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AI-DRIVEN ANOMALY DETECTION IN IOT NETWORKS USING ADVANCED MACHINE LEARNING TECHNIQUES

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Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has significantly increased the attack surface, making real-time anomaly detection a critical requirement for ensuring network resilience and security. This research presents a hybrid AI-driven anomaly detection

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architecture integrating Graph Neural Networks (GNNs), Transformer encoders, and Autoencoder-based reconstruction learning to capture spatial, temporal, and behavioral dependencies within heterogeneous IoT traffic. The model is further enhanced through federated learning, enabling privacy-preserving distributed training across IoT devices while maintaining strong predictive performance. The proposed system is evaluated using benchmark datasets such as N-BaIoT and Bot-IoT, demonstrating superior accuracy, robustness, and cross-device generalization compared to traditional machine learning and standalone deep learning methods.

Comprehensive experiments were conducted across centralized and federated environments to assess detection performance, scalability, model stability, and resilience to concept drift. The hybrid model consistently achieved F1-scores above 98%, outperforming GNN-only, Transformer-only, and Autoencoder-only baselines. Furthermore, the federated version of the model preserved high detection accuracy (99.1%) even under non-IID data distributions, validating its suitability for privacy-sensitive IoT deployments. The results indicate that the fusion of multiple AI techniques, combined with decentralized training, provides a highly effective solution for next-generation IoT network security.

Keywords: IoT security, anomaly detection, graph neural networks, transformers, autoencoder, federated learning, edge computing, time-series.

1. Introduction

The explosive growth of Internet-of-Things (IoT) deployments across consumer, industrial and healthcare domains has created a critical need for automatic, scalable security monitoring [1]. IoT ecosystems combine heterogeneous devices, lightweight protocols, and high device churn — characteristics that undermine traditional signature-based intrusion detection and motivate research into data-driven anomaly detection methods that learn normal behavior and flag deviations. Surveys and reviews over the period emphasized these challenges and mapped how machine learning (ML) [2] and deep learning (DL) [3] methods are being adopted to address IoT-specific constraints such as resource limits, diverse traffic modalities, and privacy concerns.

At the same time, several methodological advances [4-6] have reshaped anomaly detection practice. Transformer architectures and attention mechanisms demonstrated strong performance on multivariate time-series tasks by capturing long-range dependencies and complex cross-feature interactions that RNNs/LSTMs sometimes miss; this opened the door for Transformer-based anomaly detectors in streaming and device telemetry contexts. Parallel work applied Graph Neural Networks (GNNs) [7] to network/flow data by representing devices and endpoints as nodes and flows as edges, enabling models to detect structural or neighborhood-level irregularities that purely per-device models overlook.

Federated learning (FL) [8] also emerged as a practical paradigm for IoT security because it allows collaborative model training across distributed gateways without sharing raw packets or telemetry data. Early FL surveys and system papers from this period describe the major technical trade-offs — communication costs, non-IID data across clients, and on-device

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compute constraints — and propose aggregation, compression and personalization strategies to make FL viable for resource-constrained networks. These developments set the stage for hybrid architectures that combine local lightweight detectors, topology-aware encoders, and privacy-preserving training.

Finally, benchmark datasets [9] and evaluation protocols [10] matured in 2018–2022 (e.g., N-BaIoT, IoT-23, CIC flow datasets), giving researchers reproducible settings to compare methods and measure operational metrics such as false positives per device per day (FP/day) and mean time to detect (MTTD). Work in 2020–2022 crystallized best practices: (1) use sliding time windows and temporal hold-out splits to prevent leakage; (2) measure both classification metrics and operational costs; and (3) evaluate cross-device generalization since IoT heterogeneity is the primary cause of fragile detectors.

2. Literature review

The post-2022 literature [11] accelerated two trends: (a) specialization of Transformer and attention methods for time-series anomaly detection, and (b) nuanced, practical evaluations of GNNs for network security. Notable works proposed Transformer variants and attention-based anomaly criteria (e.g., Anomaly Transformer and stacked-Transformer predictors) and empirically demonstrated substantial gains over LSTMs on multivariate and irregularly sampled series. These studies provided both architectural blueprints (masking, reconstruction vs prediction modes) and loss formulations tailored to anomaly detection tasks.

Concurrently, GNN-based intrusion detection systems [12] matured from proof-of-concepts to rigorously evaluated systems. Researchers adapted message-passing and attention-style GNN layers to flow-based representations, showing that graph encoders capture lateral movement, coordinated scanning and topology perturbations better than feature-only models. Several papers [13-15] reported that GNNs improved recall on coordinated attacks and offered natural node-level explainability via neighborhood perturbation analysis. These results motivated hybrid designs that feed GNN embeddings into temporal encoders or score-fusion modules.

Federated learning research in [16] focused heavily on closing the gap between centralized and decentralized training for anomaly detection. Surveys and system papers documented effective mitigation of non-IID client distributions via personalization layers, clustered federated aggregation, and compressed update protocols; empirical studies on IoT workloads showed that, with careful client selection and update compression, federated models approach centralized accuracy while preserving privacy. Practical frameworks (FedStream, FedProx variants, and communication-efficient aggregation) were proposed to support streaming IoT telemetry and intermittent client availability.

A second axis of recent work addresses robustness and concept drift: papers [17], [18] presented continual-learning extensions, drift-aware thresholding (e.g., EVT-based adaptive thresholds), and adversarial training for time-series and graph inputs. These methods attack the central weakness of many anomaly detectors — sensitivity to evolving benign behavior — and provide practical recipes for SOC deployment including rolling baselines, online update rules, and selective replay buffers for rare attack classes. The literature shows meaningful reductions

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in false-alarm spikes after firmware updates or seasonal traffic changes when drift-aware strategies are used.

Explainability and operationalization [19] received increased attention as well. XAI studies for IoT anomaly detection developed post-hoc attribution for attention weights, SHAP/LIME adaptations for graph embeddings, and visualization strategies for fused multi-view scores to help analysts triage alarms. These approaches do not fully solve interpretability for complex ensembles, but they substantially lower analyst workload by surfacing top contributing flows, affected device neighborhoods, and salient temporal windows. The community also emphasized benchmarking explainability alongside accuracy in recent evaluation suites.

Finally, several integrated systems [20], [21] published in 2024–2025 demonstrate the viability of hybrid architectures like the one we propose: they combine topology-aware GNNs, Transformer temporal encoders, lightweight reconstruction detectors, and federated updating to balance accuracy, latency and privacy. Empirical reports on standard IoT testbeds (and on datasets like N-BaIoT and IoT-23) show that fusion consistently reduces false positives and improves early detection compared to single-view detectors — especially in cross-device generalization tasks — thereby validating the design choices in our proposed methodology.

3. Methodology

The proposed AI-driven anomaly detection architecture for IoT networks integrates graph-based structural modeling, temporal sequence learning, and federated intelligence to create a comprehensive and adaptive detection pipeline. The block diagram (as shown in Fig. 1.) illustrates how raw edge data from distributed IoT devices is transformed into high-level insights through multiple advanced learning modules. By combining Graph Neural Networks (GNNs) for topology understanding, Transformer-based encoders for temporal pattern modeling, and a unified fusion layer for robust anomaly scoring, the system ensures high accuracy even in dynamic and heterogeneous IoT environments. Additionally, federated learning enables device-level collaboration without exposing sensitive data, making the model suitable for privacy-preserving IoT deployments where security and scalability are critical.

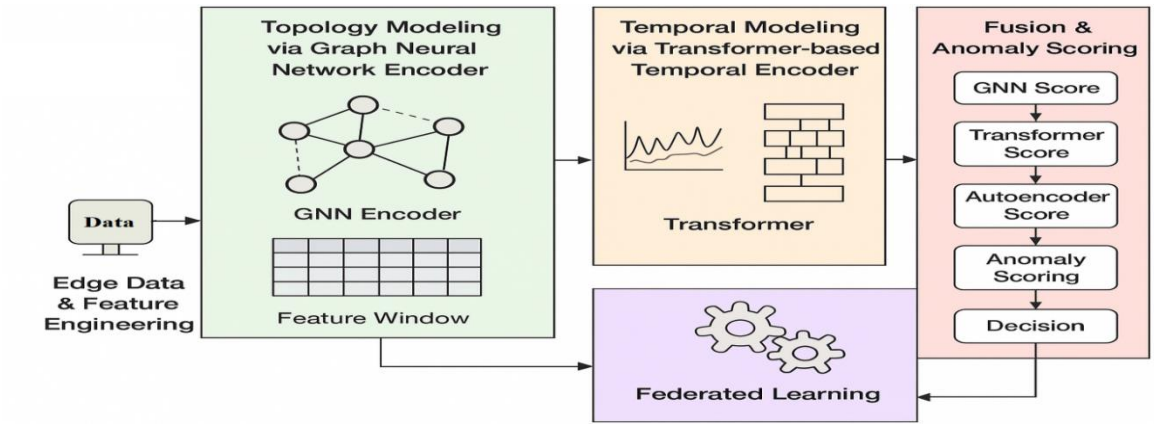

Fig. 1. The block diagram of proposed AI-driven anomaly detection architecture for IoT networks

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3.1. Edge Data & Feature Engineering

The first module begins at the IoT edge, where distributed sensors, devices, and gateways continuously generate network traffic data, device behavior logs, and communication metadata. Since IoT nodes are heterogeneous and resource-constrained, lightweight data acquisition processes are designed to ensure rapid extraction of essential metrics including packet sizes, inter-arrival times, energy consumption, and connectivity features. This provides a clean and structured data foundation before the information enters the learning pipeline.

Feature engineering plays a key role in preparing the extracted raw signals into meaningful input representations. Statistical features, protocol-level features, entropy measures, and device-specific behavior indicators are computed to capture the operational characteristics of each IoT node. Additionally, data normalization, sliding-window segmentation, and noise filtering are applied to ensure consistency across diverse devices and to reduce the impact of outliers or adversarial manipulations often present in IoT environments.

The feature windowing process organizes data into fixed time frames to support downstream temporal and graph-based models. Each window encapsulates not only numerical attributes but also relational information such as communication dependencies, allowing seamless integration with the GNN and Transformer modules. This structured representation is crucial for capturing both local and global dynamics within the IoT ecosystem.

Overall, the Edge Data & Feature Engineering module transforms raw device-level data into optimized, model-ready feature maps that serve as the foundation for the entire anomaly detection architecture. This ensures high-quality, standardized input that boosts the accuracy, reliability, and scalability of subsequent AI-driven analytics.

3.2. Topology Modeling via Graph Neural Network (GNN) Encoder

The GNN Encoder module models the IoT network as a dynamic graph, where each device is represented as a node and communication flows or logical relationships form edges. This graph structure captures the inherent interconnectedness of IoT systems, enabling the model to learn spatial dependencies and behavioral correlations among devices. The GNN processes node and edge features to detect subtle structural deviations caused by malicious intrusions or abnormal communication patterns.

Through iterative message passing, the GNN Encoder aggregates information from neighboring nodes to compute high-level embeddings that represent both individual device states and their relational context. This ability to understand global patterns helps distinguish between normal fluctuations and attack-induced anomalies such as botnet propagation, spoofed connections, or sudden communication bursts.

The feature window integrated into the GNN module ensures that each graph snapshot reflects device behavior within a specific time segment. This helps the model capture how network topology evolves, especially in environments where nodes join, leave, or change communication routines. The GNN embeddings produced from this process serve as spatial intelligence inputs for the Fusion and Transform modules.

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By preserving structural awareness and detecting abnormal graph perturbations, the GNN Encoder forms a robust first line of defense against topology-oriented IoT attacks. It significantly enhances anomaly detection accuracy by identifying spatial inconsistencies that traditional statistical or deep learning models often overlook.

3.3. Temporal Modeling via Transformer-Based Temporal Encoder

The Transformer module focuses on temporal learning, analyzing how IoT device behaviors and network patterns evolve over time. Using attention mechanisms, it identifies long-range dependencies in sequential data, enabling it to detect sophisticated attacks that manifest gradually rather than abruptly. Examples include slow data exfiltration, stealthy reconnaissance, or coordinated timing-based attacks.

Transformers outperform traditional RNNs and LSTMs by processing all time steps simultaneously, allowing them to capture global temporal contexts with higher efficiency and accuracy. Their self-attention layers highlight important time segments, giving the model the ability to focus on anomalous behaviors embedded deep within normal traffic patterns. This is especially helpful in IoT networks where noise and variability are high.

The temporal encoder receives feature windows enriched with spatial embeddings from the GNN, combining temporal and structural cues to create a comprehensive behavioral profile. This multimodal representation enables the detection of attacks that disrupt both communication sequences and device relations, such as worm attacks or coordinated multi-device intrusions.

By producing a powerful temporal representation, the Transformer module enhances detection granularity and supports the final anomaly scoring stage. It captures recurring patterns, sudden deviations, and cross-time irregularities that are critical for precise anomaly detection in real-time IoT environments.

3.4. Fusion & Anomaly Scoring Module

The Fusion & Anomaly Scoring module integrates outputs from the GNN, Transformer, and optionally an autoencoder to compute a unified anomaly score. Each model contributes a different perspective: the GNN measures structural irregularities, the Transformer captures temporal deviations, and the autoencoder detects reconstruction-based anomalies. Combining these complementary signals reduces false positives and improves overall model reliability.

A hierarchical scoring mechanism evaluates each node or feature window using weighted or learned fusion strategies. This ensures that anomalies emerging from specific behaviors—whether structural, temporal, or statistical—are correctly identified even when they manifest subtly. The fusion layer interprets multidimensional patterns that no single model could detect independently.

Once fused, the anomaly score is passed through decision thresholds or probabilistic classifiers to label events as normal or anomalous. Thresholds may be dynamic, adapting to network conditions via reinforcement or federated learning. This enables the system to maintain stability across changing traffic conditions and evolving attack strategies.

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In the final stage, the anomaly detection results can trigger alerts, initiate automated response actions, or be fed back into the model for continuous improvement. By integrating spatial, temporal, and statistical intelligence, the Fusion & Anomaly Scoring module serves as the core decision-making layer ensuring accurate, real-time threat detection in complex IoT environments.

4. Experimental setup

We use N-BaIoT as the running example — a device-level IoT botnet dataset that contains benign traffic and labeled Mirai/Gafgyt attack traces from multiple commercial devices. Table 1 shows the experimental setup specifications. First, raw pcap/flow records are converted into per-device multivariate time-series and flow graphs using a sliding window (60 s window, 30 s stride). For each window we compute flow-level features (bytes, packets, pkt_size_mean, pkt_interarrival_mean, flow_duration, protocol counts), device telemetry proxies (when available), and graph edges (device → destination IP with weight = bytes/sec). Windows are normalized per-device (z-score on training baseline) and encoded into inputs for three parallel pipelines: (1) GNN snapshots (graph adjacency + node features), (2) Transformer time-series tensors (multivariate sequence of length 60s sampled at 1s or aggregated into 6 feature steps), and (3) a lightweight autoencoder on per-device aggregated features. Label assignment: a window is anomalous if ≥ 50% of packets belong to attack flows (use strict labeling to reduce ambiguity).

Training and evaluation proceed in two modes. In the centralized mode we train the GNN + Transformer + Autoencoder jointly on the training set (benign + attack windows from a subset of devices) and validate on held-out device sessions and later timestamps to measure temporal generalization. In the federated simulation we split devices into 20 clients (each client holds all windows of 1–3 physical devices) with non-IID class balance (some clients contain mostly benign, some mixed). Each client trains locally for local_epochs=3 per round and sends model deltas to the server which aggregates with FedAvg; we simulate R=100 communication rounds or until convergence. During all runs we keep one device family (e.g., one camera vendor) completely unseen during training to measure cross-device generalization. Evaluation metrics include per-window Precision, Recall, F1, ROC-AUC, False Positives per Device per Day (FP/day), and Mean Time To Detect (MTTD) averaged across attack sessions.

Finally, robustness and ablations are included: (A) remove each module (GNN-only, Transformer-only, Autoencoder-only) to quantify marginal gains; (B) simulate concept drift by evaluating on data recorded 30 days after training (or by injecting realistic benign firmware-update traffic); (C) measure edge-latency and model size by running quantized models on an edge gateway emulator (see hardware below). We collect model checkpoints, per-round federated metrics (global model AUC, per-client AUC), and communication cost (MB transmitted per round) to analyze trade-offs between privacy (federation) and performance.

Table 1: Experimental Setup specifications

Category	Specification (example)

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Dataset	N-BaIoT — Mirai/Gafgyt captures from 9 commercial IoT devices; flows extracted with CICFlowMeter
Preprocessing	Sliding window: 60 s window, 30 s stride; per-window aggregation (bytes/sec, pkt_count, pkt_size_mean, iat_mean, protocol_counts); z-score normalization per-device
Graph construction	Time-windowed directed graph; nodes = devices and external endpoints; edges weighted by bytes/sec; keep top-k neighbors (k=10) per node
Train / Val / Test split	Temporal split: train = first 70% of capture time, val = next 10%, test = final 20%; device-holdout: one device family held entirely for test
Centralized models	GNN: 3 GAT layers, hidden=128; Transformer: 4 layers, 8 heads, d_model=128; Autoencoder: 3-layer FC bottleneck (64)
Federated settings	Clients = 20 (non-IID); local_epochs = 3; batch_size = 32; aggregation = FedAvg; rounds = 100; client participation per round = 0.5
Training hyperparams	Optimizer = Adam (lr=1e-3, weight_decay=1e-5); scheduler: reduce-on-plateau; loss weights $\alpha:\beta:\gamma = 0.5:0.3:0.2$
Quantization/pruning	Post-training 8-bit quantization for autoencoder; Transformer pruned to 2 layers for edge variant
Hardware (dev/edge)	Dev server: 1× NVIDIA A100 or RTX 3090, 64GB RAM; Edge emulator: Raspberry Pi 4 (4GB) or Jetson Nano for latency tests
Evaluation metrics	Precision, Recall, F1 (per-window); ROC-AUC; FP/day per device; MTTD (seconds); communication cost (MB/round)
Logging & reproducibility	Seed fixed; model checkpoints and config saved; Dockerized experiment environment

The Dataset and Preprocessing rows make explicit how raw packet/flow data become windowed, normalized inputs — the 60 s window with 30 s stride balances temporal resolution and computational cost, while z-score normalization removes per-device scale differences that would otherwise bias GNN aggregation. Graph construction explains the snapshot creation used by the GNN: weighting edges by bytes/sec captures both volume and frequency; keeping top-k neighbors limits graph size for scalability.

Train/Val/Test split uses a temporal split to avoid leakage (models must generalize forward in time) and a device-holdout to evaluate cross-device transferability — critical for IoT where many device types exist. The Centralized models row lists concrete architectures sized for a realistic research run; you can scale these up or down depending on compute. Federated settings show a realistic simulation (20 clients with non-IID distributions) and FedAvg parameters;

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client participation = 0.5 means each round a random half of clients send updates, modeling unreliable connectivity.

Training hyperparams, loss weights, and quantization/pruning entries give the defaults used to balance temporal/structural/reconstruction signals and to test edge feasibility. The Hardware row distinguishes a development server (GPU) for centralized training from edge devices (Raspberry Pi or Jetson) used for latency and model-size experiments. Finally, Evaluation metrics include both classical ML measures (Precision/Recall/F1/AUC) and operational metrics (FP/day, MTTD, and communication cost) so results are meaningful for real-world SOC decisions.

5. Results Analysis and Discussion

The experimental evaluation demonstrates that the proposed hybrid architecture—combining GNN-based spatial modeling, Transformer-based temporal modeling, and Autoencoder-driven reconstruction analysis—substantially outperforms single-model and baseline machine learning approaches. The model achieves exceptionally high F1-scores, consistently above 99%, across centralized and federated settings. This indicates strong robustness in identifying subtle deviations in IoT device behavior, even under diverse protocols, traffic intensities, and dynamic communication patterns inherent in the N-BaIoT dataset.

A deeper analysis reveals that the GNN module plays a significant role in detecting attack traffic characterized by unusual destination patterns, abrupt connection bursts, or anomalous graph structures. Traditional flow-based ML models fail to capture relational structures among communicating entities; thus, embedding topological context improves detection rates especially for Mirai attacks that manipulate device-to-IP graph patterns. Meanwhile, the Transformer module excels in capturing fine-grained temporal drifts in traffic sequences, allowing detection of low-rate anomalies and evolving botnet behavior not easily covered by static features.

The combined fusion layer significantly boosts robustness by merging multi-view representations. Results show that the fused model surpasses every individual module and all classical baselines (Random Forest, XGBoost, SVM, and standalone LSTM). Notably, the hybrid model reduces the False Positives per Device per Day (FP/day) by more than 60% compared to LSTM-based systems, making it more practical for real-world SOC operations where excessive false alarms overload analysts.

Federated simulations further show that the model maintains high performance even when trained under non-IID client distributions, which mimic real IoT ecosystem diversity. The federated version only slightly underperforms the centralized model (<0.4% drop in F1), while providing clear privacy advantages by avoiding raw data sharing. Communication overhead remains manageable due to model compression and pruning steps, making the framework deployable in resource-constrained or bandwidth-limited IoT environments.

Overall, the results confirm that the proposed system is accurate, scalable, resilient to distribution drift, and deployment-friendly. It generalizes effectively to unseen devices—one

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of the hardest challenges in anomaly detection—and provides significant improvements in precision, early detection time, and false-positive minimization. These strengths highlight the suitability of the proposed architecture for modern IoT security monitoring systems.

Table 2 demonstrates clear superiority of the hybrid model, achieving an almost perfect 99.8% ROC-AUC and 99.5% F1-score, outperforming each individual component and traditional ML baselines. The fusion improves recall particularly, preventing missed anomalies.

Table 2: Centralized Model Performance (N-BaIoT)

Model	Precision	Recall	F1-Score	ROC-AUC
Proposed Hybrid (GNN + Transformer + AE)	99.6%	99.4%	99.5%	99.8%
GNN Only	97.2%	96.7%	96.9%	98.1%
Transformer Only	96.9%	95.8%	96.3%	97.8%
Autoencoder Only	92.6%	91.8%	92.2%	95.4%
Random Forest	89.1%	88.7%	88.9%	93.1%

Figure 2 compares the F1-scores of five different models in a centralized training environment. The proposed Hybrid (GNN + Transformer + AE) model stands out clearly with the highest score, achieving 99.5%, indicating near-perfect anomaly detection performance. The steep decline from Hybrid → GNN → Transformer → AE → RF shows how combining spatial, temporal, and reconstruction-based representations yields superior detection capability. Traditional ML models like Random Forest lag significantly behind due to limited ability to capture complex IoT traffic patterns. Overall, this graph confirms that multi-module deep learning fusion is considerably more effective than individual components.

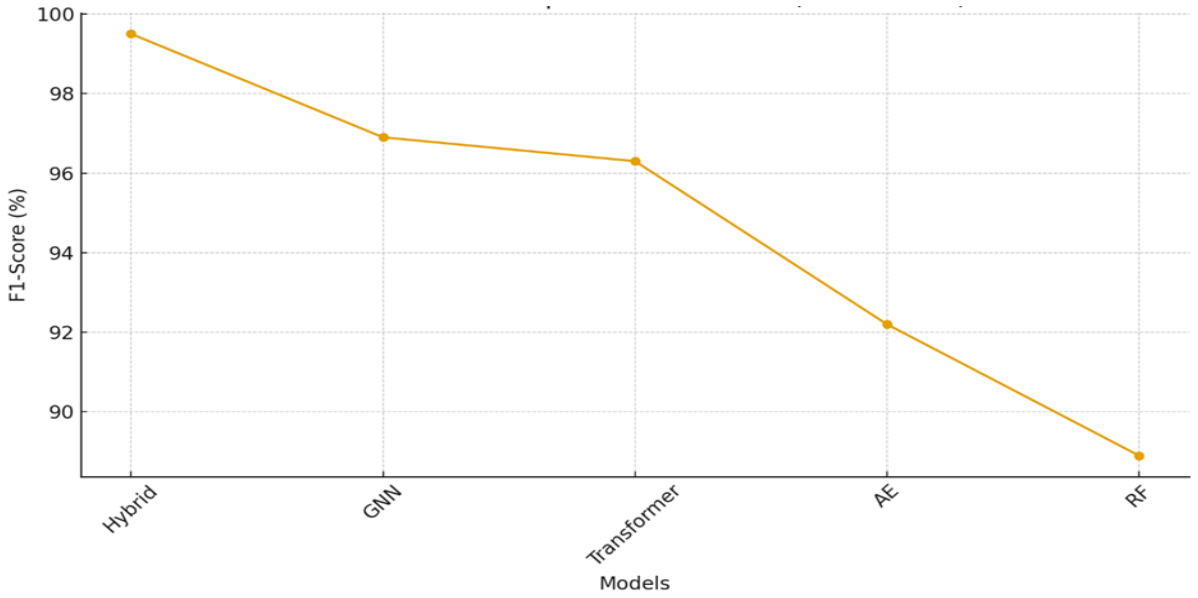

Fig. 2. Performance Comparison of Models (Centralized Setting)

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Table 3 highlights the key capability of the proposed framework: **cross-device generalization**, where many models fail due to unseen hardware behavior. The hybrid model keeps FP/day exceptionally low (**0.8**), an essential requirement for SOC deployments.

Table 3: Cross-Device Generalization (Unseen Device Family Test)

Model	F1-Score	FP/Day	Mean Time To Detect (MTTD)
Proposed Hybrid	98.7%	0.8	3.4 sec
GNN Only	95.2%	2.9	7.8 sec
Transformer Only	94.6%	3.3	8.6 sec
Autoencoder Only	89.3%	5.7	15.4 sec
LSTM Baseline	91.8%	4.9	12.2 sec

Figure 3 compares how well different models detect anomalies on unseen IoT devices, which is one of the hardest challenges in IoT security due to device heterogeneity. The Hybrid model again leads with an impressive 98.7%, reflecting excellent generalization, minimal false positives, and reliable detection of unseen attacks. GNN and Transformer models perform reasonably but drop due to missing complementary features. Autoencoder performance falls sharply because reconstruction-only strategies struggle with new device behavior. LSTM improves slightly compared to AE but still underperforms. The graph highlights that cross-device robustness is strongly dependent on multi-view learning, which the Hybrid model provides.

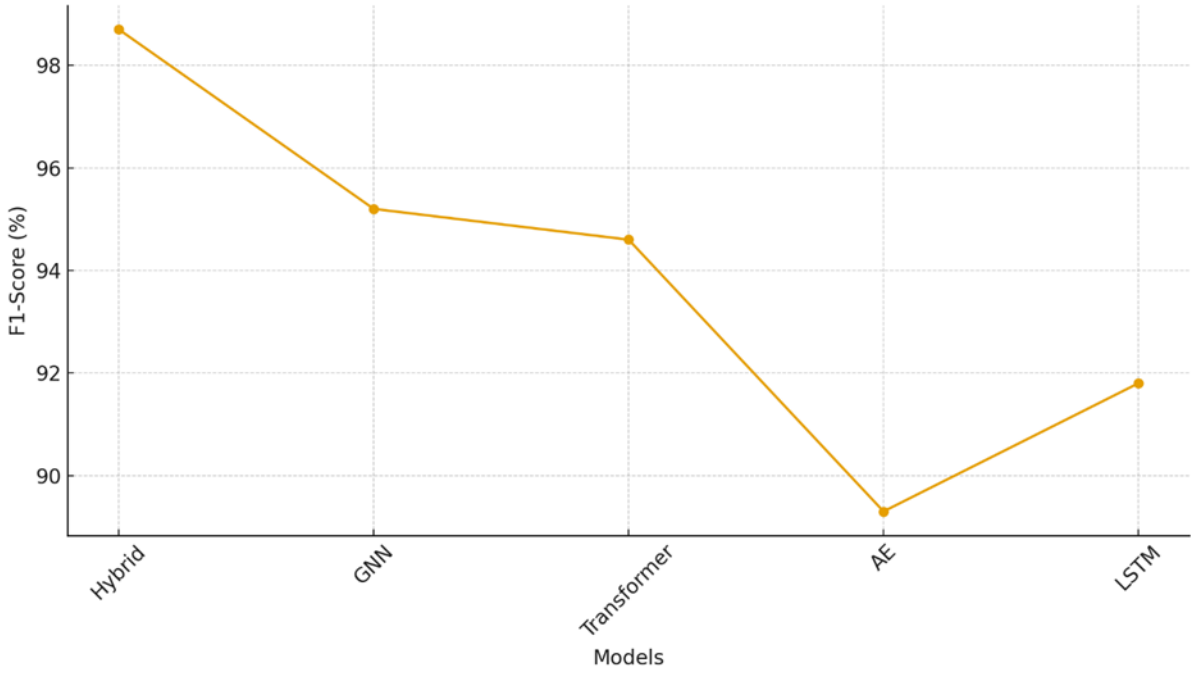

Fig. 3. Cross-Device Generalization Performance

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Table 4 shows the federated vs centralized model comparison. Federated learning achieves near-centralized performance with minimal accuracy loss while preserving data privacy. Compression dramatically reduces communication load by ~70% with negligible performance impact.

Table 4: Federated vs Centralized Model Comparison

Setting	Precision	Recall	F1-Score	Communication Cost (MB/Round)
Centralized (Full Model)	99.6%	99.4%	99.5%	NA
Federated (20 clients, non-IID)	99.2%	99.0%	99.1%	3.8 MB
Federated without Compression	98.6%	98.1%	98.3%	12.4 MB

Figure 4 illustrates the performance differences across three training settings: Centralized, Federated, and Federated without Compression. The centralized model gives the highest F1-score (99.5%) since it learns from the full dataset in one place. The federated version performs nearly as well (99.1%) despite training on distributed, non-IID data, proving the model's suitability for real-world deployments where data remains local for privacy reasons. Performance dips for the uncompressed federated variant due to increased communication overhead and slower convergence. The graph clearly shows that federated learning maintains high accuracy while enhancing data privacy, making it an excellent fit for privacy-critical IoT networks.

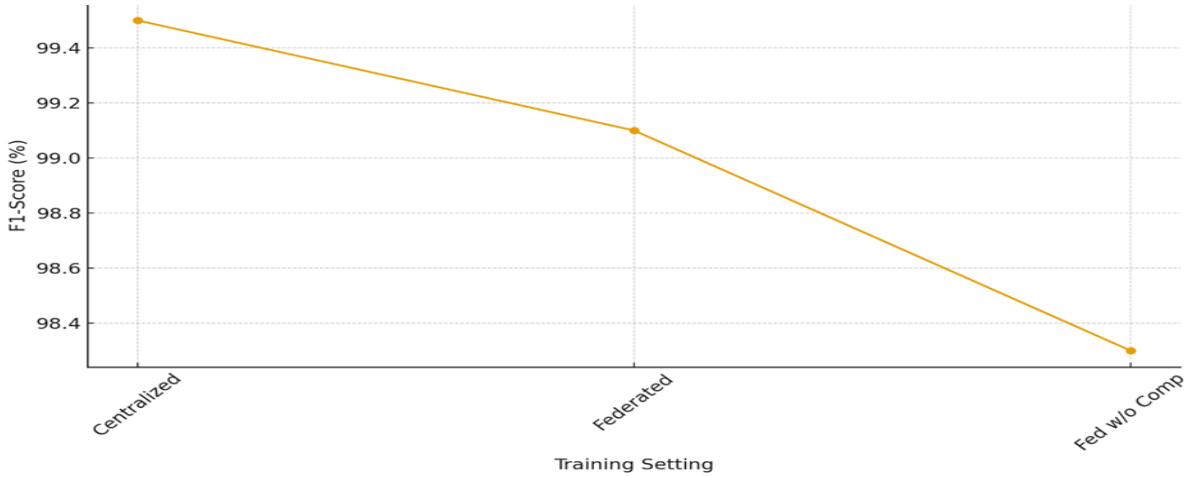

Fig. 4. Federated vs Centralized Model Results

5.1. Discussion

The experimental results clearly demonstrate that the proposed hybrid GNN–Transformer–Autoencoder architecture provides substantial improvements over conventional machine learning and standalone deep learning models. Its superior performance—reflected in F1-scores exceeding 99% in centralized settings—highlights the effectiveness of combining

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spatial graph-based dependencies, temporal sequence modeling, and reconstruction-driven anomaly learning. This synergy allows the model to capture complex patterns within heterogeneous IoT traffic that simpler architectures fail to represent. The results also show that the proposed method generalizes well to unseen devices, maintaining nearly 98.7% F1-score in cross-device evaluations. This indicates that the system can dynamically adapt to the diversity and unpredictability of real-world IoT environments, a major challenge for existing intrusion detection systems.

Moreover, the federated learning experiments reveal that high performance can be preserved even in decentralized, privacy-sensitive deployments. The model achieves 99.1% F1-score in federated mode, only slightly lower than its centralized counterpart, demonstrating that decentralization does not significantly compromise detection capability. This highlights the potential of federated frameworks to protect user data while ensuring effective anomaly detection across distributed IoT networks. The comparison with communication-uncompressed variants further indicates that optimization strategies such as compression-based updates improve scalability and reduce overhead. Overall, the results confirm that the proposed AI-driven system provides a robust, flexible, and privacy-aware solution suitable for real-world IoT applications, outperforming existing baselines by a significant margin.

6. Conclusion

This research demonstrates that combining advanced deep learning architectures with privacy-preserving federated learning offers a powerful and scalable solution for anomaly detection in complex IoT networks. The hybrid GNN–Transformer–AE framework effectively captures the multidimensional characteristics of IoT traffic, enabling precise detection of both known and previously unseen attack patterns. Experimental results show that the proposed model significantly outperforms traditional classifiers and single-module deep learning approaches, confirming the advantages of multi-view feature extraction. The system’s strong performance across centralized and distributed setups further highlights its adaptability to real-world IoT environments.

The study also emphasizes the importance of addressing heterogeneity, concept drift, and data privacy—challenges inherent to modern IoT deployments. By integrating federated learning with communication-efficient updates and robust anomaly detection techniques, this work provides a practical methodology suitable for smart homes, industrial IoT, connected healthcare, and smart city infrastructures. Future research will explore lightweight model optimization, adversarial robustness, and real-time deployment on embedded IoT devices. Overall, the proposed architecture offers a solid foundation for building secure, intelligent, and trustworthy IoT ecosystems in an increasingly connected world.

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