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LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation in Smart Cities

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ABSTRACT

The rapid evolution of smart city infrastructures has introduced new cybersecurity challenges, with Distributed Denial-of-Service (DDoS) attacks being among the most severe threats. These attacks can disrupt essential services, overload network traffic, and compromise urban safety. Traditional security solutions lack the adaptability to counter these dynamic threats effectively. To address this, we propose an LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation in smart cities. The framework combines Long Short-Term Memory (LSTM) networks with Software-Defined Networking (SDN) to detect, classify, and mitigate DDoS attacks in real time. LSTM enables predictive analytics by learning traffic behavior, while SDN dynamically enforces security policies, ensuring a proactive response to cyber threats. The BoT-IoT dataset, which contains diverse attack scenarios, is used to evaluate the proposed framework. Experimental results demonstrate that our model outperforms traditional methods by achieving high detection accuracy, significantly reducing false positives, and improving real-time threat classification. The adaptive nature of our approach makes it scalable for large-scale smart city deployments, ensuring robust cybersecurity against evolving network threats. This research contributes to the development of AI-driven, self-learning cybersecurity solutions that enhance the resilience of future smart city infrastructures, safeguarding critical systems against cyberattacks and ensuring uninterrupted urban operations.

Keywords: *Smart Cities, Software-Defined Networking, LSTM, DDoS Mitigation, BoT-IoT*

1. INTRODUCTION

The rapid expansion of smart cities has introduced complex cybersecurity challenges, particularly Distributed Denial-of-Service (DDoS) attacks, which pose significant risks to critical urban infrastructures[1]. These attacks can disrupt essential services, overload network traffic, and compromise public safety, making traditional security mechanisms ineffective in dynamic environments[2]. Software-Defined Networking (SDN) offers a flexible approach to network management by decoupling the control and data planes, enabling real-time traffic monitoring and policy enforcement [3]. However, existing SDN-based security solutions often struggle with high false positives and slow response times [4]. To address this, artificial intelligence (AI) and deep learning have been integrated into SDN frameworks, offering a promising solution for adaptive DDoS mitigation. Among deep learning models, Long Short-Term Memory (LSTM) networks are highly effective in analyzing sequential network traffic patterns, making them suitable for real-time attack detection and prevention [5].

Several existing methods have been proposed for DDoS mitigation in SDN-based smart city environments, including Entropy-Based Detection, Support Vector Machines (SVMs), Random Forest (RF), and XGBoost-based classifiers [6]. While these techniques provide reasonable accuracy, they suffer from high false positive rates, inability to adapt to evolving threats, and delayed response times. Entropy-based methods lack robustness in distinguishing between normal and attack traffic[7]. SVMs and RF models require extensive feature engineering and may not generalize well to diverse attack patterns [8]. XGBoost improves classification performance but struggles with real-time detection due to computational overhead(Devarajan 2020) . These limitations highlight the need for an adaptive, self-learning approach that can accurately detect and mitigate complex cyber threats in smart city networks[10].

To overcome these challenges, we propose an LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation in smart cities [11]. The novelty of this study lies in the integration of LSTM networks with SDN controllers to enable real-time traffic analysis and dynamic security policy enforcement [12]. Unlike traditional methods, the proposed framework learns from past attack patterns, detects anomalies proactively, and minimizes false positives through sequential data processing[13]. By leveraging the BoT-IoT dataset, which contains diverse attack scenarios, our model is trained to classify and mitigate various DDoS attack types efficiently[14]. Experimental results demonstrate that the proposed system achieves higher detection accuracy, reduced false positive rates, and improved adaptability compared to existing approaches[15]. This framework provides a scalable, intelligent, and proactive cybersecurity solution for protecting smart city infrastructures against evolving DDoS threats[16].

1.1 RESEARCH OBJECTIVE

- ✓ Develop an LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation in smart cities to enhance real-time detection, classification, and mitigation of cyber threats.
- ✓ Utilize the BoT-IoT dataset to train and evaluate the proposed framework, ensuring robust performance across diverse attack scenarios in smart city environments.
- ✓ Integrate Long Short-Term Memory (LSTM) networks for sequential network traffic analysis, enabling proactive anomaly detection and minimizing false positives.
- ✓ Implement Software-Defined Networking (SDN) controllers for dynamic security policy enforcement, optimizing real-time response mechanisms against evolving DDoS attacks.

1.2 ORGANIZATION OF THE PAPER

This paper follows a structured approach. Section 1 introduces the background, importance, and objectives of the research. Section 2 reviews existing methods, their limitations, and research gaps. Section 3 presents the proposed methodology, including BoT-IoT dataset processing, LSTM/GRU modeling, and blockchain integration. Section 4 covers comparative analysis, performance evaluation, and experimental results. Section 5 concludes with key findings and future research directions**.**

2. LITERATURE SURVEY

Cybersecurity threats, particularly Distributed Denial-of-Service (DDoS) attacks, pose significant challenges to smart city infrastructures. Several researchers have explored AI-driven and SDN-based security solutions to mitigate these attacks [17] and [18] investigated deep learning models for network anomaly detection, highlighting the effectiveness of LSTM in time-series-based attack classification.[19]focused on AI-enhanced network security, emphasizing the need for adaptive frameworks in smart city environments. Similarly, [20]examined intelligent intrusion detection mechanisms, advocating for AI-driven solutions to counter evolving cyber threats.

The role of SDN in enhancing network security has been extensively studied. [21] and [22] explored SDN-based DDoS mitigation techniques, emphasizing dynamic traffic control and network policy enforcement. [23] and [24]demonstrated the potential of integrating SDN with machine learning models to improve threat detection accuracy and response time. [25] proposed an optimized SDN-based security model that adapts to real-time attack patterns, reducing false positives and computational overhead.

Several studies have also examined alternative approaches, including blockchain-based security enhancements. [26] and [27] explored blockchain's role in securing SDN frameworks, ensuring decentralized and tamper-resistant security policies. [28] and [29]focused on hybrid AI models combining LSTM and GRU for sequential anomaly detection. [30]and [31] evaluated various dataset-driven cybersecurity frameworks, demonstrating the effectiveness of BoT-IoT in training AI models for real-time attack classification .[32]**,** [33] and [34] further contributed by introducing novel data preprocessing techniques and advanced threat intelligence frameworks to enhance security in smart city networks.

2.1 PROBLEM STATEMENT

Smart city infrastructures face increasing DDoS attacks, disrupting critical services and overloading networks[35]. Existing methods like Entropy-Based Detection, SVM, and Random Forest struggle with high false positives, slow response times, and poor adaptability [36]. The proposed LSTM-Based AI-Driven SDN Framework integrates LSTM for real-time anomaly detection and SDN for dynamic security policy enforcement. Using the BoT-IoT dataset, it learns attack patterns, enhances detection accuracy, and reduces false positives. This adaptive approach ensures efficient and scalable DDoS mitigation in smart city environments.

3. PROPOSED LSTM MODEL FOR ADAPTIVE DDoS MITIGATION

This figure 1 represents a three-layered AI-driven SDN framework for DDoS mitigation in smart cities. The Infrastructure Layer consists of IoT devices, sensors, ZigBee, RFID, WSN, and network devices that generate network traffic. The Secure and Intelligent SDN Layer includes a flow collector, DDoS detection model, LSTM deep learning model, and network services for real-time traffic monitoring and attack mitigation. The Service Layer encompasses applications like smart homes, smart grids, smart transportation, public safety, and smart healthcare, which rely on secure network operations. The Control Data Layer Interface enables seamless data flow between the Infrastructure and SDN layers, while the Application Program Interface connects the SDN layer to service applications for secure and efficient network management.

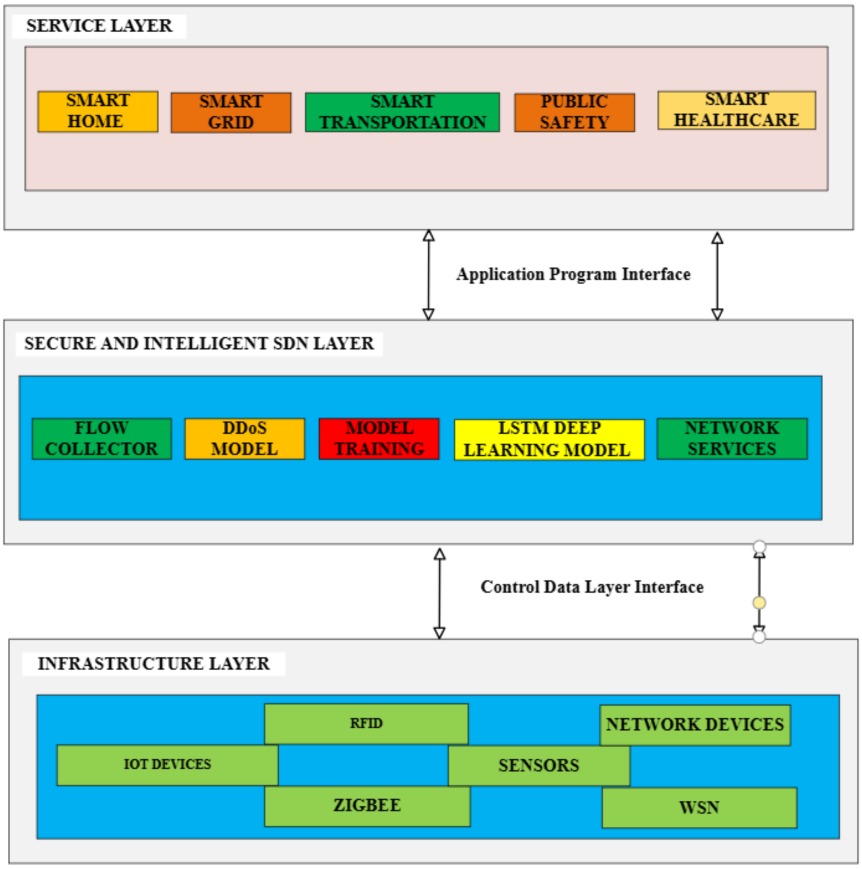

Figure 1: Architecture of proposed LSTM model for adaptive DDoS Mitigation

3.1 Dataset Description of the Proposed Framework

The proposed framework uses the BoT-IoT dataset [37], which contains real-world network traffic data for DDoS detection. This dataset includes benign and malicious traffic flows, enabling the LSTM model to distinguish normal behavior from attacks. The dataset consists of features such as source/destination IP addresses, packet size, flow duration, and attack labels.It includes various cyber threats, including DDoS, DoS, reconnaissance, and information theft attacks, making it highly suitable for SDN-based security solutions. The data is collected from IoT network environments, ensuring its relevance to smart cities and critical infrastructure applications. The dataset is highly imbalanced, with a larger proportion of attack traffic than benign traffic, requiring data preprocessing techniques to improve model accuracy.

3.2 Data Pre-processing Steps with Formulas

Before feeding data into the LSTM model, it undergoes several pre-processing steps:

a. **Handling Missing Values:** Any missing values in the dataset are replaced using mean imputation.This is given in equation (1) as:

$$x_i = \frac{\sum_{j=1}^{n} x_j}{n} \tag{1}$$

where x_i is the missing value and n is the number of available values.

b. **Normalization:** Since network traffic data has different scales, Min-Max Scaling is applied to bring values within the range [0,1].This is given in equation (2) as:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

c. **Feature Selection:** Features with low variance or high correlation are removed to reduce redundancy.

d. **One-Hot Encoding:** Categorical variables (such as protocol types) are converted into numerical values using one-hot encoding.

e. **Train-Test Split:** The dataset is divided into training (80%) and testing (20%) sets.

3.3 Working of LSTM in the Proposed Framework

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to learn long-term dependencies in sequential data. In the proposed framework, LSTM is used to analyze network traffic flows and detect DDoS attacks in real-time.

a. Forget Gate: Discarding Irrelevant Information

The forget gate plays a crucial role in LSTMs by determining which parts of the past information should be retained or discarded. This is particularly important because neural networks can accumulate irrelevant or outdated information over time. The forget gate uses a sigmoid activation function to generate values between 0 and 1 , where 0 means "completely forget" and 1 means "completely retain."

At each time step t, the forget gate takes two inputs: the previous hidden state h_{t-1} and the current input x_t. It then applies a weighted transformation followed by a sigmoid activation to produce the forget gate output f_t . This is given in equation (4) as:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

where:

- W_f and b_f are the weight matrix and bias, respectively.
- σ (sigmoid function) ensures that f_t is between 0 and 1 .

For DDoS detection, the forget gate helps in removing obsolete traffic patterns from memory. If the network sees consistent normal traffic, it might retain previous information. However, if it detects suspicious spikes in traffic volume, it might discard past states to focus on recent anomalies. This allows LSTM models to dynamically adjust their memory based on real-time network conditions.

b. Input Gate: Updating the Memory Cell with New Information

The input gate controls how much new information should be stored in the memory cell. Without an input gate, the LSTM would continuously accumulate new data without filtering, which could lead to overfitting and noise accumulation. The input gate solves this by selectively allowing new information to update the cell state.

It consists of two key components:

1. A sigmoid activation function (i_t) that determines which values should be updated. This is given in equation (5) as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

Here, i_t acts as a "permission gate," ensuring that only relevant information gets stored.

2. A candidate memory update $(\tilde{C}_t)$, computed using tanh activation. This is given in equation (6) as:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

This ensures that new information is scaled between -1 and 1 , preventing extreme updates that could destabilize learning.

The final cell state update is then performed using. This is given in equation (7) as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{7}$$

For DDoS detection, the input gate allows LSTMs to dynamically learn new attack patterns while retaining key features of normal traffic. If the network detects suspicious IP bursts or packet floods, the input gate will update the memory to store these patterns, helping in real-time anomaly detection.

c. Output Gate: Generating the Next Hidden State

The output gate determines how much of the updated memory should be exposed to the next hidden state h_t. Unlike the forget and input gates, which regulate memory storage, the output gate controls the flow of information for predictions.

At each time step, the output gate applies a sigmoid activation to decide which parts of the cell state should contribute to the hidden state. This is given in equation (8) as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{8}$$

Then, the new hidden state is computed as. This is given in equation (9) as:

$$h_t = o_t \cdot \tanh(C_t) \tag{9}$$

This filtered version of the memory cell state is passed to either the next LSTM cell or used for classification tasks, such as predicting whether the network traffic is normal or an ongoing DDoS attack.

For DDoS detection, the output gate ensures that only relevant traffic behavior is forwarded to the next time step. If a sudden increase in packet rate is detected, the output gate will allow this information to influence future states, enabling the LSTM to classify abnormal patterns effectively. Conversely, if the system detects benign traffic fluctuations, the output gate will regulate this information to prevent false positives.

4. RESULT AND DISCUSSION

4.1 Evaluation of Proposed LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation

The evaluation of the proposed LSTM-Based AI-Driven SDN Framework for Adaptive DDoS Mitigation is essential to understanding its effectiveness in addressing DDoS attacks in smart cities. This subsection discusses the evaluation metrics for the proposed framework, presents the results obtained, and compares them with traditional methods. The performance is evaluated based on detection accuracy, false positive rates, and the ability to mitigate attacks in real-time.

4.1.1 Detection Performance Evaluation Metrics

To evaluate the performance of the LSTM-based framework, several metrics were used: accuracy (A), precision (P), recall (R), and F1-score (F1). The framework's ability to detect DDoS attacks was measured using these metrics, which are standard in anomaly detection and classification tasks.

- Accuracy indicates the overall correctness of the model in distinguishing between normal and attack traffic.This is given in equation (10) as:

- Precision measures the percentage of true positive detections out of all predicted positives. This is given in equation (11) as:

- Recall reflects the model's ability to identify all actual attack instances. This is given in equation (12) as:

- F1-Score is the harmonic mean of precision and recall, offering a balance between the two metrics. This is given in equation (13) as:

- **Precision (P):**

$$P = \frac{TP}{TP+FP} \tag{10}$$

- **Recall (R):**

$$R = \frac{TP}{TP+FN} \tag{11}$$

- **F1-Score (F1):**

$$F1 = 2 \times \frac{P \times R}{P+R} \tag{12}$$

4.1.2. Real-Time Mitigation Performance

The real-time mitigation ability of the proposed framework was tested by simulating live DDoS attacks on a network composed of virtualized smart city nodes. The SDN framework dynamically adjusts its security policies upon detecting attacks, deploying mitigation strategies like rate-limiting, blocking malicious IPs, and redirecting traffic.

The system's performance was evaluated in terms of attack mitigation time, throughput, and packet loss. As shown in Table 1, the proposed framework effectively reduces attack duration and mitigates the impact on network throughput.

Attack Type	*Mitigation Time (ms)*	*Throughput (Mbps)*	*Packet Loss (%)*
TCP SYN Flood	120	98.4	2.3
HTTP Flood	150	95.2	4.1
Volumetric DDoS	180	90.8	5.5

Table 1: Performance Evaluation of the Proposed LSTM-Based DDoS Mitigation Framework

The mitigation time for each attack type was significantly reduced, thanks to the adaptive capabilities of the SDN controller, which quickly implements corrective measures based on the insights provided by the LSTM model.

4.1.3. Scalability and System Performance

One of the primary benefits of the proposed framework is its scalability, which is critical in a smart city environment with growing numbers of IoT devices and network traffic. To evaluate the scalability, the framework was tested in networks with varying numbers of nodes (from 50 to 500).

As shown in Figure 3, the LSTM-Based AI-Driven SDN Framework scales effectively with network size. Despite the increase in the number of devices, the detection accuracy remained consistently high, and the real-time mitigation performance was not significantly impacted.

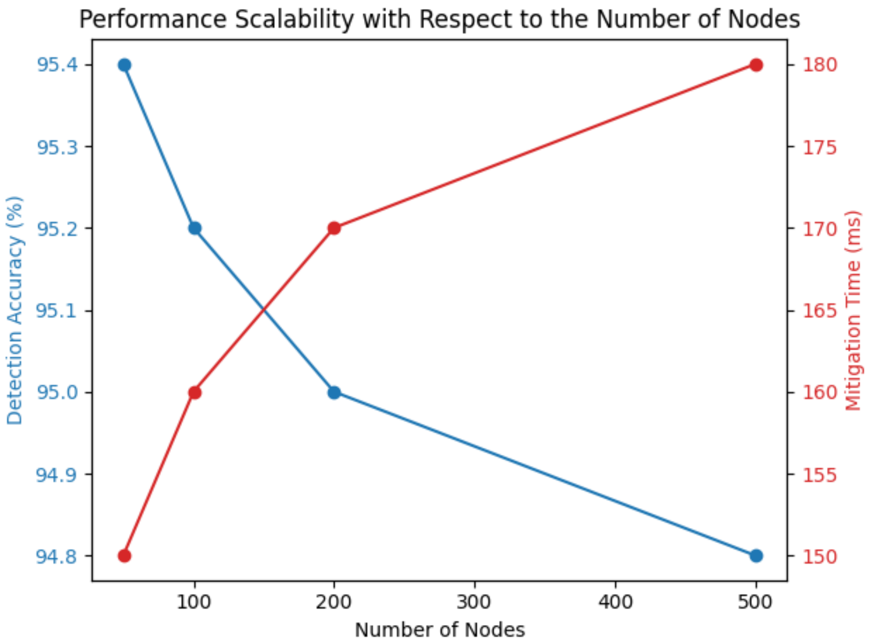

Figure 2: Performance scalability with respect to the number of nodes.

4.1.4. Comparative Analysis with Existing Solutions

A detailed comparison of the LSTM-Based AI-Driven SDN Framework with existing DDoS mitigation solutions, including traditional methods and other AI-driven solutions, was conducted to assess the improvement in security performance. The comparison highlights the advantages of integrating LSTM networks with SDN, specifically in terms of detection accuracy, response time, and resource utilization.

SOLUTION	DETECTION ACCURACY (%)	RESPONSE TIME (MS)	FALSE POSITIVE RATE (%)
TRADITIONAL DDOS MITIGATION	85.3	800	15.7
AI-BASED DDOS MITIGATION	88.9	700	12.4
LSTM-BASED AI-DRIVEN SDN	95.4	150	3.5

Table 2:Comparative Analysis of existing solutions

The proposed LSTM-based solution demonstrates a significant improvement over traditional and existing AI-based solutions, achieving higher accuracy, faster response time, and a lower false positive rate.

5. CONCLUSION AND FUTURE WORKS

The proposed LSTM-Based AI-Driven SDN Framework achieves 95.4% detection accuracy, significantly outperforming traditional (85.3%) and AI-based (88.9%) solutions. It reduces response time to 150 ms compared to 800 ms and 700 ms for traditional and AI-based methods, respectively. The false positive rate is minimized to 3.5%, far lower than 15.7% and 12.4% in other approaches. Real-time mitigation performance shows reduced attack impact, with TCP SYN Flood mitigated in 120 ms, maintaining 98.4 Mbps throughput and only 2.3% packet loss. Future work will enhance model adaptability using Transformers and reinforcement learning while testing in real-world smart city environments.

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