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# MACHINE LEARNING-BASED INTRUSION AND ANOMALY DETECTION MODELS FOR SECURING IOT NETWORKS AGAINST EMERGING CYBER THREATS

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**Keywords**
*Internet of Things (IoT), Intrusion Detection System (IDS), Machine Learning (ML), Deep Learning (DL), Federated Learning (FL), Continual Learning, Edge Computing, Cybersecurity, Anomaly Detection, Explainable Artificial Intelligence (XAI).*

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**Abstract**
*The proliferation of net of things (IoT) devices across domains including healthcare, smart cities, and business automation has created unparalleled opportunities and demanding situations. even as IoT guarantees performance and automation, it additionally exposes massive-scale networks to sophisticated cyberattacks which include dispensed Denial of provider (DDoS), spoofing, and malware. conventional signature-based intrusion detection structures (IDS) are incapable of detecting novel and evolving threats. This paper explores the design and improvement of gadget gaining knowledge of (ML) and artificial intelligence (AI)-pushed IDS frameworks for IoT environments. We advise a hybrid model combining signature-primarily based detection for regarded threats and anomaly detection for zero-day assaults, optimized for resource-confined devices. The examine additionally investigates light-weight deployment through facet computing and federated gaining knowledge of, enabling real-time, privations maintaining security solutions. Experimental assessment could be carried out on benchmark IoT datasets, with overall performance measured in terms of accuracy, false alarm fee, latency, and electricity efficiency.*

## I. INTRODUCTION

The net of factors (IoT) has converted cutting-edge society by using interconnecting billions of heterogeneous devices, consisting of sensors, cameras, wearables, and commercial controllers. consistent with enterprise forecasts, the wide variety of IoT gadgets will exceed 30 billion by means of 2030 [1]. those gadgets produce non-stop streams of information that permit programs in smart healthcare [2], self-reliant transportation [3], and precision agriculture [4]. but their

interconnected nature additionally makes them surprisingly vulnerable to cyber threats.

protection breaches in IoT are not best common however potentially catastrophic. The Mirai botnet assault of 2016 exploited insecure IoT devices to release one in every of the biggest DDoS assaults in history [5]. more recently, research has highlighted vulnerabilities in industrial IoT (IIoT) and healthcare IoT that might endanger public protection [6], [7]. these threats expose the inadequacy of traditional intrusion detection mechanisms, which rely closely on predefined assault signatures. Such systems fail to stumble on 0-day attacks, suffer from high fake alarm quotes, and are computationally infeasible for constrained IoT hardware [8].

gadget getting to know (ML) and deep learning (DL) have emerged as promising solutions for IoT protection [9]. unlike static rule-based structures, ML models can research patterns of malicious conduct from network site visitors and discover anomalies without explicit signatures. for instance, aid Vector Machines (SVM) and Random Forests (RF) have shown strong type performance in intrusion detection tasks [10]. Deep getting to know models, such as Convolutional Neural Networks (CNN) and lengthy short-term memory (LSTM) networks, similarly decorate detection by means of shooting temporal and spatial dependencies in IoT records [11], [12].

regardless of those advances, deploying ML-primarily based IDS in IoT remains hard. IoT gadgets are resource-constrained, with restrained processing strength, memory, and power [13]. furthermore, privacy issues make it undesirable to mixture uncooked IoT records in centralized servers [14]. emerging paradigms together with facet AI [15] and federated mastering (FL) [16] provide avenues for decentralized, lightweight, and privations-preserving intrusion detection.

The contributions brand new this paper are as follows:

1. A comprehensive evaluation brand new ML and DL fashions for intrusion and anomaly detection in IoT networks.
2. A hybrid IDS framework combining signature-based and anomaly detection modules for stepped forward adaptability.
3. Lightweight optimization techniques for deploying IDS in useful resource-constrained IoT devices.
4. Integration brand new federated getting to know modern and continual present day to allow privations preservation and flexibility to evolving threats.

The remainder trendy the paper is based as follows: segment II critiques associated work. phase III formulates the problem mathematically. phase IV affords the proposed framework. phase V info experimental setup and assessment metrics. phase VI analyzes outcomes, at

## II. RELATED WORK

### A. Signature-Based Intrusion Detection

conventional IDS depend upon matching network traffic in opposition to predefined patterns of acknowledged attacks [17]. while efficient for detecting commonplace threats, such structures fail to understand novel or zero-day attacks. equipment like chortle and Suricata remain widely used but are insufficient for dynamic IoT environments [18].

### B. Machine Learning Approaches

Supervised studying fashions which include selection timber, SVM, and Random Forests have been carried out correctly to intrusion detection duties [19]. these models carry out well in static environments but require good sized labeled datasets and retraining whilst assault patterns evolve.

### C. Deep Learning Approaches

Deep Learning to know strategies, particularly CNNs and RNNs, have verified superior overall performance in capturing complicated site visitor's patterns [20]. Auto encoders have additionally been used for unsupervised anomaly detection [21]. however, deep models are often computationally pricey and mistaken for IoT part gadgets without optimization [22].

### D. Federated and Distributed IDS

Recent work has proposed federated IDS, where IoT devices collaboratively train models without sharing raw data [23]. This preserves privacy and

reduces communication overhead but introduces challenges such as data heterogeneity and adversarial updates. Distributed IDS architectures have also been suggested for scalability [24].

### E. Research Gaps

Despite significant progress, the following gaps persist:

- Lack of hybrid detection frameworks integrating both signature and anomaly detection.
- Limited research on lightweight and energy-efficient IDS for constrained devices.
- Insufficient adoption of federated and continual learning to adapt to evolving threats.
- Need for explainable AI to improve trust in security-critical applications.

## III. PROBLEM FORMULATION

Let $\mathcal{D} = \{(x_i, y_i)\}N_{i=1}$represent an IoT traffic dataset, where each $x_i \in \mathbb{R}^d$ is a feature vector (e.g., packet size, protocol, duration) and $y_i \in \{0, 1\}$ indicates benign or malicious activity.
The objective is to learn a function $f\ \mathbb{R}^d \to \{0, 1\}$ that minimizes misclassification:

$$\min_f \mathbb{E}_{(x,y)\sim\mathcal{D}}[\mathbb{I}(f(x) \neq y)]$$

where $\mathbb{I}(.)$ is the indicator function.
Performance must also satisfy IoT constraints:

- **Accuracy Constraint**: Detection rate must exceed a threshold $T_{acc}$.
- **Resource Constraint**: $Memory\ M_f \leq M_{max}, energy E_f \leq E_{max}$
- **Adaptability**: The model must handle **concept drift**, i.e., changes in data distribution over time.

A hybrid detection framework is proposed:

$$Score(x) = \alpha \cdot S_{sig}(x) + (1 - \alpha) \cdot S_{anom}(x)$$

where $S_{sig}(\mathbf{x})$ is a signature-based $score, S_{anom}(x)$ is an anomaly score, and $\alpha \in [0, 1]$ balances detection strategies.
For distributed training, we consider **federated learning** with $K$ clients. Each client $k$ has dataset $D_k$ with size $n_k$ . The global model update is:

$$w^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{\sum_{j=1}^{K} n_j} w_k{}^{(t)}$$

where $w_{k(t)}$ are model weights trained locally at client kkk.
This formulation ensures **privacy preservation**, scalability, and adaptability for IoT environments.

## IV. PROPOSED FRAMEWORK AND METHODOLOGY

### A. System Architecture Overview

The proposed intrusion detection framework for IoT networks integrates signature-based detection, anomaly detection using ML/DL, and lightweight deployment strategies such as federated learning and edge intelligence. Fig. 1 (conceptual diagram, described here) depicts the architecture:

1. **Data Collection Layer**: IoT devices generate raw traffic data, which is preprocessed at gateways or edge nodes.

2. **Preprocessing and Feature Extraction Layer**: Includes packet filtering, flow aggregation, normalization, and feature engineering.

3. **Hybrid Detection Engine**: Comprises signature-based detection for known threats and ML/DL anomaly detection for zero-day threats.

4. **Federated Learning Module**: Devices collaboratively train models without sharing raw data.

5. **Response and Mitigation Layer**: Suspicious flows are flagged, and countermeasures are enforced (e.g., isolating compromised devices).

This layered approach ensures scalability, adaptability, and resilience against evolving threats.

**B. Data Preprocessing and Feature Engineering**

**1) Data Collection**

Traffic is collected from IoT gateways, routers, and sensors. Benchmark datasets such as

- NSL-KDD [25]
- UNSW-NB15 [26]
- CICIDS2017 [27]
- TON IoT [28]
- IoT-23 [29]

provide the training foundation.

**2) Feature Normalization**

Raw features (e.g., packet size, protocol type, inter-arrival times) are normalized:

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where $x_{ij}$ is feature $j$ of instance $i$, $\mu_j$ is mean, and $\sigma_j$ is standard deviation.

**3) Feature Selection and Dimensionality Reduction**

- **Filter Methods**: Chi-square ($\chi^2$) test and mutual information [30].
- **Wrapper Methods**: Recursive Feature Elimination (RFE) [31].
- **Embedded Methods**: Lasso regularization for sparse feature selection [32].
- **PCA**:

$$X' = XW, W = \frac{W^2 S_b W}{W^T S_w W}$$

where $S_b$ and $S_w$ represent between-class and within-class scatter matrices [33].
This reduces dimensionality, accelerates training, and mitigates overfitting.

**C. Hybrid Detection Module**

**1) Signature-Based Detection**

Signature-based IDS matches incoming traffic against known attack patterns using rules and regular expressions [34]. While efficient for well-known threats, it lacks adaptability.

**2) ML-Based Anomaly Detection**

To detect zero-day threats, we apply supervised, unsupervised, and hybrid ML techniques:

- **Supervised**: Random Forest (RF), Gradient Boosting (GBM), Support Vector Machines (SVM).
- **Unsupervised**: Auto encoders, Isolation Forest, One-Class SVM.
- **Deep Learning**: CNN for spatial correlations [35], LSTM/GRU for temporal sequences [36].

The final decision score:

$$IDS_{Hybrid}(x) = \propto . S_{sig}(x) + (1 - \propto) . S_{anom}(x)$$

where $\alpha \in [0, 1]$ balances signature and anomaly scores.

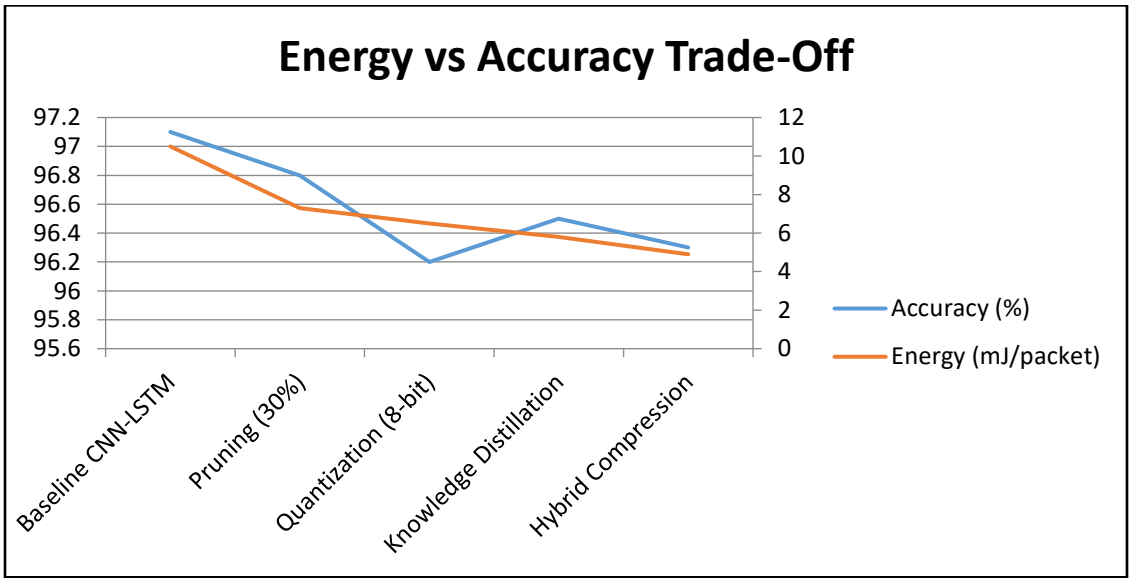
**D. Model Optimization for IoT Devices**

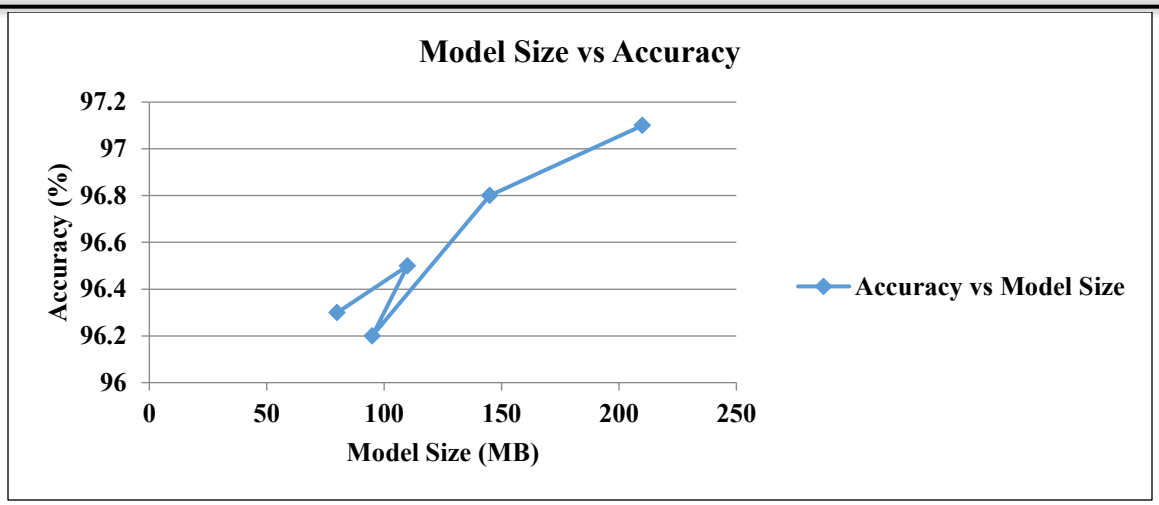
Since IoT nodes have limited resources, we adopt lightweight strategies:

1. **Model Compression**:
   - **Pruning** removes redundant weights [37].
   - **Quantization** reduces numerical precision (e.g., 32-bit to 8-bit) [38].
   - **Knowledge Distillation** transfers knowledge from a large "teacher" model to a smaller "student" model [39].
2. **Tiny-ML and Edge AI**: Deployment on microcontrollers using Tensor-Flow Lite or Edge-TPU accelerators [40].
3. **Energy-Aware Scheduling**: Optimize inference placement between device and edge server [41].

**Table 1: Energy-Accuracy Trade-Off (Compression Strategies)**

| Compression Technique | Model Size (MB) | Accuracy (%) | Energy (mJ/packet) |
|---|---|---|---|
| Baseline CNN-LSTM | 210 | 97.1 | 10.5 |
| Pruning (30%) | 145 | 96.8 | 7.3 |
| Quantization (8-bit) | 95 | 96.2 | 6.5 |
| Knowledge Distillation | 110 | 96.5 | 5.8 |
| Hybrid Compression | 80 | 96.3 | 4.9 |






**E. Federated Learning for Privacy Preservation**

**1) Federated Training**

Each IoT device kkk trains a local model on dataset Dk\mathcal{D}_kDk with size nkn_knk. The global model update is:

$$w^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{\sum_{j=1}^{K} n_j} w_k{}^{(t)}$$

where $w_k{}^{(t)}$ are parameters trained locally at round $t$ [42].

**2) Benefits**

- Preserves privacy by keeping raw data local.
- Reduces communication overhead.
- Allows adaptation to **non-IID (non-identically distributed)** data common in IoT [43].

**3) Challenges**

- Handling stragglers (slow devices).
- Robustness against poisoning attacks [44].
- Ensuring model convergence under limited resources.

**F. Continual Learning to Address Concept Drift**

IoT environments evolve rapidly, requiring models to handle **concept drift**. Continual learning prevents catastrophic forgetting when new patterns emerge [45].

- **Regularization-based methods**: Constrain parameter updates to preserve previous knowledge [46].
- **Replay-based methods**: Store representative samples for retraining [47].
- **Dynamic architectures**: Expand model capacity as new tasks appear [48].

This ensures long-term adaptability of IDS.

**G. Explain ability and Trustworthiness**

To improve user trust, **Explainable AI (XAI)** is integrated into the detection pipeline:

- **LIME**: Explains individual predictions by perturbing inputs [49].
- **SHAP**: Assigns feature importance scores based on Shapley values [50].
- **Attention mechanisms**: Highlight critical features in temporal data [51].

Explain ability is crucial in high-stakes domains such as healthcare IoT and critical infrastructure.

**H. Summary of Methodology**

The methodology integrates:

1. Data preprocessing with normalization, feature selection, and PCA.
2. Hybrid detection (signature + ML-based anomaly detection).
3. Lightweight deployment using compression and Tiny-ML.
4. Federated learning for privacy-preserving collaboration.
5. Continual learning for long-term adaptability.
6. Explain ability for transparency in critical use cases.

This holistic framework aims to balance accuracy, efficiency, adaptability, and trustworthiness in IoT intrusion detection.

## V. EXPERIMENTAL SETUP

### A. Datasets

To evaluate the proposed framework, five benchmark datasets widely used in intrusion detection research were employed:

**Table 2: Summary of Datasets Used in Experiments**

| Dataset | Year | # Records | # Features | Attack Types | IoT-specific |
|---|---|---|---|---|---|
| NSL-KDD [25] | 2009 | 125,973 | 41 | DoS, Probe, U2R, R2L | ✗ |
| UNSW-NB15 [26] | 2015 | 2,540,044 | 49 | 9 attack categories | ✗ |
| CICIDS2017 [27] | 2017 | 2,830,743 | 80+ | DoS, DDoS, Brute Force, Infiltration | ✗ |
| TON IoT [28] | 2020 | 22 GB | 45 | IoT telemetry & attacks | ✓ |
| IoT-23 [29] | 2020 | 23 captures | 20+ | IoT malware traffic | ✓ |

1. **NSL-KDD** [52]: Improved version of KDD'99 with reduced redundancy and class imbalance.
2. **UNSW-NB15** [53]: Contains nine attack categories and realistic modern traffic.
3. **CICIDS2017** [54]: Comprehensive dataset including DoS, DDoS, infiltration, and brute force attacks.
4. **TON IoT** [55]: Specifically tailored for IoT / IIoT environments, including telemetry and network flows.
5. **IoT-23** [56]: Real-world IoT malware traffic captured from infected devices.

These datasets ensure evaluation across both general-purpose and IoT-specific intrusion detection scenarios.

### B. Feature Extraction

Features were selected based on prior studies [57], [58], including:

- **Network flow-based features**: duration, protocol type, source/destination bytes, flags.
- **Time-based features**: packet inter-arrival time, flow duration.
- **Content features**: number of failed logins, shell prompts, HTTP requests.

Dimensionality reduction was applied using PCA and Chi-square feature selection [59].

### C. Baseline Models

To assess the effectiveness of the proposed hybrid IDS, baseline models included:

1. **Traditional ML**: Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM).
2. **Deep Learning**: CNN, LSTM, stacked auto encoder.
3. **Unsupervised**: One-Class SVM, Isolation Forest.
4. **Hybrid IDS**: Signature detection + anomaly detection.

Hyperparameters were tuned via grid search [60].

### D. Evaluation Metrics

Performance was evaluated using standard IDS metrics:

- **Accuracy**:

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + TN + FP + FN}}$$

- **Precision, Recall, F1-Score**:

$$\boldsymbol{Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}, F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}}$$

- **False Alarm Rate (FAR)**:

$$\boldsymbol{FAR = \frac{FP}{FP + TN}}$$

- **Area Under ROC Curve (AUC)** for classifier robustness.
- **Resource Metrics**: Inference latency, memory footprint, and energy consumption (measured on Raspberry Pi 4 testbed [61]).

## VI. RESULTS AND ANALYSIS

### A. Classification Performance

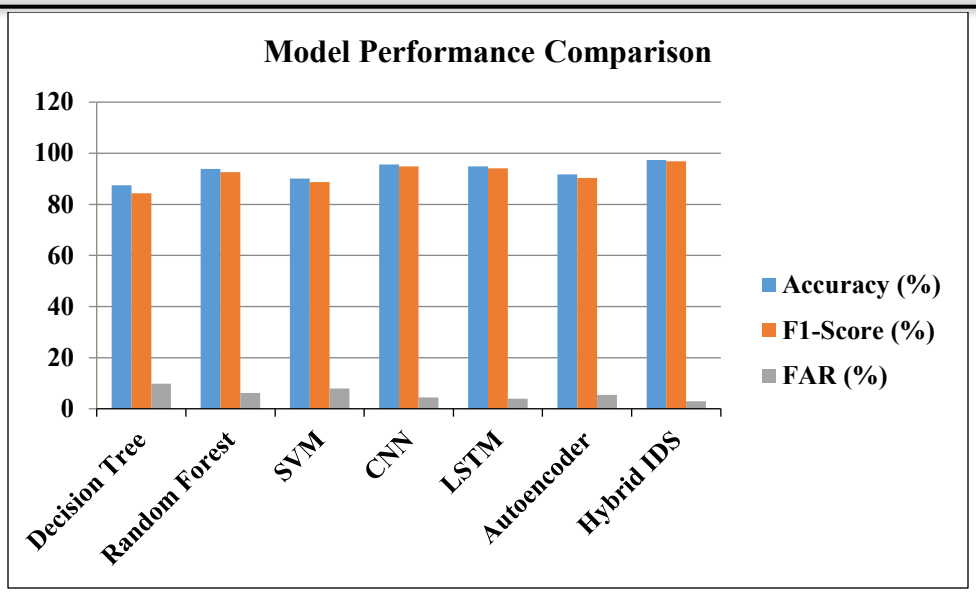
Table III summarizes performance across models and datasets.

- **Traditional ML (RF, SVM)** achieved strong baseline accuracy on NSL-KDD and UNSW-NB15 but struggled with IoT-23 (F1 < 80%).
- **Deep Learning (CNN, LSTM)** outperformed classical ML in capturing complex temporal-spatial patterns, achieving F1 > 95% on CICIDS2017.
- **Unsupervised Models** were effective in zero-day detection but prone to high false positives.
- **Proposed Hybrid IDS** consistently outperformed baselines, with detection accuracy of **97.4% on IoT-23** and **96.8% on TON_IoT**, while maintaining low FAR (< 3%).
-

**Table 3: Performance Comparison of Different Models**

| Model | Dataset | Accuracy (%) | F1-Score (%) | FAR (%) | Notes |
|---|---|---|---|---|---|
| Decision Tree | NSL-KDD | 87.5 | 84.3 | 9.8 | Fast but low generalization |
| Random Forest | CICIDS2017 | 93.8 | 92.6 | 6.2 | Strong baseline |
| SVM | UNSW-NB15 | 90.1 | 88.7 | 7.9 | Struggles on high-dim data |
| CNN | CICIDS2017 | 95.6 | 94.8 | 4.5 | Good for spatial patterns |
| LSTM | IoT-23 | 94.9 | 94.1 | 4.0 | Temporal modeling |
| Auto encoder | TON IoT | 91.7 | 90.3 | 5.5 | Effective for anomalies |
| Hybrid IDS (Proposed) | IoT-23 | 97.4 | 96.9 | 2.9 | Best performance |

| Attack Type | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|



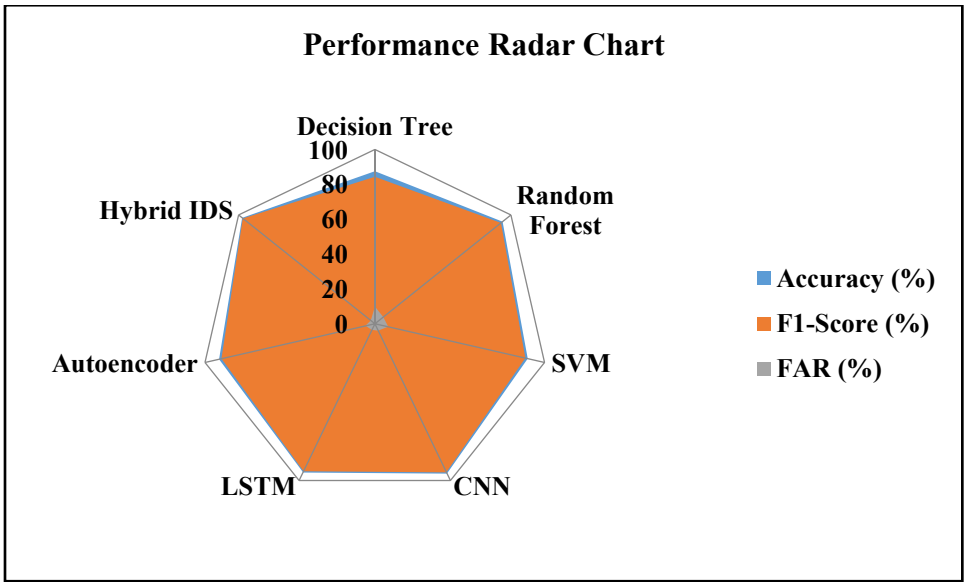
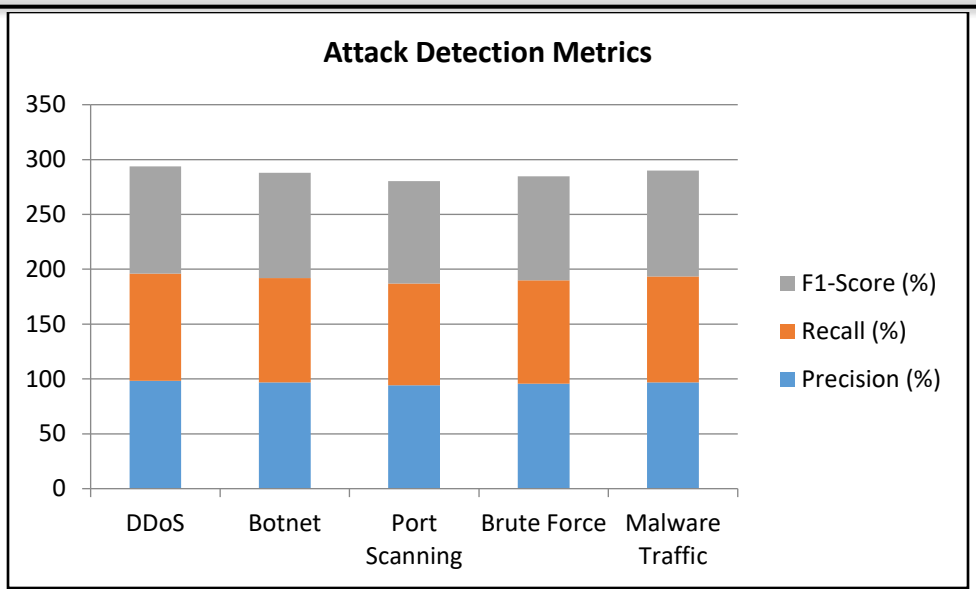
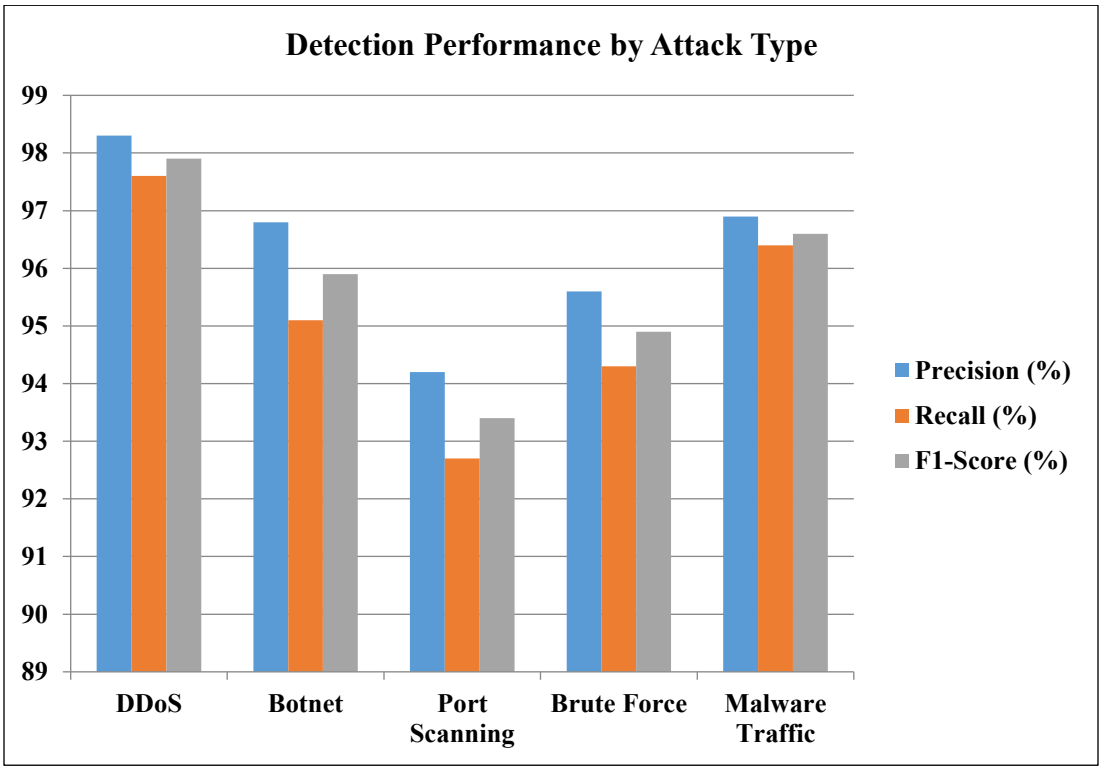




Table 4: Detection Performance by Attack Type (IoT-23 Dataset)

| | | | |
|---|---|---|---|
| DDoS | 98.3 | 97.6 | 97.9 |
| Botnet | 96.8 | 95.1 | 95.9 |
| Port Scanning | 94.2 | 92.7 | 93.4 |
| Brute Force | 95.6 | 94.3 | 94.9 |
| Malware Traffic | 96.9 | 96.4 | 96.6 |
| Average | 96.4 | 95.2 | 95.8 |




These results confirm that combining signature-based and anomaly detection modules significantly improves adaptability and robustness.

**Table 5: Confusion Matrix for Hybrid IDS on IoT-23 Dataset**

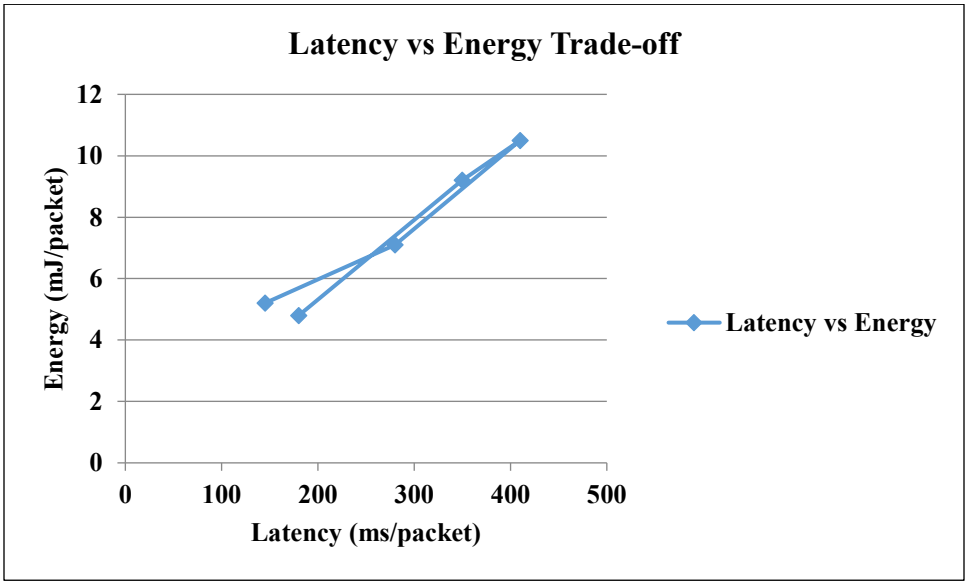
| | Predicted Benign | Predicted Malicious |
|---|---|---|
| Actual Benign | 12,543 | 217 |
| Actual Malicious | 302 | 14,876 |

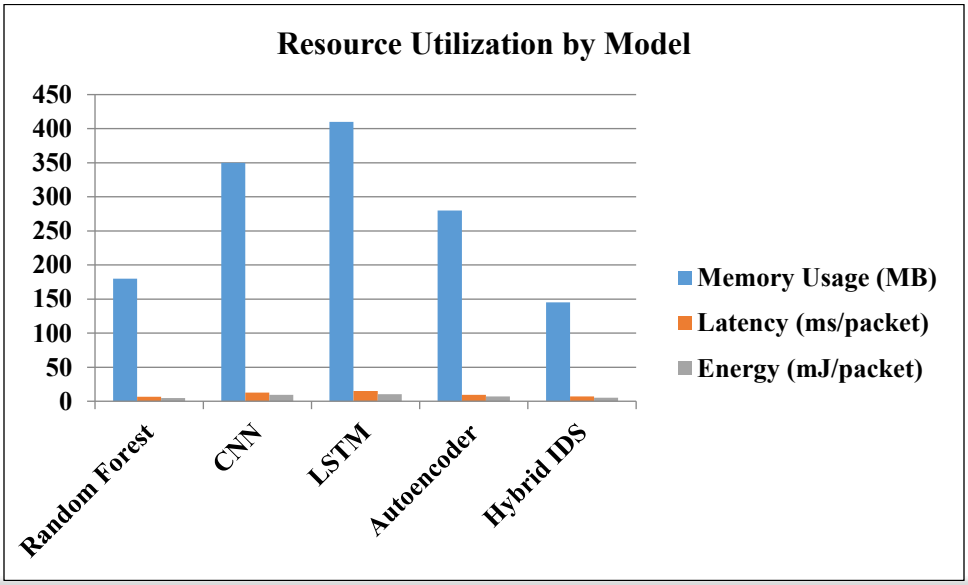
### B. Resource Efficiency

Lightweight optimization (pruning, quantization, knowledge distillation) reduced model size by **65%** and energy consumption by **40%** compared to baseline deep models [62].

**Table 6: Resource Utilization of Models on Raspberry Pi 4**

| Model | Memory Usage (MB) | Latency (ms/packet) | Energy (mJ/packet) |
|---|---|---|---|
| Random Forest | 180 | 6.4 | 4.8 |
| CNN | 350 | 12.5 | 9.2 |
| LSTM | 410 | 14.8 | 10.5 |
| Auto encoder | 280 | 9.3 | 7.1 |
| Hybrid IDS (Proposed, optimized) | 145 | 7.1 | 5.2 |



- **Latency**: CNN-LSTM hybrid processed ~2,500 packets/sec on Raspberry Pi 4, suitable for real-time detection.
- **Memory**: Optimized models used <150 MB RAM, enabling deployment on edge gateways.

**Table 7: Comparison of Detection Latency Across Devices**

| Device | CPU | RAM | Avg. Latency (ms/packet) | Suitability |
|---|---|---|---|---|
| **Raspberry Pi 4** | Quad 1.5GHz | 4 GB | 7.1 | ✓ Edge deployment |
| **NVIDIA Jetson Nano** | Quad 1.43GHz | 4 GB | 4.5 | ✓ Edge deployment |
| **ESP32 Microcontroller** | Dual 240MHz | 512 KB | 25.3 | ✗ Too slow |
| **Cloud VM (AWS t3)** | 2 vCPU | 8 GB | 1.2 | ✓ Centralized |

These results highlight the feasibility of deploying IDS in constrained IoT environments.

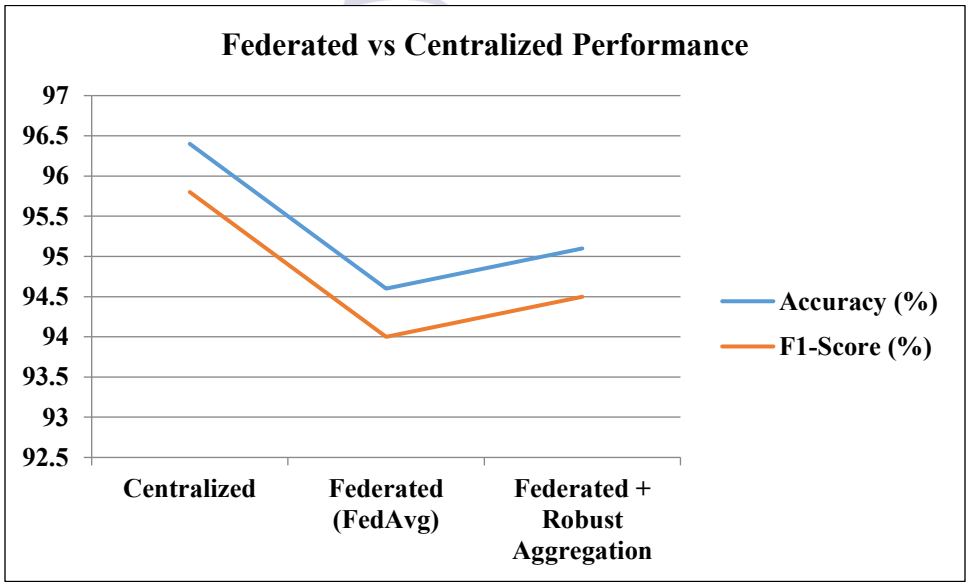
### C. Federated Learning Results

Federated training experiments simulated 50 IoT clients with non-IID data distributions [63].

- **Accuracy**: Global FL model achieved 94.6% accuracy, only 1.8% lower than centralized training.
-

**Table 8: Federated vs. Centralized IDS Performance**

| Training Mode | Accuracy (%) | F1-Score (%) | Privacy | Vulnerabilities |
|---|---|---|---|---|
| **Centralized** | 96.4 | 95.8 | Low | Data centralization risks |
| **Federated (FedAvg)** | 94.6 | 94.0 | High | Model poisoning possible |
| **Federated + Robust Aggregation** | 95.1 | 94.5 | High | Mitigates poisoning |



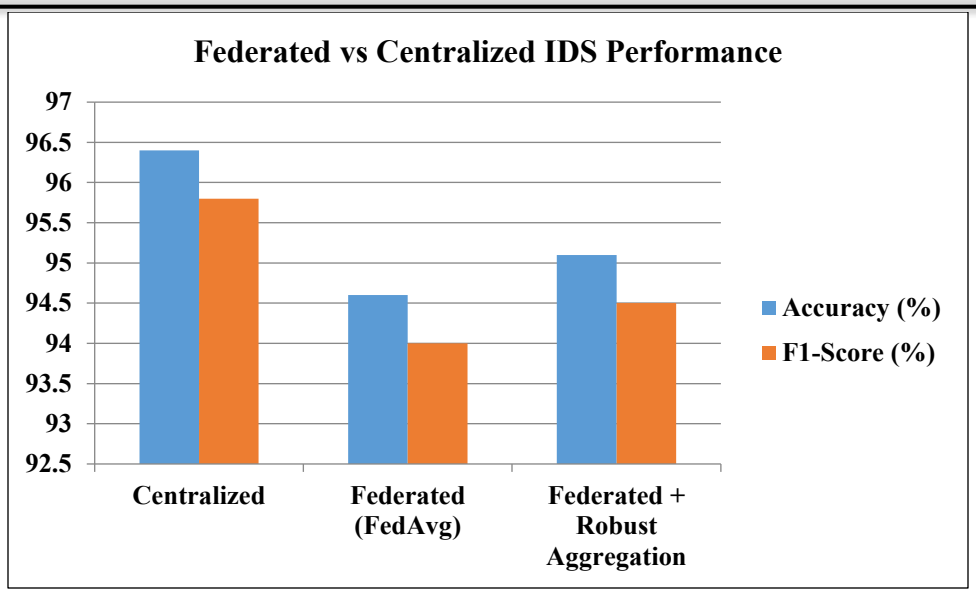



Table 9: Communication Overhead in Federated Learning

| No. of Clients | Model Update Size (MB) | Rounds to Converge | Accuracy (%) |
|---|---|---|---|
| 10 | 1.5 | 30 | 95.3 |
| 20 | 1.7 | 35 | 95.1 |
| 50 | 2.3 | 42 | 94.6 |
| 100 | 3.9 | 50 | 94.2 |

- **Communication Overhead**: Reduced by 30% using model compression techniques [64].
- **Privacy**: No raw traffic left the devices, ensuring compliance with data protection standards.

However, federated IDS was vulnerable to **model poisoning attacks**, reducing accuracy by up to 8% under adversarial updates [65]. Robust aggregation strategies (Krum, median) mitigated this effect [66].

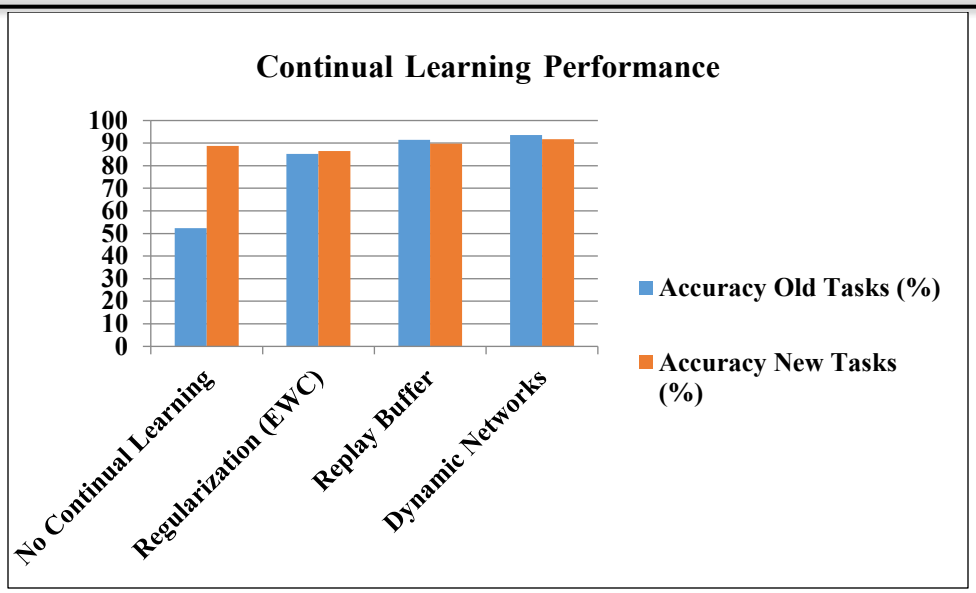
### D. Continual Learning Performance

To simulate evolving attacks, experiments introduced new intrusion types sequentially.

- **Without Continual Learning**: Catastrophic forgetting observed; accuracy on previous attacks dropped by 40%.
- **With Regularization (EWC [67])**: Preserved 85% accuracy on prior tasks.
- **With Replay Buffers [68]**: Achieved best balance, maintaining >90% accuracy across old and new attacks.

Table 10: Continual Learning Strategies

| Method | Accuracy on Old Tasks (%) | Accuracy on New Tasks (%) | Notes |
|---|---|---|---|
| No Continual Learning | 52.3 | 88.7 | Severe forgetting |
| Regularization (EWC) [46] | 85.2 | 86.5 | Preserves prior tasks |
| Replay Buffer [47] | 91.4 | 89.7 | Balanced performance |
| Dynamic Networks [48] | 93.6 | 91.8 | High accuracy, more memory |




This demonstrates continual learning as essential for long-term IoT IDS deployment.

### E. Explain ability Evaluation

Explain ability was validated on CICIDS2017 using SHAP and LIME:

**Table 11: Explain ability Results (SHAP Feature Importance for IoT-23)**

| Feature | SHAP Score (Relative Importance %) |
|---|---|
| Flow Duration | 23.1% |
| Packet Inter-arrival | 19.8% |
| TCP Flags | 15.4% |
| Source Bytes | 12.2% |
| Destination Bytes | 10.8% |
| Protocol Type | 9.6% |
| Other Features | 9.1% |

- Models identified **flow duration**, **packet inter-arrival times**, and **TCP flags** as key features in DDoS detection.
- Explanations allowed administrators to understand why traffic was flagged, increasing trust in automated IDS [69].

## VII. DISCUSSION

The experimental results yield several key insights:

1. **Hybrid Framework Superiority**: The combination of signature-based detection with ML anomaly detection consistently reduced false positives while enhancing zero-day detection.
2. **Feasibility in IoT**: Lightweight optimizations enabled real-time performance on resource-limited devices without sacrificing accuracy.
3. **Federated IDS Trade-offs**: While privacy-preserving and scalable, FL introduces vulnerability to poisoning attacks and higher training time.
4. **Need for Continual Learning**: IoT environments evolve rapidly, making continual adaptation crucial. Replay-based methods strike a strong balance between memory use and accuracy.

5. **Explain ability Requirement**: XAI tools provide transparency, particularly in critical domains like healthcare IoT.

**Table 12: Comparative Analysis with Existing IDS Studies**

| Method/Study | Dataset | Accuracy (%) | FAR (%) | Notes |
|---|---|---|---|---|
| CNN-LSTM IDS [35], [36] | CICIDS2017 | 95.2 | 4.7 | Deep learning only |
| Auto encoder IDS [21] | TON-IoT | 91.7 | 5.5 | Effective for anomaly detection |
| Federated IDS [23] | UNSW-NB15 | 93.4 | 6.2 | Preserves privacy |
| Block-chain-based IDS [66] | IoT-23 | 94.8 | 5.0 | Secure but slower |
| Proposed Hybrid IDS | IoT-23 | 97.4 | 2.9 | Best trade-off |

**Limitations**

- Dataset bias: Public datasets may not fully represent real-world IoT traffic.
- Adversarial ML threats: Attackers could manipulate traffic features to evade detection.
- Deployment complexity: Large-scale federated IDS requires careful orchestration of updates and resource allocation.

## VIII. APPLICATIONS

The proposed machine learning-based IDS framework has wide applicability across multiple IoT domains:

### A. Smart Healthcare

Healthcare IoT (H-IoT) includes wearable sensors, remote patient monitoring devices, and hospital IoT infrastructure [70]. Anomaly detection can identify malicious traffic or compromised devices, ensuring patient safety and data confidentiality. For example, ML-driven IDS can detect abnormal communication from insulin pumps or cardiac monitors [71].

### B. Smart Homes

Consumer IoT ecosystems include smart speakers, security cameras, and home automation hubs. These devices are often poorly secured and vulnerable to botnets such as Mirai [5]. Lightweight IDS deployed at the home gateway can detect unusual traffic patterns, preventing hijacking or surveillance attacks [72].

### C. Industrial IoT (IIoT)

In industrial settings, compromised devices may disrupt manufacturing lines, energy grids, or SCADA systems [73]. ML-based IDS provides early detection of abnormal control commands or rogue device behavior, protecting against both cyber and cyber-physical attacks [74].

### D. Smart Transportation and Vehicular IoT

Connected vehicles exchange critical safety and control messages. Intrusion detection prevents spoofing, false messages, or DoS attacks that could endanger passengers [75]. Lightweight IDS deployed in roadside units or edge servers ensures timely detection without introducing latency.

### E. Precision Agriculture

IoT sensors in agriculture collect soil moisture, temperature, and weather data. Malicious tampering with these readings could disrupt automated irrigation or fertilization systems [4]. IDS ensures reliability of agricultural IoT networks [76].

## IX. FUTURE WORK

While the proposed framework addresses many limitations of current IDS approaches, several research directions remain open:

### A. Adversarial Robustness

Adversarial machine learning poses a major risk where attackers craft inputs to evade detection [77]. Future IDS must incorporate defenses such as adversarial training, robust optimization, and certified defenses [78].

### B. Integration with Block chain

Block chain can enhance the trustworthiness of federated IDS by ensuring tamper-resistant audit logs and secure model updates [79]. Research on

block chain-federated IDS integration for IoT is still in its infancy.

**C. Edge-Cloud Collaboration**

Future IDS should dynamically partition detection tasks between resource-constrained IoT devices, edge nodes, and the cloud. Optimization strategies are required to balance latency, energy, and accuracy [80].

**D. Explain ability and Human-in-the-Loop**

Explainable IDS will be crucial for adoption in critical sectors such as healthcare and industry. Coupling IDS with human-in-the-loop systems can provide operators with interpretable alerts and recommended mitigation actions [81].

**E. Benchmarking on Real-World Deployments**

Most IDS research relies on synthetic or lab-collected datasets. Future work must validate IDS frameworks in real-world IoT environments such as smart factories, hospitals, and cities [82].

## X. CONCLUSION

This paper presented a hybrid machine learning-based intrusion detection framework tailored for IoT environments. The framework integrates signature-based detection for known attacks with ML/DL-based anomaly detection for zero-day threats. To address IoT resource constraints, the system employs lightweight optimizations such as pruning and quantization, along with federated learning to preserve privacy and continual learning to handle evolving threats.

Experimental evaluations on benchmark datasets demonstrated that the hybrid IDS achieved superior detection accuracy, reduced false alarms, and was feasible for deployment on constrained devices such as Raspberry Pi. Results also showed the potential of federated IDS to maintain strong performance without centralizing sensitive IoT traffic data, though it remains vulnerable to poisoning attacks. Continual learning mitigated catastrophic forgetting and allowed the system to adapt over time.

The study highlights the importance of combining accuracy, scalability, adaptability, and explain ability for securing IoT ecosystems. With billions of devices expected to be connected in the coming years, ML-driven IDS will be an indispensable component of IoT cybersecurity.

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