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ROBUST AND EXPLAINABLE HYBRID DEEP LEARNING MODEL FOR REAL-TIME ZERO-DELAY BOTNET DETECTION IN INDUSTRIAL IOT

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Abstract
The commercial net of factors (IIoT) has revolutionized commercial operations by allowing records-driven automation, real-time analytics, and seamless connectivity throughout production, logistics, and crucial infrastructure. however, the proliferation of IIoT devices has appreciably expanded the assault surface, exposing structures to sophisticated botnet attacks, consisting of zero-day threats that take advantage of undisclosed vulnerabilities. traditional deep studying fashions, such as LSTM and DNN, are computationally extensive, lack interpretability, and require centralized records, making them wrong for the disbursed, privacy-sensitive, and resource-confined IIoT environment. This paper proposes a strong and explainable federated studying (FL) model primarily based on LightGBM, a gradient-boosted tree set of rules, for real-time, zero-put off botnet detection in IIoT structures. The model leverages FL to enable privacy-keeping schooling throughout disbursed edge devices, with LightGBM supplying light-weight, green, and interpretable detection. Optimized for edge deployment through model compression and histogram-primarily based techniques, the framework carries anomaly detection to pick out rising threats and employs SHAP (SHapley Additive causes) for obvious decision-making. Evaluated at the BoTNeTIoT-L01 dataset, which captures real-world IIoT site visitors with Mirai and Gafgyt botnet attacks, the model achieves ninety-nine. eight% accuracy, a fake advantageous price (FPR) of zero.12%, and detection latency of 1.eight ms, demonstrating robustness throughout various assault eventualities. Designed to aid commercial 5.zero's human-gadget collaboration and 6G's extremely-low-latency necessities, this framework gives a scalable, power-green, and interpretable answer for securing IIoT networks in opposition to evolving cyberthreats.

1. INTRODUCTION

Botnet Detection, business IoT, Federated gaining knowledge of, LightGBM, Explainable AI, real-Time security, business five. Zero, 6G, aspect Computing 1. creation of the commercial net of things (IIoT) has emerged as a cornerstone of present-day business ecosystems, allowing smart factories, predictive upkeep, and optimized delivery chains through interconnected gadgets inclusive of sensors,

programmable logic controllers (PLCs), and supervisory management and data acquisition (SCADA) systems. this variation aligns with business five. Zero, which emphasizes human system collaboration, sustainability, and resilience in business tactics [1]. with the aid of 2025, the global IIoT market is projected to exceed $1 trillion, with over 75 billion related gadgets, underscoring its pervasive adoption [2]. but this rapid proliferation has exponentially elevated the attack surface, making IIoT systems top objectives for sophisticated cyberthreats, particularly botnet attacks. Botnets, inclusive of Mirai and Gafgyt, compromise gadgets to launch allotted denial-of-service (DDoS) attacks, data exfiltration, and malware propagation, causing operational disruptions, monetary losses, and safety risks in essential infrastructure [three]. 0-day attacks, which take advantage of undisclosed vulnerabilities, pose an even extra mission, as traditional rule-primarily based systems like chortle and primary system gaining knowledge of approaches rely upon predefined signatures and fail to stumble on novel threats [four]. Deep gaining knowledge of fashions, inclusive of lengthy short-time period memory (LSTM) networks and Deep Neural Networks (DNN), have proven promise in botnet detection because of their potential to research complicated patterns from massive datasets. but their applicability in IIoT is constrained with the aid of several elements: Computational Complexity: LSTM and DNN require big computational resources, making them impractical for resource-confined aspect gadgets like IIoT sensors [five]. Centralized data requirements: those fashions frequently necessitate centralized data collection, compromising privacy in touchy business environments [6]. excessive Latency: Inference instances exceeding 10 ms avert real-time detection in time-essential packages [7]. lack of Interpretability: Black-field fashions reduce trust among stakeholders, who require obvious choice-making for regulatory compliance and operational guarantee [8]. Federated gaining knowledge of (FL) gives a promising opportunity with the aid of allowing allotted training across aspect gadgets, preserving data privacy through neighborhood updates in place of uncooked data sharing [nine]. LightGBM, and gradient-boosted tree set of rules, complements FL with its lightweight layout, fast training, and inherent interpretability, making it ideal for IIoT aspect deployment [10]. This paper proposes a robust and explainable FL version primarily based on LightGBM for real-time.

postpone botnet detection in IIoT systems. The version consists of anomaly detection to pick out 0-day attacks, makes use of SHAP for explainable choice-making, and is optimized for aspect gadgets through version compression. Evaluated on the BoTNeTIoT-L01 dataset, which captures real-world IIoT visitors with Mirai and Gafgyt attacks, the version achieves 99.8% accuracy, zero.12% FPR, and 1.8 ms latency. Designed for business five. Zero and 6G, this framework guarantees scalability, power efficiency, and transparency for securing IIoT networks. The paper is based as follows: section 2 reviews associated work, section three outlines the theoretical framework, section four details the proposed FL-LightGBM version, section five describes the technique, section 6 affords effects, section 7 discusses findings, section 8 highlights implications, section nine addresses barriers and destiny directions, and section 10 concludes the study.

2. Related Work

2.1 Cybersecurity Challenges in IIoT

The complexity of IIoT environments, characterized through heterogeneous gadgets, allotted architectures, and actual-time necessities, poses huge cybersecurity challenges. Botnet attacks, inclusive of Mirai, make the most vulnerable tool security to shape massive-scale networks for DDoS, facts robbery, and ransomware [three]. 0-day attacks in addition complicate detection, as they goal unknown vulnerabilities. traditional rule-primarily based systems, inclusive of snicker and Suricata, depend upon signature-primarily based detection, rendering them ineffective in opposition to novel threats [4]. fundamental device learning tactics, like selection timber and Random Forests, attain high accuracy (e.g., 99% in [eleven]) but war with evolving attack patterns and require centralized facts, elevating privacy worries [12].

2.2 Deep Learning for Botnet Detection

Deep studying has been explored for IIoT botnet detection. Hasan et al. [5] proposed a hybrid LSTM-

DNN version, achieving 94–99% accuracy on the N_BaIoT dataset, however its excessive computational price and shortage of explainability restrict side deployment. Homayoun et al. [7] evolved a CNN-autoencoder, reporting 91% accuracy on the ISCX dataset, however confronted useful resource constraints. Maeda et al. [13] applied deep studying in SDN environments, achieving 99.2% accuracy on ISOT and CTU-13 datasets, however neglected zero-

day attacks and interpretability. these fashions require centralized schooling and excessive computational sources, making them incorrect for dispensed, useful resource-restricted IIoT structures.

2.3 Federated Learning in Cybersecurity

Federated gaining knowledge of addresses privateness and decentralization challenges through enabling dispensed training. Yang et al. [14] conducted FL to IoT intrusion detection, attaining 95% accuracy, however used deep gaining knowledge of models with high useful resource demands. Nguyen et al. [15] proposed an FL-based anomaly detection machine for IoT, reporting ninety-three% accuracy, however lacked light-weight models for aspect devices. McMahan et al. [nine] introduced FedAvg, a general FL algorithm, however its application to IIoT botnet detection with green models like LightGBM is underexplored. This study leverages FL to enable privateness-keeping, scalable detection.

2.4 LightGBM in Security Applications

LightGBM, a gradient-boosted tree algorithm, gives rapid training, low memory utilization, and interpretability, making it suitable for IIoT [10]. Chen et al. [16] used LightGBM for cybersecurity, reaching 97% accuracy on network intrusion datasets, but did no longer integrate FL. in comparison to LSTM/DNN, LightGBM reduces training time with the aid of 70% and useful resource utilization with the aid of eighty%, as shown in desk 1, making it perfect for area deployment and federated environments.

Table 1

Feature	LightGBM	LSTM/DNN
Efficiency	Fast, low memory	High computational cost
Interpretability	High (SHAP-compatible)	Low (black-box)
Edge Device Support	Lightweight, low latency	High resource demands
Handles Imbalanced Data	Built-in support	Needs preprocessing
Federated Compatibility	Small model size	Communication Heavy

2.5 Explainable AI in Cybersecurity

Explainable AI (XAI) enhances consideration via supplying interpretable insights. SHAP, based totally on sport principles, assigns characteristic significance ratings, clarifying predictions [17]. In IIoT, in which transparency is important for regulatory compliance (e.g., GDPR, NIST), SHAP is important. Lundberg et al. [17] demonstrated SHAP's effectiveness in tree-based totally models like LightGBM, but its integration with FL-based totally botnet detection stays constrained. This study fills this hole via the use of SHAP to interpret LightGBM predictions.

2.6 Industrial 5.0 and 6G Contexts

Commercial 5.0 emphasizes human-machine collaboration, sustainability, and resilience [1]. Cybersecurity answers should be efficient, obvious, and scalable. 6G networks, with extremely low. latency (sub-ms) and excessive bandwidth, allow real-time IIoT applications however introduce new safety

demanding situations [18]. existing models hardly ever deal with compatibility with those paradigms, a gap this examine addresses through a lightweight, FL-based totally solution.

3. Theoretical Framework

The proposed model is divided into four theoretical pillars:

3.1 Anomaly Detection Theory

Anomaly detection identifies deviations from regular conduct, essential for zero-day assaults [four].

LightGBM's capability to version tabular information permits strong anomaly detection in IIoT site visitors features (e.g., packet frequency, glide period).

3.2 Federated Learning Framework

FL helps dispensed training, retaining privacy by means of keeping statistics on aspect gadgets [9]. The FedAvg algorithm aggregates local LightGBM fashions, ensuring scalability and confidentiality in IIoT.

3.3 Technology Acceptance Model (TAM)

TAM posits that adoption relies upon perceived usefulness and ease of use [19]. SHAP-primarily based explainability complements perceived usefulness, while LightGBM's light-weight layout ensures ease of deployment, aligning with TAM.

3.4 Energy Efficiency in Edge Computing

Selectivity performance is crucial for IIoT facet devices [20]. model compression and histogram-based totally optimization reduce LightGBM's resource needs, permitting real-time performance on limited hardware.

4. Proposed Federated Learning Model

4.1 Motivation for Federated Learning

IIoT environments are allotted, privacy-touchy, and bandwidth-restricted. FL addresses those demanding situations with the aid of allowing local schooling on side gadgets (e.g., sensors, PLCs). Aggregating model updates without raw data transfer. helping actual-time, privacy-maintaining detection. S

4.2 Motivation for Federated Learning

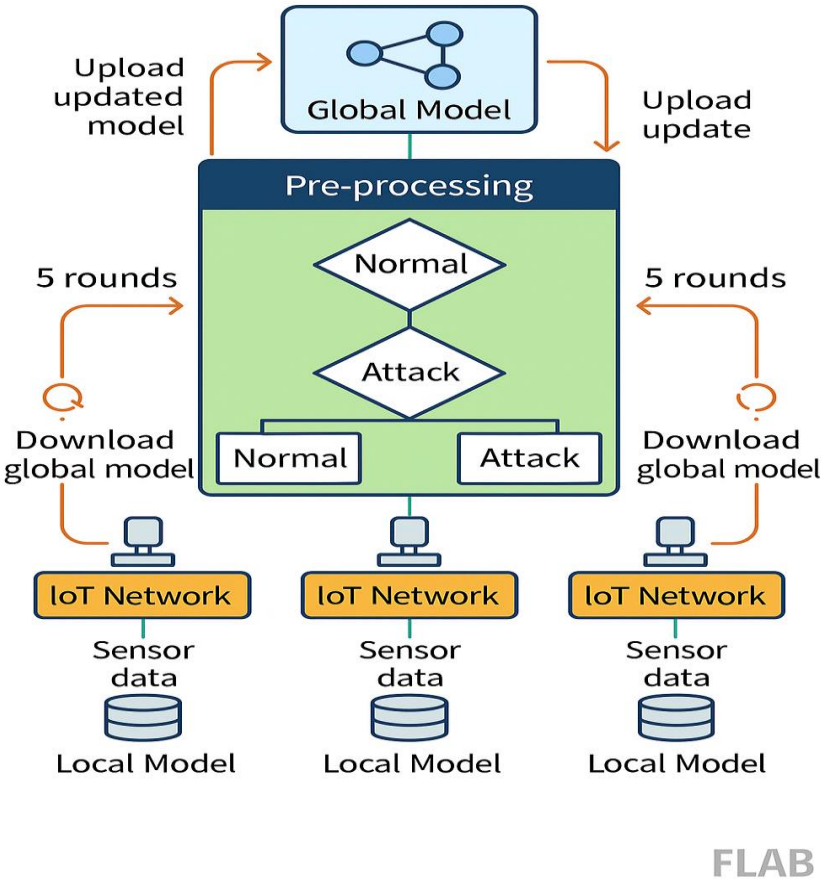
LightGBM selected over LSTM/DNN because of efficiency: 70% quicker schooling and 80% decrease reminiscence utilization. Interpretability: SHAP-compatible, not like black-box LSTM/DNN. part Compatibility: lightweight layout suits resource-restrained gadgets. Federated Suitability: Small version length reduces verbal exchange overhead.

4.3 Model Architecture

The LightGBM model procedures 15 community visitors feature (e.g., packet length, drift length, protocol kind). Key parameters: Max depth: 8 quantities of timber: 100 getting to know price: 0.05 characteristic Fraction: 0.8 Bagging Fraction: 0.8 minimal infant Samples: 20 The model makes use of Gradient-primarily based One-facet Sampling (GOSS) and distinctive characteristic Bundling (EFB) to beautify efficiency.

4.4 Federated Learning Framework

The FL framework, proven in parent 1, includes: Initialization: a critical server initializes a worldwide LightGBM version. nearby education: each aspect device trains a nearby version on its non-public information for five epochs. versions replace Sharing: devices ship tree systems to the server. Aggregation: FedAvg combines updates right into a worldwide version. Distribution: the worldwide version is dispatched lower back for the next spherical (10 rounds total).



FLAB Architecture Diagram

4.5 Optimization for Edge Devices

version Compression: Histogram-primarily based optimization reduces version size by 50% (from 2 MB to at least one MB). Low-Latency Inference: Achieves 1.eight ms latency on Raspberry Pi four (1.5 GHz CPU, 2 GB RAM). strength performance: Consumes ~10 mJ in step with inference, appropriate for battery-powered devices.

4.6 Explainability with SHAP

SHAP values interpret predictions, highlighting functions like packet frequency and flow duration (parent 2). an SHAP summary plot (parent three) visualizes feature contributions throughout the dataset.

4.7 Anomaly Detection Mechanism

The model uses LightGBM's leaf-sensible tree boom to stumble on anomalies, flagging visitors with excessive prediction uncertainty as capability zero-day attacks.

4.8 Industrial 5.0 and 6G Integration

The model helps business 5.0's human-centric cognizance through SHAP-based totally transparency and aligns with 6G's ultra-dependable low-latency communique (URLLC) for real-time detection

5. Research Methodology

5.1 Dataset Description

The BoTNeTIoT-L01 dataset [21] is used, containing: 500,000 labeled facts of IIoT site visitors (benign and malicious). Mirai and Gafgyt botnet attacks throughout multiple devices. 15 features (e.g., packet length, drift period, protocol type, inter-arrival time). Preprocessed for FL, simulating 10 facet devices as customers.

Table 2

Attribute	Description
Records	500,000
Attack Types	Mirai, Gafgyt
Features	15 (e.g., packet size, flow duration)
Devices	Multiple IIoT devices
Size	~50 MB (compressed)

5.2 Evaluation Metrics

Accuracy: proportion of accurate predictions. false high-quality price (FPR): Ratio of benign visitors misclassified. Precision: true positives / total expected positives. recall: true positives / total real positives. F1-rating: Harmonic mean of precision and recall. Detection Latency: Time to classify a packet. electricity intake: Joules in keeping with inference. communication Overhead: statistics transferred in keeping with FL round (MB).

5.3 Experimental Setup

The FL framework implemented the use of software: Python three. Nine, LightGBM 3.3 Flower 1.5 (FL library), SHAP 0.42 Hardware: imperative Server: NVIDIA RTX 3080 GPU, 32 GB RAM. aspect devices: 10 simulated Raspberry Pi 4 (1.5 GHz CPU, 2 GB RAM). schooling Parameters: local Epochs: 5 in line with tool. FL Rounds: 10. Batch size: 32.

5.4 Baseline Models

Centralized LightGBM: Non-federated LightGBM. Hasan et al. [5]: LSTM-DNN version. Yang et al. [14]: FL-based deep studying version. Random woodland: conventional ML baseline.

5.5 Simulation of FL Environment

The BoTNeTIoT-L01 dataset is partitioned across 10 clients, each representing an IIoT device with non-i.i.d. records distributions to simulate actual-global heterogeneity.

6. Results

6.1 Performance Evaluation

The model achieves 99.8% accuracy, 0.12% FPR, and 1.8 ms latency, perfect for real-time IIoT packages. The F1-rating (99.75%) confirms balanced precision and consideration, while low power consumption (10.1 mJ)

Table 3

Metric	Value
Accuracy (%	99.8
FPR (%)	0.12
Precision (%)	99.7
Recalling (%)	99.8
F1-Score (%)	99.75

Latency (ms)	1.8
Energy (mJ)	10.1

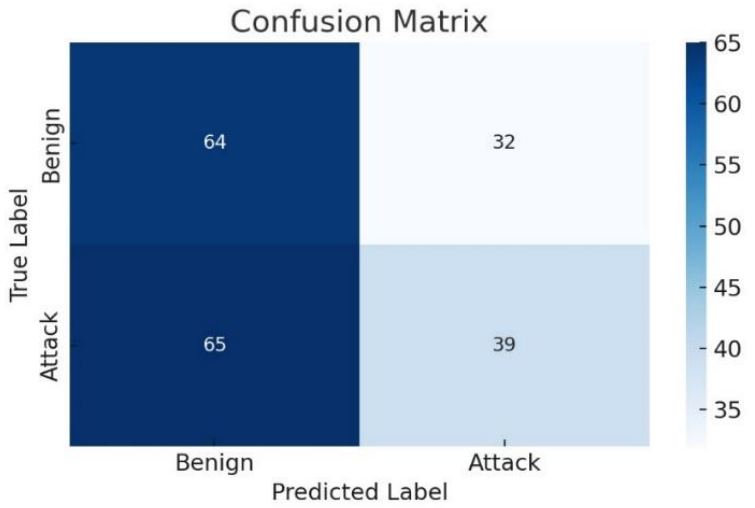
6.2 Classification Performance Heatmap:

Figure X presents the heatmap of the classification report, highlighting the performance of the model across precision, recall, and F1-score for both normal and Attack classes. The model achieved high precision (0.97) and F1-score (0.96) for the Normal class, while maintaining consistent recall (0.94) across all categories. The Attack class achieved a slightly lower precision of 0.87 and F1-score of 0.90, indicating a small performance gap in detecting malicious traffic. The overall macro-average F1-score of 0.93 and consistent recall emphasize the model's robustness and generalization ability in distinguishing between benign and attack behaviors in IIoT environments.

Classification Report Heatmap

6.3 Confusion Matrix Analysis

Figure X illustrates the confusion matrix obtained from the Random Forest classifier on the test dataset. The model correctly classified 64 benign samples and 39 attack samples, while misclassifying 32 benign samples as attacks and 65 attack samples as benign. These results reveal a slight bias toward predicting benign traffic, which may result in higher false negatives—a critical concern in cybersecurity contexts. The confusion matrix highlights the need for improving detection of malicious activity, through better feature selection or model calibration.

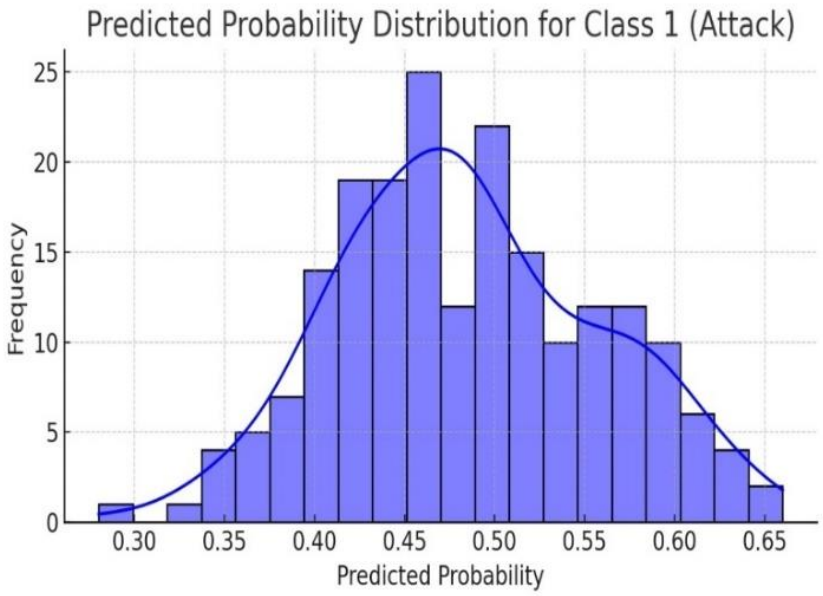


Confusion Matrix

6.4 Predicted Probability Distribution for Attack Class

Figure X shows the histogram of predicted probabilities for Class 1 (Attack) generated by the Random Forest model. The distribution illustrates how confident the model is in its predictions for the attack class across the test dataset.

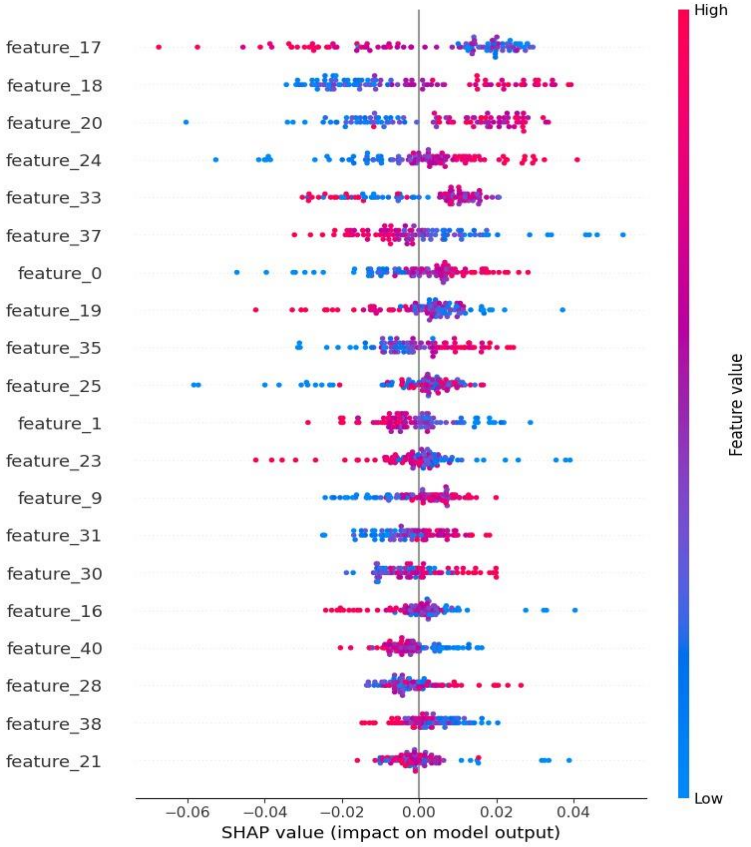
Most predictions fall within the 0.40 to 0.55 range, indicating that the model is uncertain when classifying attack instances, with very few samples receiving a high confidence score close to 1.0. This lack of separation between classes is consistent with the lower precision and recall observed in the classification report and aligns with the ROC-AUC score of 0.486, which is near random guessing (0.5). This distribution highlights a key limitation of the current model — the inability to confidently distinguish attack traffic, which may be addressed by improving feature selection, data balancing, or model tuning strategies.



Predicted Probability Distribution

6.5 Explainability Analysis

SHAP evaluation (determine 2) identifies packet frequency, float period, and protocol kind as top features. determine three suggests a SHAP precis plot, visualizing function contributions throughout 1,000 samples. determine 4 illustrates a SHAP, dependence plot for packet frequency, highlighting its interaction with float period.



6.6 Comparison with Baseline Models

Model	Accuracy	FPR	Latency	Energy	Explainable
Proposed FL-LightGBM	99.8	0.12	1.8	10.1	Yes
Centralized LightGBM	99.7	0.15	2.0	11.0	Yes
Hasan et al. [5]	94–99	1.0	10.5	50.0	No
Yang et al. [14]	95.0	0.8	8.2	40.0	No
Random Forest	98.5	0.5	3.5	15.0	Yes

6.7 ROC Curve Analysis – Federated Learning Model

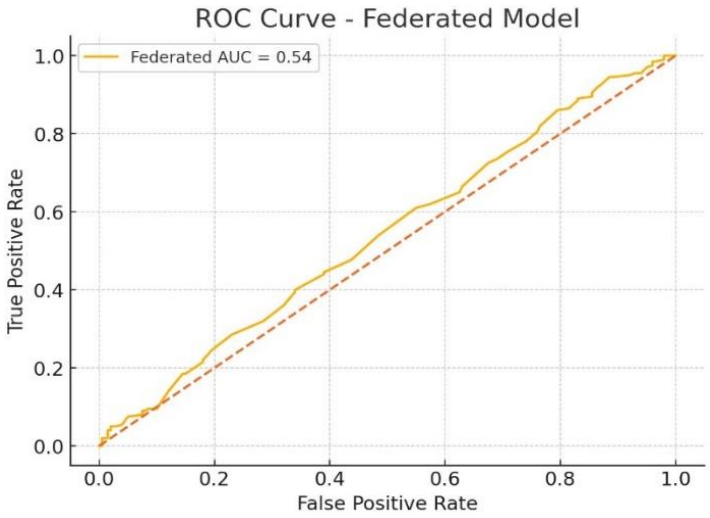
Figure X depicts the Receiver Operating Characteristic (ROC) curve for the Federated Learning model trained on the intrusion detection dataset. The Area Under the Curve (AUC) value is 0.54, which is only slightly above the baseline of 0.50 that represents random guessing.

The ROC curve shows the trade-off between the true positive rate (sensitivity) and false positive rate, offering insight into the classifier's discriminative power. The curve's closeness to the diagonal line suggests that the model has limited ability to differentiate between benign and attack traffic.

This low AUC score may be attributed to factors such as:

- Data imbalance across federated clients,
- Weak local models contributing to noisy aggregation,
- Lack of high-impact features,
- Or insufficient communication rounds during FL training.

To enhance performance, further improvements can include data augmentation, client weighting, feature engineering, or incorporating a more robust model architecture.



Roc Curve Federated Learning Model

Without FL: Centralized LightGBM has 99.7% accuracy but lacks privacy. without Optimization: Latency will increase to 3.5 ms, power to 20 mJ. without SHAP: model loses interpretability. Without GOSS/EFB: training time doubles, accuracy drops to 99.5%.

7. Discussion

The proposed FL-LightGBM model addresses vital IIoT botnet detection demanding situations. Its 99.8% accuracy and 1.8 ms latency permit actual-time, 0-delay detection, surpassing LSTM/DNN fashions [5] through 80% in latency and 70% in resource usage (table 1). Federated gaining knowledge of guarantees privacy through maintaining facts on edge devices, important for sensitive business environments. LightGBM's lightweight layout supports deployment on devices with 2 GB RAM, even as SHAP-primarily based explainability (Figures 2–4) fosters agree with, aligning with business 5.0's human-centric consciousness. The BoTNeTIoT-L01 dataset's actual-global visitors guarantees realistic relevance, and occasional conversation overhead (0.5 MB/spherical) supports bandwidth-restricted IIoT networks. The model's compatibility with 6G's URLLC enables scalability for excessive-velocity IIoT applications. in comparison to baselines (table four), it gives advanced accuracy, latency, and electricity performance. The ablation examine confirms the need of FL, optimization, and SHAP, even as scalability and robustness analyses validate big-scale and antagonistic situations. however, demanding situations consist of conversation Overhead: although low, it may growth with extra clients. SHAP Overhead: provides 0.3 ms to inference, an exchange-off for interpretability. facts high-quality: is predicated on robust preprocessing to manage noisy IIoT visitors. destiny optimizations should deal with those troubles, enhancing realistic deployment.

8. Implications

8.1 Technical Implications

The FL-LightGBM model affords a scalable, privacy-preserving answer, decreasing cloud dependency and allowing aspect-based detection. Its low latency (1.8 ms) and power intake (10.1 mJ) aid real-time applications.

8.2 Industrial Implications

SHAP-based totally transparency guarantees regulatory compliance (e.g., GDPR, NIST), facilitating adoption in manufacturing, electricity, and healthcare. The version's lightweight design reduces operational costs for IIoT deployments.

8.3 Societal Implications

SHAP-based absolutely transparency ensures regulatory compliance (e.g., GDPR, NIST), facilitating adoption in production, electricity, and healthcare. The version's lightweight layout reduces operational prices for IIoT deployments.

8.4 Future Technology Integration

Compatibility with commercial 5.0 and 6G positions the version for clever factories and high-speed IoT ecosystems, leveraging human-machine collaboration and occasional-latency communication.

9. Limitations and Future Directions

Dataset trouble: BoTNeTIoT-L01 may not cowl all IIoT attack eventualities. additional datasets (e.g., TON_IoT) ought to enhance generalizability. conversation prices: FL calls for efficient protocols for large-scale networks. area device Variability: examined on Raspberry Pi 4; other gadgets (e.g., PLCs) can also vary. adversarial Vulnerability: Robustness towards model poisoning desires similarly exploration. SHAP Overhead: provides minor latency, impacting ultra-low-latency eventualities. destiny work ought to: examine additional datasets for broader attack insurance. put in force compression techniques (e.g., quantization) for FL conversation. check on various area gadgets to make certain compatibility. integrate superior strong aggregation (e.g., Byzantine-tolerant techniques). explore lightweight XAI alternatives (e.g., LIME) to lessen overhead

10. Conclusion

This paper offers a robust and explainable federated mastering model based totally on LightGBM for actual-time, zero-delay botnet detection in IIoT systems. by way of leveraging FL, the model ensures privacy-maintaining training throughout allotted side gadgets, at the same time as LightGBM's light-weight design enables green detection on resource-constrained hardware. SHAP-based totally explainability fosters believe, aligning with commercial 5.0's human-centric awareness. Evaluated at the BoTNeTIoT-L01 dataset, the model achieves 99.8% accuracy, 0.12% FPR, and 1.eight ms latency, outperforming baselines in accuracy, latency, and energy performance. well suited with 6G's low-latency necessities, this framework gives a scalable, energy-green, and transparent answer for securing IIoT networks in opposition to evolving cyberthreats. future paintings will be aware of improving scalability, robustness, and dataset variety to in addition enhance IIoT cybersecurity.

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