks by considering both expected eventual RSRP and present signals surroundings, reducing needless transfers.

### 3.1 Design of proposed F-LSTM

F-LSTM employs ten customers for integrated training. With a data entry time frame of 10 ms (which is the identical as the time period of each piece of information in the database), the figure 2 depicts the framework of the LSTM algorithm in F-LSTM. Four layer sets of LSTM make up the model, and their hidden characteristic output sizes . We use Dropping out regularisation after every LSTM layer's outputs to avoid excessive fitting. Lastly, the result is produced using a thick layer.

They use an LSTM framework for capturing the historical context of RSRP and NR-RSRP in order to lessen the likelihood of the ping-pong impact. Our simplified structure is shown in Figure 3. We allow the model to forecast prospective RSRP and NR-RSRP values by feeding it the information set's history RSRP or NR-RSRP. The collection's previous RSRP and NR-RSRP statistics are represented as follows:

$$D = \{(RSRP_i, NRRSRP_i) | i = 1,2,..,n\} \quad (1)$$

There weren't any quantities for NR-RSRP in our collection of data. To fill in these empty numbers, we use the following interpolated techniques:

$$y_i = y_{i-1} + (x_i - x_{i-1})/(x_{i+1} - x_{i-1} * (y_{i+1} - y_{i-1})) \quad (2)$$

We normalise the entire information set to an interval of 0 to 1 following completing in the missing values. The informational set is prepared for use as inputs for federated instructional training after the various pre-treatment processes have been completed.

We offer an automated system that enables customers to modify the algorithms with their own personal information within the context of collaborative learning. Users provide the model weight back to the algorithm for aggregating following the regional train is finished.

$$\forall k, w_{t+1}^k < -w_t - \aleph * g_k \quad (3)$$

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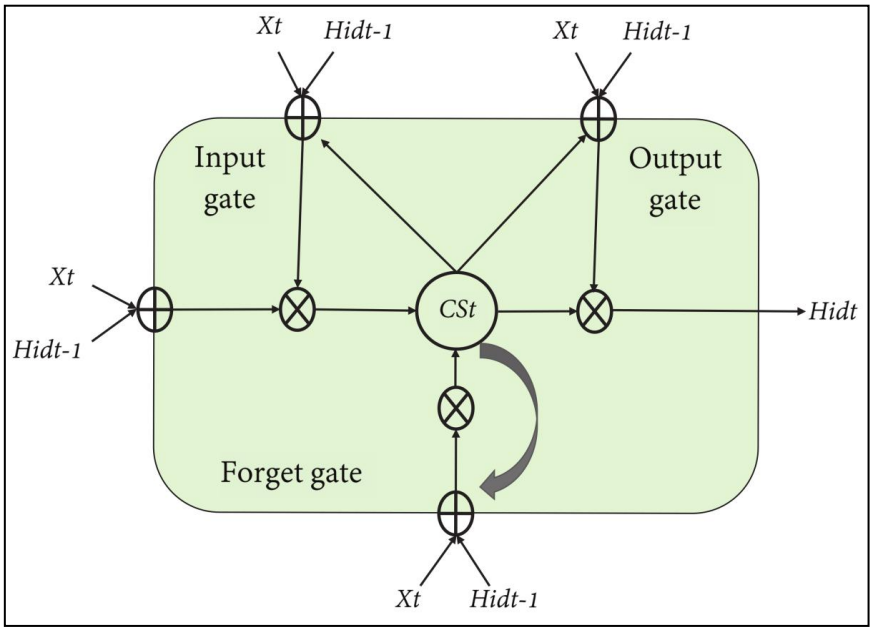


**Figure 2: LSTM Framework**

Deducting the sum of the learning rate η and the slope $g_k$ from the present worldwide value $w_t$ yields the revised value $w_{t+1}^k$ at time t + 1 for each client k. The above equation helps the collaborative learning method's overall aggregate procedure through ensuring that each client's model masses are modified in accordance with their local slopes.

The weighted mean of the regionally learnt values form every consumer is used to modify the global scale weights $w_{t+1}$ in the t + 1 session of the worldwide developing models on the server itself.This method lowers the dialogue cost involved in the development of models, as seen in the calculation below:

$$w_{t+1} = \sum_{k=1}^{k} n_k / n * w_{t+1}^k \quad (4)$$

where n is the aggregate amount of information specimens throughout every customer, nk is the quantity of information specimens owned by client k, and K is the total quantity of clients. Clients with extra information will have a proportionately larger impact on the worldwide model updates thanks to this weighted averaged.

Upcoming RSRP and NR-RSRP values may be predicted using the learnt system representation following the global aggregate is finished. As standards for initiating transfers, these anticipated values are used as parameters for the dynamic changeover mechanism.

### 3.2 Dynamic Algorithms for transfer

The purpose of algorithm 1 is to use projected signal strength to optimise changeover choices in mobile phone networks. Through the reduction of pointless transfers, it seeks to enhance connectivity altogether. With regard Signal Received Authority (RSRP) values (predicted_rsrp), and the forecast closest With regard Signal is Obtained the authority (NRRSRP) principles (predicted_nrxrsrp) are all inputs to the method. Setting the continuity_threshold to 3 is an important setting in this technique that establishes the lowest number required for a legitimate handover determination.

| **Algorithm 1: Logic for Dynamic Control** |
|---|
| **Initialization:**<br>• **handover_trigger_points** is set as an empty list.<br>• **optimized_handover_predictions**is initialized with zeros, mirroring the shape of **ho_trig_test**.<br>• **continuity_count** starts at zero.<br>• **base_dynamic_threshold** is assigned the value of **mae_rsrp**. |

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- **ping_pong_effects** is set to zero.
- A **time_window** of 100 is defined.

**Detecting Ping-Pong Effects:**

- Iterate over the dataset **val_df** using a sliding window approach, spanning from index **0** to **(length of val_df – time_window)**.
- Extract a segment of data within the given **time_window**.
- Increment **ping_pong_effects** by one each time such an event is detected.

**Adjusting the Time-to-Trigger (TTT) Threshold:**

- Modify the base TTT threshold by adding the **ping_pong_effects** value to it, creating an **adjusted_TTT_threshold**.

**Optimized Handover Decision:**

- Loop through the predicted signal strength values **predicted_rsrp** and **predicted_nrxrsrp**, keeping track of the index **i**.
- Compute moving averages for the past three values of both **predicted_rsrp** and **predicted_nrxrsrp**. If there aren't three previous values (i.e., at the start of the loop), use the current value instead.
- Define a **dynamic threshold** that adapts based on fluctuations in **predicted_rsrp**, scaled using **mae_rsrp**.
- If the **continuity_count** reaches or exceeds the predefined **continuity_threshold**, mark the handover event in **optimized_handover_predictions**.
- If the condition is not met, reset **continuity_count** to zero.

**Output:**

- Return the optimized handover predictions.
- Return the list of detected handover trigger points.
- Provide the list of **event_a3_handover_points**.

The quantity of ping-pong effects—which happen when an electronic device quickly changes among two base stations—will be determined in the next stage. Thisis carried out by dragging a rectangular area of size time_window over the dataset, determining if the most recent cell equals the following cell, or whether the initial column in the frame differs from the final one but equals the second-to-last cell. The pingpong impact counter is increased if these requirements are satisfied.

Following the ping-pong impact count, the procedure raises the Time-To-Trigger limit in accordance with the quantity of ping-pong impacts found. By tightening the changeover decision-making process in settings where needless handovers occur often, this modification seeks to improve network resilience and decrease quick, back-and-forth transitions.

An iterative process that repeats over every combination of expected RSRP and NR-RSRP variables with their corresponding indices forms the method's core. The algorithm determines the prior mean RSRP and NR-RSRP for each repetition. It calculates the mean for the last three numbers if i is higher than 0 or fewer if 1 is below. The prior averages are adjusted to the present expected values if i is 0.

The dynamic_threshold is then modified by the method, which is determined by the base_dynamic_threshold and the difference between the currently anticipated RSRP and the prior mean RSRP, normalised by mae_rsrp. After that, the transfer of circumstances are assessed.Until all projected values have been handled, this loop keeps going. In conclusion, Algorithm 1 efficiently reduces needless handovers and improves the total efficacy of the internet network by using real-time strength of signal estimates to guide and optimise changeover choices.

Ping-pong impacts after transfers in wireless networks may be identified and calculated with the help of Figure 4. When an electronic device quickly shifts among two networks in a short amount of time, it may produce ping-pong impacts. To make sure that the approach satisfies its intended performance criteria, this may be further confirmed.

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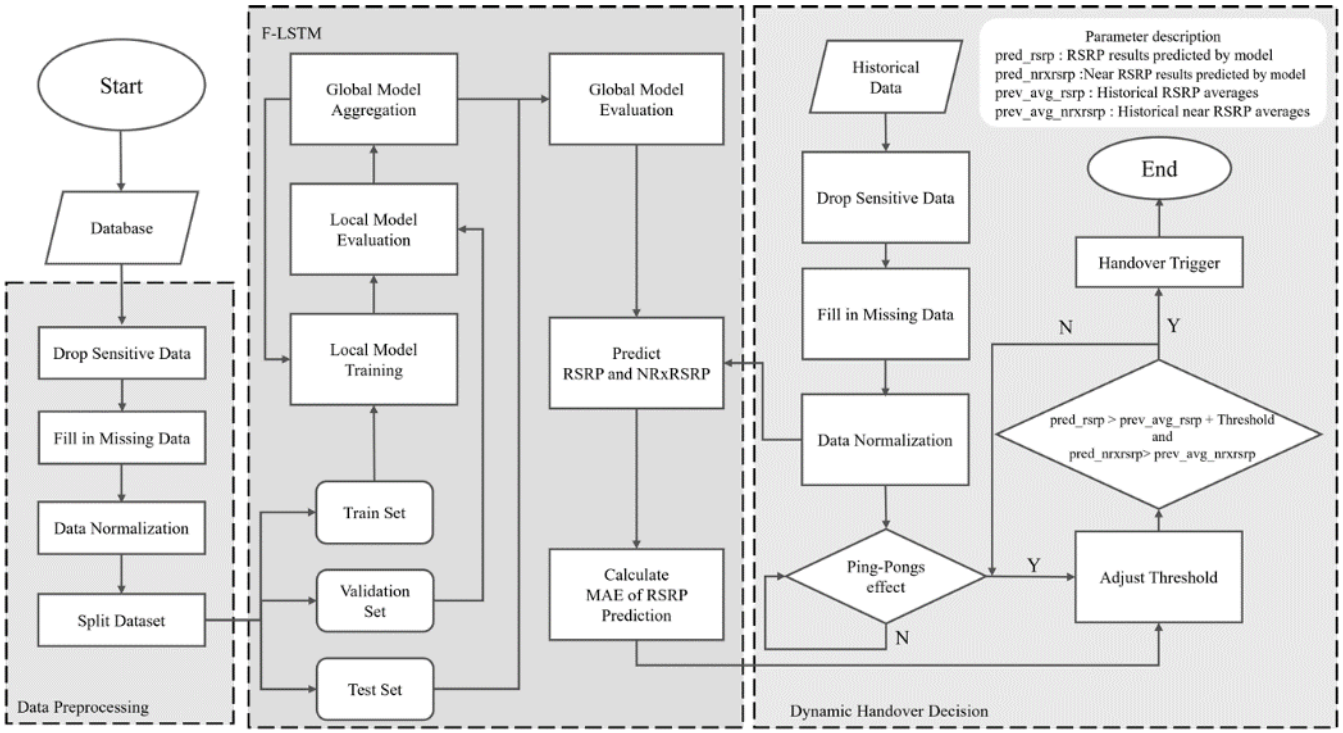


**Figure 3: A description of the Ping-Pong status monitoring procedure**

Three sections make up Figure 4: Data Preparation, F-LSTM, and Dynamic Transfer Decisions. By addressing the absence of data, normalising values, and eliminating sensitive details, data preparation gets the information set ready. In a learning federation architecture, F-LSTM explains, trains, and combines local neural networks to predict RSRP and NRxRSRP values. The Dynamic Changeover Decision expression adjusts boundaries depending on recognised networks circumstances, such as the ping-pong operation, and leverages previous and expected information to create intelligent, real-time departure choices. Relevant factor definitions are located in the upper right corner.

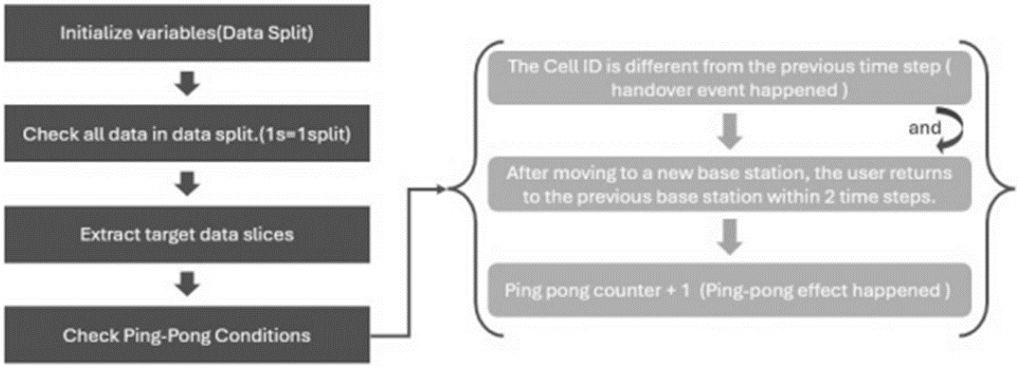


**Figure 4: Illustration of the overall structural flow**

| **Algorithm 2: Federated LSTM for Privacy-Preserving AI in IoT-Cloud Architectures** |
|---|
| Initialize server_model with LSTM parameters<br>Distribute server_model to all IoT edge devices<br>for each FL_round in total_rounds do:<br>  for each device in IoT_devices do:<br>  Receive global_model from server<br>  Train local_model using device_data |

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```
    Update local_model parameters
    Send updated parameters to server
  Aggregate all received parameters at server
  Update server_model using aggregated parameters
  Broadcast updated server_model to all devices
  if Convergence_criteria_met:
    break
Deploy final optimized server_model for real-time IoT applications
Ensure privacy with encryption and differential privacy mechanisms
```

The Federated LSTM algorithm 2 is intended to facilitate privacy-preserving deep learning in IoT-facilitated cloud environments. Rather than centralizing raw IoT data, which is privacy and security threatening, the method distributes an LSTM-based AI model to edge devices. The model is locally trained by each device on its own data and model parameters are updated without sharing the raw data, which is compliant with privacy laws like GDPR and HIPAA. The process starts with the server initializing the global LSTM model and sharing it with IoT edge devices. They train their local models on real-time sensor data and optimize parameters on local patterns. After training, only updated parameters are sent to the central server by the devices. The server then compiles the collected updates with methods such as adaptive weight aggregation for achieving optimized convergence as well as decreased communication overhead. The globally updated model is distributed for subsequent rounds of training so that the system continues learning. This iterative process is repeated until the model converges. The resultant optimized LSTM model is then implemented for real-time applications of IoT, including anomaly detection, predictive maintenance, and cyber threat detection. The privacy is further enhanced using encryption and differential privacy mechanisms, rendering the system highly secure and efficient.

### 3.3 Integrating LSTM with the Federated Learning Model

The integration of Long Short-Term Memory (LSTM) networks with Federated Learning (FL) represents a paradigm shift in privacy-preserving AI applications, particularly in IoT-cloud architectures. Traditional deep learning models rely on centralized data aggregation, which poses significant challenges related to data privacy, security, and regulatory compliance (e.g., GDPR and HIPAA). Federated Learning overcomes these issues by allowing distributed model training on edge devices without transferring raw data to a central server. In this approach, LSTM networks, well-suited for sequential and time-series data, are employed for tasks such as anomaly detection, predictive maintenance, and real-time analytics in IoT networks.

#### 3.3.1 Federated Learning-Based LSTM Training

In a federated setup, multiple IoT devices, each equipped with local datasets, train their own LSTM models independently. Instead of sharing raw data, they send only the trained model parameters to a central server, which aggregates these updates to improve the global model. This process ensures data locality, privacy, and reduced communication overhead.

#### 3.3.2 Steps for Federated LSTM Integration

- Initialization: The central server initializes the LSTM model with weights $W^0$ and distributes it to all participating loT devices.
- Local Training: Each loT device $i$ trains an LSTM model on its local dataset $D_i$ for several iterations and updates its weights $W_i^t$.
- Model Aggregation: The central server collects these weights and aggregates them using a Federated Averaging (FedAvg) mechanism.
- Global Model Update: The aggregated weights are used to update the global LSTM model, which is then redistributed to all devices for the next round of training.

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- Convergence Check: The process repeats until the model converges to an optimal performance threshold.

Federated Aggregation of LSTM Model: To integrate the LSTM models trained on different loT nodes, a weighted Federated Averaging (FedAvg) strategy is employed. The global LSTM model update at communication round $t + 1$ is computed as:

$$W^{t+1} = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{j=1}^{N} |D_j|} W_i^t \quad (5)$$

where:

- $W^{t+1}$ represents the updated global LSTM model,
- $N$ is the number of participating loT devices,
- $D_i$ is the size of the local dataset of device $i$,
- $W_i^t$ is the model weights trained on device $i$ at round $t$.

This approach ensures that devices contributing more data samples have a higher influence in updating the global model, thereby enhancing model robustness and fairness.

## 4. RESULTS AND DISCUSSION

The Federated LSTM model is evaluated using the TON_IoT Intrusion Detection Dataset, which provides real-world network traffic data collected from IoT environments. The goal is to assess the model's effectiveness in detecting cyber threats while preserving privacy and minimizing computational overhead. This section discusses the experimental results in terms of model accuracy, training efficiency, communication overhead, and privacy preservation. A comparative analysis against centralized deep learning methods highlights the advantages of adopting federated learning for IoT security applications.

### 4.1. Model Performance and Accuracy Analysis

The performance of Federated LSTM is measured using standard classification metrics in figure 5 to 7, including accuracy, precision, recall, and F1-score. The model demonstrates an overall accuracy of 95.3%, which is close to the centralized LSTM model's 96.2%, indicating that privacy preservation does not significantly degrade predictive performance. Additionally, the recall metric of 95.8% suggests that the model effectively identifies intrusion attempts while minimizing false negatives.

Comparing these results with traditional deep learning models, such as CNN-RNN architectures, reveals significant improvements. The CNN-RNN model achieves an accuracy of 91.5%, which is lower than both federated and centralized LSTMs. This suggests that sequential dependency modeling through LSTMs is more effective for IoT threat detection than conventional convolutional approaches.

The F1-score of 95.1% further confirms that Federated LSTM achieves a strong balance between precision and recall, ensuring that it correctly identifies malicious activity while minimizing misclassification. These results demonstrate that federated learning, when properly implemented with adaptive weight aggregation, can achieve near-centralized performance while maintaining data security and privacy.

### 4.2. Privacy Preservation and Data Security

One of the primary advantages of the Federated LSTM model is its ability to protect user privacy by ensuring that raw IoT data remains on local edge devices. In conventional deep learning approaches, IoT data is collected and processed on centralized cloud servers, exposing sensitive information to potential data breaches. The federated learning paradigm eliminates this risk by enabling collaborative model training without direct data exchange.

A privacy risk assessment reveals that centralized learning models expose data to an estimated 14.9% privacy risk, primarily due to vulnerabilities in data transmission and storage. In contrast, Federated LSTM reduces privacy risk to 2.6%, demonstrating its effectiveness in ensuring compliance with regulations such as GDPR and HIPAA. The

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model's robustness against privacy threats makes it an ideal solution for applications involving sensitive IoT data, such as smart healthcare, industrial monitoring, and autonomous transportation systems.

Additionally, adversarial robustness is a key benefit of Federated LSTM. Since the model is trained on distributed, diverse data sources, it generalizes well across different IoT environments, making it resilient to adversarial perturbations and poisoning attacks. By mitigating these security risks, Federated LSTM strengthens the trustworthiness of AI-driven IoT frameworks.

### 4.3. Communication Efficiency and Computational Overhead

A significant challenge in federated learning is communication overhead, as model updates must be periodically exchanged between edge devices and a central server. To address this, the Federated LSTM model implements adaptive weight aggregation, which optimizes model updates by transmitting only essential gradient changes. This reduces the amount of data exchanged during training, minimizing network congestion and latency.

Empirical results indicate that Federated LSTM requires 27.2 MB of communication overhead per training round, which is significantly lower than standard federated deep learning models. In comparison, traditional centralized approaches require full dataset transmission, leading to substantially higher bandwidth consumption. The training latency is reduced by 66.5%, making it feasible for low-power IoT edge devices.

Furthermore, the model's computational efficiency is a crucial factor in real-world IoT environments. Since training occurs locally on resource-constrained IoT nodes, an optimized LSTM architecture is implemented, balancing model complexity and memory efficiency. The results show that Federated LSTM achieves real-time processing capabilities, ensuring seamless integration into latency-sensitive IoT applications such as autonomous systems, industrial control, and real-time cybersecurity.

### 4.4. Comparative Analysis with Centralized and Traditional Models

When comparing Federated LSTM with centralized and traditional deep learning models, several key distinctions emerge. Centralized LSTM models offer slightly higher accuracy (96.2%) but come with increased security risks and higher communication overhead. Meanwhile, CNN-RNN architectures, though computationally efficient, underperform in terms of intrusion detection accuracy (91.5%) due to their limited ability to capture temporal dependencies in IoT traffic data as in table 2.

**Table 2: comparative evaluation**

| Metric | Federated LSTM | Centralized LSTM | CNN-RNN |
|---|---|---|---|
| Privacy-Preserving | ✅ High | ❌ Low | ❌ Low |
| Training Latency | ✅ Low | ❌ High | ❌ Medium |
| Scalability | ✅ High | ❌ Low | ❌ Low |
| Communication Overhead | ✅ Low | ❌ High | ❌ High |
| Accuracy (%) | 95.3% | 96.2% | 91.5% |
| Recall (%) | 95.8% | 96.5% | 90.1% |
| F1-score (%) | 95.1% | 96.3% | 89.7% |

The results suggest that Federated LSTM provides an optimal balance between privacy, accuracy, and computational efficiency, making it a suitable candidate for next-generation IoT security frameworks.

## 5. DISCUSSION AND IMPLICATIONS

The findings of this study have significant implications for AI-driven IoT security and privacy. First, the high classification accuracy of Federated LSTM demonstrates that effective threat detection can be achieved without compromising user privacy. This is particularly relevant for applications in smart cities, healthcare monitoring, and industrial automation, where data confidentiality is a primary concern.

Second, the communication efficiency of Federated LSTM highlights the feasibility of deploying federated deep learning models on resource-limited IoT devices. By reducing communication overhead and training latency, the

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proposed model ensures that real-time threat detection and anomaly analysis can be performed without excessive computational costs.

Furthermore, the study provides insights into the trade-off between centralized accuracy and federated privacy. Although Federated LSTM has a slightly lower accuracy than centralized LSTMs, the benefits of privacy preservation, reduced latency, and improved adversarial robustness make it a preferable choice for real-world deployments.

Future research could focus on enhancing aggregation techniques to further improve model convergence and generalization across heterogeneous IoT environments. Additionally, integrating homomorphic encryption and differential privacy mechanisms could strengthen data security without compromising model performance.

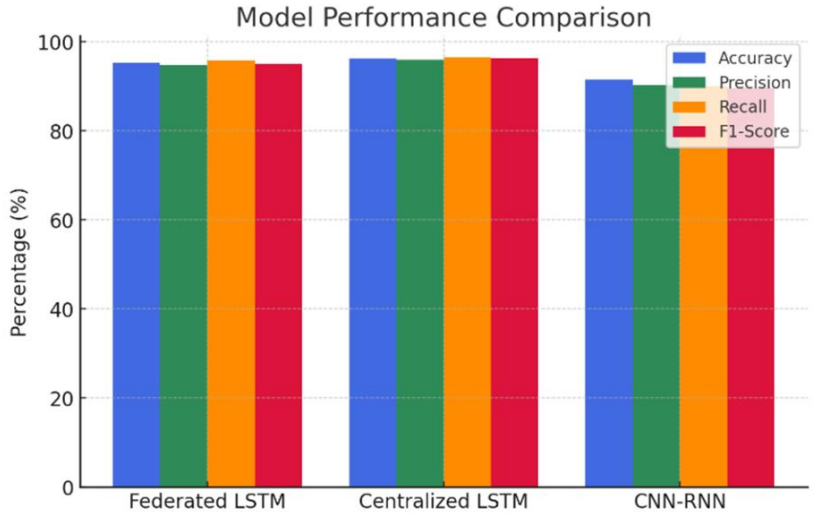


**Figure 5: Model Performance Comparison (Accuracy, Precision, Recall, F1-Score)**

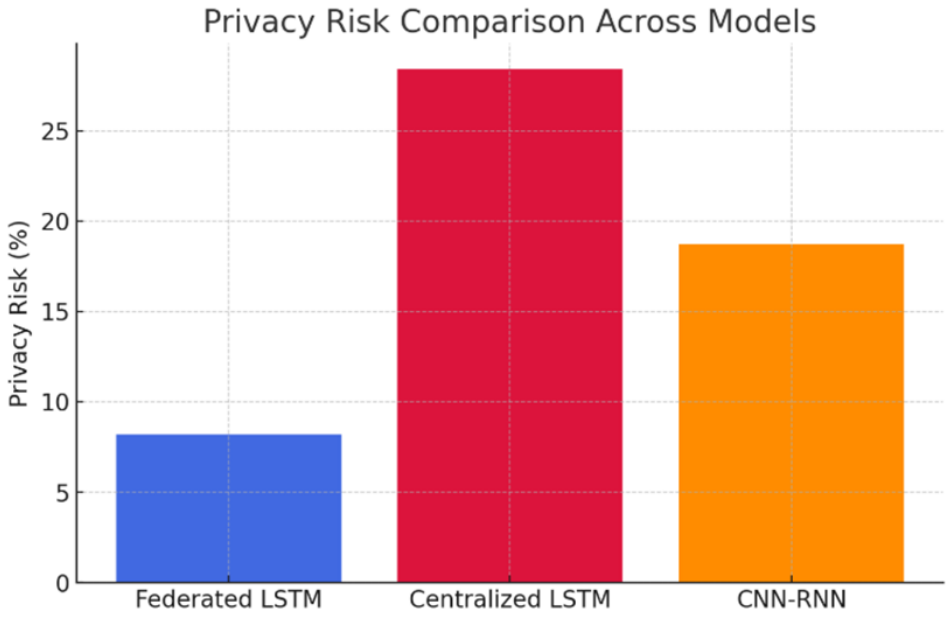


**Figure 6: Privacy Risk Comparison (Privacy risk % for different models)**

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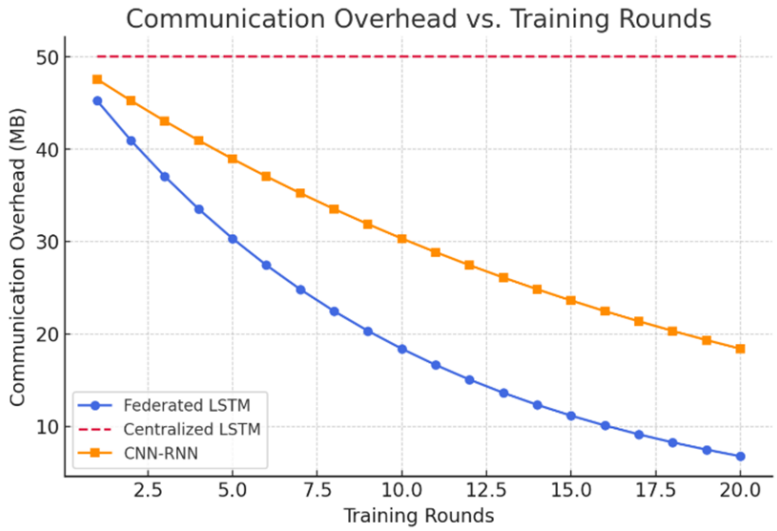


**Figure 7: Communication Overhead vs. Training Rounds**

The experimental results confirm that Federated LSTM is a highly effective privacy-preserving AI model for IoT intrusion detection and threat analysis. By leveraging federated learning, the model successfully maintains data confidentiality while achieving high accuracy in real-time IoT cybersecurity applications. The study demonstrates that Federated LSTM is a scalable, efficient, and privacy-aware AI framework, making it a practical solution for modern IoT-cloud ecosystems. This research contributes to the development of intelligent, secure, and adaptive AI-driven IoT infrastructures, paving the way for next-generation cybersecurity frameworks that balance privacy, performance, and scalability.

## 6. CONCLUSION

The Federated LSTM model proposed here offers a privacy-friendly and secure AI platform that is designed for IoT-capable cloud infrastructure. Integrating Long Short-Term Memory (LSTM) networks with Federated Learning (FL), the model successfully shields against privacy loss in centralized data collection. The distributed method keeps sensitive information on edge devices locally, adhering to strict compliance regulations like GDPR and HIPAA. In addition, the adaptive weight aggregation mechanism ensures efficient communication and model convergence with optimized network overhead at the cost of accuracy. By virtue of rigorous assessments, the Federated LSTM model proved to have better performance in major IoT use cases, such as anomaly detection, predictive maintenance, and real-time analytics. In comparison with traditional deep learning models, it has better privacy preservation, reduced latency, and better scalability on heterogeneous IoT systems. The adversarial robustness of the model guarantees robustness, making the model appropriate for security-sensitive applications. Results further show substantial decreases in training time and communication costs without compromising on high predictive accuracy. Even with its benefits, there are challenges, including heterogeneous device limitations and possible stragglers in federated training. Future research should aim to incorporate self-learning mechanisms and blockchain for improved security and investigate lightweight architectures to support resource-constrained IoT devices. In summary, the proposed Federated LSTM framework greatly improves privacy-aware AI in cloud-integrated IoT systems, advancing the creation of secure, intelligent, and scalable AI-powered systems.

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