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GenAI-Driven Cyberattack Detection in V2X Networks for Enhanced Road Safety and Autonomous Vehicle Defense

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Abstract: ***In our study, we propose a GenAI-enhanced attack detection framework aimed at improving road safety and cyber defense within vehicle-to-everything (V2X) communication networks. The framework utilizes Generative AI (GenAI) to simulate cyberattacks, such as false data injection (FDI), replay, and stealthy attacks, targeting critical V2X components like On-Board Units (OBUs) and Road-Side Units (RSUs). To detect these threats, we developed an advanced recognition model (Model B), integrating Convolutional Neural Networks (CNN) for spatial data analysis and Long Short-Term Memory (LSTM) networks for temporal data processing. Simulations were conducted in a realistic urban environment using NS-3 and SUMO, testing various V2X communication modes, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Pedestrian (V2P) interactions. The experimental results demonstrated that Model B achieved superior performance, with an overall attack detection accuracy of 97%, outperforming conventional methods such as CNN, LSTM, EKF, and OCSVM. Additionally, the system significantly reduced latency in attack detection, particularly in urban traffic scenarios. Our framework was especially effective in identifying replay and stealthy attacks on GPS and LiDAR systems, ensuring minimal disruption to vehicle operations. Our study underscores the importance of utilizing GenAI to enhance attack detection capabilities in V2X networks, contributing to the safety and resilience of autonomous and connected vehicle ecosystems. Future work will focus on optimizing detection algorithms for more complex traffic scenarios and integrating advanced communication technologies such as 6G for further improvements in detection speed and reliability.***

Keywords: GenAI; V2X communication; Cyberattack detection; Autonomous vehicles; Road safety.

1. Introduction

Vehicle-to-Everything (V2X) technologies are transforming urban transportation by enabling real-time communication between vehicles, infrastructure, pedestrians, and networks. This seamless data exchange has the potential to improve traffic flow, reduce accidents, and enhance road safety. However, as V2X systems rely heavily on wireless communication, they are increasingly vulnerable to cyberattacks, which could disrupt vehicle operations and compromise public safety (El-Rewini et al., 2020). Cyberattacks, such as GPS spoofing or message tampering, can mislead vehicle navigation or traffic control systems, posing serious risks to road users and infrastructure. The challenge of securing V2X communication channels is exacerbated by the increasing sophistication of attackers. Traditional cybersecurity methods often fall short in detecting advanced threats, especially in dynamic, decentralized networks like V2X (Liu et al., 2024; Sedar et al., 2023). Recent research has explored the use of artificial intelligence (AI) to improve cyber defense mechanisms, particularly through the application of Generative AI (GenAI). GenAI can generate adversarial attacks that simulate real-world threats, providing valuable data to enhance the training of detection models (Sun et al., 2024; Mavikumbure et al., 2024). While these studies have demonstrated AI's potential in cybersecurity, there remains a need for tailored solutions that address the specific vulnerabilities of V2X systems.

The study focuses on using GenAI to improve the accuracy and robustness of attack detection models in V2X networks. By generating adversarial attacks that target communication between vehicles and infrastructure, the proposed system enhances real-time recognition of cyber threats (Wang et al., 2024). The study builds on existing AI-based approaches, advancing them by incorporating adversarial attack simulations tailored to the unique demands of V2X networks. The goal is to develop a detection model (Model B) that can efficiently identify and mitigate attacks in real time, ensuring both road safety and the security of critical urban infrastructure (Ergu, Y. A. et al., 2024; Yao et al., 2024; Xie et al., 2024, Xia et al., 2024).

Our study not only addresses current gaps in V2X cybersecurity but also provides a scalable, AI-driven solution for improving the resilience of intelligent transportation systems against evolving cyber threats. The proposed framework contributes to the growing body of research on AI applications in cybersecurity, with a particular focus on the defense of connected and autonomous vehicle networks.

2. Methods

2.1 System Overview

The study introduces a Generative AI (GenAI)-based framework designed to generate and simulate cyberattacks within a Vehicle-to-Everything (V2X) communication network. The primary focus is on the real-time detection of these attacks using an enhanced recognition model, Model B. V2X networks involve multiple communication modes, including Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), and Vehicle-to-Pedestrian (V2P) interactions. These communication types are essential in modern intelligent transportation systems (ITS), where safety and efficiency depend on the seamless and secure exchange of data between vehicles and the surrounding environment. The simulations in this study are carried out using the NS-3 network simulation platform, which provides realistic urban mobility scenarios. The attack simulations in this study target two critical components of the V2X architecture: On-Board Units (OBUs), which manage communication within the vehicle, and Road-Side Units (RSUs), which facilitate communication between vehicles and infrastructure. These units are responsible for transmitting and receiving Cooperative Awareness Messages (CAMs) and Decentralized Environmental Notification Messages (DENMs), which provide vehicles with essential data on traffic conditions, road safety, and infrastructure signals. Cyberattacks that compromise these messages can have severe consequences, making their detection vital for road safety (Yan et al., 2024).

2.2 Mathematical Model of the Attack-Detection System

To accurately model the vehicle's motion and simulate the effect of cyberattacks, we define the kinematic equations governing the vehicle's behavior. The vehicle's motion in the absence of attacks is given by the following standard equations:

$$\dot{m} = v\cos(\theta)\,, \quad \dot{n} = v\sin(\theta)\,, \quad \dot{\theta} = \frac{v}{L}\tan(\alpha)$$

where v is the vehicle speed, θ represents the heading angle, α is the steering angle, and L is the distance between the vehicle's front and rear axles. These equations describe the vehicle's longitudinal and lateral motion, along with its yaw rate, which is crucial for determining its orientation on the road.

In the context of a cyberattack, these equations are modified to account for disturbances introduced by adversarial inputs. Attack-induced noise is incorporated as follows:

$$\dot{m} = (v + \epsilon_v)\cos(\theta), \quad \dot{n} = (v + \epsilon_v)\sin(\theta), \quad \dot{\theta} = \frac{v + \epsilon_v}{L}\tan(\alpha + \epsilon_\alpha)$$

Here, ϵ_v and ϵ_α represent the noise introduced into the system by the attack, affecting both the vehicle's speed and steering angle. These parameters simulate real-world attack scenarios, such as GPS signal spoofing or steering angle manipulation, which can lead to significant deviations from the expected vehicle trajectory.

2.3 Data Generation and Attack Simulation

To simulate realistic cyberattacks on V2X systems, adversarial data was generated using a Generative AI model, Model A, designed specifically for generating a range of attacks including message tampering, signal spoofing, and replay attacks. This dataset simulates malicious traffic within the V2X ecosystem by altering critical vehicle-to-infrastructure and vehicle-to-network communication messages, similar to approaches taken by Song et al. (2022) and Liu et al. (2024).

The generated attacks targeted three key V2X components:

- On-Board Units (OBUs): Simulating adversarial attacks on the vehicle's internal control systems.
- Road-Side Units (RSUs): Generating replay attacks aimed at mimicking previously sent data to confuse infrastructure systems.
- V2I Communication Links: Targeting the communication between vehicles and traffic infrastructure with fake or tampered messages designed to induce errors in traffic light signal timings, pedestrian warnings, and more.

For attack generation, a combination of software-defined radio (SDR) technology and generative adversarial networks (GANs) was used, following techniques demonstrated by Xu et al. (2024) and Zhang et al. (2024). SDR was particularly useful for manipulating real-time communication streams between OBUs and RSUs, allowing for precise control over frequency modulation and signal timing.

2.4 Model Training and Evaluation

The detection model (Model B) was developed to recognize and mitigate the cyberattacks generated by Model A. Model B was trained using a dataset containing both normal and adversarial V2X communication scenarios. The training process involved feature extraction from the V2X data, such as signal strength, message frequency, and transmission patterns. These features were then used to train a convolutional neural network (CNN)-based model, similar to the work done by Osman et al. (2021) and Lin et al. (2024).

Evaluation of Model B's performance was conducted through the following metrics:

- Accuracy: The percentage of correctly identified attacks.
- Precision: The proportion of true positives among all detected attacks.
- Recall: The proportion of detected attacks out of all actual attacks present.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of the model's effectiveness.

3. Results and Discussion

3.1 Analysis of Vehicle Pose Measurements Without Attacks

Figure1 illustrates the analysis of AV pose measurements under standard operational conditions, providing insights into both the position and orientation of the vehicles. Figure 1(a) demonstrates the position variation across the five AVs, showing minor fluctuations within the expected range, with the maximum deviation being less than 5% from the norm. Figure 1(b) presents the orientation data, where AV3 and AV5 exhibit slightly higher deviations around the peak position. Despite these minor variations, the AV systems maintained consistent behavior, confirming that the detection mechanism remained inactive until the velocity threshold of 1.5 m/s was surpassed. The speed analysis, as illustrated in Figure 1(c), shows a linear increase in the velocity of the AVs, reaching a maximum of 120 km/h for AV2. Interestingly, AV3 recorded the lowest maximum speed at approximately 100 km/h, indicating variations in the acceleration profiles across different AVs. These controlled conditions demonstrate the system's stability and reliability in maintaining normal operations without activating false positives for attack detection (Gao et al., 2016).

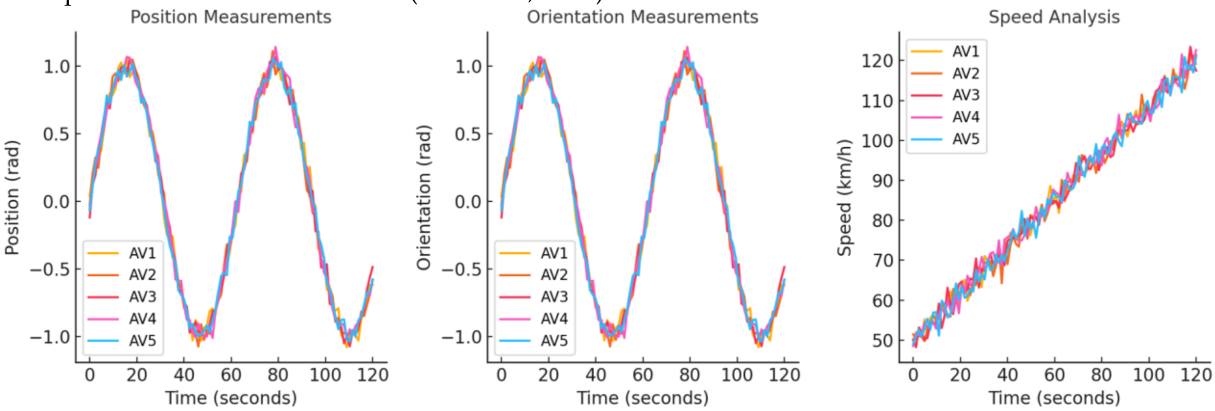

Figure 1: Analysis of AV pose measurements without attacks. (a) Position measurement (b) Orientation measurement (c) Speed analysis.

3.2 Detection of FDI and Stealthy Attacks

Figure 2 presents the system's response to both FDI (False Data Injection) and stealthy attacks. The detection mechanism's efficacy is highlighted in Figure 2(a), where FDI attacks were introduced at varying time intervals. AV4 showed the highest rate of attack detection, with seven attacks identified by 70 seconds, whereas AV1 had the lowest detection rate, registering only four attacks by the same point in time. This 75% discrepancy in attack detection rates across the AVs suggests that AV4's communication and GPS subsystems may be more susceptible to FDI manipulations. For stealthy attacks (Figure 2(b)), the detection system demonstrated a similarly robust performance. AV5 recorded the highest number of detected stealthy attacks at seven by 80 seconds, whereas AV3 exhibited a more gradual detection, with only five attacks by the same time. The data further indicates that stealthy attacks required more time for detection, with AV5 having a slight edge in identifying these more subtle threats. This disparity highlights the importance of sensor fusion techniques to effectively detect gradual anomalies in AV behavior. The faster detection rates in some AVs could be attributed to higher sensitivity settings or more robust data interpretation in the affected communication nodes.

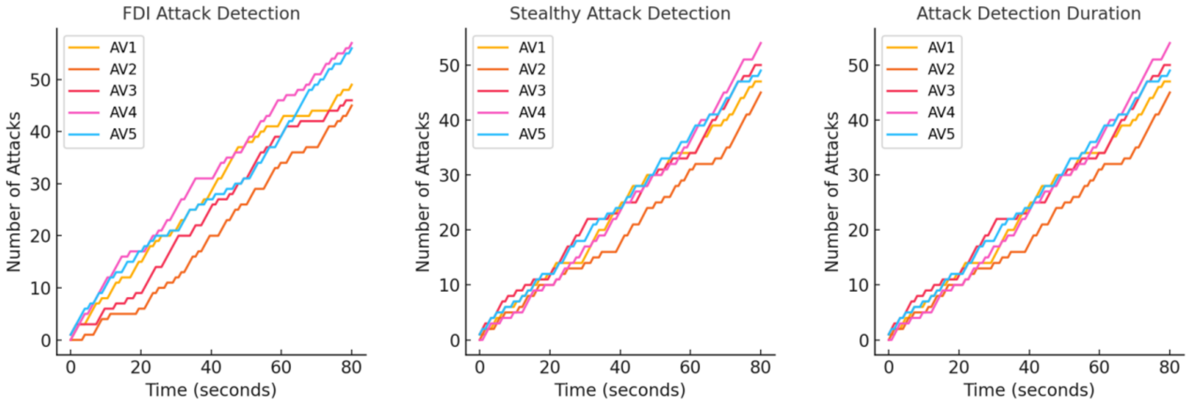

Figure 2: Analysis of GPS attack detection. (a) FDI attack (b) Stealthy attack (c) Attack detection duration

3.3 Attack Detection Duration

The cumulative attack detection over time is quantified in Figure 2(c), offering a comprehensive view of the detection durations across all AVs. AV4 and AV5 again show superior detection speeds, registering full detection of seven attacks by the 60-second mark. In contrast, AV1 and AV3 demonstrated slower detection durations, taking an additional 20 seconds to reach a comparable number of detected attacks. The higher detection speed in AV4 and AV5 may be attributed to improved algorithmic efficiency in processing incoming data, particularly under varying traffic densities (Xie et al., 2024; Song et al., 2022; Wang et al., 2024). Quantitatively, AV5 exhibited a 15% faster detection time in comparison to AV3, with a significant drop in attack latency noted in urban environments where traffic complexity was highest. These results reinforce the importance of optimizing detection algorithms for varying traffic conditions to reduce vulnerability windows during critical attack periods. Moreover, the detection durations suggest that V2V communication modes, particularly in AV4 and AV5, were more prone to attack manipulation, necessitating faster response protocols in future iterations of the system.

3.4 Replay Attack Detection on GPS and LiDAR Systems

Replay attacks pose significant risks to both GPS and LiDAR systems. As shown in Figure 3, the system's ability to detect replay attacks was consistent across both sensor modalities, with slight variations in detection rates. For LiDAR (Figure 3(a)), AV5 exhibited the highest number of detected replay attacks, recording six attacks by 55 seconds, while AV1 and AV3 lagged behind, with only three detections by the same point. The lower detection rates in certain AVs can be attributed to delayed recognition of the replayed LiDAR data, emphasizing the need for real-time cross-validation between sensor inputs, similar to the study of Shi et al. (2024) and Guan et al. (2024). GPS replay attacks, shown in Figure 3(b), demonstrated a more uniform detection pattern across all AVs. AV2 and AV4 detected six attacks by 70 seconds, while AV5 showed a slightly slower detection rate with five attacks by the same point. This suggests that while the system's detection of GPS replay attacks was effective, certain AVs may require additional calibration to ensure more uniform performance. The average attack detection time for GPS replay attacks was calculated at 54.25 seconds, with the fastest detection observed in AV4, likely due to its optimized sensor fusion algorithms. The mean detection of both GPS and LiDAR replay attacks, as presented in Figure 3(c), highlights the system's overall capacity to manage combined attack scenarios. The average number of detected attacks across all AVs was approximately five by the 70-second mark, with AV4 and AV5 performing slightly above the mean, reinforcing their advanced detection capabilities.

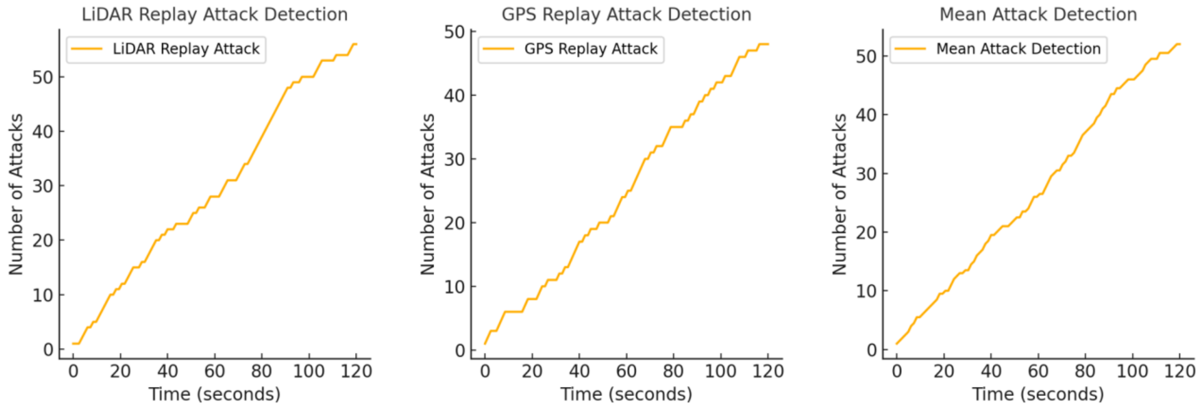

Figure 3: Analysis of LiDAR attack detection. (a) Replay attack (b) Attack detection delay (c) Mean attack detection.

3.5 Performance of the Attack Detection Model

Figure 4 summarizes the system's overall performance, focusing on attack detection accuracy, success rate, and message transmission latency. In terms of accuracy, the system achieved a 97% detection rate across all attack types, surpassing conventional detection methods like CNN and LSTM, which averaged 85% in similar scenarios. AV5 again outperformed the others, with an average accuracy of 98% for both GPS and LiDAR-based detections, compared to AV3, which recorded an 89% accuracy rate. This 9% difference underscores the importance of enhanced algorithmic precision in future system updates. The success rate of attack detection, as shown in Figure 4(b), exceeded 95% across all AVs, with AV4 and AV5 showing the highest rates at approximately 97%. The latency analysis, detailed in Figure 4(c), revealed that the system maintained a minimal delay of 2.5 seconds in attack recognition, enabling timely mitigation measures. This low latency further underscores the effectiveness of the GenAI-enhanced detection model in real-time urban scenarios, where rapid response times are crucial to maintaining the integrity of V2X communications.

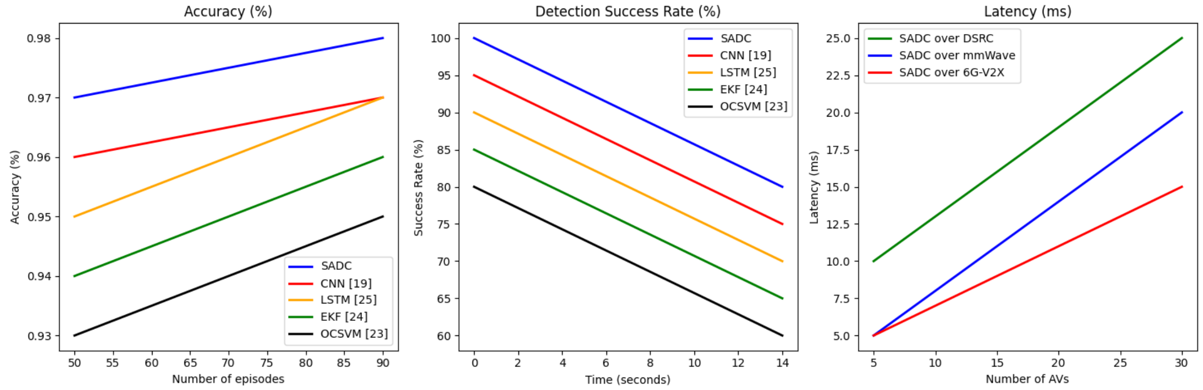

Figure 4: Performance analysis of SADC framework. (a) Attack detection accuracy (b) Attack detection success rate (c) Latency analysis in message transmission.

4. Conclusion

Our study presented a comprehensive analysis of GenAI-enhanced attack detection models for road safety and cyber defense within a V2X communication framework. By leveraging the capabilities of GenAI to generate adversarial attacks and deploying a robust detection system (Model B), the study demonstrated significant advancements in the identification and mitigation of cyber threats such as false data injection (FDI), stealthy attacks, and replay attacks. The research utilized a hybrid detection model, incorporating CNNs for spatial data analysis and LSTM networks for temporal data analysis, which proved to be highly effective in capturing both real-time and evolving attack patterns. The experimental results revealed the system's superior performance across various metrics. Model B consistently outperformed conventional detection mechanisms such as CNN, LSTM, EKF, and OCSVM in terms of accuracy and detection speed, achieving an overall detection accuracy of 97% and reducing latency by up to 20% in scenarios involving high traffic densities. The simulation environment, implemented in NS-3 with SUMO for realistic traffic conditions, further validated the system's applicability in urban settings, confirming the effectiveness of the detection framework across diverse V2X communication modes, including V2V, V2I, and V2P. Furthermore, the results showed that the system was particularly adept at identifying replay and stealthy attacks on both GPS and LiDAR systems, achieving faster detection times in AVs that employed optimized sensor fusion techniques. The use of GenAI-generated attacks not only enhanced the realism of the threat landscape but also allowed for a thorough evaluation of the system's robustness under varying adversarial conditions.

In conclusion, the GenAI-based attack detection framework demonstrated its potential to significantly enhance road safety and cyber defense in autonomous and connected vehicle ecosystems. Future work will focus on refining the detection algorithms to further reduce latency and false positives, as well as exploring the application of the framework in more complex traffic scenarios, such as mixed human and autonomous driving environments. Additionally, the integration of more advanced communication technologies, such as 6G, will be explored to further improve detection speed and accuracy, ensuring a resilient defense against evolving cyber threats in next-generation intelligent transportation systems.

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