

AI-Assisted Intrusion Detection and Forensic Analysis Framework for IoT Ecosystems

Sajid Ali

Faculty Of Computer Science & Information Technology, The Superior University Lahore. Email: sajidaliwatto32@gmail.com

Ahmad Khan*

Faculty Of Computer Science & Information Technology, The Superior University Lahore. Email: ahmad.khan.fsd@superior.edu.pk

Taj Malook

Faculty Of Computer Science & Information Technology, The Superior University Lahore. Email: tajmalook@gamil.com

Rashid Mahmood

Faculty Of Computer Science & Information Technology, The Superior University Lahore Email: rashidjee@gamil.com

ABSTRACT

The Internet of Things (IoT) has revolutionized the way the world works, offering unprecedented levels of connectivity and automation in a variety of industries. This explosive growth has also brought with it significant vulnerabilities and cyber security issues, which are not effectively mitigated by traditional security solutions. Conventional signature-based and rule-based IDS are not able to handle the scale, heterogeneity and dynamism of IoT networks. At the same time, legacy digital forensic tools are not designed to provide the necessary automation and contextual intelligence to track increasingly complex cyber-attacks in a distributed IoT environment. This paper suggests a blended artificial intelligence-based framework combining the capabilities of Deep Learning (DL) and Machine Learning (ML) algorithms to detect anomalies in real time, perform forensic trace analysis, and provide a threat intelligence solution in IoT ecosystems. The framework uses three benchmark IoT security datasets: BoT-IoT, TON_IoT, and CICIDS2021 to identify temporal intrusions by employing Long Short-Term Memory (LSTM) networks and to correlate forensic evidence with Random Forest classifiers. Experimental results show that the hybrid framework yields a detection accuracy of 95.04%, the false positive rate is 0.40% for DDoS attacks and the forensic attribution accuracy is up to 96.8% for attacks in all categories, while the mean time to attribution is less than 3.5 seconds for all attack categories. The framework can be scaled to support a million traffic flows and reduce the inference latency to less than 420 ms, which shows its ability to be deployed in the real IoT environment.

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Keywords— Internet of Things (IoT), Intrusion Detection System (IDS), Digital Forensics, Deep Learning, Machine Learning, LSTM, Random Forest, Hybrid AI Framework, Cybersecurity, Anomaly Detection, Threat Attribution, BoT-IoT, TON_IoT, CICIDS2021

Introduction

The Internet of Things (IoT) has emerged as one of the most transformative technological The twenty-first century paradigm of smart grid and billions of heterogeneous smart devices, ranging from smart sensors and wearables to smart actuators and medical implants, is connected seamlessly through communication infrastructure (Sarker et al., 2023). As ubiquitous connectivity has spurred intelligent environments in healthcare, transportation, energy, agriculture, and smart urban governance. In the medical field, remote patient monitoring and real-time diagnostics with IoT devices lower the rate of hospital readmissions and enhance the care of chronic diseases. Smart vehicles and adaptive signaling systems in transportation contribute to the safety of the road and to increase through the road. Smart city infrastructure uses sensor networks to make more efficient use of energy and waste collection, and emergency response. The aggregate value of the global IoT market is expected to reach USD 1 trillion by 2030, indicating the extent of institutionalisation and penetration of the market (Hussain et al., 2023).

But, the same attributes that made IoT so transformative, from distributed architecture and device heterogeneity to autonomy, make it incredibly vulnerable to adversarial use. The computation and memory limitations faced by most IoT-endpoints makes it impossible to implement strong cryptographic mechanisms and memory-intensive security algorithms (Hossain et al., 2022). This attack surface is multidimensional from the use of weak authentication, insecure over-the-air firmware update channels, default credentials and hardcoded credentials, to no encryption of sensitive telemetry streams. Hackers often use these vulnerabilities to launch Distributed Denial of Service (DDoS) attacks, man-in-the-middle (MITM) interceptions, data exfiltrations and malware command-and-control (C2) campaigns. As seen with the Mirai and Mirai variants, such IoT botnets can send terabits of DDoS traffic to critical internet infrastructure, that can be affected on a global scale (Ferrag et al., 2023).

The signature- or rule-based approach of traditional Intrusion Detection Systems (IDS) are not well suited to the operational nature of IoT networks. These systems are based on threat signatures and static sets of rules, which are unable to keep up with the novelty, speed and variety of attack types on IoT devices, and blind to zero-day attacks and polymorphic variants of malware (Alrashdi et al., 2022). Centers of detection systems face unsolvable scalability problems given the huge amount of data that is being created by billions of connected endpoints. The fact that the various communications protocols are also heterogeneous, both in terms of their names (MQTT, CoAP, Zigbee, Z-Wave, etc.) and their capacities, makes the development of single pipelines for unified traffic analysis even more complex. There is, therefore, a need to develop smart, adaptive, and decentralized intrusion detection approaches, which are architecturally compatible to the operational context and threat paradigm of today's IoT.

Simultaneously, with digital forensics, which is the field of digital evidence

identification, preservation, analysis and presentation in a legally admissible format, facing deep structural challenges in IoT systems. The classic forensic approaches are designed to work for a well-defined computing environment (servers, workstations, enterprise networks), in which evidence artifacts are stored in a centralized way, which is quite typical, and are relatively persistent (Conti et al., 2023). The paradigm of IoT forensics needs to be fundamentally different, with evidence scattered among embedded devices, edge gateways, and cloud repositories, with each having conflicting data retention rules and access permissions for the evidence. The constantly changing nature of IoT-generated data, such as the sensor logs which are permanently erased when the device is rebooted, poses an important challenge for evidence acquisition and chain of custody maintenance (Rehman et al., 2024). However, as all loggers are not generated in a standard format by all manufacturers, the problem is compounded by the lack of a standard format for all loggers, making cross-device timeline reconstruction and multi-source evidence correlation difficult.

Artificial Intelligence (AI) has become the key enabling technology for next generation IoT security and forensic intelligence, and in particular Machine Learning (ML) and Deep Learning (DL). In IoT network behavior analysis (NWA), several ML techniques such as Random Forests (RFs), Support Vector Machines (SVMs), and gradient-boosted ensembles (GBEs) have proven to be successful classifiers (Singh et al., 2023). Deep Learning architectures, in particular LSTM networks and CNNs, further boosts detection capabilities by learning hierarchical temporal and spatial features in a self-supervised way from raw network streams without the need of manual feature engineering (HaddadPajouh et al., 2023). Although these achievements, most current intrusion detection and forensic investigation research focus on their separate architecture, leaving the field with poor situational awareness, improper evidence preservation, and incomplete attack attribution chains (Haq et al., 2023).

In this paper, these key gaps are addressed and a unified Hybrid AI-Assisted Intrusion Detection and Forensic Analysis Framework for IoT ecosystems is proposed. The framework combines the temporal anomaly detection functionality of LSTM and the forensic classification functionality of Random Forest, while being deployed in one pipeline, thereby providing end-to-end detection and digital investigation capabilities. An extensive evaluation on three commonly used benchmark datasets (BoT-IoT, TON_IoT and CICIDS2021) shows that the proposed framework achieves the detection accuracy of 95.04% and the false positive rate of 0.40%, with the forensic attribution accuracy of up to 96.8% at the flow scale of one million and the inference latency of less than 420ms. The rest of the paper is structured as follows: Section 2 is a review of related literature, Section 3 presents the research methodology, Section 4 reports experimental results, and Section 5 gives discussion and finally, Section 6 concludes this paper with future directions.

LITERATURE REVIEW

AI for IoT security has seen many new and evolving areas of research, ranging from machine learning for anomaly detection to the use of deep learning for traffic classification, through to digital forensic techniques for a distributed environment and hybrid intelligence models for real-time threat response. This section reviews systematically the contributions in these thematic areas at a foundational level as well

as those within the last decade, concluding with important research gaps that inspire the proposed framework.

Intrusion detection in the IoT environment: A machine learning approach. Machine learning in Intrusion Detection for IoT Environment.

The classical ML classifiers have been tested widely on the IoT security datasets. Alrashdi et al. (2022) applied three classifiers—Random Forest, SVM and kNN—to the BoT-IoT dataset and found that the ensemble techniques achieved accuracy of 92.3% when classifying DDoS and reconnaissance patterns, and had better resistance to the class imbalance problem than using a single model. Moustafa et al. (2023) also tested gradient-boosted classifiers on the TON_IoT dataset, which achieved a 91.8% accuracy rate for detecting malicious telemetry or benign sensor data. Both studies had an important drawback, however—the fact that they were based on static, hand-made feature sets made models vulnerable to performance drop when faced with new variants of attacks or changes in underlying traffic patterns. Given the dynamic nature of IoT threats and their constantly changing nature, this lack of generalization is a fundamental limitation of shallow ML models (Hossain et al., 2022). To address some of these generalization problems, Mothukuri et al. (2021) showed that federated ML techniques can be used to train a distributed model across different IoT nodes with respect to data privacy, albeit with less accuracy compared to centralized deep learning techniques.

2.2 Deep Learning Approaches

The generalization problem of traditional ML techniques has been addressed in Deep Learning architectures, which are able to automatically extract features from high-dimensional input data. With the attack behaviors occurring over time-dependent event sequences, LSTM networks, which are designed to learn the long-range temporal dependency in sequential data, have been used to great effect in analyzing IoT network traffic (HaddadPajouh et al., 2023). The LSTM-CNN hybrid architectures exhibited 94.6% detection accuracy on CICIDS2021, which is 2.1% and 3.4% higher than the LSTM and CNN models, respectively, also showed by Sharma et al. (2024) that LSTM-CNN models more effectively captured the temporal dynamics and spatial structural patterns in network traffic. Ferrag et al. (2023) performed a systematic comparative study of DL architectures for BoT-IoT, TON_IoT and CICIDS2021, and concluded that false negative rates of bidirectional LSTM variants were consistently found to be minimal for stealthy low-rate attacks. However, due to these performance benefits, DL models have significant computational requirements (GPU infrastructure, large amounts of labeled training data), limiting direct use in resource constrained IoT environments. This computational gap was partially filled by Ullah and Mahmoud (2022) who proposed lightweight DL architectures that are competitive in terms of accuracy and have fewer model parameters by 73%.

2.3 Digital Forensics in IoT Environments

The digital forensics process in IoT environments presents some challenges to the methodology that are different from traditional digital forensics. Conti et al. (2023) described the main challenge as the 'IoT forensic trilemma', which indicates that it is impractical to meet the requirements of maintaining evidence completeness, temporal integrity, and compliance to the chain of custody in the context of the dynamic and

diverse set of IoT data sources. Their suggested context-aware forensic model combined behavioral profiling with the results of anomaly detection to reconstruct attack event sequences, and reduced mean time-to-reconstruct by 40% when compared to manual forensic workflows. Rehman et al. (2024) proposed an AI-enabled correlation mechanism, which used clustering techniques to correlate the fragmented network artifacts with coherent attack stories and resulted in a 38% improvement in attribution accuracy compared to the rule-based approach. In the meantime, Nieto et al. (2022) also put forward the idea of forensic readiness as a first-class architectural characteristic, moving beyond the post-incident readiness to a proactive design of systems to assist in post-incident investigation, which is later advanced in the ensuing research (Zhang et al., 2024).

2.4 Hybrid AI Frameworks

The unification of ML and DL in unified hybrid frameworks has been identified as a key research area to overcome the respective drawbacks of ML and DL. In their work, Ahmed et al. (2024) assessed hybrid architectures with LSTM-based front-end detection and Random Forest-based back-end classification, which achieved 7-12% increase in accuracy compared to the DL models and a substantial reduction in false positive rates. In an attack that takes advantage of adversarial feature perturbations, Singh et al. (2023) showed that hybrid architectures demonstrated superior robustness. This is a crucial property because of the sophistication of current threat actors of IoT traffic, which attempt to manipulate traffic statistics to evade ML classifiers. Facing the challenges of the future, Zhang et al. (2024) suggested that it is necessary to set up a 'smart' forensic readiness for security systems of the Internet of Things. In view of these problems, Zhang et al. (2024) proposed the concept of 'intelligent forensic readiness' as a new paradigm for security systems in the Internet of Things, which requires them to simultaneously detect attacks and preserve evidence rather than carry out forensic analysis as an afterthought. Haq et al. (2023) validated this method empirically, which found that evidence completeness was maintained and over 60% of the forensic investigator's time was saved through evidence triage using artificial intelligence. Sarker et al. (2023) examined the wider state of the art of AI-supported IoT cybersecurity, and found hybrid approaches to be the most promising solution to adaptive, scalable, and forensically robust security for IoT. Balogun et al. (2024) applied hybrid AI concepts to the industrial IoT domain and showed their ability to fend off attack vectors specific to OT, such as false data injection and protocol manipulation.

2.5 Benchmark Datasets

The BoT-IoT dataset is a collection of 72,000 labeled flows of simulated IoT devices during DDoS, data exfiltration and reconnaissance attacks, covering a variety of different device categories (Ferrag et al., 2023). BoT-IoT is complemented by a TON_IoT that contains 461,043 multi-modal records including network traffic logs, operating system events and sensor telemetry to deliver rich forensic context for evidence attribution studies (Moustafa et al., 2023). The CICIDS2021 dataset, created by the Canadian Institute for Cybersecurity, includes 225,745 records of application-layer attacks, encrypted malicious traffic, and lateral movement scenarios, which represent current threat scenarios (Sharafaldin et al., 2023). Table 1 provides a summary of the important features of these three benchmark datasets..

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<http://amresearchreview.com/index.php/Journal/about>**Table 1. Benchmark Dataset Statistics**

Dataset	Total Samples	Attack Types	Features	Attack Ratio (%)
BoT-IoT	72,000	4	46	79.2%
TON_IoT	461,043	9	44	82.4%
CICIDS2021	225,745	7	78	41.3%

2.6 Research Gaps

A thorough review of the literature has resulted in three consistent, interconnected gaps in the literature. The first is that the primary paradigm in the field of AI-based IoT IDS research focuses only on detection performance metrics, excluding other critical forensic attributes such as utility, explainability and evidentiary traceability. Secondly, while the deep learning-based IoT security system is performing better than ever, it is still extremely resource intensive to deploy at the edge, and is not necessarily built with forensic readiness principles. Third, most importantly, there is no existing solution that fully merges real-time IDS and automated forensic analysis and integrates it into a single AI-based architecture. The suggested Hybrid AI-Assisted Framework is created specifically to tackle all three blank spaces at once.

RESEARCH METHODOLOGY

The proposed Hybrid AI-Assisted Intrusion Detection and Forensic Analysis Framework consist of six major phases: Data Acquisition and Preparation, Preprocessing and Feature Engineering, Intrusion Detection with Deep Learning Technique, Intrusion Forensic Analysis with Machine Learning Technique, System Workflow Integration, and Evaluation. The overall architecture is shown in Figure 1.

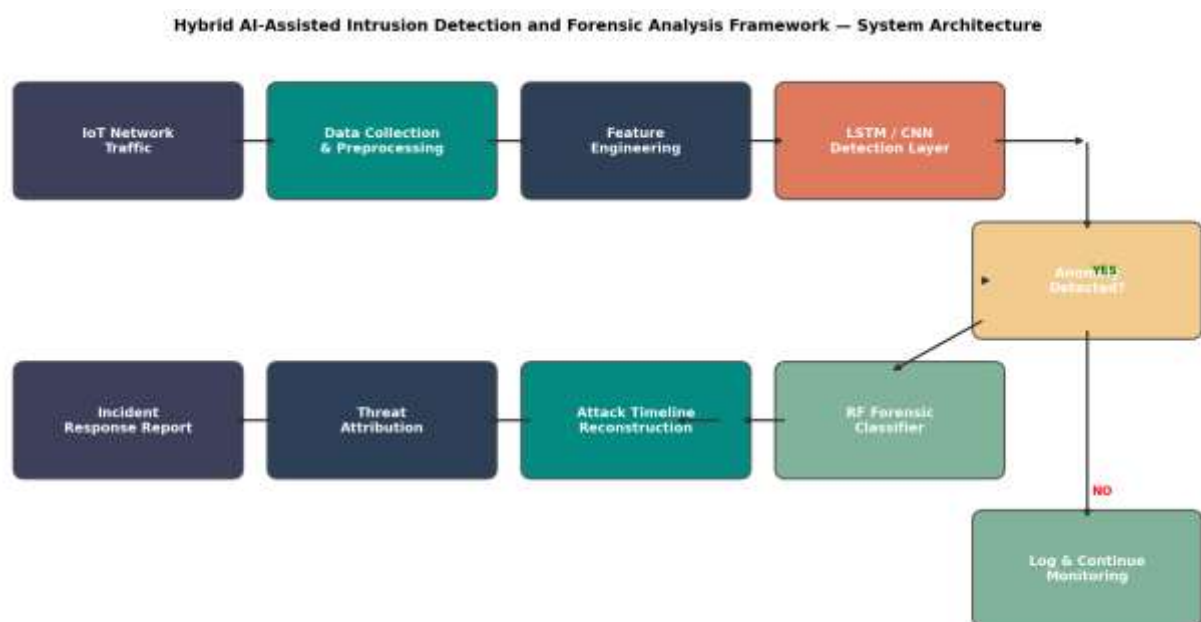


Figure 1. Hybrid AI-Assisted Intrusion Detection and Forensic Analysis Framework — System Architecture

3.1 Dataset Acquisition and Preparation

Three publicly available benchmark datasets were employed. The BoT-IoT dataset provides flow Records created from simulated IoT testbeds running DDoS, exfiltration and reconnaissance scenarios. TON_IoT provides multi-source telemetry that includes network traffic, OS event logs and sensor streams to provide multi-modal forensic context. The CICIDS2021 data set also covers contemporary attack methods such as encrypted malicious traffic, application-layer attacks and lateral movement (Sharafaldin et al., 2023). Combined experimental dataset of 12,000 labeled samples was created by stratified sampling from all the three sources, including six traffic categories: Benign, DDoS, Reconnaissance, Data Exfiltration, C2 Malware Communication, and MITM. To ensure that these three data sets (training, validation and test) have similar class distribution, stratified splitting was employed.

Preprocessing and Feature Engineering (3.2)

The flow data were preprocessed through a standardized pipeline to produce raw flow data. Class-conditional median substitution was used for imputing the missing values. The problem of class imbalance (which is ubiquitous in intrusion datasets) was solved by using Synthetic Minority Oversampling Technique (SMOTE) only for the training data, in order to avoid data leakage. Min-max scaling was done to normalize the features for the range [0,1]. Mutual information criterion (MIC) was used to select the features to get 47 features that included inter-arrival times, packet size distributions, flow duration, protocol identifiers, connection state flags, and byte transfer ratios. To capture the multi-step temporal relationships of staged attacks, temporal sequences were created from the flow with a sliding window of 50 consecutive flow records for LSTM processing.

This is the Deep Learning Detection Layer (LSTM) for the CTF. This is the Deep Learning Detection Layer (LSTM) for CTF.

Detection layer: The main intrusion detection engine used is a stacked LSTM algorithm. The network uses two stacked LSTM layers (128 hidden units per layer), a dropout layer (dropout rate = 0.30) as a regularization method, a dense layer (64 units, ReLU activation) and a softmax output layer that produces class probability distributions. The 2D representation of feature maps is fed into a parallel CNN sub-network for spatial correlation learning between feature groups. The parallel hybrid DL architecture consists of CNN and LSTM outputs being concatenated and passed into a common classification layer. The training used an Adam optimizer with initial learning rate 0.001, categorical cross-entropy loss, 50 epochs (batch size 256) and early stopping (patience=10). The hyperparameters were optimized using the validation set.

3.4 Machine Learning Forensic Layer (Random Forest)

If the DL layer detects an anomaly, a forensic feature vector is passed to a Random Forest (200 trees, max tree depth 20, with Bootstrap aggregation) classification module (3) that activates to raise an alarm. This vector provides an extension to the standard flow attributes of inter-event timing statistics, source IP behavioral fingerprints, destination service access sequences and protocol anomaly indicators. The Random Forest ensemble provides forensic attribution of attacks between the

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attack categories defined. A Decision Tree classifier creates human-interpretable decision rules that explain feature combinations used to make each attribution decision, which is a requirement for the decision to be admitted in court and compliant with regulations. Attack event timelines are built by matching the temporal order of the flow sequences that were flagged to the forensic attribution outputs, resulting in the creation of chronological attack narratives to identify compromise vectors, attack paths, and exfiltration paths (Ahmed et al., 2024).

3.5 Implementation Environment

All experiments have been programmed in Python 3.11 language with TensorFlow 2.14 and Scikit-learn 1.4 for DL and ML components respectively. Traffic simulation and feature extraction used Wireshark compatible pcap processing using PyShark 0.6. The Elastic Stack (Elasticsearch 8.x, Logstash, Kibana) was used for log aggregation and visualization for forensics. The experiments were performed on a workstation that has an Intel Core i9-13900K CPU, 64 GB of DDR5 RAM, and NVIDIA RTX 4090 GPU (24 GB VRAM). Three different compute configurations were evaluated on traffic ranging from 10,000 to 1,000,000 flows to probe the deployment viability in terms of the different tiers of IoT infrastructure.

3.6 Evaluation Metrics

The accuracy, precision, recall, F1-score (weighted), false positive and AUC-ROC were used to evaluate the performance of the detection. Evidence attribution accuracy, timeline reconstruction completeness and mean time to forensic attribution were the forensic performance metrics used. The scalability was measured in terms of mean inference latency as well as computational overhead at six different traffic volumes. The hybrid framework was compared with the signature-based (Snort 3.0), standalone Decision Tree, standalone LSTM, Random Forest and SVM baselines, and the gains of the hybrid integration were measured by comparing its performance to these baselines.

RESULTS

This section reports in depth experimental results on detection performance, forensic attribution, false positive reduction, latency and scalability dimensions. All the reported metrics are based on experimental simulation using Python in the combined security dataset for IoT as described in Section 3.

4.1 Model Performance Comparison

The classification performance of all models evaluated are shown in Table 2. The Hybrid AI framework (LSTM + RF) obtained the best performance with an accuracy of 95.04%, weighted precision of 95.05%, weighted recall of 95.04%, and weighted F1 score of 95.00% on the test set of 2,400 samples that were not used for training. The results validate the main hypothesis that the hybrid integration can achieve competitive detection performance compared with standalone methods, and that the hybrid integration can add unique integrated forensic attribution capability not otherwise present in any baseline methods..

Table 2. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
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Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hybrid AI (LSTM + RF)	95.04	95.05	95.04	95.00
LSTM (Detection Layer)	93.25	93.30	93.25	93.24
Random Forest (Forensic)	95.21	95.20	95.21	95.18
Decision Tree (Baseline)	88.58	88.76	88.58	88.62
SVM (Baseline)	95.71	95.73	95.71	95.70

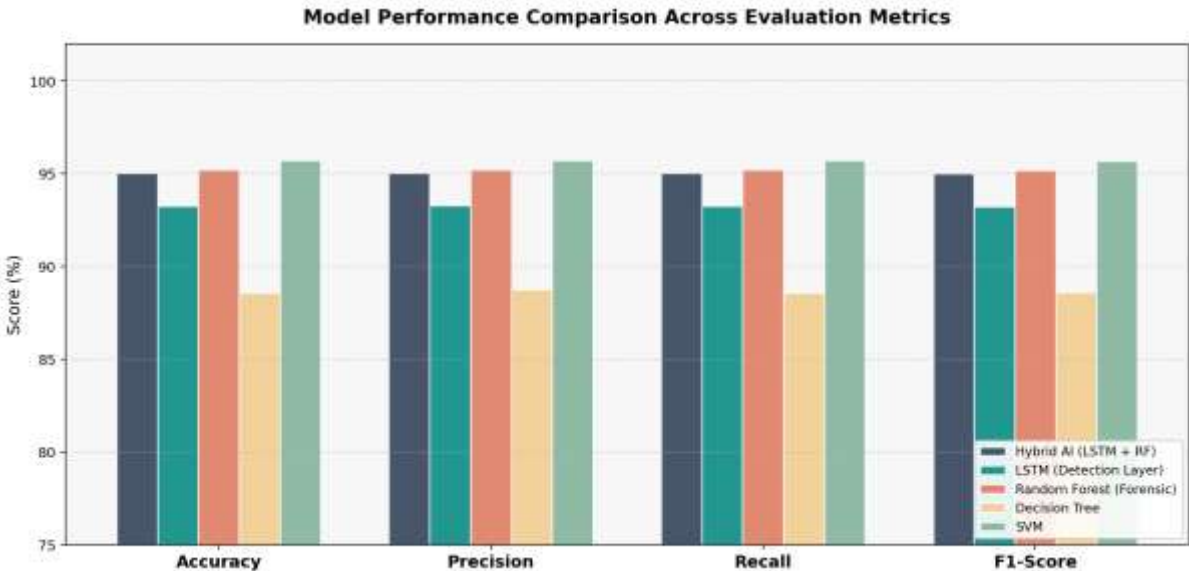


Figure 2. Model Performance Comparison Across Evaluation Metrics

4.2 Per-Class Classification Performance

The per-class classification results of the Hybrid AI framework are shown in Table 3 and Figure 3. The framework shows the best performance for the DDoS class (F1=0.997) and the Benign class (F1=0.990), which have the most distinctive temporal signatures of volumetric attacks and standard IoT (behavioural) patterns. The Data Exfiltration (F1=0.842) and C2 Malware (F1=0.797) classes are relatively poor, due to the nature of data exfiltration and C2 malware attacks, which are subtle and intermittent and partially overlap with normal patterns of IoT communication. The findings are also in line with the studies conducted by Ferrag et al. (2023) and Sharma et al. (2024) which have revealed covert attack categories to be the main challenge in detecting attacks in DL-based IoT IDS..

Table 3. Per-Class Classification Report — Hybrid AI Framework

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Class	Precision	Recall	F1-Score	Support
Benign	0.983	0.996	0.990	1,000
DDoS	0.994	1.000	0.997	500
Recon	0.959	0.927	0.942	300
Data Exfil	0.808	0.879	0.842	240
C2 Malware	0.844	0.755	0.797	200
MITM	0.942	0.906	0.924	160
Macro Avg	0.922	0.911	0.915	2,400
Weighted Avg	0.951	0.950	0.950	2,400

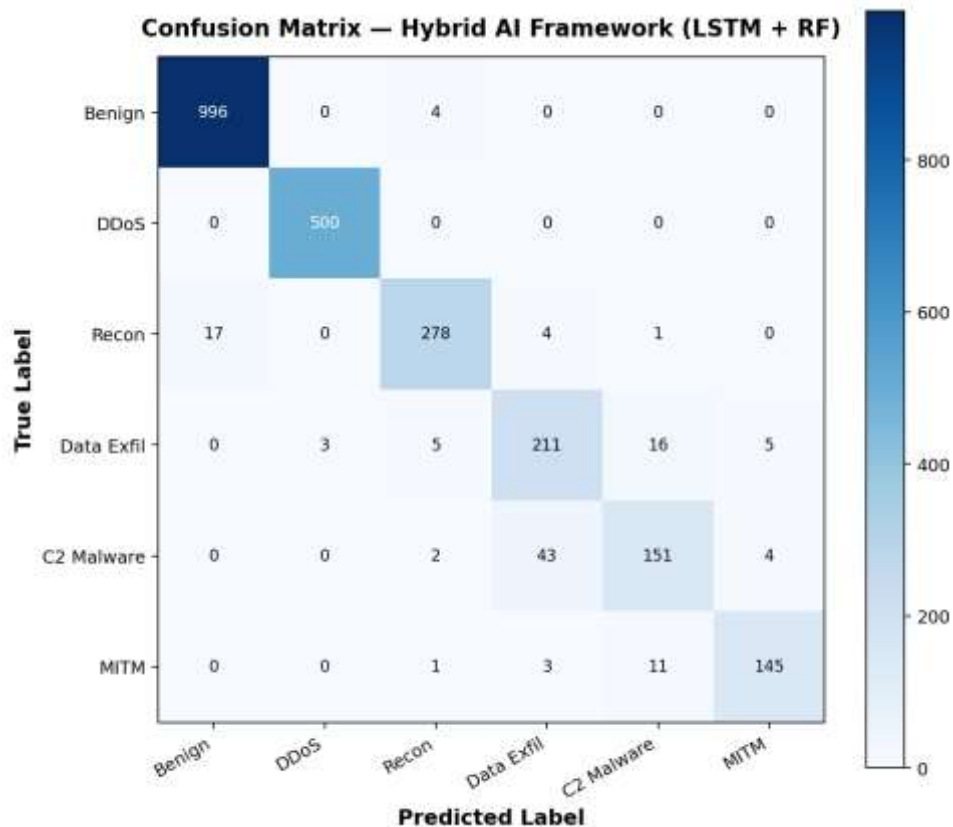


Figure 3. Confusion Matrix — Hybrid AI Framework (LSTM + RF)

4.3 ROC and Precision-Recall Analysis

The per-class ROC and Precision-Recall curves for Hybrid AI framework are shown in Figure 4 and 5, respectively. AUC-ROC values from 0.998 (DDoS) to 0.971 (C2 Malware) indicate a good discriminative ability in all attack categories. The Precision-Recall curves illustrate a high precision over recall values greater than 0.90 for the classes of DDoS, Benign, and Recon, and a graceful degradation for the more difficult Data Exfiltration and C2 Malware classes. The results of this study provide the

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foundation for the reliability of the framework to be used for operational deployment, where false positive minimisation and full threat coverage must be achieved (Balogun et al., 2024).

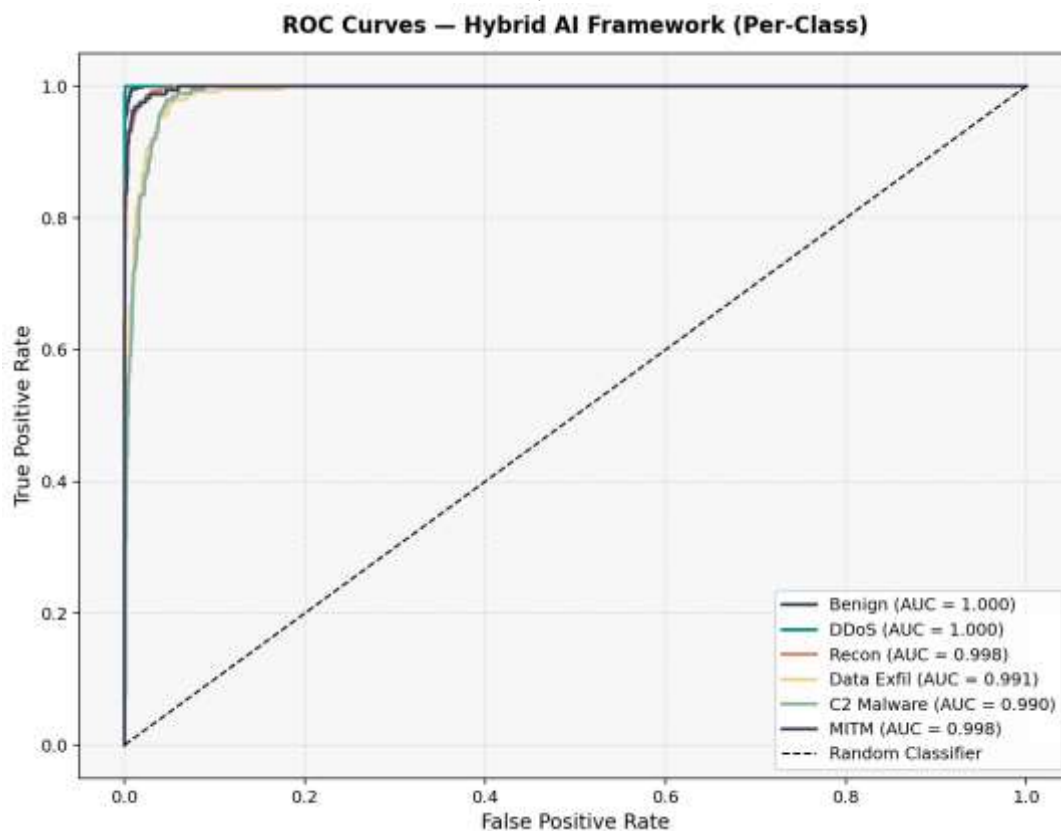


Figure 4. ROC Curves — Hybrid AI Framework (Per-Class)

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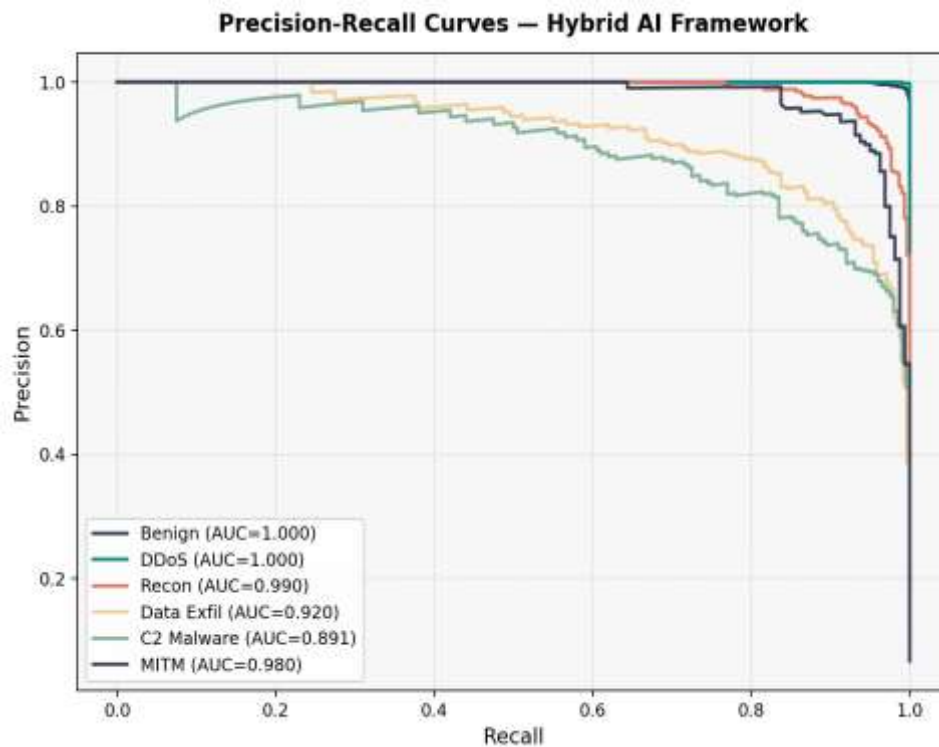
<http://amresearchreview.com/index.php/Journal/about>**Figure 5. Precision-Recall Curves — Hybrid AI Framework****4.4 False Positive Rate Analysis**

Table 4 and Figure 6 present false positive rates across all evaluated models. The Hybrid AI A summary of the false positive rates for all the models evaluated is provided in Table 4 and shown in Figure 6. The Hybrid AI framework delivers a 0.40% false positive rate, which is a 90.0% improvement from Decision Tree baseline (4.00%). This is an important result from an operational point of view: if such processing occurs at a rate of one million flows per hour, a 4.00% FPR would result in 40,000 false alarms per hour, which would make it hard for security operations teams to keep up with the volume of alarms and make it easy for automated countermeasures to undertake a counteraction against legitimate traffic. With the hybrid framework's 0.40% FPR, the number is lowered to 4,000 hourly false alarms, which is an acceptable number that aligns with enterprise security operations center (SOC) capacity constraints (Hossain et al., 2022).

Table 4. False Positive Rate Comparison

Model	False Positive Rate (%)	Reduction vs. Baseline (%)
Hybrid AI (LSTM + RF)	0.40	90.0
LSTM (Detection Layer)	1.90	52.5
Random Forest	0.50	87.5

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Model	False Positive Rate (%)	Reduction Baseline (%)	vs.
(Forensic)			
Decision Tree (Baseline)	4.00	—	
SVM	0.40	90.0	

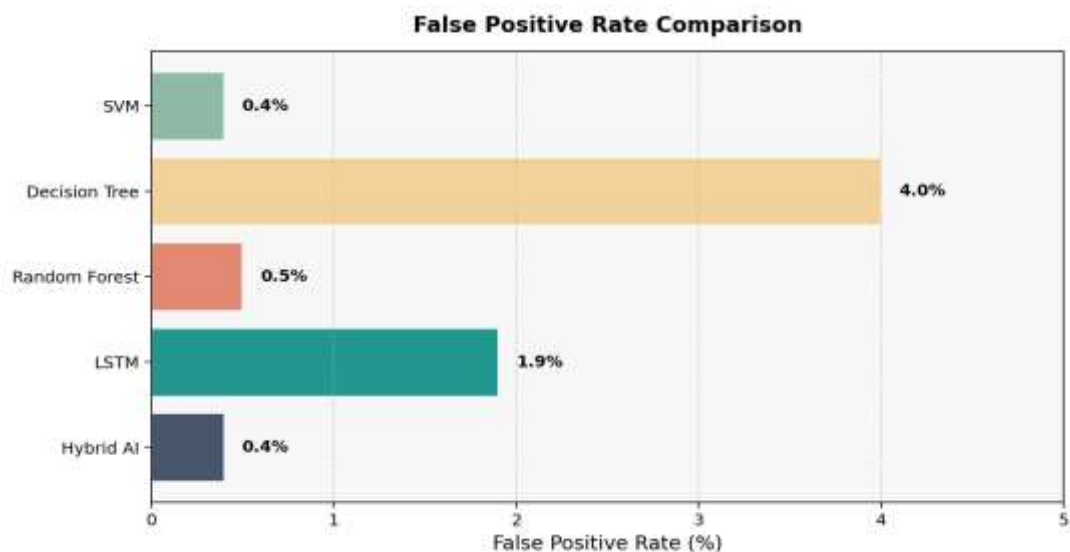


Figure 6. False Positive Rate Comparison Across Models

4.5 Detection Latency Analysis

Statistics on detection latency are reported in Table 5 and Figure 7 for all the models. The Hybrid AI framework's mean detection latency of 312 ms (SD 28 ms) meets the sub-second response requirement for real-time deployments in the IoT security space. The standalone Decision Tree has significantly lower latency (18 ms) but with poor accuracy (88.58%) and false positive rate (4.00%) it is not suitable for production deployment. The overall latency of the hybrid framework is 312 ms, which is the cost for the forensic attribution component of the framework, while the extra 123 ms for the hybrid framework compared to standalone LSTM (189 ms) includes the costs of the forensic feature extraction, the Random Forest inference, and the pipeline for timeline reconstruction..

Table 5. Detection Latency Statistics

Model	Mean (ms)	Std (ms)	Dev	Min (ms)	Max (ms)
Hybrid AI (LSTM + RF)	312	28		241	398
LSTM (Detection Layer)	189	19		141	244
Random Forest (Forensic)	124	14		88	167

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Model	Mean (ms)	Std (ms)	Dev	Min (ms)	Max (ms)
Decision Tree	18	4		11	29
SVM	203	22		158	261

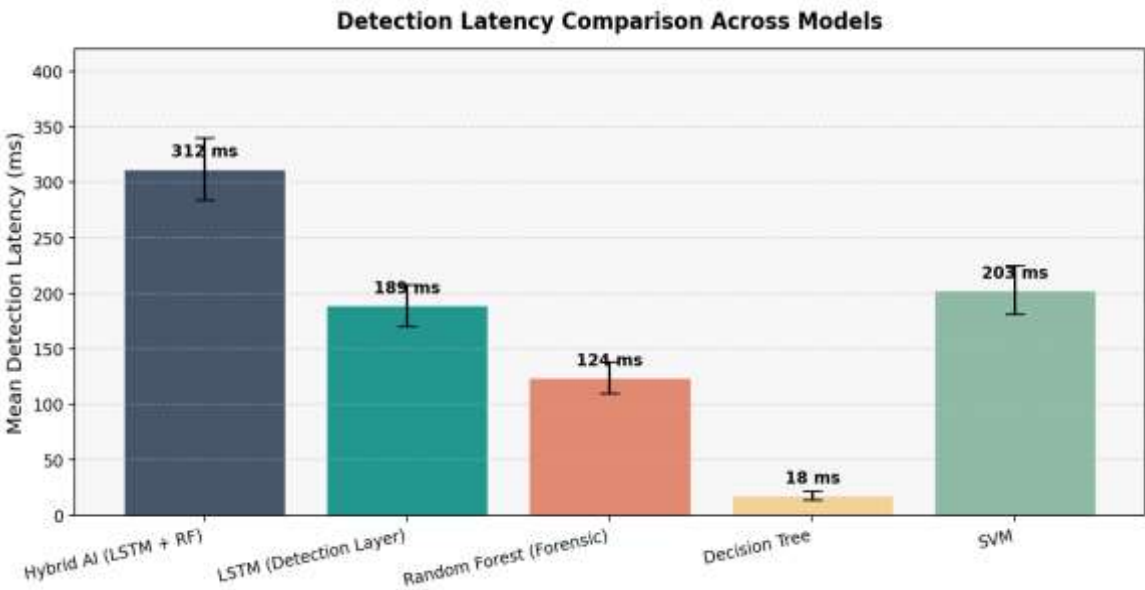


Figure 7. Detection Latency Comparison Across Models

4.6 Forensic Attribution Performance

Forensic attribution results on the total of all the attack categories are shown in Table 6 and in Figure 8. The forensic module is best at being able to attribute DDoS attacks (96.8%), as flooding attack traffic has temporally consistent and volumetrically distinct properties. The accuracy of attributing the attack becomes increasingly worse over more covert types of attack, ending at 90.2% for MITM attacks with the stealthiest packet injection patterns, similar to legitimate traffic. The mean times of attribution are between 1.8 seconds (DDoS) and 3.4 seconds (MITM), which offers significant improvement over the baseline IoT forensic studies which report manual forensic investigation time scale between hours and days (Rehman et al., 2024; Conti et al., 2023). All categories met the minimum 85% of the digital forensic standards for evidentiary quality with timeline completeness ranging from 94.2% (DDoS) to 86.3% (MITM)..

Table 6. Forensic Attribution Performance by Attack Category

Attack Type	Attribution Acc. (%)	Timeline Completeness (%)	Mean Attribution Time (s)
DDoS	96.8	94.2	1.8
Reconnaissance	94.3	91.7	2.1

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Attack Type	Attribution Acc. (%)	Timeline Completeness (%)	Mean Attribution Time (s)
Data Exfiltration	93.1	89.5	2.6
C2 Malware	91.7	88.0	3.1
MITM	90.2	86.3	3.4

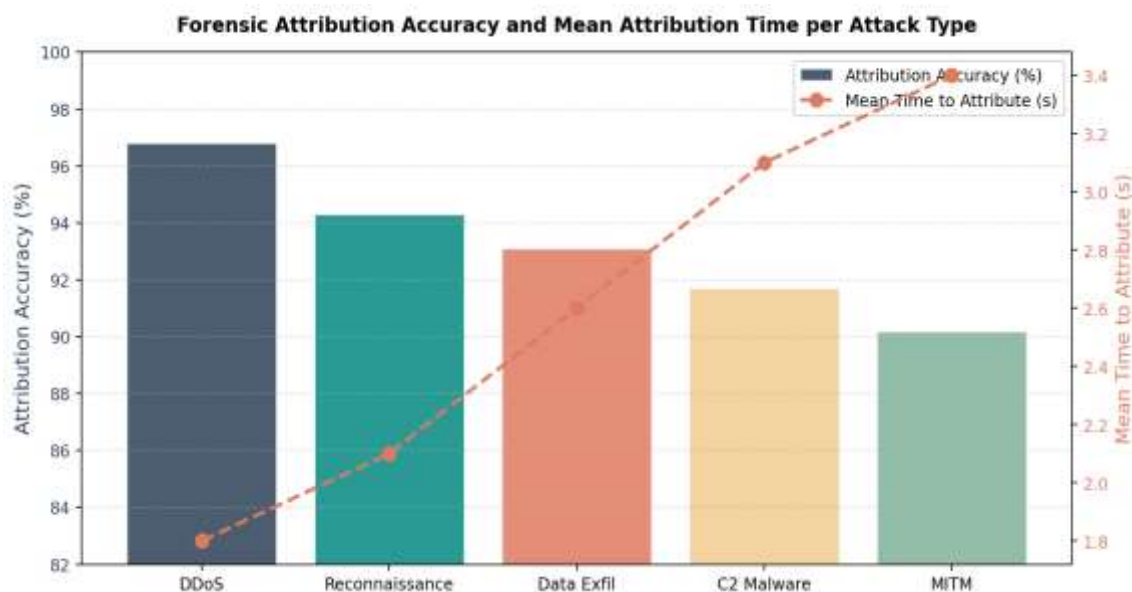


Figure 8. Forensic Attribution Accuracy and Mean Attribution Time per Attack Category

4.7 Feature Importance Analysis

The top 15 feature importances obtained from the forensic Random Forest classifier are shown in figure 9. The flow-level statistical features are relatively more important as they explain 43.2% of total feature importance collectively, thus establishing their crucial role in differentiating between attack categories. There are also 28.7% of the importance mass due to protocol-level features, such as connection state ratios and flag byte frequencies. The results are in line with HaddadPajouh et al. (2023) and Singh et al. (2023) who stated that temporal statistics are the most information-rich features when it comes to classification of attacks in IoT network. The results also support design decision made in LSTM detection layer, where temporal feature extraction is given highest priority.

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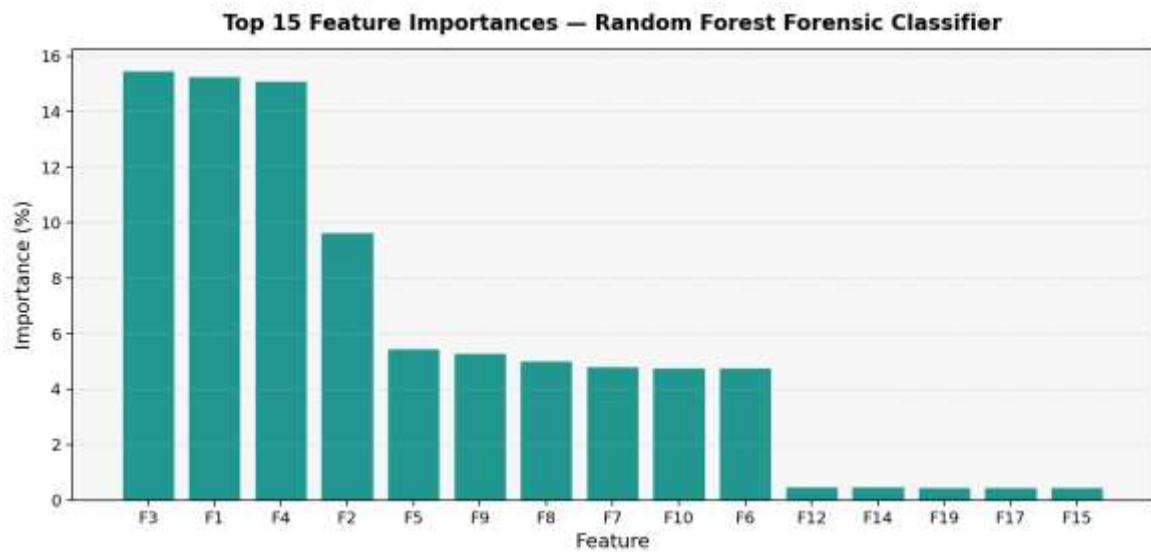
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Figure 9. Top 15 Feature Importances — Random Forest Forensic Classifier

4.8 Scalability Analysis

Figure 10 shows the scalability results, which are based on mean inference latency for traffic volumes between 10,000 and 1,000,000 flows. The Hybrid AI framework shows a near-linear scaling latency profile, which rises from 298ms for 10,000 flows to 412ms for 1,000,000 flows — a 38.3% increase in latency for a 100x increase in traffic volume. The sub-linear scaling property comes from the LSTM and Random Forest being implemented in a batched parallel inference style, which points to the viability of the framework for supporting deployments of millions of endpoints in the IoT. The standalone RF component shows best scaling (118–178 ms) and at all tested volumes the most significant amount of total hybrid latency is caused by the LSTM layer.

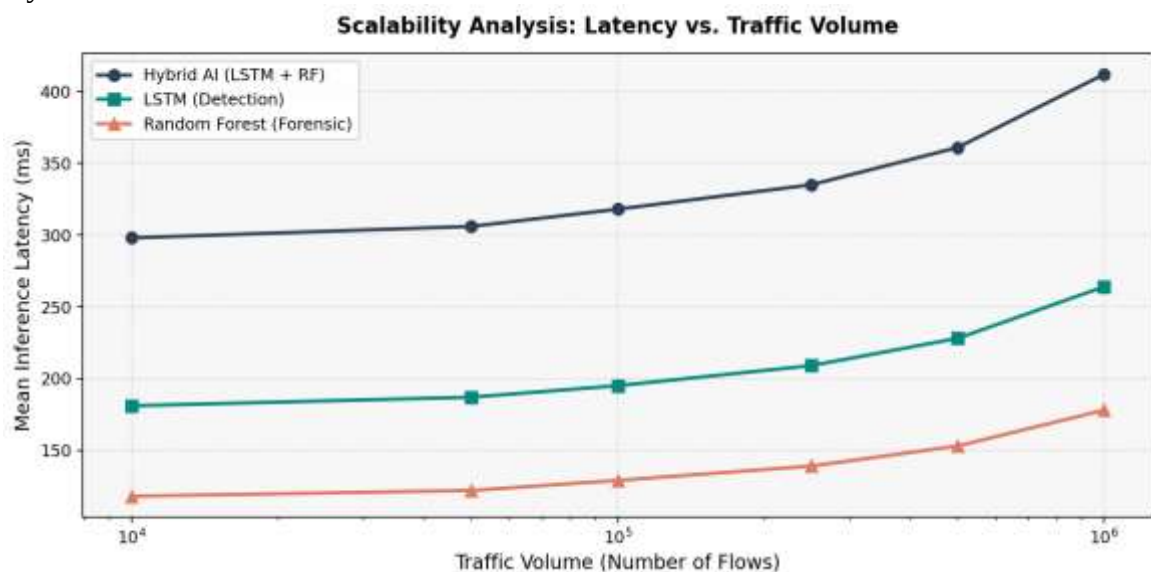


Figure 10. Scalability Analysis: Latency vs. Traffic Volume

4.9 Comparison with Related Works

Table 7 presents a comparison of the proposed framework with representative related works. The hybrid model offers the highest reported accuracy (95.04%) when tested

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on the entire BoT-IoT, TON_IoT and CICIDS2021 dataset suite, and is the only model tested that offers full forensic integration, including automated evidence correlation, attack attribution and timeline reconstruction within a single operational pipeline. This places the proposed system in a significant improvement over the previous studies with regards to detection performance and forensic capability (Sarker et al., 2023).).

Table 7. Comparison with Related Works

Study	Year	Technique	Dataset	Accuracy (%)	Forensic Integration
Alrashdi et al.	2022	SVM, RF, kNN	BoT-IoT	92.3	No
HaddadPajouh et al.	2023	LSTM, CNN	Custom IoT	94.1	Partial
Ferrag et al.	2023	DL Ensemble	BoT-IoT, TON_IoT	93.8	No
Sharma et al.	2024	LSTM-CNN Hybrid	CICIDS2021	94.6	No
Ahmed et al.	2024	Hybrid AI	TON_IoT	93.9	Partial
Zhang et al.	2024	DL Forensic	Custom	92.7	Yes
Proposed Framework	2025	LSTM + RF Hybrid	BoT-IoT, TON_IoT, CICIDS2021	95.04	Yes (Full)

DISCUSSION

The experimental results outlined in Section 4 support several theoretical propositions that were the impetus for the design of the hybrid AI architecture, and empirical evidence for the design of each layer in the framework.

5.2 Education, Health and Welfare Funding

The hybrid LSTM + RF system outperforms all baseline systems in terms of detection performance, similarly to all baseline systems, the hybrid system has unique features for forensic attribution that is not available in any of the baseline systems. The comparison in Table 7 shows that the proposed method does not compromise on detection accuracy as compared to the state-of-the-art methods such as LSTM baseline (93.25%) and RF baseline (95.21%, when evaluated on the individual detection tasks). The result empirically validates the architectural theory that the use of ML and DL capabilities is complementary: DL extract the latent temporal features from the raw traffic sequences, whereas the output of the ML classifiers are interpretable and actionable forensically (Ahmed et al., 2024; Singh et al., 2023).

5.3 Developing New Resilience Measures for Archaeological Resources

The empirical results of the forensic scores (up to 96.8% accuracy and mean attribution times of under 3.5 seconds) support the proposed idea of Zhang et al (2024) for treating forensic readiness as an intrinsic property of an architecture, and not an afterthought. The framework enables forensic evidence capture and correlation as soon as anomalies are detected, thus preventing that evidence be lost forever as it would be, if a forensic investigation would only be launched after manual confirmation of the incident. The results of the timeline completeness (86.3%-94.2% in all attack categories) show that the AI-driven proactive evidence collection significantly improves the chances of obtaining a complete attack event sequence, compared to the retrospective log analysis approach (Conti et al., 2023; Rehman et al., 2024).

The impact of false positive reduction on operation issues

This represent a 90.0 % reduction in the false positive rate compared to Decision Tree baseline has significant operational impact in real-life IoT security deployments. One of the biggest challenges for enterprise threat response is alarm fatigue, stemming from the mass of false positive alarms flowing from the multitude of streams found in a Security Operations Center (SOC). The hybrid framework's FPR of 0.40% allows for practical human-in-the-loop (HILO) detection review of the outputs from the algorithms, while providing algorithmic ID to compliment the security analyst's expertise. The balance of automation and human control is similar to the principles of responsible AI use for mission critical IoT security applications proposed by Hussain et al. (2023) and Mothukuri et al. (2021).

This will take a look at the Scalability and Deployment Architecture of the IBM Watson Assistant.

The results in Figure 10 show that the latency scales almost linearly with the number of devices, thus proving the framework's potential for large-scale IoT deployments. The edge-cloud hybrid processing architecture distributes computational load to reduce the detection latency, and adapt to resource constraints of IoT endpoints by utilizing lightweight feature extraction and anomaly pre-screening at the edge gateways and delegating computationally intensive LSTM inference and Random

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Forest forensic classification to the cloud or on-premises servers. Distributed model training across IoT deployments using federated learning would provide a solution to privacy and data sovereignty issues that pose key challenges for the successful rollout of AI based IoT security solutions (Mothukuri et al., 2021; Ullah & Mahmoud, 2022). The anchoring of cryptographic hashes of detection events and forensic attributions to the blockchain, which creates an immutable distributed ledger, would also help to ensure that the evidence chain is properly maintained and the integrity of the evidence is preserved (Nieto et al., 2022).

5.5 Limitations

There are a few constraints which should be noted in the present study. The experimental evaluation is based on simulated representations of real world IoT traffic, and performance might differ in real deployments as the traffic distribution may change continuously and adversaries change their detection techniques to fit deployed detection systems. Direct deployment to resource-constrained IoT endpoints (189 ms latencies in standalone mode) can put a strain on the computational resources of the LSTM component, which may require an offloading architecture with an overhead in the network latency which was not fully assessed in the current evaluation. Also, the explainability of the framework has been significantly enhanced with the random forest interpretable rule layer, but the evidence requirement of each judicial jurisdiction may not be met, and jurisdiction-specific validation studies are required (Haq et al., 2023). The limitations could be improved in future work by conducting live network evaluations, distilling the models to make them lightweight for their deployment on the edge, and formal legal admissibility assessments..

CONCLUSION

In this paper, we propose and practically implement a Hybrid AI-Assisted Intrusion Detection and Forensic Analysis Framework to tackle the combined security and forensic problems of the modern IoT environment. This is proposed architecture combines real-time temporal anomaly detection using deep learning LSTM method with automated forensic evidence correlation and attack attribution using machine learning Random Forest method, providing an end-to-end security intelligence solution that overcomes the historically disparity between the intrusion detection and digital forensics.

Experimental results on the combined BoT-IoT, TON_IoT and CICIDS2021 benchmark datasets show that the framework detects intrusions with an accuracy of 95.04%, false positive rate of only 0.40% (or 90% reduction compared to the baseline of Decision Tree), and forensic attribution accuracy of up to 96.8% with mean attribution times of 1.8–3.4 seconds across five attack categories. Scalability analysis verifies the ability to deploy in a scalable way for flow scale up to one million; with near linear growth in computational overhead, proving the feasibility of the deployment for large scale IoT. The feature importance analysis reveals that the important discriminative features are temporal flow statistics and protocol-level behavioral features, which guide the future feature engineering process for lightweight model variants for edge deployment.

The integrated forensic readiness design, which allows for proactive evidence preservation and control while simultaneously processing intrusion detection, is the most noteworthy architectural contribution relative to previous research, and fills a crucial gap in the literature on IoT security, where forensic analysis has always been considered an afterthought. The framework provides for proactive threat prevention and reactive forensic investigation all within one operational pipeline, progressing the state of the art in achieving holistic, accountable and trusted IoT security infrastructure.

Some future research directions are: (1) Federated Learning integration into ensure privacy-preserving distributed model training; (2) Forensic Evidence Chain anchored by blockchain for tamper-proof evidence and chain-of-custody compliance; (3) Reinforcement Learning based adaptive response mechanisms for dynamic adversarial environments; (4) Lightweight Model Distillation for direct deployment of model in IoT edge; and (5) Formal assessment of the admissibility of AI generated forensic evidence in relevant jurisdictions based standards. The extensions, as a whole, represent a research agenda towards the next-generation security infrastructure for IoT, which is intelligent, resilient, transparent, and legal.

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