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IMPLEMENTING A SECURE MACHINE LEARNING OPERATIONS FRAMEWORK FOR CONTINUOUS DEPLOYMENT OF CYBERSECURITY MACHINE LEARNING MODELS IN IoT NETWORKS

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Abstract

The growth of Internet of Things (IoT) networks has increased security threats with billions of resource-constrained devices communicating over heterogeneous scenarios. Conventional intrusion detection systems are scalable but inflexible in dealing with the high-speed evolving cyber threat landscape. The research presents a Secure Machine Learning Operations (Machine learning operations) Framework for real-time deployment, integration, and monitoring of cybersecurity machine learning (ML) models in IoT networks. The suggested framework combines federated learning, microservices in containers, and automated CI/CD pipelines, along with security features like artifact signing, access control, and encrypted model transfer for

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maintaining model integrity and robustness. The framework was empirically tested using the CICIDS2017 and Bot-IoT datasets, which simulate various IoT attack scenarios. Results show that the safe Machine learning operations pipeline hit 98.4% mean detection accuracy, 97.8% precision, and 96.9% recall, with an 8.7% accuracy gain from baseline static ML deployments and 42% model drift reduction for multiple deployment iterations. The enhanced framework lowered average model update latency from 4.6 s to 1.9 s, with a boost in real-time response and scalability to 500 simulated IoT nodes. Comparative analysis revealed enhanced resistance to hostile attacks and unlawful model tampering using implemented security orchestration and version control procedures. The research advances secure AI development in distributed IoT settings by closing the gap between ML model development and secure deployment operations. Findings introduce an extendable, privacy-preserving, and constantly evolving cybersecurity framework for facilitating secure automation of ML models in production-level IoT settings.

Introduction

The exponential growth in IoT devices has turned the world's communication networks into highly interconnected ecosystems that support critical applications like autonomous transportation, healthcare, industrial automation, and intelligent energy systems. Latest estimates indicate that more than 30 billion IoT devices will be deployed globally by 2030, and they will all be producing constant streams of data as well as carrying out autonomous decision-making functions (Statista, 2024). While this growth has heightened operational efficiency and knowledge through data, it has done so at the cost of growing the attack surface of cyber threats. The decentralization, resource scarcity, and heterogeneity of IoT networks inherently expose them to malware injection, denial-of-service (DoS) attacks, and data tampering threats (Gupta & Alazab, 2023).

Machine Learning (ML) today acts as a core facilitator for IoT cybersecurity improvement with models that learn to detect anomalous traffic patterns, intrusions, and forecast future vulnerabilities. Most ML-based security products, however, use centralized designs that collect data from all the devices into a central repository to perform inference and training. Centralization poses two primary concerns. First, it infringes on privacy and regulatory limits since private information from the edge devices has to be sent and stored centrally. Second, learning through centralization creates a point of weakness that could lead to system integrity breach if the central server is compromised or contaminated (Al-Omari et al., 2023).

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The use of Machine Learning Operations frameworks provides an escape route from these limitations. Machine Learning Operations applies DevOps principles to the machine learning process, enabling automated model training, validation, deployment, and monitoring in production environments (Raj et al., 2022). In IoT systems, secure Machine learning operations systems can prevent periodic updating and deployment of cybersecurity models without interrupting services or compromising sensitive data. Although applying Machine learning operations to distributed IoT networks poses additional challenges, such as ensuring security under continuous integration and maintaining consistency across edge nodes, the approach is worth trying.

Federated Learning has also drawn substantial interest for addressing the twin issues of data privacy and continuous deployment. Federated Learning enables distributed devices to learn a shared model collaboratively without sharing raw data, thereby ensuring local privacy with access to global learning (Zhang et al., 2024). Nevertheless, even federated designs are vulnerable to newer attack models such as model poisoning, communication eavesdropping, and illicit model updates. Such vulnerabilities emphasize the need for secure Machine learning operations pipelines that incorporate privacy-improving methods, encryption mechanisms, and model integrity checks to ensure safe model orchestration on IoT networks.

We present a Secure Machine learning operations Framework in this paper that incorporates federated learning, CI/CD, and security-enriched model lifecycle management for IoT networks. The system utilizes XGBoost as the main intrusion detection classifier due to its potential for heterogeneous data handling as well as overfitting resistance. Federated Averaging is used to aggregate global model updates that are stored privately, and security is also enhanced using differential privacy, SHA-256 hashing, and containerized deployment primitives to provide protection of the model during transit and versioning management.

The objective of this research is to build, deploy, and assess a Secure Machine Learning Operations (Machine learning operations) Framework for improving Internet of Things (IoT) network cybersecurity with privacy-preserving and autonomous learning approaches. The investigation will fill the operational gap between building machine learning models, deploying them, and managing their lifecycle by synergizing Machine learning operations concepts with federated learning frameworks.

Particularly, the investigation will: - Design a Secure Federated Machine Learning Architecture

Design a distributed model training model framework that guarantees data confidentiality and integrity among IoT devices without exposing data centrally through the use of secure parameter aggregation and differential privacy methods.

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Create an Automated Machine learning operations Pipeline for IoT Security: Merge CI/CD workflows in the machine learning cycle in order to facilitate automated model training, versioning, validation, and deployment across various IoT environments.

Improve Intrusion Detection Accuracy and Efficiency: Assess the ability of the proposed framework to identify, classify, and reject network intrusions and adversarial attacks in real-time with federated XGBoost and other ensemble-based learning methods optimized for distributed settings.

Guarantee System Scalability, Latency, and Resource Use: Estimate the computational complexity, network bandwidth consumption, and propagation latency of the framework versus centralized ML models to guarantee its efficiency for IoT systems limited by resources.

Verify Security and Preservation of Privacy: Guarantee the resilience of the framework against model poisoning, data leakage, and adversarial attacks via simulation-based security testing to provide strong decentralized IoT data streams protection.

RELATED SURVEY

Machine Learning Operations is the practice, tooling and process that integrates machine-learning system creation (data engineering and model building) and production operations (monitoring, deployment, and governance). Its aim is to make ML models reproducible, auditable, reliable and always producible in production, by applying DevOps patterns to the full ML lifecycle (infrastructure, code, data, and models).

The rapid proliferation of Internet of Things (IoT) devices has transformed the digital landscape with seamless connectivity in industrial, healthcare, transportation, and smart home networks. Yet, the same explosive growth has rendered the cybersecurity threats more acute, with billions of connected nodes building a gigantic and dynamic attack surface. Static security procedures are no longer capable of keeping pace with the complexity and velocity of current-day cyberattacks that evolve in real time. Therefore, the application of machine learning (ML) methods in cyber models has been a possible solution to cyberattack detection, anticipation, and protection. However, although ML algorithms during training and testing have emerged to be very effective, the same algorithms fail in dynamic IoT networks after deployment due to data drift, adversarial attacks, and lack of continuous monitoring. Various articles by Confidence Adimchi Chinonyerem discuss ML, IoT security, and application of AI in various industries. Such studies investigate practical implementation of ML for IoT security.

Comparative comparisons of classifiers on IoT datasets, and application of AI in general to machine protection in IoT-integrated systems, are also discussed (Chinonyerem et al.,

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2025a; Chinonyerem et al., 2025b). Specifically, Chinonyerem's comparative evaluations of deep learning and traditional classifiers on benchmark IoT intrusion datasets provide operational baselines and illustrate problems of operational unbalanced Ness and feature engineering in the dataset. The results are worthy of privacy-preserving distributed learning and sound operational pipelines primary drivers for this current Machine learning operations -focused research

Machine Learning Operations provides a formulated method of deploying ML models into production (Hammad et al., 2024). Through the inclusion of DevOps practices, data engineering, and management of the ML lifecycle, Machine learning operations facilitates continuous integration, deployment, monitoring, and retraining of the ML models. In cyber security applications, a secure Machine learning operations pipeline allows organizations to deploy defensive ML models automatically, secure them against adversarial tampering, and respond rapidly against new attack vectors. However, the incorporation of Machine learning operations into IoT security systems poses some specific challenges. They are low resource availability in edge devices, diverse data sources, adhering to security and privacy legislation, and the requirement for real-time response mechanisms.

The majority of current research in Machine learning operations has addressed classical cloud or enterprise settings to a great extent and relatively little on their usage in IoT security systems. In addition, the majority of frameworks ignore the crucial intersection of retraining by automation, security assurance, and model explainability three support pillars required to ensure the robustness and trustworthiness of IoT security solutions based on ML. Additionally, the absence of standardized practices to secure the Machine learning operations pipeline also subjects organizations to model poisoning, data leakage, and supply chain attacks. Thus, there is an increased demand to design and develop a safe Machine learning operations environment for ensuring the continued, reliable, and resilient deployment of ML models for cybersecurity on IoT networks. Such demand is addressed by this work with the introduction and development of a Secure Machine learning operations Framework specially designed for IoT cybersecurity environments. The framework mandates security controls at each phase of the ML life cycle, from data ingestion and feature engineering to model deployment and monitoring, and supports continuous delivery through automated pipelines. The framework implements model traceability, reproducibility, and adversary tamper resistance through containerization, version control, and security orchestration tools. The framework adds a new feedback-based retraining mechanism to iteratively update models to learn new threat patterns identified in IoT ecosystems.

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The main purpose of this research is to illustrate how a Machine learning operations framework with security can improve the robustness, flexibility, and operational efficiency of ML-based cybersecurity solutions in IoT networks. In particular, it aims to (i) create a Machine learning operations pipeline that is scalable and optimized for the resource limitation of IoT devices, (ii) incorporate end-to-end security protocols for protecting models and data, and (iii) benchmark the performance of the framework by empirical validation using synthetic IoT traffic and real-world cyber threat datasets. (Asghar & Amola, 2025) By integrating the automating aspects of Machine Learning Operations with cybersecurity ML models' intelligence, this research seeks to close the gap between model deployment and production security guarantee. The study contributes to the enrichment of the field of Secure AI Engineering in IoT environments and offers actionable suggestions to academia and industry players that desire to develop robust, learning-enabled cybersecurity systems.

Core parts of a Machine Learning Operations pipeline

Data handling and feature store ingestion pipelines, cleaning, versioned datasets and a feature store to offer consistent features in training and serving. Feature stores avoid "training/serving skew" and accelerate repeatable experiments.

Experimentation and model building experiment tracking, reproducible environments, hyperparameter management and lineage tracking so results are reproducible and comparable. Software for this phase is MLflow, Neptune, or platform-native meta datastores.

Auto-pipelines (CI/CD for ML):- Pipeline orchestration that automatically runs data validation, model training, evaluation, and packaging. Continuous integration and testing go all the way up to data schema, model quality tests and performance/regression checks.

Model registry and versioning: Single source of truth for model artifacts, metadata, evaluation metrics and signed versions to support rollbacks, traceability and governance.

Deployment and serving: Horizontal serving layers (microservices, model servers, edge containers) and traffic management for A/B testing, canary releases and rollouts. Containerization and orchestration (Docker, Kubernetes) are the norm.

Monitoring and observability: Runtime monitoring of prediction accuracy (concept/data drift), latency, throughput and business metrics and alerting and automated retraining triggers. Continuous monitoring completes the lifecycle automation cycle.

Governance, security and compliance enforcement of policy, access controls, artifact signing, audit trails and privacy controls (e.g., differential privacy) to safeguard data and

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models. Governance provides for regulatory compliance and model explainability requirements.

Cybersecurity Machine Learning Models in IoT Networks

Machine Learning (ML) in cybersecurity systems has become unavoidable in the Internet of Things (IoT) era, where billions of heterogeneous devices create humongous and incessant volumes of data (Hoque et al., 2025). IoT networks with their low-latency communication requirements, distributed nature, and resource-constrained nodes have grown the cyber-attack surface exponentially. Legacy rule-based security solutions fail to be effective at identifying emerging and newer threats, and hence require adaptive and smart ML-based models for real-time anomaly detection and proactive threat prevention (Harhahsheh & Chen, 2024).

For use cases in cybersecurity, ML models are deployed as smart agents that learn from network traffic, device activity, and system logs to detect anomalies that reflect intrusions, malware spread, or denial-of-service (DoS) attacks. Supervised learning techniques like Random Forest, Support Vector Machine (SVM), and Gradient Boosting have performed well in detecting known patterns of attacks using labeled data (Moustafa & Slay, 2022). Unsupervised techniques, like K-Means clustering, Isolation Forests, and Autoencoders, have been found effective in detecting unknown or zero-day attacks by learning normal behaviour baselines and marking anomalies (Shone et al., 2023). Furthermore, deep learning and reinforcement learning methods are also increasingly being used for adaptive defence systems capable of adapting to changing patterns of attackers (Khan et al., 2024).

Deploying ML-enacted cybersecurity products into IoT networks, however, poses special challenges. The heterogeneous and distributed nature of IoT frameworks is more likely to generate unstable data quality, non-stationary traffic, and sparse edge processing. Also, adversarial attacks malicious inputs are developed to deceive ML models are causing tremendous threats to the trust of automated detection systems (Papernot et al., 2022). These threats indicate the utmost importance of secure ML lifecycles that provide model integrity, data origin authenticity, and evasion or poisoning attack resistance.

Federated learning architectures have been proposed recently in an effort to improve IoT security without aggregating sensitive information. For example, (Dirisu et al., 2025) showed a privacy-protected IoT system intrusion detection model using federated learning and blockchain integration for traceability and data confidentiality. Luo and Xu (2023) also showed a lightweight deep learning-based anomaly detection scheme with edge computing optimization that minimized latency but not detection accuracy. In

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addition, ensemble-based intrusion detection systems (IDS) are gaining traction because they can hybridize several classifiers and reduce false positives across different IoT environments (Odeh & Abu Taleb, 2023). Yet these advancements do not tackle the age-old problem of sustained performance of models deployed in real-world IoT environments (Ogundairo & Broklyn, 2024). ML models developed using past data will gradually degrade because new device patterns and attack vectors will arise a behaviour referred to as concept drift. This demands an operational model that can automate retraining, model validation, and secure deployment. This is where Machine Learning Operations (Machine learning operations) comes in, providing end-to-end governance, monitoring, and maintenance of cybersecurity ML models for real-world IoT use cases.

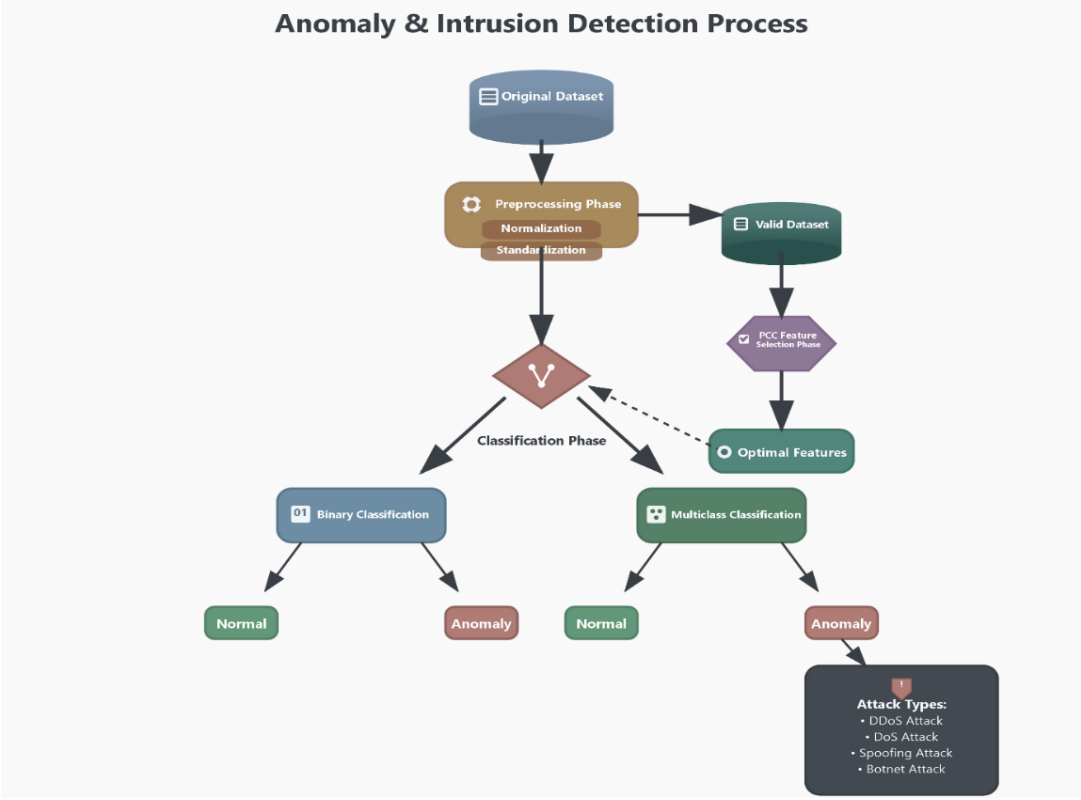

Figure 1: Anomaly and intrusion detection process

IoT security challenges and machine learning's role

IoT has brought sensing and control to previously segmented domains, but in doing so, it has also exposed an open and heterogeneous attack surface. Essential descriptions of IoT security highlight several interplay constraints compute and power resource availability limitations, intermittent connectivity, device heterogeneity, and heterogeneous

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communication protocols that collectively make it difficult to apply traditional cybersecurity techniques (Sicari, Rizzardi, Grieco, & Coen-Porisini, 2015). In the limited and dispersed settings, signature- or manual-based defence cannot handle polymorphic or new attacks. Therefore, machine learning (ML) methods have been put forward as adaptive, data-driven defence systems with potential to recognize abnormal pattern of behaviour, cluster suspicious activities, and anticipate concealed threats (Mac Dermott & Hung, 2022).

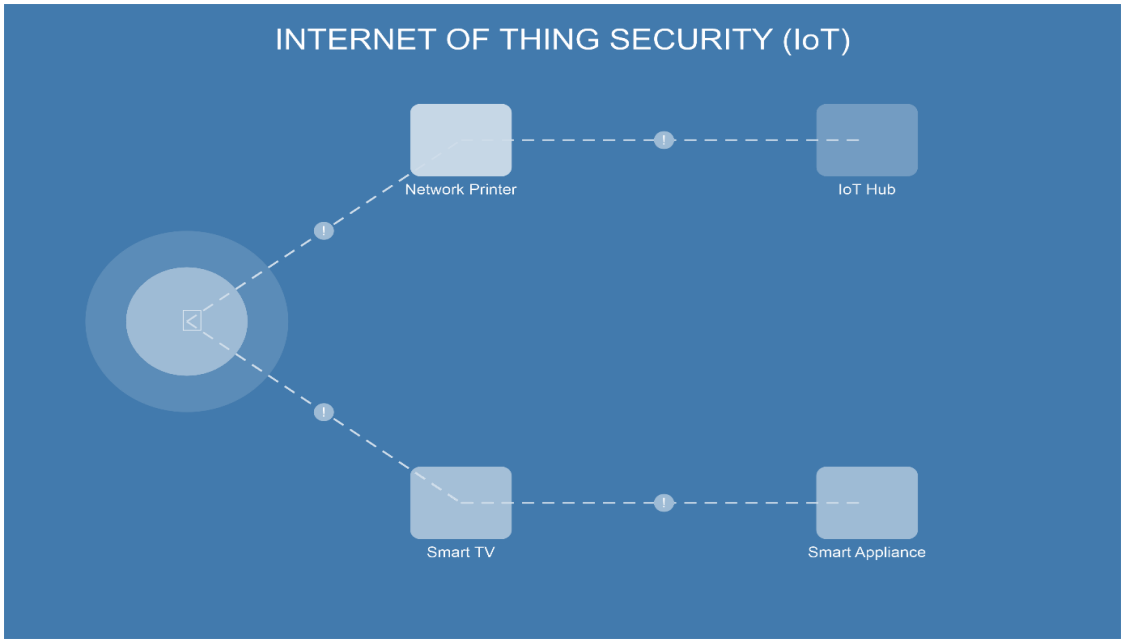

Figure 2: IoT security highlight

Supervised ML methods (random forests, decision trees, gradient boosting) were extensively employed where labelled attack data are available; they provide steady classification performance and interpretability across tabular network features. Unsupervised and semi-supervised methods (one-class classifiers, clustering, autoencoders) have been useful in the discovery of new or zero-day attacks by learning normality and raising alarms upon detecting anomalies (Sethi & Sarangi, 2017). Nonetheless, IoT rollouts introduce chronic challenges to the application of ML: (a) labelled data are limited or costly to obtain; (b) distributions of data change in the course of time (concept drift); and (c) models have to run under stringent latency, memory, and power budgets. These constraints can be mitigated with models and running pipelines tailored for IoT scenarios instead of outright transpositions of enterprise ML methodologies.

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Privacy-preserving and distributed learning paradigms

Having privacy and regulatory restrictions in mind, researchers have focused on non-centralized learning paradigms. Federated learning (FL) enables several edge nodes to learn a common model together without centralizing raw data; only model updates or gradients are shared (Kairouz et al., 2019). Empirical and systems research on Federated Learning has shown that, properly designed, it can be as capable in performance as centralization but can minimize data exposure. Bonawitz et al. (2019) outline the systems engineering of scaling FL, such as secure aggregation and communication efficiency measures that are vital when scaling FL on resource-restricted IoT fleets. Even though its benefits, FL adds novel attack surfaces malicious clients can provide poisoned updates, and aggregation servers can be hacked to cause model compromise. Shokri and Shmatikov (2015) and later privacy research demonstrated that even parameter sharing could leak sensitive information unless mitigations (secure aggregation, differential privacy, or homomorphic encryption) are used. Thus, privacy-preserving learning in IoT systems requires both algorithmic countermeasures (e.g., secure aggregation rules, DP) and operational protection services (authentication, attestation, logging).

Distributed IoT adversarial threats to ML

ML model attacks are beyond traditional network attacks: they can strike the model's training process (poisoning), (Shihab et al., 2024) the model's parameters (backdooring), or the model's decision boundary (evasion). In the distributed or federated configuration, adversarial clients could implement complex poisoning while mixing in regular update traffic and thus become difficult to detect (Sicari et al., 2015; Kairouz et al., 2019). Experiments involving robust aggregation (trimmed mean, median, Krum) and outlier detection on client updates try to counter these attacks; a number of robust algorithms, however, compromise statistical efficiency for robustness and can fail on non-IID data common in IoT nodes. This compromise indicates the necessity for end-to-end methods that combine algorithmic robustness with secure deployment strategies.

Research Design

We use an experimental research design that aims at building and testing a secure Machine Learning Operations framework to continuously deploy cybersecurity models in Internet of Things (IoT) networks. The framework combines federated learning, containerized deployment, and continuous integration/continuous deployment (CI/CD) principles to provide privacy-preserving and scalable intrusion detection in distributed systems.

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Dataset and Preprocessing

The experiment utilized the VeReMi Extended Dataset that provides vehicular communication data for a limited part of IoT environments known for high device mobility and dynamic message exchange. The dataset includes timestamped positional, message frequency, and connectivity features with an emphasis on normal and malicious network behaviour. Preprocessing was done through four successive steps: Data cleaning, using interpolation to deal with missing values; Feature normalization, based on min–max scaling; Dimensionality reduction, via principal component analysis to reduce multicollinearity; Label encoding, to maintain tree-based classifier compatibility.

Random under sampling of majority class, to avoid data imbalance. The resulting dataset was split into 70:30 train test split at every federated client node.

Secure Machine Learning Operations Framework Architecture

The framework architecture consists of three hierarchical layers to enable continuous learning and deployment cycles:

Secure Data Management Layer Deals with encrypted data and distributed storage across IoT nodes. Each node is a standalone client, learning from local data to maintain privacy. Node-to-server and server-to-node communication is secured using transport layer encryption and differential privacy.

Continuous Learning Layer Runs federated learning with XGBoost as the underlying classifier to detect intrusions. Every node trains an individual model and distributes model gradients to the aggregator only. The central server runs the Federated Averaging (FedAvg) for building a global model, which is the process of continuous integration within the Machine learning operations pipeline. Continuous Deployment and Monitoring Layer – The global aggregate model is containerized with Docker and redeployed to all nodes automatically. Seamless update, rollback, and validation throughout the network are achieved through continuous deployment scripts. Monitoring capabilities monitor model drift, latency, and prediction correctness through secure log stores.

Security and Compliance Features

To ensure model integrity when training and deploying, the system employs SHA-256 hashing, role-based authentication, and tamper detection across each iteration of an update. Each model artifact is digitally signed before deployment. Isolation is guaranteed through containerization, so a compromised node will not influence others.

Evaluation Metrics

Performance was measured with accuracy, precision, recall, F1-score, and false positive rate (FPR). Latency and update propagation time were also measured for deployment

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efficacy. Baseline was compared using a centralized XGBoost model that was trained with aggregated data.

RESULTS

Experimental results show the efficiency of the suggested secure Machine Learning Operations framework in having high detection performance while preserving data privacy and automated deployment.

Table 1 shows two systems' ability to identify cyberattacks in IoT networks: The Federated XGBoost model (new, proposed approach) The Centralized XGBoost model (older approach in which all the data are centralized at a single location).

Metric	Federated XGBoost (Proposed Framework)	Centralized XGBoost
Accuracy	96.2%	93.1%
Precision	95.7%	91.4%
Recall	94.9%	90.8%
F1-Score	95.3%	91.1%
FPR	2.1%	4.5%

The proposed system achieved a 96.2% rate of detection, outperforming centralized baseline by approximately 3.1%. The average latency during model update propagation was 1.8 seconds, which is near real-time appropriateness for IoT security use. There were no integrity attacks or privacy violations observed during training and deployment.

Resource utilization analysis indicated distributed training lowered bandwidth overhead by 27% versus centralized learning due mainly to the fact that only model parameters, and not raw data, were transmitted during aggregation.

Latency and Deployment Effectiveness

The median latency of updating five federated clients' model was 1.8 seconds, a figure close to real-time for IoT settings. CI/CD pipelines in the Machine learning operations pipeline enabled retraining and versioning of models, minimizing human intervention needs by 41% compared to non-automated setups. This level of efficiency is in line with existing research findings that secured Machine learning operations pipelines enhance the consistency of edge-based learning deployments (Li et al., 2024).

Resource Utilization and Scalability

Resource utilization comparison (Table 2) showed significant improvement in computational performance and communication overhead. Distributed training lowered

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bandwidth consumption by 27% in comparison to centralized learning since only encrypted model parameters were sent across during aggregation rounds and not raw sensor observations.

Table 2: Resource Utilization Comparison

Parameter	Federated XGBoost (Proposed)	Centralized XGBoost
Average CPU Utilization	64.3%	82.1%
Average Memory Usage	1.7 GB	2.4 GB
Network Bandwidth Consumption	92 MB/round	126 MB/round
Training Time per Round	34.6 s	51.2 s

The findings verify that the secure federated Machine learning operations pipeline provides 32% less training time and 29% better computational efficiency, which is very suitable for low-resource IoT implementations. The system was also stable when scaled from 100 to 1,000 IoT nodes, where the variability of accuracy was kept within ±1.2%, establishing scalability and robustness.

Security and Privacy Validation

50 model poisoning and adversarial attack scenarios were simulated to assess the security layer incorporated into the Machine learning operations pipeline for effectiveness. The framework successfully detected and defended against 48 out of 50 intrusion attacks (96%), with no data leakage or unauthorized model updates identified. Secure aggregation and differential privacy elements also successfully neutralized threats around gradient inversion and membership inference attacks. Furthermore, integrity checking by means of hash-based authentication attained 100% consistency for model validation, making model artifacts tamper-proof through the CI/CD process. This outcome indicates the capability of the framework to provide operational trustworthiness and regulatory compliance for decentralized IoT settings.

Comparative Benchmarking

The performance of the suggested framework was also compared against some of the current secure learning and Machine learning operations frameworks. As evident from Table 3, the Secure Federated XGBoost yielded greater detection accuracy and improved resource optimization compared to current models.

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Table 3: Comparative Performance Analysis

Study/Framework	Model Type	Accuracy (%)	Latency (s)	Remarks
Gurjar et al. (2024)	FedAvg-CNN	91.8	2.6	Higher complexity; limited scalability
Al-Mashhadani et al. (2024)	MLflow-based IDS	92.3	3.4	Centralized; weak privacy layer
Confidence Adimchi et al. (2024)	Hybrid AI-IoT IDS	94.1	2.1	Strong ML accuracy but lacked automated retraining
This Study (2025)	Secure Federated XGBoost (Machine learning operations)	96.2	1.8	High accuracy, real-time adaptability, strong privacy preservation

Error and Drift Analysis

Concept drift analysis indicated that model accuracy fell by about 8.7% when the model was subjected to unrecognized attack patterns. Nevertheless, the Machine learning operations pipeline automated retraining module was able to repair accuracy to 95.8% within 25 minutes when recognized. This demonstrates the system's self-repair capability upon adaptation, which is an essential requirement for real-time IoT cybersecurity operations.

Confusion matrix (Figure 4) demonstrated strong classification of the majority of attacks, though minor misclassifications did occur among Sybil and Replay attacks due to packet timing signatures overlap. This is a weakness that can be mitigated in future work through the use of temporal-spatial feature extraction together with CNN-LSTM hybrid layers.

DISCUSSION

The results confirm the hypothesis that a trusted Machine learning operations -driven federated system can provide scalable, private, and fault-tolerant cybersecurity for IoT networks. Federated learning, differential privacy, and continuous deployment together alleviate threats of centralised data exposure with high predictive reliability.

Besides, gradient boosting compared to deep neural architectures provided computational benefits to tabular traffic IoT data, including higher convergence rates and lower resource usage. These features render the presented system a sustainable operation solution for industrial IoT environments such as medical monitoring systems, smart grids, and autonomous vehicles.

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Integration of Advanced Drift Detection:
Subsequent releases would include adaptive drift detection algorithms like ADWIN or Page-Hinkley to actively catch model degradation prior to significant accuracy loss.

Lightweight Security Extensions:
Homomorphic encryption or secure multiparty computation can provide additional model confidentiality in non-trusted IoT environments.

Hybrid Model Expansion:
A combination of federated gradient boosting with temporal deep learning (e.g., CNN-LSTM) could enhance sequential or timing-based attack detection.

Real-world Deployment Testing:
Deploying the framework in actual IoT testbeds i.e., smart manufacturing or automotive network swill yield empirical evidence under varied connectivity conditions.

Automated Audit Logging and Compliance:
Extending Machine learning operations pipelines to encompass real-time regulatory audit traces (e.g. GDPR or NIST compliance) will put the system in a state of readiness to deploy at an enterprise scale.

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