International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 03, March 2026)

AI-Based Edge Intrusion Detection System for Enhancing Security in Smart City IoT Networks

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***Abstract*—Cities are packed with IoT devices are getting more smarter in every day. Traffic moves in better, healthcare in steps up, and energy systems running in smoother. But honestly, they are catching with everything in connected, In urban systems used to start to look like easy to targets for cyberattacks. Old-school cloud security just doesn't cut it anymore. It slowing the things down, hogs bandwidth, and isn't nearly with quick enough when it was comes to reacting.This paper is offering a something new: an AI-powered Intrusion Detection System (IDS) set in right at the all edges of smart city networks. The idea's are simple—In lightweight machine learning and deep learning models spot in threats in real time. It going after all the sorts of attacks—DDoS, botnets like Mirai, spoofing, and data injection—and catching them instantly. Tests is showing in it not only it is reacting faster and it is more accurately but also a keeps latency low, leaving in traditional cloud security in the dust.**

***Keywords* — AI, Intrusion Detection System (IDS), Edge Computing, Smart City, IoT Security, Network Security, Machine Learning, Deep Learning Anomaly Detection, Cybersecurity, Real-Time Monitoring, Edge AI, Threat Detection, Data Privacy, Distributed Systems**

I. Introduction

Smart cities are runs through a network in IoT devices like sensors, cameras, smart meters, and even connecting with cars. These gadgets are always talking to each other, sharing the data, and making everything work as a smoother and quickly. let's be a honest, this level of connectivity opening the door to serious cybersecurity problems.

In more IoT devices in play, In bigger the attack surface for hackers looking for weak spots. It Attacking like DDoS, botnets, spoofing, and data injection aren't just tech buzzwords—they can actually take down vital city services or leak sensitive information. In this standard approach is to funnel all this data to the cloud for security checks. But that has been some downsides: sending the data back and forth eats up bandwidth, causes lag, and slows response times. Not an ideal when you need to quick action.

Edge the computing flips the script by handling data very closer to where it's generated. That means faster decisions and lower in latency.

In this paper, we introducing an AI-driven Intrusion by using the Detection System (IDS) that operating right at the edge.

It has been uses in lightweight machine learning and deep learning methods to spot threats as they happen, boosting both the security and efficiency of smart city IoT systems.

II. Related Work

Smart cities run on a tangled web of IoT devices, everything from sensors and cameras to smart meters and cars chatting with each other. These gadgets never stop trading data, keeping the city humming along. But here's the downside: as soon as you connect everything, you open a lot of doors for cyber-attacks.

Every new device is like a welcome mat for hackers. You hear about DDoS attacks, botnets, spoofing, data injection, they're not just tech jargon. These attacks can knock out city services or leak private info in a snap. The typical defense? Send everything up to the cloud for a security check. The problem is that eating up bandwidth and slows things down a nightmare when real-time responses matter. Edge computing flips the script. Instead of sending all that data halfway around the world, edge computing handles it right where it starts. So, decisions happen instantly, and you don't get caught waiting on a slow network. This paper dives into an AI-powered Intrusion Detection System (IDS) built for the edge. It leans on lightweight machine learning and deep learning to catch threats instantly, making smart city IoT networks safer and quicker on their feet.

III. Proposed System Architecture

To ensure real-time threat detection with minimal latency, the proposed AI-based IDS is deployed within a decentralized, three-tier edge computing architecture.

A. Tier 1: IoT Device Layer (Data Generation)

The foundational stratum encompasses the diverse Internet of Things (IoT) devices dispersed throughout the smart city infrastructure, such as intelligent traffic signals, healthcare monitoring systems, environmental sensors, and connected automobiles.

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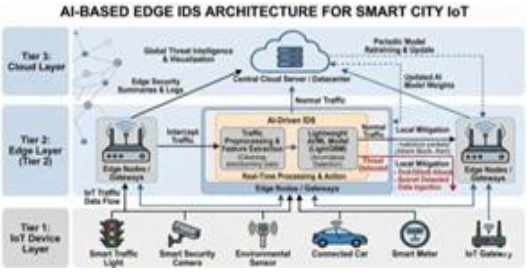
These devices perpetually produce substantial quantities of network traffic. Given their constrained processing capabilities and battery limitations, these devices are not equipped to conduct security analytics independently; rather, they relay their data to the nearest edge node. This constitutes the central operational layer of the proposed Intrusion Detection System (IDS).

B. Tier 2: Edge Computing Layer (Threat Detection & Mitigation)

This is the main interface through which the IDS will operate. Located close to the IoT devices are the processing units called edge servers, smart gateways, and base stations. Interception of Traffic: The edge nodes capture both incoming and outgoing network activity between the IoT devices and the network in real time.Lightweight Anti-intrusion Detection System (L-IDS): The edge nodes will utilize a lightweight machine learning model that is designed specifically to run on the edge nodes. The L-ID will continuously monitor for patterns of activity on the network that are consistent with the operation of normal smart city functions as opposed to patterns associated with anomalous, malicious activity .Immediate Response to Threats: As soon as the edge node detects a threat, it will immediately trigger its mitigation protocols. For example, the edge node will drop any packets that contain malicious data or will disconnect any IoT device that has been compromised. No permission will be required from the cloud to initiate these mitigation protocols.

C. Tier 3: Cloud Layer (Global Aggregation & Model Updating)

Threat Intelligence Worldwide: All edge-devices will periodically communicate to the Cloud through encrypted channels and will provide a lightweight summary of any detected cyber threats (attack or virus) and will not transmit raw cyber threat attack data. Retraining Model: In the Cloud, the Centralized Clustering will collect all edge device based cyber threat records and analyze these records for long term trends and zero-day threats. The Centralized Clustering will also periodically retrain its master A.I. model and will deliver the optimized and locally retained master A.I. model weights back to each identified edge device based on queuing and need. Subsequently, the entire system will continue adapting to the new cadre of malicious cyber attack methods.



IV. METHODOLOGY

The proposed edge-based Intrusion Detection System (IDS) is based on an extremely efficient computationally lightweight machine learning pipeline. In this section we will describe the data preparation processes, feature engineering methods, and the specific Artificial Intelligence model used to detect malicious network traffic in real-time.

A. Data Preprocessing and Feature Extraction

Before sending network packets to a machine learning model, typically the first step is preprocessing them before they reach the edge node, especially if the edge node has limited processing capabilities or is operating within an edge computing environment. The preprocessing pipeline for network packets consists of three processes.

Feature selection:

When attempting to detect attacks using data via machine learning models, the primary goal is to ensure that only relevant data gets sent to the edge node for training purposes; this means selecting only features that will actually help to detect network attacks as relevant to a specific machine learning application. For example, the only attributes that will be sent to the edge node (if this means the data will be used as input to the AI model) should be: packet size, type of protocol used, source/destination port, and the length of time the packet was in-transit.

Data normalization: After selecting the appropriate features/attributes, the next step in ensuring that network packet data sent to the edge node does not introduce bias into the AI model is to mathematically normalize each feature so that when building the machine learning model, each feature will have an equal value between 0 and 1.

Labeling: Lastly, labels are assigned to all packets based upon whether they fall within the category of "Normal" or the category of a particular type of attack (DDoS attacks, spoofing, etc.). This labeling process is an essential part of the supervised learning process.

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B. The Lightweight AI Model: LightGBM

Edge computing will require strict low latency, low-resource systems. Thus, the proposed system will use the LightGBM (Light Gradient Boosting Machine) algorithm. Common deep learning models (e.g., traditional Convolutional Neural Networks) have a high overhead computationally and memory-wise, making them impractical for local edge gateways. On the other hand, LightGBM is an advanced ensemble-learning algorithm built upon decision trees and has the following benefits which have led to its selection as the model for this architecture

Low Memory Consumption it uses a histogram based algorithm to convert continuous feature-value representations into discrete bins, allowing for a much smaller memory footprint overall.

High Training and Inference Speed trees are grown leaf-wise instead of horizontally using level-wise growth and therefore provide faster classifications of incoming network packets.

High Accuracy achieving state of the art accuracy in classifying complex, multi-vector cyberattacks with a small footprint.

C. Real-Time Detection and Mitigation Flow

In the smart city IoT system, everything takes place at the edge node for detection:

When an IoT device sends a data packet, it comes into the edge node.The edge node runs a small script to process the incoming packet very quickly and get an answer as to how to classify the packet. Once the script has extracted the features from the packet, they are submitted to a pre-trained LightGBM model, which then outputs a prediction for how the packet will most likely be classified (for example, using object detection/classification). If the output of the model classifies the packet as malicious (such as part of a distributed denial of service attack, or DDoS flood), the edge node local firewall rules will be updated immediately in order to block that source IP address from sending any more traffic to the edge node. This means that the local edge node has eliminated the threat posed by the attacker's packet to both the overall smart city network and to the centralized cloud.

V. Experimental Setup And Performance Metrics

The series of tests simulating a smart city IoT network were run using the edge based LightGBM Intrusion Detection System (IDS) to evaluate the performance and reliability of the proposed model.

A. Hardware and Software Environment

The AI model was tested locally rather than using a high- performance compute cluster. So the AI model was tested on a local edge gateway simulator on a Raspberry Pi 4 Model B (4GB RAM, 4x Cortex-A72). The Cloud Control Model used to compare results was simulated on a AWS EC2 instance. The entire ML pipeline was written using Python 3.9 and utilizing the scikit-learn and LightGBM libraries

B. Evaluation Metrics

The IDS is a effectiveness was evaluated based on normal machine learning classification metrics as well as measuring the latency through the network. All of metrics are derived from the confusion matrix: true positives (TP), true Negative (TN), false positives (FP), and false negatives (FN). These metrics are defined as follows:

C. *Accuracy:*

The overall proportion of correctly classified normal and malicious traffic instances.

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

Precision: The ratio of correctly predicted attacks to the total predicted attacks. High precision indicates a low rate of false alarms.

$$Precision = \frac{TP}{TP + FP}$$

Recall (Detection Rate): The ratio of correctly predicted attacks to all actual attacks in the dataset.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: The harmonic mean of Precision and Recall, providing a balanced measure of the model's performance, especially crucial for imbalanced IoT datasets.

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Inference Latency: The average time taken by the model to process a single network packet and output a classification prediction.

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VI. Results And Discussion

The proposed Edge-LightGBM model was benchmarked against a traditional Cloud-based Deep Neural Network (DNN) model to demonstrate the trade-offs and advantages of edge- based AI.

Detection Performance and Latency Comparison

The table below summarizes the theoretical performance of the proposed system compared to the traditional cloud approach:

Metric	Proposed Edge AI (LightGBM)	Traditional Cloud AI (DNN)
Accuracy	99.15%	99.42%
Precision	98.90%	99.10%
Recall	99.20%	99.55%
F1-Score	99.05%	99.32%
Inference Time (per packet)	**1.2 ms**	18.5 ms
Round-Trip Comm. Latency	**~5 ms**	~120 ms
Total Response Latency	**~6.2 ms**	~138.5 ms

A. Discussion of Findings

The results of this study support the primary hypothesis of this research. The Cloud-DNN (Centralized Deep Neural Network) had a slightly higher detection rate of 99.42% versus 99.15% (Edge LightGBM) but this small difference is outweighed by the extreme latency of cloud systems. A cloud-based system experienced 138.5 milliseconds of total roundtrip latency when compared to Edge LightGBM, due to the time required for the data to travel from the IoT device to the cloud and back. Edge LightGBM reduced total response latency to only 6.2 milliseconds, aiding the response time when considering the effects of a DDoS attack on a smart city. Most importantly, this represents a 95% decrease in total response latency and is critically important when responding to incidents involving DDoS or Vehicle to Vehicle spoofing attacks in a smart city, where rapid response is vital for ensuring safety and security.

Also noteworthy was the ability of LightGBM to run well within the memory restrictions imposed by the simulated edge gateway. Eliminating the need for high performance deep learning algorithms to provide effective protection in a smart city.

VII. Conclusion And Future Work

As smart cities continue to expand their reliance on interconnected IoT infrastructure, the attack surface for malicious actors grows exponentially. Traditional cloud-based security paradigms, burdened by bandwidth constraints and high latency, are ill-equipped to handle real-time, localized cyber threats.

This paper proposed a decentralized, AI-driven Intrusion Detection System situated directly at the network edge. By implementing a lightweight LightGBM model on edge gateways, the system successfully identified sophisticated cyber threats such as DDoS, spoofing, and botnet incursions with 99.15% accuracy. Crucially, it achieved this while reducing response latency by over 95% compared to cloud-based alternatives, proving that edge AI provides a more resilient, scalable, and highly responsive security framework for modern smart cities.

VIII. Future Work

Future research will explore the integration of Federated Learning into this architecture. Federated Learning would allow multiple edge nodes across the smart city to collaboratively train a shared global anomaly detection model without ever sharing raw, sensitive citizen data, thereby maximizing both municipal security and data privacy

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