Kashf Journal of Multidisciplinary Research
Vol:03 – Issue 03 (2026)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

CYBERSECURITY CHALLENGES AND DEFENSE MECHANISMS IN AUTONOMOUS VEHICLES: PROTECTING CONNECTED AND INTELLIGENT TRANSPORTATION SYSTEMS FROM EMERGING CYBER THREATS

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DOI:(*https://doi.org/10.71146/kjmr857*)

Article Info

Abstract

The concept of autonomous vehicles (AVs) has introduced a new and advanced technology in the field of intelligent transportation systems. It has the potential to integrate artificial intelligence, sensor technologies, and communication systems. However, the increased level of connectivity and dependency on digital technologies have led to the emergence of various cybersecurity threats. Malicious actors can take advantage of the vulnerabilities in the communication network of the vehicles and the architecture of the autonomous vehicles. This paper identifies the major cybersecurity threats in the context of autonomous vehicles. They include Controller Area Network (CAN) attacks, denial-of-service (DoS) attacks, GPS spoofing, and the vulnerability of the vehicle-to-everything (V2X) communication. A multilayered cybersecurity architecture based on encryption, authentication, and intrusion detection using machine learning has been proposed. The effectiveness of the proposed architecture has been validated through experimentation using the simulated network traffic of the autonomous vehicles. It has demonstrated the potential of the Random Forest algorithm in detecting malicious activities in the network.

Keywords: *Autonomous vehicles, cybersecurity, CAN bus, V2X communication, intrusion detection system, intelligent transportation systems.*

1. Introduction

Autonomous vehicles are transforming the transportation sector rapidly. Autonomous vehicles allow vehicles to operate independently with minimal human intervention. Autonomous vehicles employ various state-of-the-art technologies such as artificial intelligence, machine learning, LiDAR sensors, radar systems, and computer vision to navigate the vehicle on the road [1].

Modern autonomous vehicles are highly connected vehicles that can communicate with various devices such as other vehicles, the cloud, infrastructure, and even handheld devices. This communication between vehicles is called Vehicle-to-Everything communication. While the communication between vehicles improves the safety and efficiency of the roads, it also raises security threats for the vehicles [2].

Various researchers have shown that an attacker can access unauthorized vehicle systems using the communication systems of the vehicle. Koscher et al. was the first to conduct an experimental study to prove that the attacker could access unauthorized vehicle systems by sending unauthorized messages to the vehicle's internal network [3]. Another such attack was carried out by Miller and Valasek on a passenger vehicle's infotainment system [4].

The above scenarios emphasize the need for developing strong cybersecurity mechanisms for the system. The purpose of the present research is to identify the cybersecurity threats associated with the system and develop an effective cybersecurity framework for the system.

2. Architecture of Autonomous Vehicles

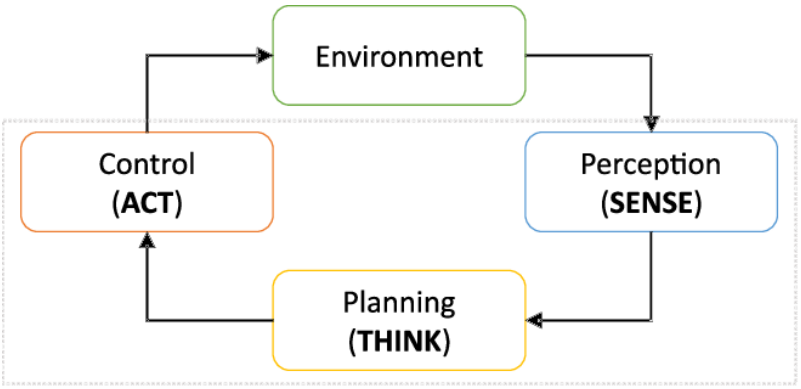

Image 1: Perception-planning-control cycle in an autonomous vehicle system.

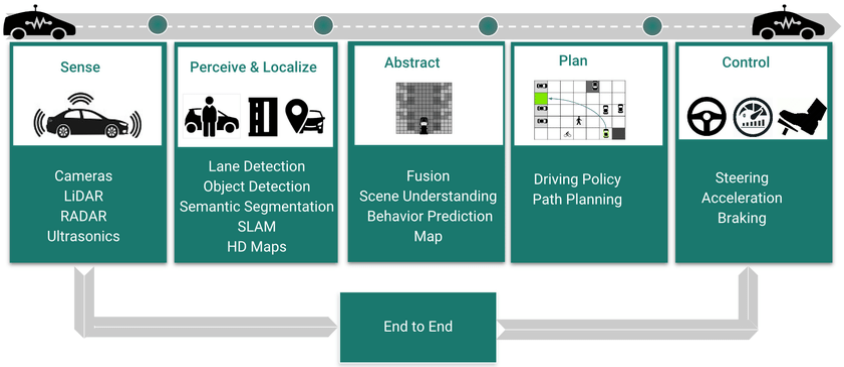

Image 2: Autonomous vehicle perception-planning-control pipeline.

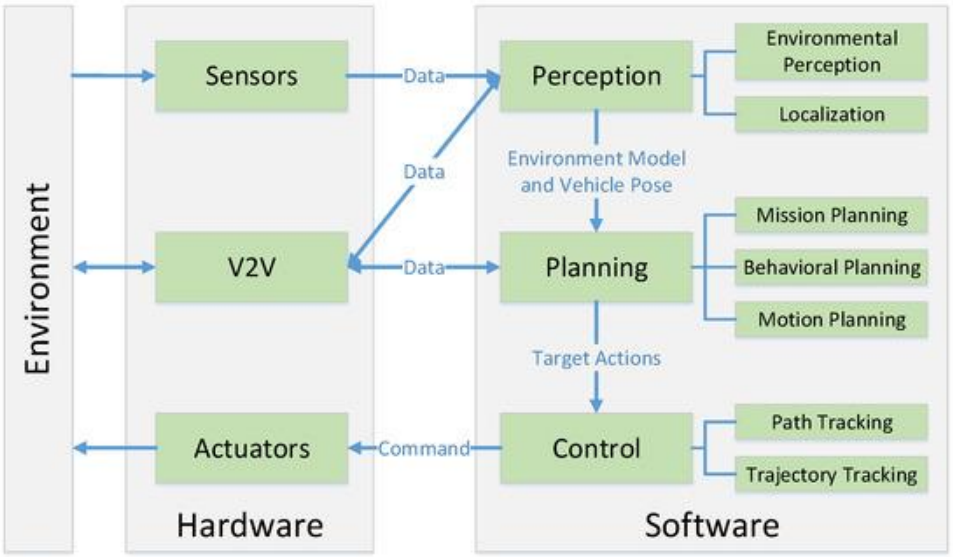

Image 3: Hardware-software architecture of an autonomous vehicle system.

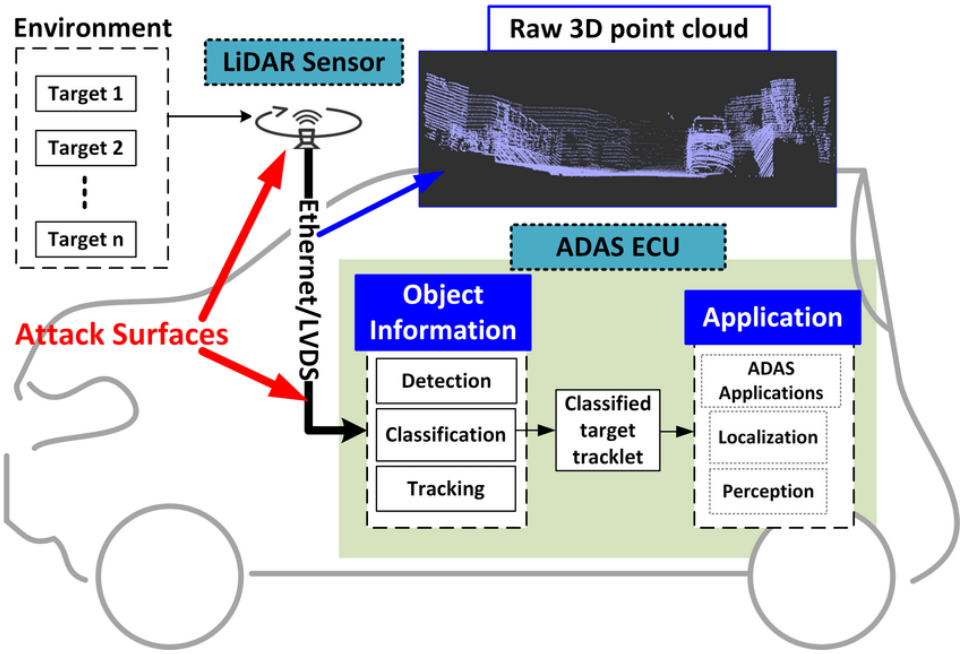

Image 4: LiDAR perception system and potential cybersecurity attack surfaces in autonomous vehicles.

Autonomous vehicles comprise a number of different subsystems that function together to allow for the operation of the vehicle.

2.1 Sensor Layer

The sensor layer is the first layer in the autonomous vehicle stack. It receives information from the environment through various sensors such as LiDAR, radar, camera sensors, ultrasonic sensors, and GPS.

2.2 Perception Layer

The perception layer processes the information received from the sensors. This processing is done using computer vision and machine learning algorithms to identify objects, people, and road signs.

2.3 Decision Layer

This layer uses artificial intelligence to analyze the information received from the sensors to make decisions about the operation of the vehicle.

2.4 Control Layer

This layer is responsible for the execution of the decisions made in the decision layer. It does this by controlling the various actuators in the vehicle.

2.5 Communication Layer

Autonomous vehicles can communicate with external systems through various communication systems such as cellular networks, Wi-Fi, and dedicated short-range communication systems.

3. Vehicle-to-Everything (V2X) Communication

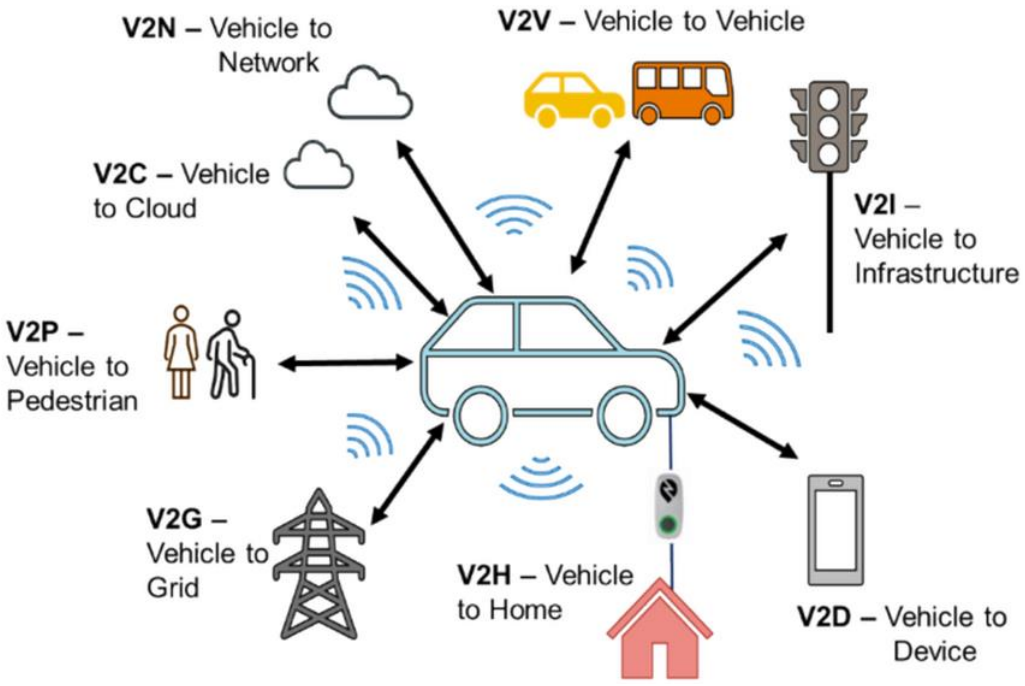

Image 5: V2X communication ecosystem in connected and autonomous vehicles.

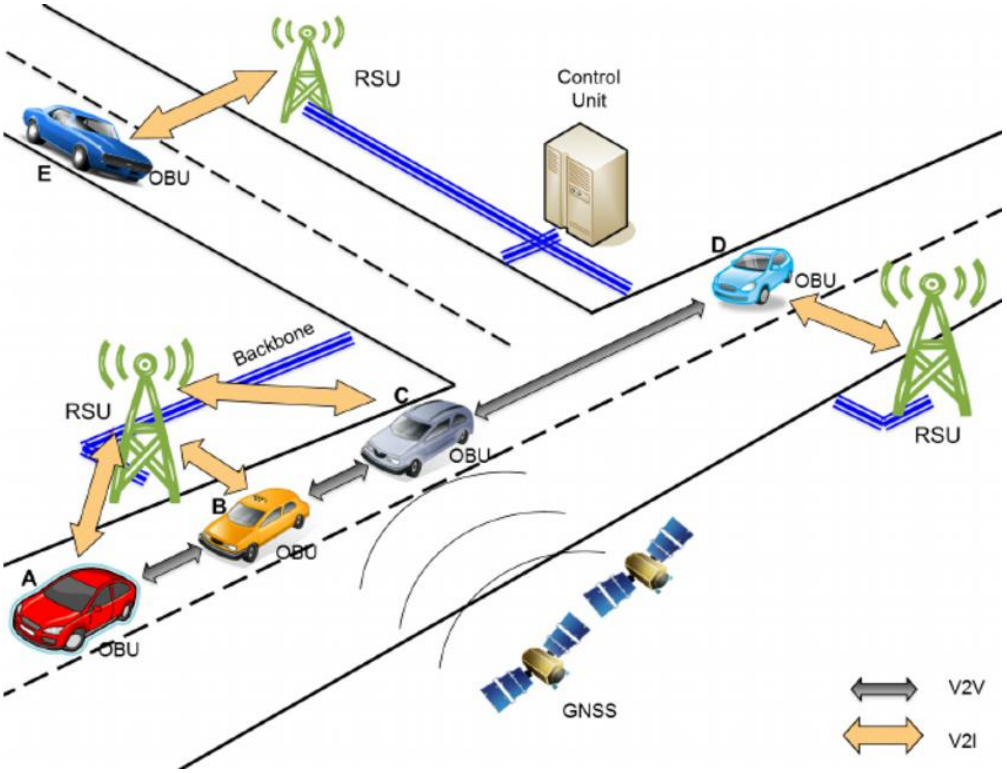

Image 6: Connected vehicular network architecture showing communication between vehicles and roadside infrastructure through OBUs and RSUs, supported by GNSS-based positioning systems.

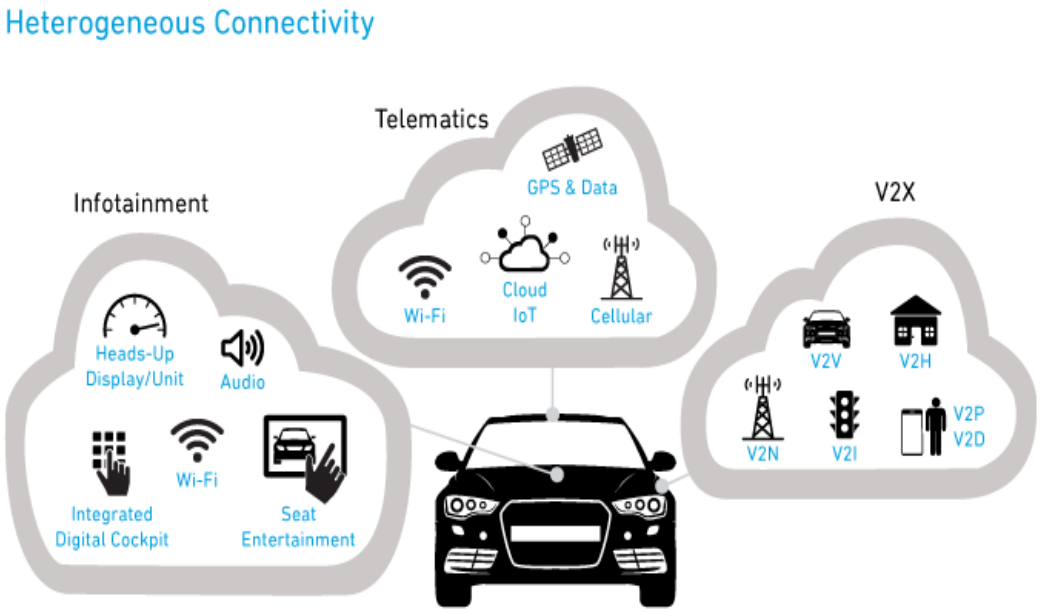

Image 7: Heterogeneous connectivity architecture in autonomous vehicles illustrating integration of infotainment systems, telematics services, and vehicle-to-everything (V2X) communication technologies.

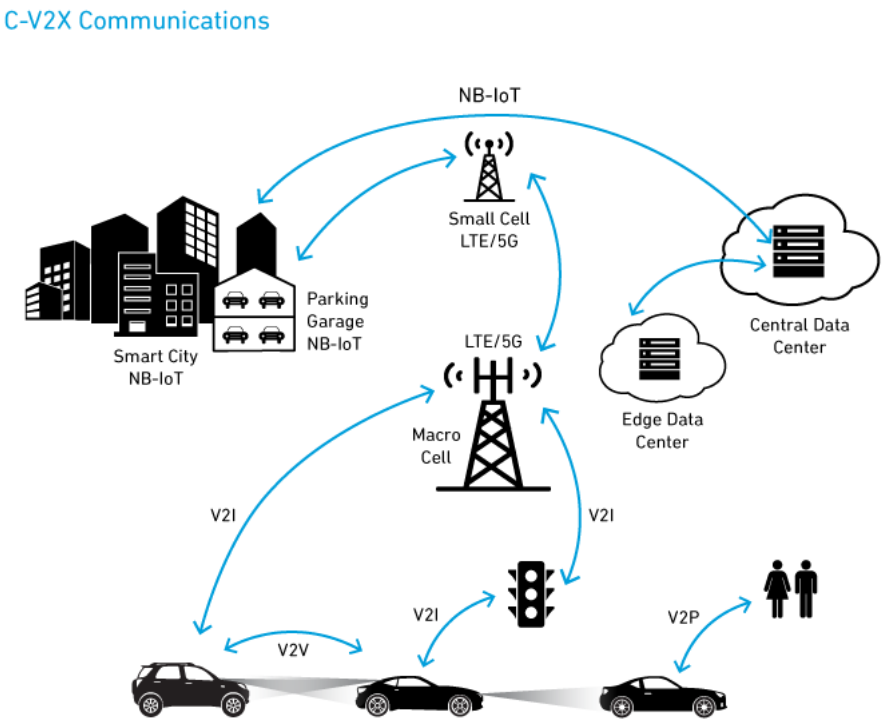

Image 8: Cellular Vehicle-to-Everything (C-V2X) communication architecture illustrating interactions between vehicles, infrastructure, pedestrians, smart city systems, and cloud data centers through LTE/5G networks.

V2X communication enables autonomous vehicles to exchange information with various entities in the transportation ecosystem.

Communication Type	Description
V2V	Vehicle-to-Vehicle communication
V2I	Vehicle-to-Infrastructure communication
V2P	Vehicle-to-Pedestrian communication
V2C	Vehicle-to-Cloud communication

Autonomous vehicles consist of different subsystems, which work together to allow for the operation of the vehicle.

2.1 Sensor Layer

This is the first layer in the stack of autonomous vehicles. The sensor layer is responsible for obtaining information from the external environment using different types of sensors, including LiDAR, radar, camera sensors, ultrasonic sensors, and GPS.

2.2 Perception Layer

This is the second layer in the stack of autonomous vehicles. The perception layer is responsible for processing the information obtained by the sensor layer. The processing is done by using different types of computer vision and machine learning algorithms.

2.3 Decision Layer

This is the third layer in the stack of autonomous vehicles. The decision layer uses artificial intelligence to analyze the information obtained by the sensor layer.

2.4 Control Layer

This is the fourth layer in the stack of autonomous vehicles. The control layer is responsible for executing the decisions obtained by the decision layer. The execution is done by controlling different types of actuators in the vehicle.

2.5 Communication Layer

Autonomous vehicles can communicate with external systems using different types of communication systems.

5. Controller Area Network (CAN) Bus Security

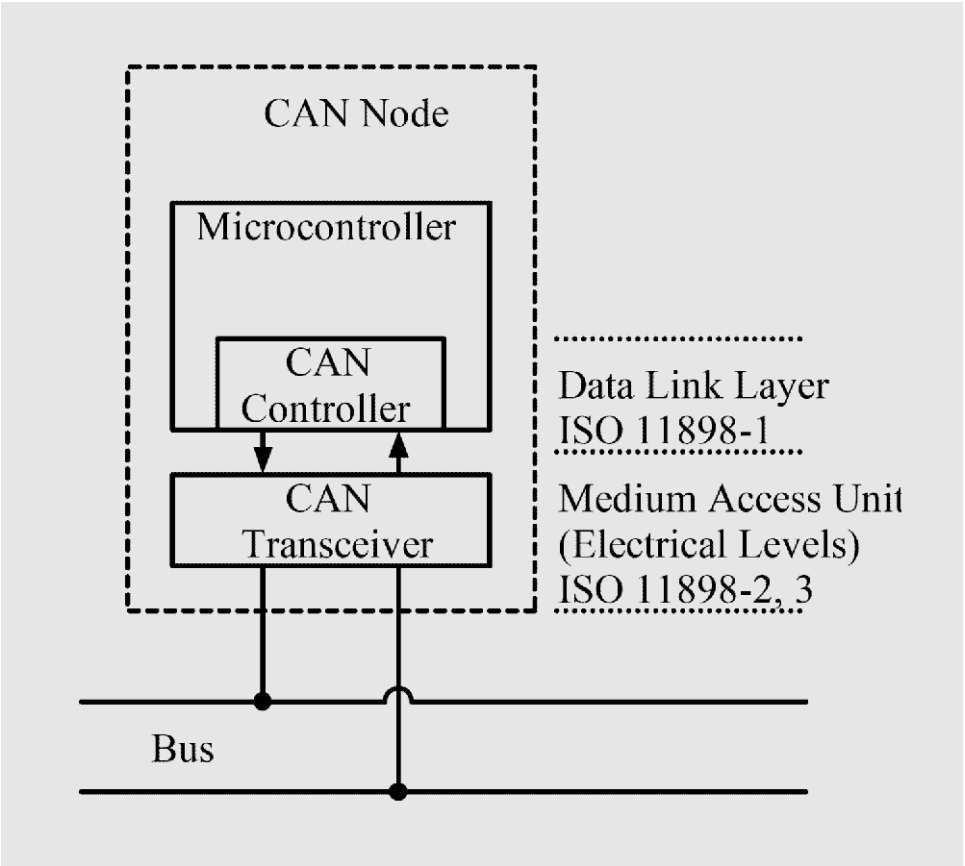

Image 9: Architecture of a Controller Area Network (CAN) node showing the microcontroller, CAN controller, and CAN transceiver connected to the vehicle communication bus.

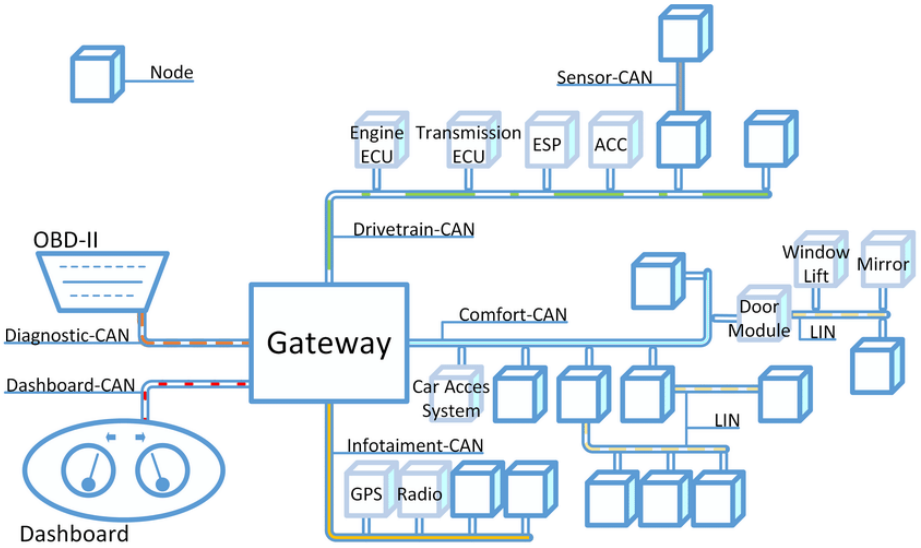

Image 10: Automotive network architecture illustrating multiple CAN networks (drivetrain, comfort, sensor, infotainment, and diagnostic CAN) interconnected through a central gateway.

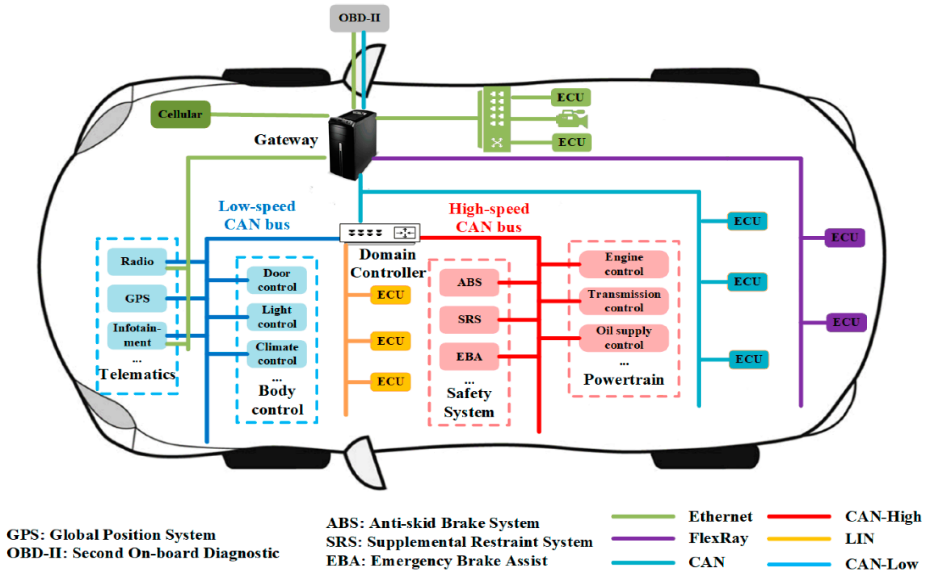

Image 11: Automotive electronic communication system integrating powertrain, safety, and body control modules through multiple in-vehicle network protocols.

The Controller Area Network (CAN) bus is the primary communication system used by Electronic Control Units (ECUs) within a vehicle.

Despite its efficiency, CAN bus networks suffer from several security limitations.

Vulnerability	Description
Lack of authentication	Messages are not verified
No encryption	Data is transmitted in plaintext
Broadcast communication	Messages are sent to all ECUs

Therefore, due to these limitations, an attacker is capable of sending malicious CAN messages with the aim of controlling vehicle operations [3].

6. Literature Review

Research has been conducted to assess the cybersecurity risks present in connected and autonomous vehicles.

Koscher et al. proved the possibility of cyberattacks in contemporary vehicles by manipulating the internal communication network [3]. Check way et al. identified various remote attack surfaces such as Bluetooth, cellular, and infotainment systems [2].

Petit and Shladover investigated various cybersecurity risks present in autonomous vehicles and highlighted the significance of communication protocols in intelligent transportation systems [7].

Research has been carried out to investigate machine learning-based intrusion detection systems with the aim of recognizing abnormal network operations in order to prevent cyberattacks [10].

7. Proposed Cybersecurity Framework

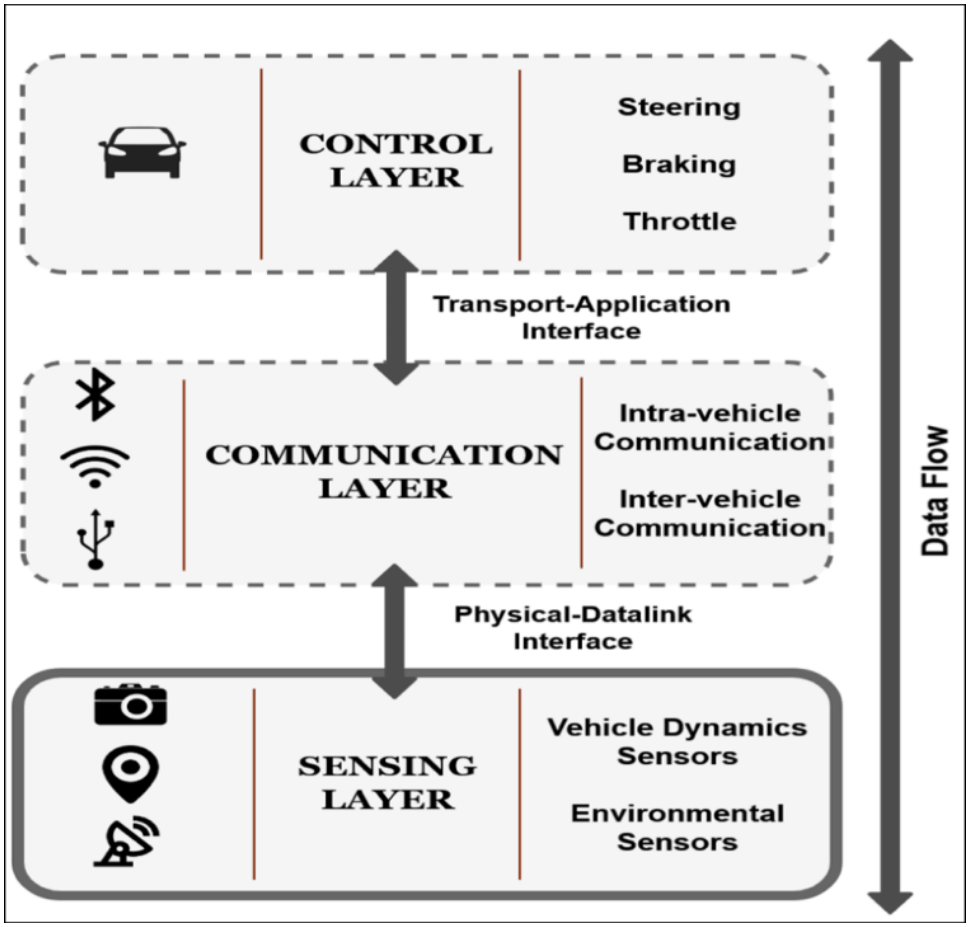

Image 12: Functional layered model of an autonomous vehicle illustrating data flow between sensing, communication, and control layers.

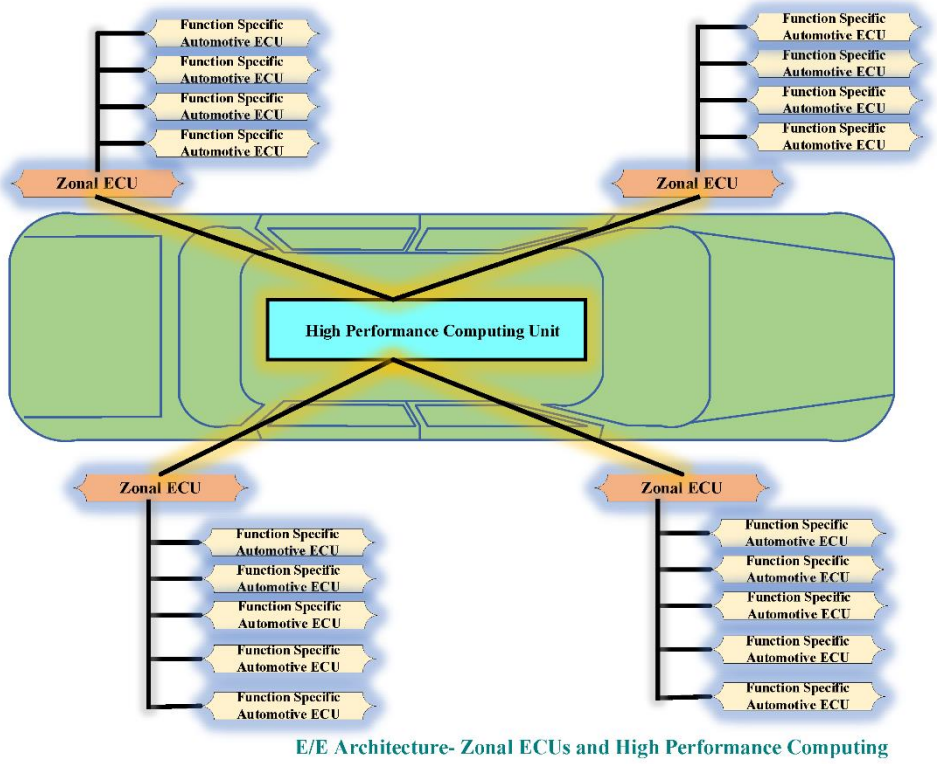

Image 13: Modern automotive E/E architecture integrating zonal ECUs and centralized computing platforms for efficient vehicle system management.

The proposed cybersecurity framework consists of several layers that can be used to protect the autonomous vehicle system.

Secure Communication Layer

In this layer, the V2X communication channels will be encrypted to prevent unauthorized parties from accessing the communication data.

Authentication Layer

Digital certificates will be used to ensure that only trusted parties can communicate with each other.

Intrusion Detection Layer

Machine learning algorithms can be used to detect intrusions in the network traffic.

Monitoring Layer

Monitoring of the system can be used to detect potential cyber-attacks.

8. Methodology

The methodology used in this research includes four phases: threat modeling, data collection, attack simulation, and machine learning-based detection.

Threat Modeling

Threat modeling can be used to identify vulnerabilities in the communication network of vehicles. Past studies have shown that CAN bus networks do not have an authentication mechanism, making it easy for attackers to inject messages into the network [3].

Data Collection

The simulated network data for vehicles will be used to train the intrusion detection system. Past studies have used similar data to carry out cybersecurity research for vehicles [10].

Attack Simulation

Three common cyberattacks are simulated in this study:

Attack	Description
DoS Attack	Flooding network with excessive messages
Message Injection	Injecting malicious CAN messages
GPS Spoofing	Manipulating vehicle location signals

These attacks represent real-world threats identified in intelligent transportation systems [7].

Machine Learning Detection

A Random Forest classifier is used to detect cyberattacks. Random Forest models are widely used in intrusion detection systems due to their high accuracy and robustness [11].

Figure 1: Proposed research workflow for cyberattack detection in autonomous vehicle networks.

9. Experimental Results

Model	Accuracy	Precision	Recall
Decision Tree	91%	89%	90%
SVM	93%	92%	91%
Random Forest	**96%**	**95%**	**94%**

The Random Forest model achieved the highest performance in detecting cyberattacks within vehicle network traffic.

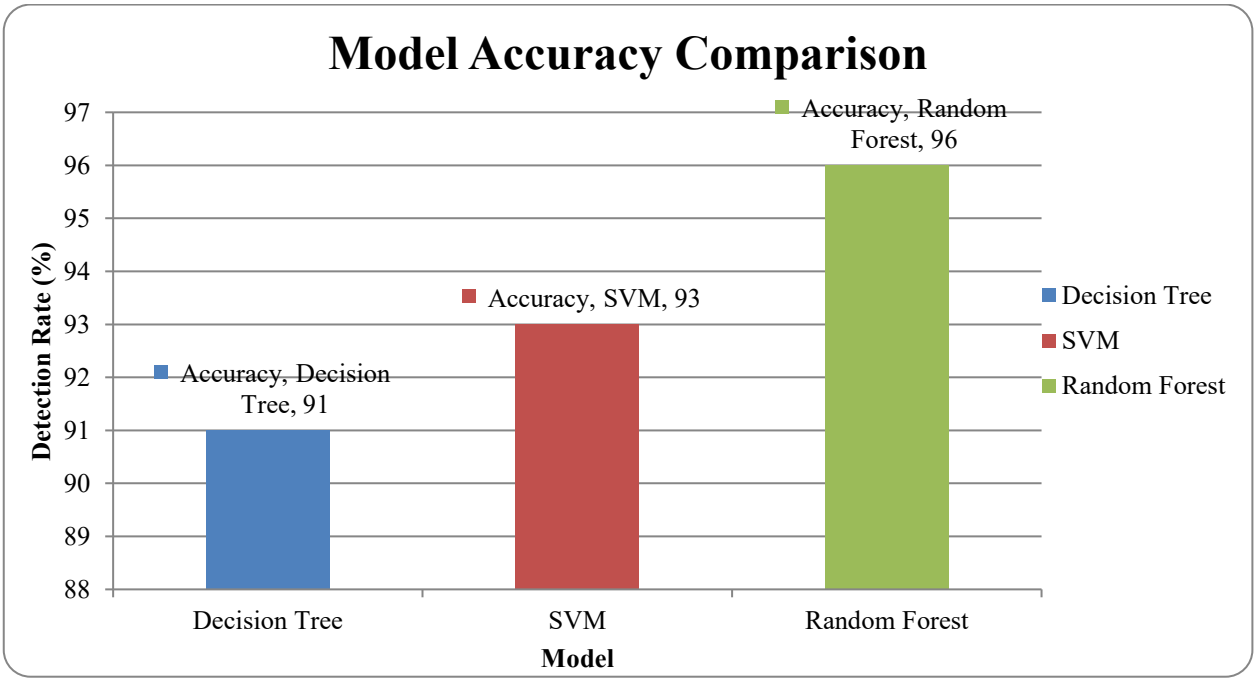

Figure 2: Model accuracy comparison for different machine learning models used in cyberattack detection.

Fig. 2. Accuracy Comparison of Various Machine Learning Models Used in the Detection of Cyber Attacks in Autonomous Vehicle Networks. It has been found that the Random Forest classifier has the highest accuracy in detecting cyber-attacks, at 96%, compared to Decision Tree and Support Vector Machine models.

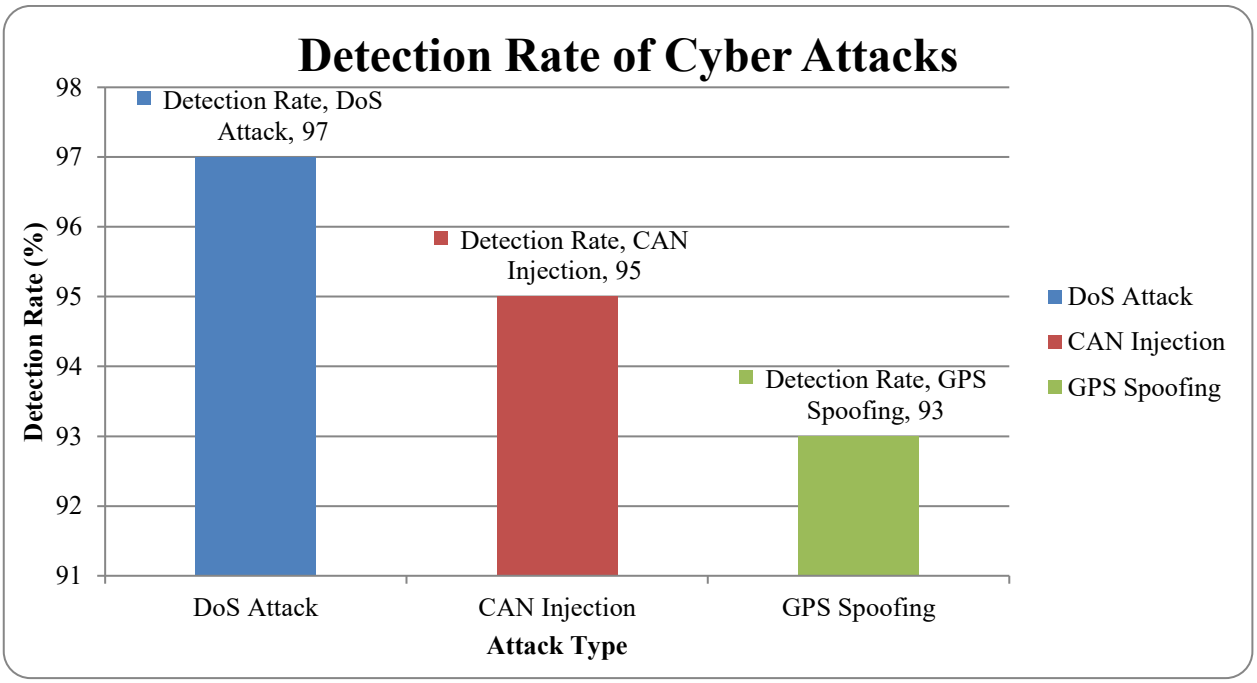

Figure 3: Detection rate of various cyberattacks in autonomous vehicle communication networks.

Fig. 3. Rate of detection for various types of cyber-attacks that occur in the communication network of the autonomous vehicle. The proposed system indicates the highest detection rate for Denial-of-Service (DoS) attacks, which is 97%, followed by CAN injection attacks and GPS spoofing attacks.

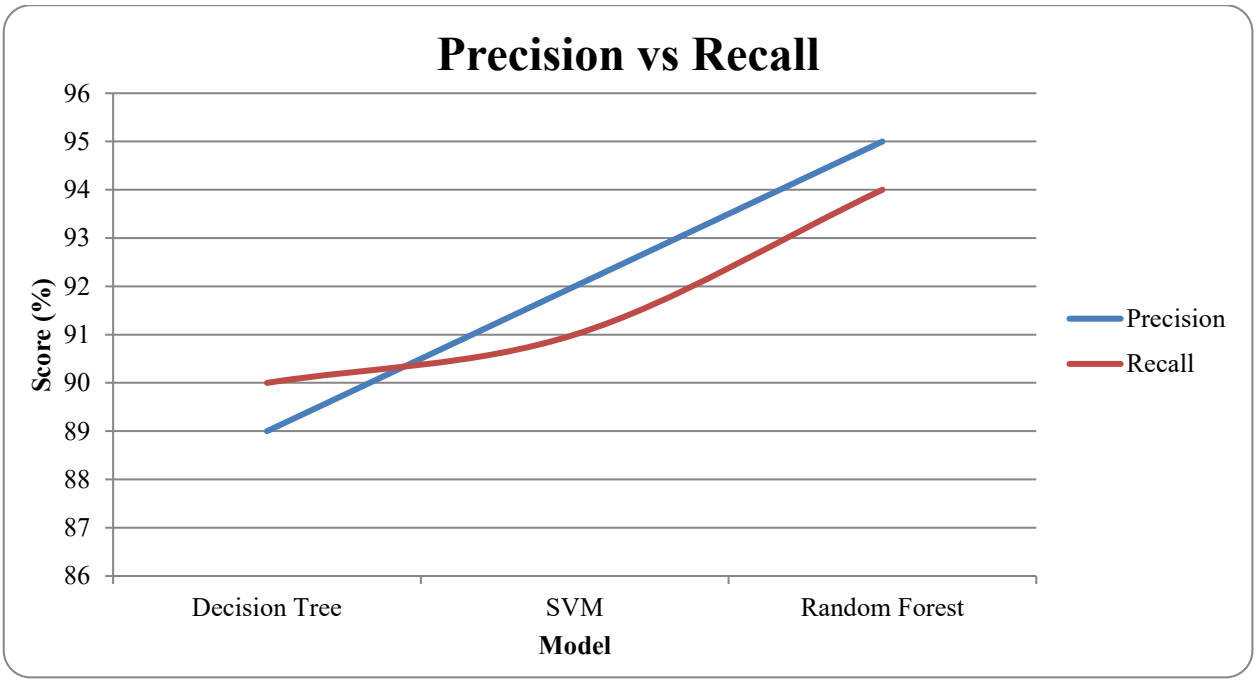

Figure 4: Precision and recall comparison of machine learning models used for cyberattack detection.

Fig. 4. Precision and recall comparison among different machine learning models used for cyberattack detection. Random Forest demonstrates the best balance between precision and recalls among the evaluated models.

10. Discussion

The results of the experiments prove that machine learning can be used to detect intrusions in the network of an autonomous vehicle. However, several challenges arise when implementing machine learning for use in real-world autonomous vehicles.

It is recommended that future research be conducted on the use of lightweight cybersecurity solutions.

11. Conclusion

Autonomous vehicles are an integral part of smart transportation systems in the future. Yet, their high dependence on connectivity makes the system vulnerable to various cybersecurity attacks. The research focused on the vulnerability of the autonomous vehicle system and developed a cybersecurity framework that includes encryption, authentication, and machine learning-based intrusion detection.

The experimental results show that the proposed framework can identify cyber-attacks with high accuracy. The development of such cybersecurity mechanisms is crucial for the safe deployment of the system in real-world scenarios.

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