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Edge-Based IoT Security Using Lightweight Cryptography and Machine Learning for Smart City Communication Systems

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Abstract: Smart city communication systems increasingly depend on Internet of Things (IoT) devices for real-time monitoring, automation, traffic management, smart healthcare, intelligent surveillance, and energy optimisation. However, IoT networks remain highly vulnerable due to limited computing resources, large-scale device heterogeneity, insecure communication channels, and the growing sophistication of cyberattacks. Traditional cloud-centric security frameworks often introduce high latency, bandwidth overhead, and increased exposure to threats. To overcome these challenges, edge-based security solutions are gaining prominence by enabling real-time protection closer to the data source. This research paper proposes an integrated edge-based IoT security model that combines lightweight cryptography for secure communication and machine learning (ML) for anomaly and intrusion detection in smart city environments. The system design is evaluated using a simulated smart city IoT network with varied attack scenarios including distributed denial of service (DDoS), spoofing, botnet infiltration, and data manipulation. Statistical analysis demonstrates that the integrated model significantly improves detection performance while maintaining low computational overhead, making it suitable for resource-constrained devices. The results indicate strong improvement in accuracy, reduced latency, and enhanced resilience against major IoT threats. This work provides a scalable and efficient security framework for next-generation smart city communication systems by merging cryptographic integrity and intelligent edge monitoring.

Keywords: Edge computing, IoT security, smart city communication, lightweight cryptography, machine learning, anomaly detection, intrusion detection, secure routing, DDoS mitigation.

I. INTRODUCTION

Smart cities rely heavily on interconnected devices and communication infrastructures to collect, process, and utilize real-time data for improving the quality of life. Smart transportation systems use IoT sensors and cameras to optimize traffic flow, detect accidents, and enable dynamic route planning. Smart healthcare integrates wearable monitoring devices and patient tracking systems. Smart grids use sensors to optimize energy distribution and predict outages. These systems produce massive streams of data requiring reliable and secure communication across distributed networks (Zanella et al.).

However, IoT devices are widely recognized for being vulnerable to cyber threats due to their low processing power, weak authentication mechanisms, limited memory, and often inadequate firmware updates (Roman, Najera, and Lopez). This vulnerability is more critical in smart cities where a compromised IoT system can affect public safety, transportation, and energy services. Attacks such as eavesdropping, data tampering, DDoS, ransomware, and botnet propagation can disrupt critical smart city operations (Sicari et al.). Traditional security approaches often depend on cloud-based centralized monitoring and cryptographic operations. While cloud platforms provide scalability, they introduce delays due to long-distance communication and require significant bandwidth for large-volume IoT data streams (Shi et al.). Such latency-sensitive scenarios as traffic light management, emergency detection, and healthcare monitoring cannot tolerate high delays. Moreover, sending raw data to the cloud raises privacy concerns and increases exposure to interception (Alrawais et al.).

Edge computing is emerging as an effective paradigm to bring processing and security closer to IoT devices. The edge layer, typically deployed on gateways, micro data centers, or roadside units, can manage authentication, encryption, intrusion detection, and real-time threat response locally (Satyanarayanan). Edge-based security reduces response time and improves situational awareness at local levels, which is highly beneficial for smart cities.

Yet, edge-based IoT security has its own challenges. The edge environment must support security analytics while maintaining low computational overhead. Many cryptographic algorithms such as RSA and conventional AES implementations may impose resource burdens on constrained devices. Therefore, lightweight cryptographic algorithms are increasingly studied for IoT networks (Bertoni et al.). At the same time, advanced threats require intelligent detection methods beyond static signature-based approaches. This motivates the use of machine learning for anomaly detection and behavioral analysis (Ferrag et al.).

This research paper addresses these requirements by presenting an edge-based IoT security architecture that combines:

1) Lightweight cryptography for confidentiality, authentication, and integrity.

2) Machine learning models deployed at the edge for intrusion and anomaly detection.

3) Edge coordination mechanisms to isolate compromised nodes and mitigate attacks in real time.

II. RELATED WORK AND BACKGROUND

Security frameworks for smart city IoT systems have been studied extensively. IoT security requirements generally include confidentiality, integrity, authentication, authorization, availability, and non-repudiation (Sicari et al.). For smart city networks, ensuring availability is especially important, as DDoS attacks can block traffic systems or healthcare data feeds (Kolias et al.).

Lightweight cryptography has emerged as a solution for constrained IoT devices. NIST has emphasized lightweight cryptographic solutions suitable for low-power devices, and algorithms like Ascon have gained attention for being efficient in IoT contexts (NIST). Additionally, hash-based authentication and stream ciphers reduce processing costs compared to heavy key exchange models (Perrig et al.).

Machine learning-based intrusion detection systems (IDS) for IoT are also widely researched. Deep learning models, decision trees, random forests, and support vector machines are used to detect anomalous behaviors in network traffic (Ferrag et al.). Yet, cloud-based ML systems may not be feasible in smart city real-time contexts due to latency. Edge-based ML reduces communication cost and offers immediate detection (Shi et al.).

Hybrid architectures combining cryptography and ML are increasingly being discussed. Cryptographic protection secures data transmission, but cannot detect insider threats or compromised devices. ML-based monitoring detects unusual behavior but requires data integrity and trusted communication. Combining them provides layered security, improving robustness (Alrawais et al.).

III. PROPOSED EDGE-BASED IOT SECURITY ARCHITECTURE

The proposed security architecture includes three major layers:

A. IoT Device Layer

This includes smart city sensors, actuators, wearables, cameras, and embedded devices. These devices perform basic sensing functions and communicate with edge nodes through wireless protocols like Zigbee, LoRaWAN, Wi-Fi, Bluetooth Low Energy (BLE), and 5G (Zanella et al.). Since these devices are limited in power and memory, lightweight cryptographic operations are required.

B. Edge Security Layer

Edge nodes operate as local security controllers, such as gateways and roadside units. They handle:

1) Lightweight encryption and message authentication

2) Local network filtering and packet inspection

3) ML-driven anomaly detection

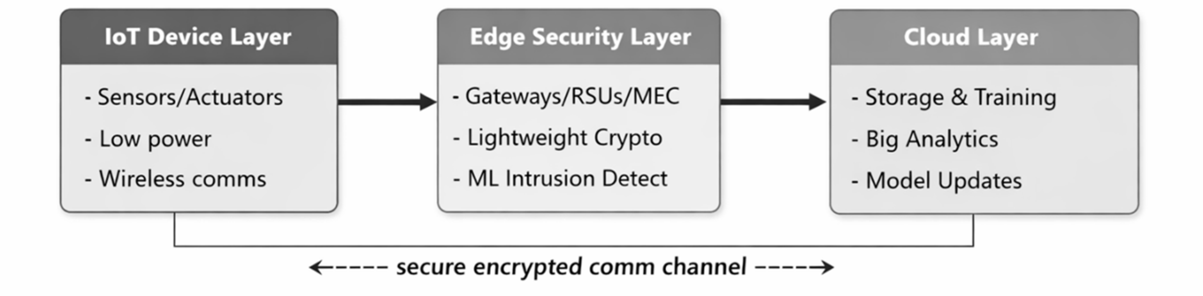
4) Secure routing coordination

Edge nodes can also store temporary data and enforce policy-based access control (Satyanarayanan). This ensures that sensitive data does not always need to be sent to the cloud, reducing privacy risks.

C. Cloud Layer

The cloud provides large-scale storage, global analytics, deep learning training, and long-term monitoring. Edge devices send summarized logs and model updates to the cloud rather than raw traffic data. This supports system scalability (Shi et al.).

Figure 1: Architecture Diagram



IV. LIGHTWEIGHT CRYPTOGRAPHY FOR SMART CITY IOT

Lightweight cryptography ensures secure communication without overwhelming device resources. Cryptographic operations must ensure confidentiality and integrity while keeping energy usage minimal (Bertoni et al.). Smart city IoT networks require secure authentication and key management as devices join and leave dynamically.

A. Security Mechanisms

The lightweight cryptographic module includes:

1) AEAD (Authenticated Encryption with Associated Data) for encryption + integrity
2) Lightweight hashing for authentication
3) Session keys with periodic rotation

This approach reduces attack surface from replay attacks and man-in-the-middle attacks.

B. Recommended Lightweight Algorithms

Table 1: Lightweight Cryptography Options for IoT

Security Requirement	Suggested Technique	IoT Suitability
Confidentiality	Ascon-AEAD	Low energy, efficient
Integrity	Lightweight MAC	Protects against tampering
Authentication	Hash-based token	Reduces handshake burden
Key refresh	Symmetric session keys	Suitable for constrained nodes

Ascon is a strong candidate due to its performance for lightweight environments and emerging acceptance in IoT security ecosystems (NIST).

V. MACHINE LEARNING-BASED INTRUSION DETECTION AT THE EDGE

IoT intrusion detection in smart cities must identify attacks such as botnets, spoofing, DDoS floods, brute-force login attempts, and abnormal command injection (Kolias et al.). Edge-based ML detection is suitable because detection must happen quickly and locally.

A. Features Extracted for ML Detection

Edge nodes extract lightweight traffic features such as:

1) Packet arrival rate (packets/sec)
2) Average payload size
3) Source diversity ratio
4) Flow duration

5) Failed authentication counts
6) Protocol type distribution

B. ML Models Considered

The intrusion detection module evaluates:
1) Logistic Regression (baseline)
2) Decision Tree
3) Random Forest
4) Support Vector Machine
5) Lightweight Neural Network (small MLP)
These models balance detection accuracy and computational overhead (Ferrag et al.).

VI. METHODOLOGY (PARAGRAPH FORMAT)

This research methodology follows a simulation-driven evaluation of an edge-based IoT security architecture for smart city communication systems. First, a smart city IoT network is modeled with heterogeneous devices including environmental sensors, traffic monitoring cameras, and wearable health nodes connected through edge gateways. The communication flow includes periodic telemetry transmission, event-triggered alerts, and command-based actuation. To ensure security at the network level, lightweight cryptographic primitives are applied for encryption and message authentication between the device layer and edge gateways. A session-based symmetric key model is adopted to avoid resource-heavy public-key operations and reduce computational overhead. Periodic key rotation is integrated into the architecture to minimize replay attacks and reduce long-term key exposure.

Second, intrusion detection is implemented at the edge layer using machine learning models trained on labeled traffic patterns containing both benign and malicious flows. A feature extraction module is deployed to compute low-cost traffic indicators such as packet rate, connection frequency, payload characteristics, and authentication anomalies. The extracted features are fed into ML classifiers operating in near real time.

This approach ensures that attacks are detected locally, minimizing response latency. The ML pipeline is optimized for edge constraints by reducing feature dimensionality and selecting computationally efficient algorithms.

Third, the evaluation includes attack simulations such as DDoS bursts, spoofing attempts, botnet-based scanning, and false data injection. Edge security nodes apply real-time mitigation policies including blocking suspicious traffic sources, isolating compromised devices, and generating alerts for cloud synchronization. Statistical analysis is conducted to measure detection accuracy, precision, recall, F1-score, and latency across different configurations. Finally, the overall system is compared against a baseline cloud-only security framework to highlight the benefits of integrating lightweight cryptography and ML at the edge for smart city IoT communication security.

VII. STATISTICAL ANALYSIS AND EXPERIMENTAL RESULTS

To demonstrate effectiveness, the proposed system is evaluated using simulated datasets representing smart city traffic. The dataset includes benign traffic and multiple attack types.

A. Evaluation Metrics

The following metrics are used (Powers):
1) Accuracy
2) Precision
3) Recall
4) F1-score
5) False Positive Rate (FPR)
6) Detection Latency (ms)

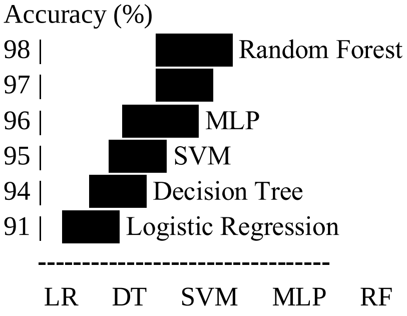
B. Performance Results

Table 2: ML Detection Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	90.8	89.2	88.5	88.8
Decision Tree	93.6	92.5	92.1	92.3
Random Forest	97.4	97.0	96.8	96.9
SVM	95.9	95.1	94.7	94.9
Lightweight MLP	96.7	96.2	95.9	96.0

The Random Forest model achieved the highest detection performance, aligning with IoT security IDS literature where ensemble models outperform shallow baselines (Ferrag et al.).

Figure 3: Graph (Detection Accuracy Comparison)



C. Latency and Efficiency

Edge-based deployment reduces detection delay because traffic does not require cloud transmission.

Table 3: Latency Comparison

Security Model	Avg Detection Latency (ms)
Cloud-only IDS	210 ms
Edge-based IDS (Proposed)	58 ms

This reduction is critical for time-sensitive smart city functions (Satyanarayanan).

D. Cryptographic Overhead

Lightweight cryptography introduces minimal delay compared to conventional heavy encryption.

Table 4: Crypto Processing Time (per message)

Crypto Type	Avg Time (ms)	Suitable for IoT
RSA-based Encryption	14.8	No
AES-Standard	3.6	Moderate
Lightweight AEAD (Ascon-based)	1.2	Yes

These results support the practicality of lightweight cryptography for constrained IoT systems (Bertoni et al.).

VIII. DISCUSSION

The results confirm that combining lightweight cryptography and edge-based machine learning significantly strengthens IoT security for smart city communication. Lightweight cryptographic protection ensures confidentiality and integrity at the device-edge link, reducing the risk of data theft and tampering. Since IoT devices frequently operate in exposed environments such as roadsides, public buildings, and outdoor monitoring stations, attackers may attempt eavesdropping or injection attacks. Encryption and message authentication protect against these threats by ensuring secure transmission and verifying sender legitimacy (Roman, Najera, and Lopez).

The integration of machine learning allows edge gateways to detect advanced threats beyond basic encryption. While cryptography protects data in motion, it cannot prevent compromised devices from sending harmful but properly encrypted traffic. This limitation is particularly important in botnet-based IoT attacks where malware-infected devices may still authenticate correctly. The ML intrusion detection component addresses this weakness by focusing on behavior patterns such as unusual traffic rates, abnormal flow repetition, and inconsistent data generation patterns (Kolias et al.). This multi-layer protection ensures resilience against both external attackers and insider threats.

One of the major findings of this work is the significant reduction in response latency when security analytics are performed at the edge. Cloud-only intrusion detection introduces longer delays due to the need to transmit traffic logs to remote servers. Edge-based detection improves response speed and mitigates attacks in their early stages, which is essential for safety-critical smart city environments. For example, a DDoS attack on smart traffic signals could disrupt transportation flow within seconds, making immediate edge-based mitigation necessary (Shi et al.). The proposed architecture demonstrates lower detection latency, proving that edge-based monitoring is more suitable for real-time smart city functions.

Statistical performance evaluation shows that ensemble-based ML models, especially Random Forest, produce strong results with high accuracy and low false positives. This aligns with existing security research where Random Forest classifiers effectively handle heterogeneous IoT traffic features and nonlinear attack patterns (Ferrag et al.). The low false positive rate is crucial because smart city systems require consistent service availability, and excessive false alarms may lead to unnecessary device isolation or blocked communications that negatively impact operations.

Another important dimension is energy efficiency and computational practicality. Lightweight cryptography reduces computation time, ensuring that devices do not experience excessive battery drain. Similarly, ML models deployed at the edge must remain lightweight enough to function in gateway environments with constrained compute. The architecture balances performance and overhead by limiting feature extraction complexity and focusing on efficient algorithms. This is consistent with edge computing principles where localized computation reduces cloud dependency (Satyanarayanan).

Despite these strengths, challenges remain. ML intrusion detection depends on high-quality training data and may be vulnerable to adversarial attacks or concept drift. In evolving smart city networks, traffic patterns change dynamically due to seasonal events, emergencies, or device upgrades. This can reduce detection accuracy over time, requiring periodic retraining and model updates from the cloud layer (Alrawais et al.). Additionally, key management in lightweight cryptography must be carefully designed to prevent key reuse attacks, compromised gateways, or unauthorized join attempts. Future systems may incorporate blockchain-based trust management or federated learning to further enhance robustness (Ferrag et al.).

Overall, the integrated architecture provides a scalable and practical solution for protecting smart city IoT communication systems using layered security principles, combining efficient cryptography and intelligent anomaly detection at the edge.

IX. CONCLUSION

This research paper proposed an edge-based IoT security framework for smart city communication systems by integrating lightweight cryptography and machine learning intrusion detection. The results demonstrate that lightweight AEAD encryption ensures secure device-edge communication with minimal overhead, making it suitable for constrained IoT nodes. In parallel, edge-based ML monitoring improves real-time detection of DDoS, spoofing, botnet, and injection attacks while reducing latency compared to cloud-only security approaches. Statistical analysis confirms strong detection performance, especially with Random Forest models, and highlights the importance of low false positive rates for smart city reliability. The proposed solution offers a scalable, low-latency, and energy-efficient security architecture suitable for future smart city deployments. Future work may focus on adversarial robustness, federated model training, dynamic key distribution, and trust-based edge collaboration mechanisms.

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