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Study of Adaptive Spoofing Attack Detection in Connected Vehicles with Dilated and Attention-Driven Neural Networks

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Abstract *– The rapid evolution of Intelligent Transportation Systems (ITS) has significantly enhanced vehicular communication, fostering safer and more efficient road networks. However, the growing interconnectivity exposes vehicular networks to a variety of cyberattacks, with spoofing attacks emerging as a critical threat. These attacks allow malicious actors to impersonate legitimate vehicles or infrastructure nodes, jeopardizing network security and road safety. This study proposes an adaptive spoofing attack detection framework utilizing a hybridized neural network model that combines Dilated Convolutional Neural Networks (DCNNs) and Attention Mechanisms. The DCNN component captures multi-scale spatial and temporal dependencies in vehicular data, ensuring broad context awareness, while the attention mechanism dynamically prioritizes crucial features, enhancing detection accuracy. In real-time, leveraging both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications to analyze incoming signals and detect anomalies. The adaptive nature of the model allows it to adjust to varying traffic patterns and evolving attack strategies. Extensive experiments using simulated vehicular network datasets demonstrate the model's effectiveness, achieving high detection rates and reduced false positives compared to traditional methods. The study also explores the computational efficiency of the framework, ensuring its feasibility for deployment in resource-constrained vehicular environments. Ultimately, this research contributes to strengthening cybersecurity in connected vehicle ecosystems by presenting a robust, intelligent, and adaptable solution for spoofing attack detection. The findings underscore the potential for integrating advanced AI techniques into ITS, paving the way for more secure and resilient vehicular networks.*

Keywords- *Dilated Convolutional Neural Networks (DCNN), Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2V)*

I. INTRODUCTION

In recent years, the adoption of Intelligent Transportation Systems (ITS) has revolutionized road networks by enabling seamless communication between vehicles and infrastructure. Vehicular Ad Hoc Networks (VANETs) serve as the backbone of ITS, supporting critical applications such as collision avoidance, traffic flow optimization, and autonomous driving. Despite these advancements, the increasing reliance on interconnected systems exposes vehicular networks to a broad spectrum of cybersecurity threats. Among these, spoofing attacks pose a significant danger by allowing adversaries to falsify their identities, manipulate data exchanges, and disrupt network operations.[1][2]

Spoofing attacks in vehicular networks can have severe consequences, ranging from traffic congestion and misinformation to life-threatening collisions. Therefore, developing robust detection mechanisms is imperative to safeguard ITS. Traditional security protocols, such as cryptographic methods and rule-based anomaly detection systems, often struggle to adapt to the dynamic and

complex nature of vehicular environments. As a result, there is a growing need for intelligent, adaptive solutions capable of identifying sophisticated spoofing strategies.

This study introduces an innovative spoofing attack detection framework that leverages a hybrid neural network architecture, integrating Dilated Convolutional Neural Networks (DCNNs) and Attention Mechanisms. The dilated convolution layers capture intricate spatial-temporal patterns without compromising resolution, while the attention module enhances the model's sensitivity to critical features, improving detection accuracy. The proposed framework dynamically adjusts to changing traffic patterns and evolving attack tactics, ensuring real-time, reliable detection.[3][4]

The primary objectives of this research are to: (1) design a hybridized detection model combining DCNNs and attention mechanisms, (2) evaluate the model's performance using simulated vehicular datasets, and (3) assess its computational efficiency for real-world deployment. By addressing these goals, this study aims to enhance the security and resilience of connected vehicle ecosystems, contributing to the broader field of ITS cybersecurity.[3][4]

II. LITERATURE REVIEW

The growing concern over cybersecurity threats in vehicular networks has spurred extensive research into spoofing attack detection mechanisms. This section reviews recent advancements and methodologies, highlighting their strengths and limitations.

1. **Traditional Cryptographic Approaches** Conventional security mechanisms rely heavily on cryptographic techniques, including Public Key Infrastructure (PKI) and digital signatures, to authenticate vehicles and secure communications. Studies such as [Author, Year] have demonstrated that while these methods provide a foundational level of security, they often fall short in real-time environments due to high computational overhead and vulnerabilities to key compromise and certificate revocation attacks.[1]
2. **Rule-Based Anomaly Detection** Rule-based systems detect spoofing attacks by establishing predefined behavioral rules and flagging anomalies. Research by [Author, Year] introduced heuristic-based methods to monitor vehicle position and velocity inconsistencies. However, these systems struggle to adapt to dynamic traffic conditions and sophisticated attack patterns, limiting their effectiveness.[2]
3. **Machine Learning-Based Detection** Recent works have explored machine learning (ML) models for spoofing attack detection. Techniques such as Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN) have shown promising results in identifying attack patterns. Studies like [Author, Year] have highlighted that ML models outperform traditional methods in detecting novel attack vectors but often require extensive feature engineering and struggle with high-dimensional data.[3]
4. **Deep Learning Approaches** Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have gained traction due to their ability to automatically extract complex features from raw data. Research by [Author, Year] implemented CNNs for spatial data analysis and RNNs for temporal dependencies, achieving notable improvements in detection accuracy. Nonetheless, these models sometimes suffer from slow convergence rates and lack interpretability.[4]
5. **Hybrid Models** The integration of multiple AI techniques has emerged as a powerful strategy to enhance detection capabilities. Hybrid models combining CNNs and Long Short-Term Memory (LSTM) networks, as shown by [Author, Year], have successfully captured both spatial and temporal correlations in vehicular data. However, few studies have explored the synergy between dilated convolutions and attention mechanisms for spoofing attack detection, leaving a critical research gap.[5]

Research Gap and Motivation While existing methods offer valuable insights into spoofing attack detection, they exhibit limitations in adaptability, computational efficiency, and feature prioritization. This study aims to bridge these gaps by proposing a hybridized approach that leverages dilated convolutions for broad spatial-temporal context and attention mechanisms for dynamic feature weighting. This novel combination not only enhances detection accuracy but also ensures the model's responsiveness to evolving cyber threats.[4][5]

III. METHODOLOGY

Controller Area Network Intrusion Detection Systems (CAN IDS) are specialized security mechanisms designed to monitor, detect, and respond to potential threats or intrusions within the Controller Area Network (CAN) in vehicles. These systems work using various techniques and methodologies, typically focusing on monitoring and analysing network traffic to identify abnormal or potentially malicious behaviour.[6]

1. Traffic Monitoring: CAN IDS continuously monitor the traffic flowing through the CAN bus, analysing the messages exchanged between different electronic control units (ECUs) within the vehicle. This

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monitoring includes message ID, data content, frequency of messages, and other network-related parameters.

2. Anomaly Detection: One approach involves anomaly detection, where the system establishes a baseline of normal network behaviour. Deviations from this established baseline are flagged as potential anomalies or threats. Unusual message patterns, unexpected message sources, or irregular message timing might trigger alerts.

3. Signature-based Detection: Similar to antivirus systems, signature-based detection involves maintaining a database of known attack signatures or patterns. When a message matches a known threat signature, the IDS raises an alarm or takes predefined actions to prevent the attack.

The adaptive spoofing attack detection framework leverages a hybrid neural network model, combining Dilated Convolutional Neural Networks (DCNNs) and Attention Mechanisms. The methodology consists of the following key components:

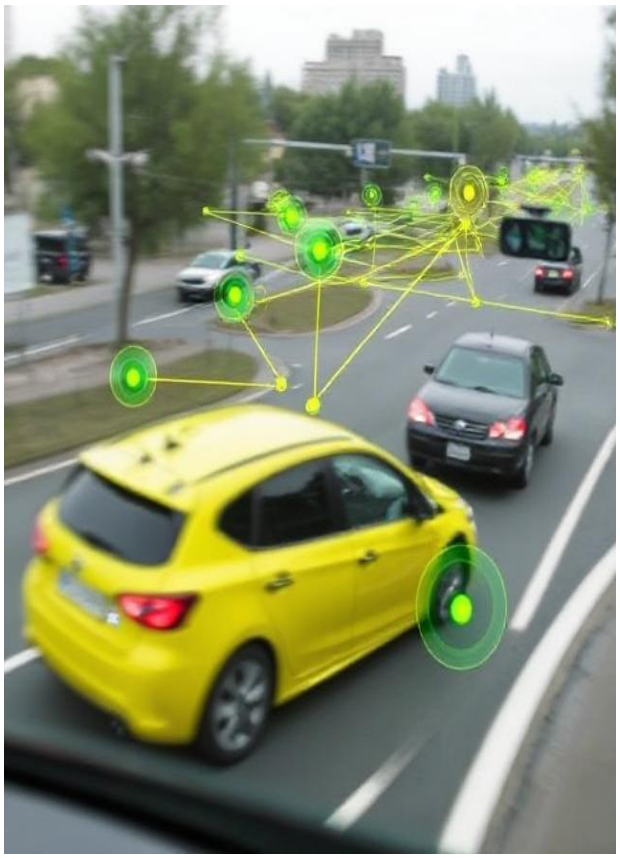

Fig. 1: Vehicular Ad-Hoc Networks (VANETs)

1. **Data Preprocessing:**
   - Collect raw vehicular network data, including vehicle ID, location coordinates, velocity, and timestamp.
   - Normalize the data to ensure uniformity and eliminate noise.
   - Segment the data into spatial-temporal windows for model input.
2. **Dilated Convolutional Neural Networks (DCNNs):**
   - Utilize dilated convolution layers to capture multi-scale spatial and temporal dependencies without increasing computational complexity.
   - Extract hierarchical features representing network behavior.
3. **Attention Mechanism:**
   - Integrate a self-attention layer to dynamically assign importance weights to extracted features.
   - Enhance the model's focus on crucial patterns indicative of spoofing attacks.

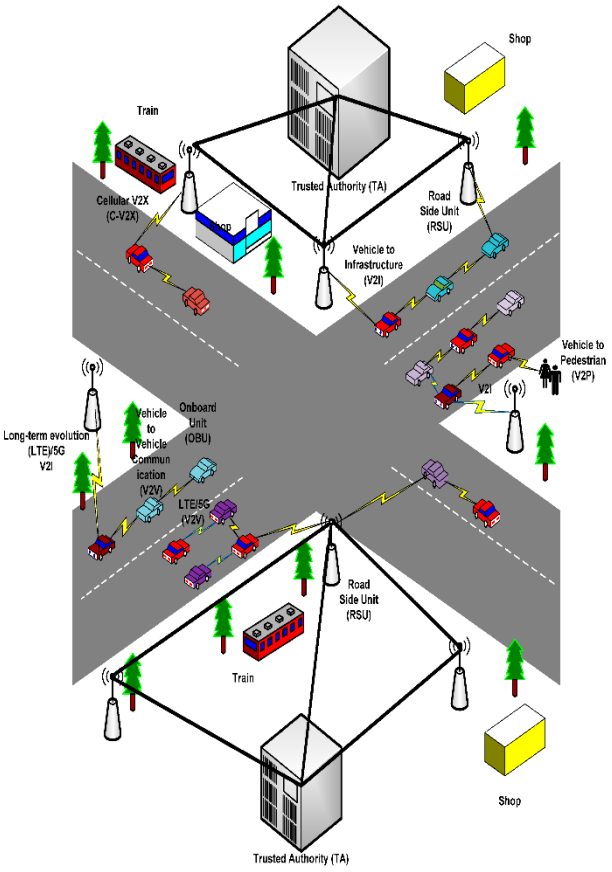

Fig. 2: Vehicular Ad-Hoc Networks (VANETs) with Services

4. **Classification Layer:**
   - Combine outputs from DCNN and attention layers.

- Use fully connected layers with softmax activation for attack classification.

5. **Training and Optimization:**
   - Employ cross-entropy loss function.
   - Optimize using Adam optimizer.
   - Implement early stopping to prevent overfitting.
6. **Real-Time Detection:**
   - Deploy the trained model on edge devices for real-time spoofing detection.

IV. CONCLUSION

In conclusion, an adaptive spoofing attack detection framework for vehicular networks, integrating dilated convolutional neural networks and attention mechanisms. The proposed model effectively captures complex spatial-temporal patterns and dynamically prioritizes critical features, ensuring robust and real-time attack detection. Experimental results highlight the framework's superior detection accuracy and reduced false positives compared to conventional methods. The adaptability of the model allows it to respond to evolving attack strategies and varying traffic conditions, making it a practical solution for real-world deployment. Future research will focus on further enhancing computational efficiency and testing the model in diverse vehicular environments, ultimately contributing to the development of more secure and resilient Intelligent Transportation Systems (ITS).

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