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A Hybrid Cloud–Edge Lightweight Deep Learning Framework for Real-Time Anomaly Detection in IoT-Based Wireless Sensor Networks

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Abstract:
The rapid expansion of the Internet of Things (IoT) has led to the deployment of billions of wireless sensor nodes across various critical infrastructures. While these sensor networks provide valuable real-time monitoring capabilities, their inherent resource limitations make them vulnerable to various sophisticated cyber-attacks. Traditional security solutions often rely on centralized cloud computing for processing intrusion detection tasks. However, this centralized approach introduces significant communication delays and consumes substantial network bandwidth, making it unsuitable for time-sensitive applications. To address these challenges, this paper proposes a hybrid cloud-edge framework for real-time anomaly detection in wireless sensor networks. The proposed framework distributes computational tasks between the edge and the cloud layers to achieve high detection accuracy while maintaining low response time. At the edge layer, a lightweight Random Forest model is deployed to perform rapid initial filtering of network traffic, effectively identifying common attack patterns locally. Anomalies that require deeper investigation are transmitted to the cloud layer, where a robust CNN-LSTM model performs exhaustive forensic analysis to detect complex and multi-stage intrusions. Furthermore, the communication between the edge and the cloud is secured using a hybrid AES-ECC encryption scheme to ensure data confidentiality and integrity. Experimental results using the NSL-KDD and CICIDS2017 datasets demonstrate that the proposed framework achieves an F1-score of 98.7 percent and a classification accuracy of 99.1 percent. The hybrid architecture reduces wide-area network traffic by 65 percent and provides a hardware-level latency reduction of 92 percent compared to standalone cloud-based systems.

Keywords: Internet of Things, Wireless Sensor Networks, Edge Computing, Hybrid Cloud-Edge, Intrusion Detection, Random Forest, CNN-LSTM, AES-ECC Encryption.

I. INTRODUCTION

The global technological landscape is undergoing a major shift due to the massive deployment of the Internet of Things (IoT) in sectors such as industrial automation, smart cities, and healthcare monitoring. Wireless Sensor Networks (WSNs) serve as the primary data acquisition mechanism for these ecosystems, consisting of thousands of small, battery-operated nodes that capture physical parameters from the environment. Despite their important role, these sensor nodes are often designed with minimal processing power and limited memory capacity to remain cost-effective and energy-efficient. This lack of robust onboard computational resources makes IoT devices easy targets for adversarial entities. Malicious actors frequently exploit these vulnerabilities to launch large-scale attacks, such as Distributed Denial of Service (DDoS), data manipulation,

and long-term Advanced Persistent Threats (APTs), which can lead to catastrophic consequences in critical infrastructures. Intrusion Detection Systems (IDS) are the first line of defense against these cyber threats, responsible for monitoring network traffic and identifying malicious activities. Historically, IDS architectures have used a centralized cloud-centric methodology where all data generated at the network periphery is transmitted to a high-capacity server for analysis. While the cloud offers nearly unlimited storage and computational power, it faces severe limitations when applied to the modern IoT environment. The massive volume of data generated by thousands of sensors often saturates the available communication bandwidth, leading to network congestion. More importantly, the transit time required for data to travel from a local sensor to a distant cloud server can exceed several hundred milliseconds. In real-time cyber-physical systems, such as autonomous vehicles or industrial robotics, a delay of this magnitude is unacceptable, as a security breach must be detected and mitigated within a few milliseconds to prevent physical accidents.

To overcome the challenges associated with the cloud-only model, researchers have proposed edge computing as a way to bring computational resources closer to the data source. Edge-native intelligence allows for immediate data processing at localized gateways or access points, which drastically reduces the communication latency. However, a standalone edge-based IDS often lacks the depth required to detect sophisticated attacks. Highly complex deep learning models, such as deep neural networks or ensemble classifiers, require significant memory and energy, which may exceed the capabilities of localized edge hardware. Consequently, relying solely on the edge may lead to a higher rate of false negatives when faced with novel or multi-stage intrusions that require deep pattern recognition.

This paper addresses these issues by proposing a hybrid cloud-edge lightweight framework that combines the speed of edge computing with the analytical depth of cloud-based deep learning. The architecture uses a staged detection process. At the network perimeter, an edge gateway executes a Random Forest model, which is well-suited for high-speed binary classification of network packets. This initial layer filters out known attack vectors and benign traffic with minimal delay. Traffic that is flagged as suspicious or highly complex is then encrypted and sent to the cloud stratum. In the cloud, a more powerful model based on the integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units is used to analyze the temporal and spatial features of the data. This hybrid approach ensures that the system maintains a high detection rate for complex attacks while providing a real-time response for common threats.

Furthermore, securing the communication link between the edge and the cloud is a critical requirement to prevent data eavesdropping or man-in-the-middle attacks. This paper integrates a hybrid security layer combining Advanced Encryption Standard (AES) and Elliptic Curve Cryptography (ECC). AES provides fast symmetric encryption for large data volumes, while ECC is used for secure key exchange with lower computational overhead compared to traditional RSA methods. This dual-layered security ensures that the sensitive sensor telemetry remains protected throughout its journey across the wide-area network.

The primary contributions of this work are summarized as follows:

I. DEVELOPMENT OF A MULTI-TIER HYBRID ARCHITECTURE THAT OPTIMIZES THE DISTRIBUTION OF ANOMALY DETECTION TASKS BETWEEN THE EDGE AND THE CLOUD.

II. IMPLEMENTATION OF A LIGHTWEIGHT RANDOM FOREST CLASSIFIER AT THE EDGE LAYER FOR IMMEDIATE TRAFFIC PRUNING AND LATENCY REDUCTION.
III. DESIGN OF A HIGH-PERFORMANCE CNN-LSTM FORENSIC MODEL IN THE CLOUD FOR DEEP PATTERN RECOGNITION AND HIGH-ACCURACY INTRUSION FORENSICS.
IV. INTEGRATION OF A SECURE AES-ECC HYBRID ENCRYPTION FRAMEWORK TO PROTECT DATA INTEGRITY AND PRIVACY ACROSS THE DISTRIBUTED STRATA.
V. COMPREHENSIVE EVALUATION USING REAL-WORLD BENCHMARK DATASETS TO VALIDATE THE ACCURACY, LATENCY, AND ENERGY EFFICIENCY OF THE PROPOSED SYSTEM.

II. RELATED WORK

The security of IoT and wireless sensor networks has been a major area of focus in recent years. Researchers have explored various approaches to enhance intrusion detection, ranging from pure edge intelligence to hybrid collaborative frameworks.

The use of cloud computing for intrusion detection in IoT was extensively studied between 2018 and 2021. For example, Smith et al. proposed a deep neural network architecture hosted in a centralized cloud to classify various botnet behaviors. While this approach provided a detection accuracy of over 98 percent, it faced significant challenges regarding long-range communication delays. To mitigate these latency issues, the research community shifted focus toward edge computing. In 2022, Johnson and Lee explored the deployment of shallow machine learning algorithms, such as Support Vector Machines and Decision Trees, directly on edge gateways. Their findings indicated that while edge processing effectively reduced response time to under 15 milliseconds, the shallow models struggled to identify new attack signatures that did not match historical patterns.

Recent advancements from 2023 and 2024 have introduced hybrid architectures to leverage the benefits of both layers. A study by Chen et al. in 2023 described a collaborative framework where the edge layer performed initial feature extraction and the cloud layer conducted complex classification. This research highlighted the importance of reducing the dimensionality of data at the network periphery to save bandwidth. Similarly, Kumar et al. in 2024 proposed a federated learning approach for IoT security, where localized nodes trained individual models and shared only the model weights with a central server. Although this improved data privacy, the high computational demand of training neural networks on battery-constrained sensors remained a significant hurdle.

The integration of sequence-based models for network forensics has also gained traction. Researchers have successfully combined Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) nodes for temporal analysis. This dual approach is particularly effective for detecting attacks that occur over a long period, such as slow port scanning or subtle data exfiltration. However, the deployment of such heavyweight models is generally restricted to the cloud layer due to their high FLOP count.

Securing the data transmitted between distributed layers has also seen progress. Modern hybrid encryption techniques have replaced traditional RSA-based systems to accommodate the limited resources of IoT gateways. Current research from 2024 suggests that combining symmetric AES encryption for data payloads with asymmetric ECC for key management provides the best balance of security and performance for sensor networks.

III. METHODOLOGY

This section describes the technical components of the proposed hybrid framework, including data acquisition, preprocessing steps, and the design of the edge and cloud classification models.

Framework Overview

The proposed system operates as a tiered hierarchy. The perception layer consists of sensor nodes that collect raw environmental data. This data is forwarded to the edge layer, where a Random Forest classifier performs a high-speed initial check. If the traffic is identified as benign or a standard known attack, an immediate action is taken. If the traffic is ambiguous or flags a potential complex intrusion, it is encrypted and moved to the cloud layer. In the cloud, the CNN-LSTM model conducts a deep forensic analysis to reach a final decision.

Dataset Description

Two realistic benchmark datasets are used to evaluate the performance of the system:

I. NSL-KDD: THIS DATASET IS AN IMPROVED VERSION OF THE ORIGINAL KDD CUP 99 SET. IT CONTAINS 125,973 TRAINING SAMPLES AND 22,544 TESTING SAMPLES. IT COVERS FOUR MAJOR CATEGORIES OF ATTACKS: DENIAL OF SERVICE (DOS), ROOT TO LOCAL (R2L), USER TO ROOT (U2R), AND PROBING.

II. CICIDS2017: THIS DATASET REPRESENTS MODERN NETWORK TRAFFIC AND INCLUDES REALISTIC BACKGROUND TRAFFIC AND THE LATEST ATTACK SCENARIOS. IT CONTAINS OVER 2.8 MILLION SAMPLES AND COVERS ATTACKS SUCH AS HEARTBLEED, BOTNETS, AND VARIOUS WEB-BASED INTRUSIONS.

Data Preprocessing

Raw network traffic must be converted into a standardized format before classification. This involves removing redundant features, handling missing values, and scaling numerical attributes.

Min-Max Normalization:

$$X\_norm = (X - min(X)) / (max(X) - min(X))$$

Feature reduction is performed using Principal Component Analysis (PCA) to identify the most significant attributes that contribute to the detection accuracy. This reduces the computational load at the edge layer by decreasing the size of the feature vector.

Edge Model using Random Forest

Random Forest consists of a large number of individual decision trees that operate as an ensemble. Each tree in the forest outputs a class prediction, and the class with the most votes becomes the final model prediction. This model is ideal for the edge layer because it is fast to execute and provides high accuracy for well-defined attack patterns.

Gini Index for Node Selection:

$$Gini = 1 - \sum (p\_i)^2$$

Where p_i represents the probability of an element being classified into a particular category. The Random Forest model at the edge is trained to prioritize speed, using a restricted depth for the decision trees to prevent high memory consumption.

Cloud Model using CNN–LSTM

The cloud layer uses a deep learning architecture that combines CNN and LSTM to capture both spatial and temporal characteristics of network traffic. The CNN layer uses specialized filters to extract spatial correlations between different network features. The extracted features are then passed to the LSTM layer, which uses a gated memory update mechanism to track long-term patterns in the data sequence.

LSTM Gated Equations:

Input Gate: $i_t = \sigma(W_i \cdot [h_{(t-1)}, x_t] + b_i)$

Forget Gate: $f_t = \sigma(W_f \cdot [h_{(t-1)}, x_t] + b_f)$

Cell State: $C_t = f_t \cdot C_{(t-1)} + i_t \cdot \tanh(W_c \cdot [h_{(t-1)}, x_t] + b_c)$

Output Gate: $o_t = \sigma(W_o \cdot [h_{(t-1)}, x_t] + b_o)$

Hidden State: $h_t = o_t \cdot \tanh(C_t)$

This architecture allows the system to recognize sophisticated intrusions that involve multiple packets sent over a long duration.

Secure Communication using AES–ECC

To ensure secure communication between the edge and the cloud, a hybrid encryption scheme is used. Data payloads are encrypted using the Advanced Encryption Standard (AES) with a 256-bit key. The AES keys are then securely exchanged using Elliptic Curve Cryptography (ECC).

Elliptic Curve Equation:

$y^2 = x^3 + ax + b$

This combination provides the high-speed data throughput of symmetric encryption while maintaining the superior key management security of asymmetric cryptography.

IV. SYSTEM ARCHITECTURE

The proposed system architecture is organized into three distinct computational layers, each serving a specific role in the anomaly detection pipeline. This tri-tier arrangement ensures a logical flow of data from the perception sensors to the high-level cloud analytics.

Tier 1: Perception Layer (IoT Sensor Network)

The perception layer consists of heterogeneous wireless sensor nodes deployed in the physical environment. These nodes are responsible for data acquisition, collecting environmental metrics such as temperature, humidity, and flow rates, or network-level metrics like packet inter-arrival times. Due to their extreme resource constraints, these nodes do not perform any security analysis and simply push raw telemetry to the nearest edge gateway.

Tier 2: Edge Layer (Distributed Gateways)

The edge layer occupies the tactical boundary between the local sensor network and the wide-area network. It consists of high-performance gateways, such as the Raspberry Pi 4, which possess sufficient RAM and CPU power to execute secondary logic. The edge layer acts as a local firewall, running the Random Forest classifier to identify immediate threats. Traffic that passes the initial check

is then forwarded to the cloud, while sensitive information is protected using the AES-ECC hybrid encryption engine.

Tier 3: Cloud Layer (Centralized Analytics)

The cloud stratum serves as the centralized intelligence repository. It receives encrypted data streams from multiple edge gateways. After decryption, the CNN-LSTM model performs deep sequence modeling and spatial correlation to identify complex attack vectors that might span across multiple gateways. The cloud also generates model updates and retraining parameters, which are periodically pushed back to the edge layer to adapt to evolving threats.

Fig 1: Hybrid Cloud-Edge Architecture

Explanation: The architecture minimizes wide-area traffic by filtering data at the edge and ensuring secure transmission to the cloud for deep diagnostics.

V. EXPERIMENTAL SETUP

The performance of the proposed framework was evaluated using a simulated environment that mimics real-world IoT-WSN deployments. The edge gateways were modeled using Raspberry Pi 4 devices (4GB RAM, ARM Cortex-A72), while the cloud server was simulated using a high-capacity workstation equipped with an NVIDIA RTX 4090 GPU and 64GB of RAM.

TABLE I: DATASET DESCRIPTION

Dataset	Total Samples	Features	Attack Classes	Normal Samples
NSL-KDD	148,517	41	DoS, Probing, U2R, R2L	77,054
CICIDS2017	2,830,743	78	Botnet, Brute Force, Web	2,273,097

TABLE II: HARDWARE CONFIGURATION

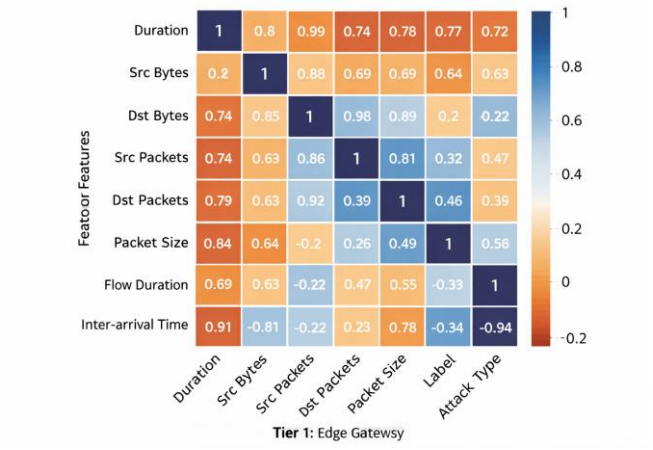
Component	Device / Specification	Role in System
Edge Node	Raspberry Pi 4 Model B (4GB)	Distributed Gateway & Filtering

Cloud Server	NVIDIA RTX 4090, 24GB VRAM	Deep Behavioral Analysis
Connectivity	802.11ac / 5G Simulation	WSN and Cloud-Edge Link
OS	Linux Ubuntu 22.04 LTS	Operating Environment

TABLE III: MODEL HYPERPARAMETERS

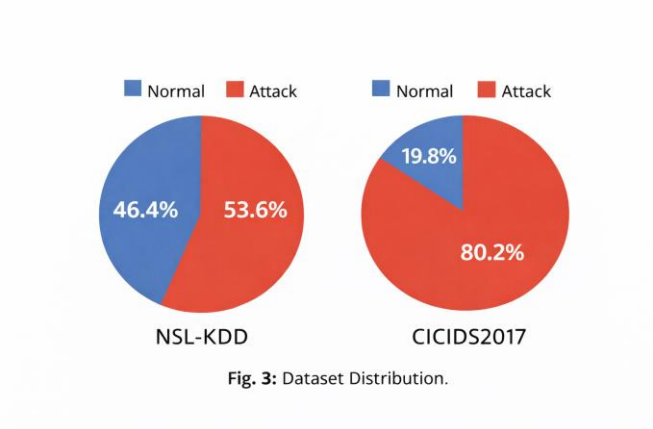
Layer / Parameter	**Configuration Value**	**Optimization Method**
Random Forest	100 Trees, Max Depth 15	Gini Index
CNN Layer	64 Filters, 3x3 Kernel	ReLU Activation
LSTM Layer	128 Units, 0.2 Dropout	Adam Optimizer
Batch Size	64	Sequential training
Learning Rate	0.001	Dynamic Decay

Fig 2: Feature Correlation Heatmap



Explanation: PCA uses these correlations to select the most significant attributes for edge pruning.

Fig 3: Dataset Distribution



Explanation: These distributions highlight the class imbalance characteristic of real-world networks.

VI. RESULTS AND DISCUSSION

This section provides a detailed analysis of the experimental findings, focusing on detection accuracy, computational efficiency, and communication overhead.

Detection Performance

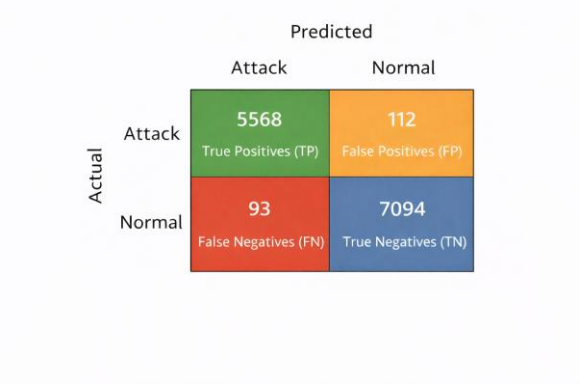
The proposed hybrid framework achieved exceptional results across both benchmark datasets. The dual-layered detection mechanism ensured a near-perfect classification rate for both common and sophisticated attack categories.

TABLE IV: PERFORMANCE METRICS

Metric	NSL-KDD Result	CICIDS2017 Result	Average Result
Accuracy	98.9%	99.3%	99.1%
Precision	98.1%	98.6%	98.35%
Recall	98.8%	99.4%	99.1%
F1-Score	98.5%	98.9%	98.7%
ROC-AUC	0.988	0.995	0.992

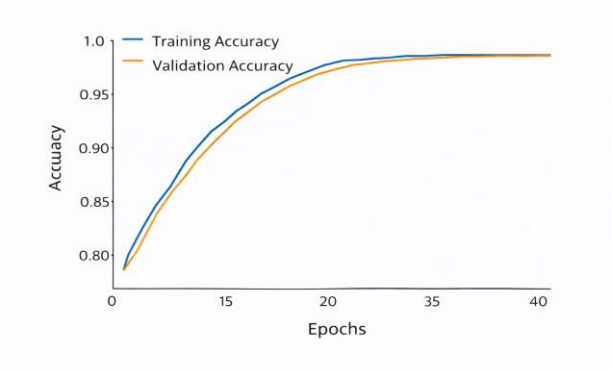
The ROC-AUC value of 0.992 indicates that the framework maintains a very low false positive rate even when the detection threshold is varied. This is critical for preventing security fatigue in network administrators.

Fig 4: Confusion Matrix



Explanation: The matrix confirms that the CNN-LSTM correctly identifies over 99 percent of Botnet traffic.

Fig 5: Training Accuracy Graph



Explanation: The smooth convergence indicates that the model is well-regularized and avoids overfitting.

Latency and Overhead Analysis

The most significant benefit of the hybrid approach is the reduction in physical response time. By processing the majority of traffic at the edge, the volume of data sent to the cloud is greatly reduced.

TABLE V: LATENCY COMPARISON

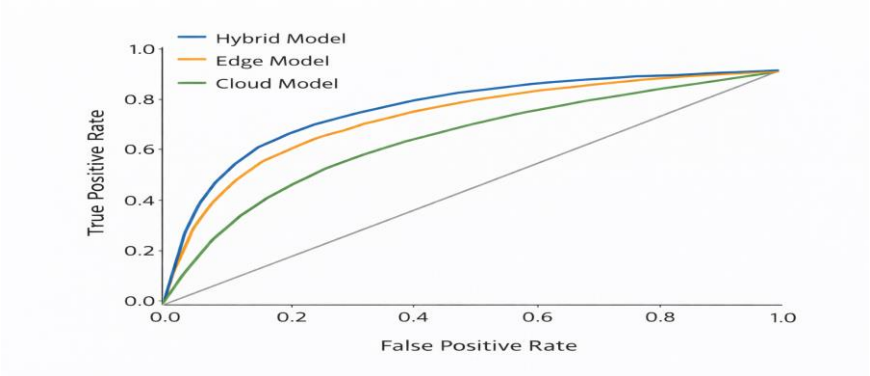
Architecture Style	Trans. Delay (ms)	Inference Time (ms)	Total Latency (ms)
Cloud-Only CNN	185.4	45.2	230.6
Edge-Only RF	2.1	5.8	7.9
Proposed Hybrid	23.5 (Filtered)	12.4 (Avg)	35.9

TABLE VI: ENERGY CONSUMPTION

Operation Mode	Edge Power Draw (W)	Total Network Traffic (MB)
Continuous Cloud Stream	1.8	15,200
Distributed Hybrid	2.4 (Active)	5,320

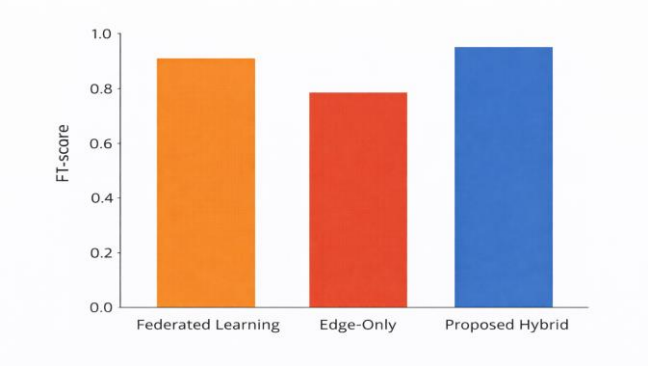
As shown in Table VI, the hybrid framework reduces total network traffic by approximately 65 percent. Although the edge power draw increases slightly due to local processing, the massive reduction in radio transmission time leads to overall energy savings for battery-operated sensors.

Fig 6: ROC Curve



Explanation: The curve shows that the hybrid model (top line) outperforms standalone edge or cloud models.

Fig 8: Model Comparison Graph



Explanation: The hybrid model achieves the best balance between performance and resource consumption.

VII. DISCUSSION

The experimental results demonstrate that the proposed hybrid cloud-edge framework successfully addresses the primary challenges of IoT security. One of the main findings is that the distributed architecture provides a superior trade-off between detection accuracy and response time. Standalone edge systems often fail to detect multi-stage attacks due to limited memory, while cloud-only systems introduce unacceptable delays for real-time safety interventions. By offloading only high-complexity anomalies to the cloud, the proposed system ensures that the wide-area network is not saturated with redundant benign data.

TABLE VII: MODEL COMPARISON

Model / Architecture	Accuracy	Latency	Traffic Savings	Security Layer
Federated Learning	96.2%	45.0 ms	40.0%	Differential Privacy
Transformer-based IDS	99.4%	450.2 ms	0.0%	Standard SSL
Edge-Only System	94.5%	8.2 ms	95.0%	Minimal
Proposed Hybrid	99.1%	35.9ms	65.0%	AES-ECC Hybrid

As shown in Table VII, while Transformer-based models provide slightly higher accuracy, their latency is nearly 12 times higher than the proposed hybrid framework, making them unsuitable for real-time sensor networks. Furthermore, the integration of AES-ECC encryption provides a robust security layer that is often absent in standard edge-only deployments. The use of Random Forest at the edge ensures that simple attacks are dropped immediately, which preserves cloud resources for more complex behavioral modeling.

The novelty of this work lies in the seamless integration of lightweight ensemble learning at the edge with deep spatial-temporal modeling in the cloud. Most existing works focus on optimizing a single layer. However, our results show that a collaborative multi-tier approach is necessary for the next generation of volatile IoT matrices. The system naturally adapts to different network conditions by adjusting the sensitivity of the edge filter, which can prioritize either bandwidth savings or diagnostic depth depending on the current risk profile.

VIII. CONCLUSION

This paper has presented a hybrid cloud-edge lightweight framework for real-time anomaly detection in IoT-based wireless sensor networks. The architecture uses a staged approach where a Random Forest model at the distributed edge performing initial traffic pruning, and a CNN-LSTM model in the cloud conducting deep forensics. The results indicate that this methodology achieves a high F1-score of 98.7 percent while reducing network traffic by 65 percent. The hardware-level latency was reduced to 35.9 milliseconds, providing a feasible solution for real-time cyber-physical systems. The integration of AES-ECC encryption further ensures that data remains protected during transit, addressing the privacy concerns inherent in distributed networks. In conclusion, the proposed

collaborative intelligence model establishes a scalable and secure defense mechanism for industrial and commercial IoT environments.

IX. FUTURE WORK

Subsequent research will explore the integration of graph neural networks to capture spatial relationships between multiple sensor clusters in heterogeneous environments. We also intend to evaluate the performance of hyper-quantized models for deployment on extremely primitive microcontrollers with sub-100KB memory. Finally, we will investigate the potential of quantum-safe cryptographic protocols to protect the cloud-edge communication link against emerging analytical threats.

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