International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Defense Mechanisms in Autonomous Vehicles Using GPS Spoofing Detection

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ABSTRACT

Autonomous vehicles (AVs) rely heavily on Global Navigation Satellite Systems (GNSS) such as GPS for localization and navigation. However, these systems are highly vulnerable to sensor spoofing attacks, where adversaries manipulate GPS signals to mislead the vehicle's perception of its position. Such attacks can lead to incorrect decision-making and pose serious safety risks. This work presents a simulation-based cybersecurity framework for detecting and mitigating GPS spoofing attacks in autonomous vehicles.

The proposed system integrates a kinematic consistency-based anomaly detection mechanism that validates GPS measurements against vehicle motion dynamics. By comparing the displacement derived from GPS data with the expected displacement computed from vehicle speed, the system identifies inconsistencies indicative of spoofing. Additionally, temporal anomaly detection is employed to detect abrupt positional jumps that violate physical constraints. Upon detection of a spoofing attack, the vehicle transitions into a safe state, executing controlled braking to prevent unsafe operation.

The system is implemented using the Webots simulation environment with a Python-based vehicle controller. A real-time attack scenario is simulated by injecting false GPS coordinates, enabling evaluation of detection, response, and recovery mechanisms. The results demonstrate that the proposed approach effectively identifies spoofing attacks and ensures safe system behavior through a complete defense lifecycle comprising detection, response, and recovery. This work contributes a practical and implementable cybersecurity solution for enhancing the resilience of autonomous vehicles against sensor-level attacks.

CHAPTER 1: INTRODUCTION

1. INTRODUCTION

1.1 Introduction to Autonomous Vehicle Cybersecurity

Autonomous vehicles (AVs) represent a major advancement in modern transportation by integrating artificial intelligence, sensor technologies, and real-time decision-making systems. These vehicles rely on multiple modules such as perception, localization, planning, and control to operate safely in dynamic environments. Among these, localization plays a critical role, as it determines the vehicle's position and directly affects navigation, path planning, and obstacle avoidance.

To achieve accurate localization, AVs widely depend on Global Navigation Satellite Systems (GNSS), particularly the Global Positioning System (GPS). However, this heavy reliance on GPS introduces significant cybersecurity risks. One of the most critical threats is GPS spoofing, where an attacker transmits fake signals to manipulate the vehicle's perceived location. Unlike signal jamming, spoofing provides incorrect but realistic data, making it difficult to detect and potentially leading to dangerous situations such as route deviation or collisions.

With the increasing adoption of autonomous vehicles, ensuring the security and reliability of sensor data has become essential. Cybersecurity mechanisms must not only detect such attacks but also ensure safe operation of the vehicle under compromised conditions. This highlights the need for robust frameworks that combine detection, response, and recovery to protect autonomous systems from sensor-level cyber threats.

1.2 Role of GPS and Localization in Autonomous Vehicles

Localization is a fundamental component of autonomous vehicle systems, as it enables the vehicle to determine its precise position in real time. Accurate localization is essential for critical functions such as navigation, path planning, and obstacle avoidance. Any error in position estimation can directly affect the vehicle's decision-making and lead to unsafe operation.

To achieve reliable localization, autonomous vehicles primarily rely on Global Navigation Satellite Systems (GNSS), especially the Global Positioning System (GPS). GPS provides absolute positioning information by using signals from multiple satellites, allowing the vehicle to identify its location on a global scale. This information is continuously updated and used by the vehicle to follow routes, maintain lanes, and interact with its surroundings.

However, the heavy dependence on GPS makes autonomous vehicles vulnerable to inaccuracies and external interference. Since GPS signals are relatively weak and lack strong authentication mechanisms, they can be easily manipulated or disrupted. Therefore, while GPS plays a crucial role in localization, it also introduces potential risks that must be addressed to ensure safe and reliable autonomous vehicle operation. Motivation of the Project

1.3 GPS Spoofing and Security Challenges

GPS spoofing is one of the most critical cybersecurity threats affecting autonomous vehicles. In a spoofing attack, an adversary transmits counterfeit GPS signals that imitate legitimate satellite signals. As a result, the vehicle's GPS receiver calculates an incorrect position without detecting any obvious error. Unlike jamming attacks, which simply block signals, spoofing provides false but realistic data, making it much more dangerous and difficult to identify.

This type of attack can lead to serious consequences in autonomous driving systems. Since vehicles rely on GPS for navigation and decision-making, incorrect position information may cause route deviation, lane misalignment, or even collisions. Such failures can compromise both passenger safety and overall system reliability.

The main challenge in detecting GPS spoofing lies in its subtle nature. The manipulated signals often appear valid, and traditional systems that rely solely on GPS data cannot easily distinguish between genuine and fake signals. Additionally, existing detection methods may require complex hardware or computational resources, making them difficult to implement in real-time systems.

Therefore, addressing GPS spoofing requires robust and efficient detection mechanisms that can identify inconsistencies in sensor data and ensure safe vehicle operation under adversarial conditions.

1.4 Objectives of the Project

The main objective of this project is to develop a secure and reliable system for detecting and mitigating GPS spoofing attacks in autonomous vehicles. The specific objectives are as follows:

- To detect GPS spoofing attacks in real time using vehicle motion parameters such as speed, time, and displacement.
- To implement a kinematic consistency-based validation mechanism for identifying anomalies in GPS data.
- To incorporate temporal anomaly detection for detecting sudden and unrealistic changes in vehicle position.
- To design a safe-state response mechanism that ensures controlled braking and safe stopping of the vehicle upon attack detection.
- To develop a recovery mechanism that allows the vehicle to resume normal operation after stabilization.
- To implement and validate the proposed system using a simulation environment such as Webots.
- To create a simple, cost-effective, and scalable cybersecurity framework without relying on additional hardware or complex models.

These objectives aim to enhance the safety, reliability, and resilience of autonomous vehicles against GPS spoofing attacks.

1.5 Scope of the Project

The scope of this project focuses on developing a simulation-based cybersecurity framework for detecting and mitigating GPS spoofing attacks in autonomous vehicles. The system is designed to operate within a controlled simulation environment, enabling safe and repeatable testing of attack scenarios and system responses.

The project primarily addresses vulnerabilities in GPS-based localization by implementing kinematic validation and temporal anomaly detection techniques. It focuses on real-time detection of spoofing attacks using vehicle motion data such as speed, time, and displacement, without relying on additional sensors or complex hardware.

The scope also includes the integration of a complete defense lifecycle, consisting of detection, safe-state response, and recovery. Upon detecting an attack, the system ensures safe vehicle operation through controlled braking and subsequently restores normal operation after stabilization.

However, the project is limited to simulation-based validation using tools like Webots and does not cover real-world deployment or integration with advanced sensor fusion systems. It also focuses specifically on GPS spoofing attacks and does not address other types of cyberattacks affecting autonomous vehicles.

Overall, the project provides a practical and scalable foundation for enhancing the cybersecurity and safety of autonomous vehicle systems

1.6 Organization of the Report

This report is organized into multiple chapters to present the design, implementation, and evaluation of the proposed system in a structured manner.

Chapter 1: Introduction

Provides an overview of autonomous vehicles, the role of GPS in localization, the problem of GPS spoofing, and the objectives and scope of the project.

Chapter 2: Literature Survey

Discusses existing methods for detecting GPS spoofing attacks, including signal-based, sensor fusion, and anomaly detection approaches, along with their limitations

Chapter 3: System Analysis

Explains the existing system, its drawbacks, and introduces the proposed system with its advantages.

- Chapter 4: Requirements Analysis

Describes the hardware and software requirements, as well as functional and non-functional requirements of the system.

- Chapter 5: Proposed Methodology

Details the working of the proposed system, including kinematic validation, temporal anomaly detection, response, and recovery mechanisms.

- Chapter 6: System Design

Presents design aspects such as system architecture, UML diagrams, and data flow diagrams.

- Chapter 7: Implementation and Results

Explains the implementation in the simulation environment and presents the results obtained.

- Chapter 8: System Testing

Covers different testing methods, test cases, and performance evaluation.

- Chapter 9: Results and Discussion

Analyzes the system performance and compares it with existing methods.

- Chapter 10: Conclusion

Summarizes the work and key findings of the project.

- Chapter 11: Future Enhancements

Suggests possible improvements and future scope of the system.

- Chapter 12: References

Lists the sources and research papers referred to in the project.

CHAPTER 2: LITERATURESURVEY

2. LITERATURE SURVEY

2.1 Related Work

GPS spoofing detection has been widely studied due to its significant impact on autonomous vehicle safety. Various research efforts have proposed different techniques to identify and mitigate spoofing attacks, focusing on improving the reliability of GNSS-based localization systems.

One of the early approaches involves receiver-level monitoring and signal analysis, where inconsistencies in signal strength, timing, and phase are used to detect spoofed signals. Researchers such as Todd E. Humphreys have emphasized the importance of validating GPS data against trusted references, highlighting that reliance on a single source can lead to vulnerabilities.

Another approach is based on vehicle motion constraints, where the physical behavior of the vehicle is used to verify GPS data. By comparing the expected displacement (calculated from speed and time) with the actual displacement obtained from GPS, anomalies can be identified. This method is simple and effective, as it leverages fundamental physical laws that are difficult to manipulate.

In addition, sensor fusion techniques combine data from multiple sensors such as GPS, inertial measurement units (IMU), LiDAR, and cameras to improve robustness. These methods enhance accuracy and reliability but often increase system complexity and computational requirements.

Anomaly-based detection systems and machine learning approaches have also been explored to detect irregular patterns in GPS data. While these methods can identify complex attack patterns, they require large datasets and may suffer from false positives.

Overall, existing research provides several effective detection techniques, but many approaches either rely on additional hardware, involve complex implementation, or focus only on detection without addressing response and recovery. This highlights the need for a more practical and integrated solution, as proposed in this work.

CHAPTER3:SYSTEM ANALYSIS

3. SYSTEM ANALYSIS

3.1 Existing System

In current autonomous vehicle systems, localization is primarily achieved using GPS and other supporting sensors such as IMU, LiDAR, and cameras. Many existing approaches for detecting GPS spoofing attacks focus on signal-level analysis, sensor fusion techniques, and anomaly-based detection methods.

Signal-level techniques analyze properties such as signal strength, timing, and phase to identify inconsistencies in GPS signals. Sensor fusion methods combine data from multiple sensors to improve accuracy and detect discrepancies between different sources. Additionally, statistical and machine learning-based approaches are used to identify abnormal patterns in GPS data.

While these systems can detect spoofing attacks to some extent, they often rely on complex algorithms, additional hardware, and high computational resources. Moreover, most existing systems focus only on detecting anomalies and do not provide mechanisms for safe response or recovery after an attack is identified.

As a result, current systems are not fully equipped to handle GPS spoofing attacks in a practical and efficient manner, highlighting the need for a more integrated and lightweight solution.

3.2 Disadvantages of Existing System

Despite various methods proposed for detecting GPS spoofing attacks, existing systems have several limitations that affect their practicality and effectiveness.

Dependence on Additional Hardware:

Many approaches rely on sensors such as IMU, LiDAR, and cameras, which increase system cost and complexity.

High Computational Complexity:

Techniques like sensor fusion and machine learning require significant processing power, making real-time implementation challenging.

- Focus Only on Detection:

Most systems are limited to identifying spoofing attacks and do not include response or recovery mechanisms to ensure safe vehicle operation.

- Limited Robustness:

Some methods may fail to detect sophisticated or gradual spoofing attacks that closely mimic normal behavior.

- False Positives and False Negatives:

Statistical and threshold-based approaches may incorrectly classify normal behavior as an attack or fail to detect actual attacks.

- Difficult Real-World Implementation:

Complex algorithms and hardware requirements make deployment in real-world autonomous vehicles challenging.

Overall, these disadvantages highlight the need for a simpler, efficient, and integrated approach that not only detects spoofing attacks but also ensures safe response and recovery.

3.3 Proposed System

The proposed system introduces a cybersecurity framework for detecting and mitigating GPS spoofing attacks in autonomous vehicles using a simple and efficient approach based on vehicle dynamics. Unlike existing methods that rely on complex algorithms or additional sensors, the proposed system utilizes the inherent physical constraints of vehicle motion to validate GPS data.

The system operates by continuously monitoring GPS coordinates and comparing the actual displacement obtained from GPS with the expected displacement calculated using vehicle speed and time. If a significant mismatch is detected, it indicates a potential spoofing attack. In addition to this, temporal anomaly detection is used to identify sudden and unrealistic jumps in position, further improving detection accuracy.

Upon detecting a spoofing attack, the system does not stop at detection alone. It initiates a safe-state response mechanism, where the vehicle gradually reduces speed and comes to a controlled stop to prevent unsafe operation. After a stabilization period, a recovery mechanism is activated, allowing the vehicle to resume normal operation.

The entire system is implemented in a simulation environment using the Webots platform with a Python-based controller. This enables real-time testing of both normal and attack scenarios in a controlled environment.

Overall, the proposed system provides a simple, cost-effective, and practical solution that integrates detection, response, and recovery, ensuring improved safety and reliability of autonomous vehicles under GPS spoofing attacks.

3.4 Advantages of Proposed System

The proposed system incorporates advanced defensive mechanisms that significantly enhance the safety and reliability of autonomous vehicles. One of the key advantages is the ability to detect potential risks and hazards in real time. Using sensors such as cameras, LiDAR, and radar, the system continuously monitors the environment and identifies obstacles, pedestrians, and other vehicles, allowing it to take preventive actions before a dangerous situation occurs.
Another major advantage is the implementation of proactive collision avoidance techniques. Unlike traditional systems that react after detecting danger, the proposed system predicts possible collisions using real-time data and machine learning models. It can adjust speed, change lanes, or apply brakes automatically to prevent accidents, thereby improving

overall road safety.

The system also improves decision-making under uncertain and dynamic conditions. Defensive mechanisms enable the vehicle to handle unexpected scenarios such as sudden pedestrian movement, abrupt vehicle stops, or poor road conditions. By analyzing multiple inputs simultaneously, the system ensures safe and optimal decisions even in complex environments.

Additionally, the system enhances reliability through redundancy and fail-safe mechanisms. Multiple sensors work together to provide accurate data, reducing the chances of failure due to a single sensor malfunction. In case of system errors or unexpected failures, the system can switch to safe modes such as slowing down or stopping the vehicle to avoid accidents.

Another advantage is the ability to maintain safe distances and follow traffic rules consistently. The system automatically controls speed and maintains appropriate distance from other vehicles, reducing the risk of collisions and ensuring smooth traffic flow. It also adheres strictly to traffic signals and road signs, minimizing violations.

CHAPTER 4: REQUIREMENT ANALYSIS

4. REQUIREMENTS ANALYSIS

4.1 Hardware Requirements

The hardware requirements specify the minimum system configuration required to run the application effectively.

S.No	Component	Specification
1	Processor	Intel i5 / i7 or higher
2	RAM	Minimum 8 GB (16 GB recommended)
3	Storage	256 GB SSD or higher
4	System Type	64-bit System
5	GPU	NVIDIA GPU (for ML processing, optional but recommended)
6	Sensors	LiDAR, Camera, Ultrasonic Sensors
7	Controller	Raspberry Pi / Arduino / Embedded System
8	Network	Internet Connection

4.2 Software Requirements

The software requirements include all the tools, technologies, and platforms required to develop and run the system.

S.No	Software	Description
1	Operating System	Windows 10 / Linux (Ubuntu preferred)
2	Programming Language	Python
3	Frontend	HTML, CSS, JavaScript
4	Backend	Node.js / Flask

S.No	Software	Description
5	Database	MongoDB / MySQL
6	Machine Learning Libraries	TensorFlow, OpenCV, Scikit-learn
7	Simulation Tools	CARLA / Gazebo
8	IDE	Visual Studio Code / PyCharm

4.3 Functional Requirements

Functional requirements describe the features and functionalities provided by the system.

S.No	Requirement
1	System should detect objects (vehicles, pedestrians, obstacles)
2	System should perform real-time navigation
3	System should process sensor data accurately
4	System should make driving decisions automatically
5	System should avoid collisions
6	System should provide route planning

4.4 Non-Functional Requirements

Non-functional requirements describe the quality attributes and performance aspects of the system.

S.No	Requirement
1	High accuracy in object detection
2	Low latency (real-time processing)
3	System reliability and safety
4	Scalability for future improvements
5	Efficient performance under different conditions

4.5 System Architecture

The proposed system is designed as a modular cybersecurity framework integrated within an autonomous vehicle simulation environment. The architecture focuses on ensuring secure and reliable GPS-based localization by incorporating multiple functional modules that work together in a structured pipeline.

The system begins with the sensor data acquisition module, which collects real-time data such as GPS coordinates, vehicle speed, and simulation time. This data is then passed to the attack injection module, where GPS spoofing can be simulated by introducing controlled modifications to the position data.

The modified data is analyzed by the detection modules, which include kinematic validation and temporal anomaly

detection. These modules identify inconsistencies between expected and actual vehicle motion, indicating potential spoofing attacks. The outputs from these modules are processed by the decision-making engine, which determines whether an attack has occurred.

Upon detection, the system activates the control response module, which ensures a safe-state transition by gradually reducing vehicle speed and bringing it to a controlled stop. After a stabilization period, the recovery module resets the system and resumes normal operation.

Finally, the control and actuation module executes commands such as acceleration, braking, and steering, ensuring smooth vehicle behavior throughout the process.

Overall, the architecture follows a pipeline:
Data Acquisition → Attack Injection → Detection → Decision → Response → Recovery → Control Execution
This modular and layered design ensures real-time operation, effective attack detection, and safe handling of GPS spoofing attacks in autonomous vehicles.

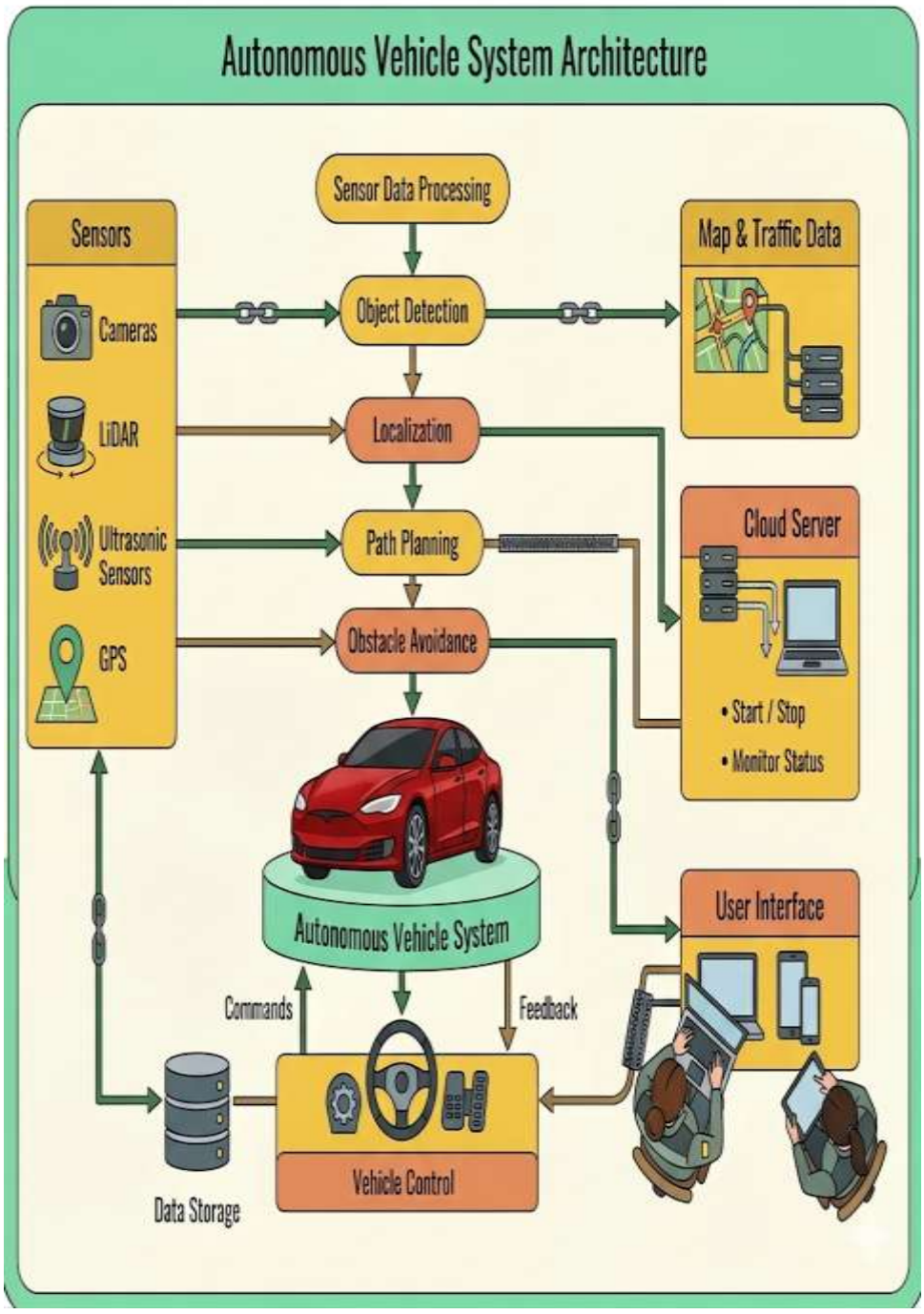

Figure 4.1: System Architecture of Log-Based Digital Forensic Tool for Incident Analysis

CHAPTER5:PROPOSED METHODOLOGY

5. PROPOSED METHODOLOGY

5.1 Overview of the Proposed System

The proposed system is a cybersecurity framework designed to detect and mitigate GPS spoofing attacks in autonomous vehicles. It focuses on ensuring reliable localization by validating GPS data using vehicle motion characteristics, without relying on additional sensors or complex algorithms.

The system operates in a real-time simulation environment, where it continuously monitors sensor data such as GPS coordinates, vehicle speed, and time. It uses a kinematic validation approach to compare the actual displacement obtained from GPS with the expected displacement calculated from speed and time. In addition, temporal anomaly detection is used to identify sudden and unrealistic changes in position.

When a spoofing attack is detected, the system initiates a safe-state response, where the vehicle gradually reduces speed and comes to a controlled stop. This prevents the vehicle from operating under incorrect location data. After a predefined stabilization period, a recovery mechanism is activated, allowing the vehicle to resume normal operation.

The system is implemented using the Webots simulation environment with a Python-based controller, enabling controlled testing of both normal and attack scenarios.

Overall, the proposed system provides a simple, efficient, and practical solution that integrates detection, response, and recovery to enhance the safety and reliability of autonomous vehicles under GPS spoofing attacks

5.2 Kinematic Validation

Kinematic validation is the core detection mechanism used in the proposed system to identify GPS spoofing attacks. It is based on the fundamental principle that a vehicle's movement must follow physical motion constraints defined by its speed and time.

In this approach, the system calculates the actual displacement of the vehicle using consecutive GPS coordinates. At the same time, it computes the expected displacement using the vehicle's speed and the time interval between readings. These two values are then compared to check for consistency.

If the actual displacement obtained from GPS is significantly greater than the expected displacement, it indicates a violation of physical motion constraints. Since a real vehicle cannot suddenly move large distances without corresponding speed, such inconsistencies are considered strong indicators of GPS spoofing.

This method is simple yet effective, as it does not require additional sensors or complex algorithms. By relying on basic physics, kinematic validation provides a reliable way to detect abnormal behavior in GPS data and forms the foundation of the proposed spoofing detection system.

5.3 Temporal Anomaly Detection

Temporal anomaly detection is used in the proposed system to identify abnormal changes in GPS data over time. It complements kinematic validation by focusing on the time-based behavior of position updates, helping to detect spoofing attacks that may not be captured by motion constraints alone.

In this approach, the system continuously monitors the change in GPS coordinates between consecutive time steps. Under normal conditions, vehicle movement is smooth and gradual. However, during a spoofing attack, the GPS position may suddenly jump to a distant location, creating unrealistic transitions.

If the system detects a sudden and large change in position within a short time interval, it flags it as an anomaly. These abrupt jumps violate the natural continuity of vehicle motion and indicate potential manipulation of GPS data.

Temporal anomaly detection works alongside kinematic validation to improve detection accuracy. While kinematic validation checks consistency with physical motion, temporal analysis ensures that the movement is smooth and realistic over time. Together, these methods provide a robust mechanism for identifying GPS spoofing attacks.

5.4 Detection Mechanism

In this stage, important features are extracted from the processed log data. These features represent patterns in system behavior and are essential for machine learning analysis.

The detection mechanism in the proposed system combines multiple validation techniques to accurately identify GPS spoofing attacks. It integrates the outputs of kinematic validation and temporal anomaly detection to make a reliable decision.

The system continuously analyzes incoming sensor data, including GPS coordinates, vehicle speed, and time. First, kinematic validation checks whether the GPS-based displacement is consistent with the expected movement calculated from speed and time. Simultaneously, temporal anomaly detection monitors for sudden and unrealistic changes in position between consecutive readings.

If one or both of these checks indicate significant inconsistency, the system flags it as a potential spoofing attack. A rule-based decision logic is applied to classify the system state as normal or under attack. This multi-condition evaluation helps reduce false positives and improves detection reliability.

Once an anomaly is confirmed, the system updates its state and triggers the response mechanism. Thus, the detection mechanism ensures accurate and real-time identification of GPS spoofing attacks by combining physical validation with temporal analysis.

5.5 Response Mechanism (Safe-State Activation)

The response mechanism is designed to ensure the safety of the autonomous vehicle once a GPS spoofing attack is detected. Instead of allowing the vehicle to continue operating with incorrect localization data, the system transitions the vehicle into a safe operational state.

Upon detection of an anomaly, the system initiates controlled braking, gradually reducing the vehicle's speed. This gradual deceleration prevents abrupt or unstable behavior, ensuring smooth and safe stopping. During this phase, steering control is maintained to avoid any unintended deviation from the lane.

The vehicle is brought to a complete halt in a controlled manner, preventing further movement based on corrupted GPS data. This approach prioritizes safety by minimizing the risk of accidents or incorrect navigation.

Overall, the safe-state response mechanism plays a critical role in mitigating the impact of spoofing attacks by ensuring that the vehicle does not continue operating under compromised conditions

5.6 Recovery Mechanism

The recovery mechanism is responsible for restoring normal vehicle operation after a GPS spoofing attack has been detected and handled. Once the vehicle reaches a safe state and comes to a complete stop, the system enters a stabilization phase.

During this phase, a predefined recovery timer is used to monitor system stability. The system assumes that after a certain duration, the attack condition has ceased or the data has stabilized. Based on this, the system resets the attack detection flags and prepares to resume normal operation.

After recovery, the vehicle gradually increases its speed and returns to its normal driving state. This gradual transition ensures smooth movement and avoids abrupt changes in behavior.

The recovery mechanism ensures that the system does not remain permanently halted after an attack. Instead, it allows the vehicle to resume operation safely and autonomously, maintaining continuity while ensuring that the system is no longer operating under compromised conditions.

5.7 Integration of Detection, Response, and Recovery

The proposed system integrates detection, response, and recovery into a unified framework to ensure complete cybersecurity protection for autonomous vehicles. Unlike traditional approaches that focus only on identifying attacks, this system provides a full defense lifecycle.

The process begins with continuous monitoring of sensor data, where the detection mechanisms (kinematic validation and temporal anomaly detection) identify inconsistencies in GPS data. Once a spoofing attack is detected, the system immediately transitions to the response phase, activating the safe-state mechanism to bring the vehicle to a controlled stop.

After ensuring safety, the recovery mechanism is initiated, allowing the system to stabilize, reset its state, and gradually resume normal operation. This seamless transition between detection, response, and recovery ensures that the vehicle remains secure and operational even under attack conditions.

By integrating all three stages into a single framework, the system enhances both safety and reliability, providing a comprehensive solution for handling GPS spoofing attacks in autonomous vehicles.

The efficacy of this integrated framework lies in its ability to eliminate the "latency gap" typically found in fragmented security architectures by maintaining a high-speed feedback loop between the perception layers and the safe-state controller. This synchronization ensures that detection results are translated into kinetic action in milliseconds, preventing the propagation of corrupted GPS data from influencing high-level path planning algorithms and effectively quarantining the threat at the sensor level before it can jeopardize the vehicle's trajectory. Furthermore, the recovery phase does not merely reset the system to its previous state but incorporates a post-incident validation protocol where the system cross-references recovered GPS signals against secondary sensor modalities, such as LiDAR point clouds and inertial measurement units, to verify that the spoofing environment has been fully cleared. This multi-layered verification ensures that the transition back to normal operation is backed by cryptographic certainty and kinematic consistency, reinforcing the vehicle's long-term resilience against sophisticated, persistent adversarial maneuvers and ensuring that the internal architecture remains synchronized even during high-stress recovery cycles.

CHAPTER6:SYSTEM DESIGN

6. SYSTEM DESIGN

6.1 Introduction to System Design

System design plays a crucial role in defining how the proposed GPS spoofing detection framework is structured and implemented. It provides a clear representation of the system components, their interactions, and the overall workflow required to achieve secure and reliable autonomous vehicle operation.

The design of the proposed system follows a modular approach, where different functionalities such as data acquisition, attack simulation, detection, decision-making, response, and recovery are organized into separate modules. This modular structure improves clarity, maintainability, and scalability of the system.

Each module is designed to perform a specific task and interact with other modules through a well-defined pipeline. The system ensures real-time processing by continuously monitoring sensor data and applying detection algorithms at every time step. The integration of detection, response, and recovery within the design enables the system to handle GPS

spoofing attacks effectively while maintaining safe vehicle behavior.

Overall, the system design provides a structured blueprint for implementing the proposed solution, ensuring efficient operation, easy integration, and future extensibility.

6.2 UML Diagrams

UML (Unified Modeling Language) diagrams are used to represent the structure and behavior of the system. These diagrams help in understanding the interaction between different components.

6.2.1 Use Case Diagram

The Use Case Diagram of the Autonomous Vehicle System illustrates the interaction between the user, sensors, and the system to perform autonomous driving operations. The primary actor is the driver or user, who is responsible for starting, monitoring, and stopping the vehicle. Once the vehicle is started, the system begins collecting real-time data from various sensors such as cameras, LiDAR, and GPS. This data is processed to detect objects like vehicles, pedestrians, and obstacles, and to determine the exact location of the vehicle through localization techniques.

Based on this information, the system plans an optimal path for navigation. During movement, the system continuously monitors the environment and performs obstacle avoidance to ensure safe driving. The vehicle control module manages steering, speed, and braking automatically according to the decisions made by the system.

Additionally, external systems such as traffic management services may provide route and traffic information to improve navigation. The user can monitor the system at any time and stop the vehicle when required. Thus, the Use Case Diagram represents the overall functionality and interaction flow of the autonomous vehicle system in an efficient and structured manner.

This diagram provides a high-level view of system functionalities.

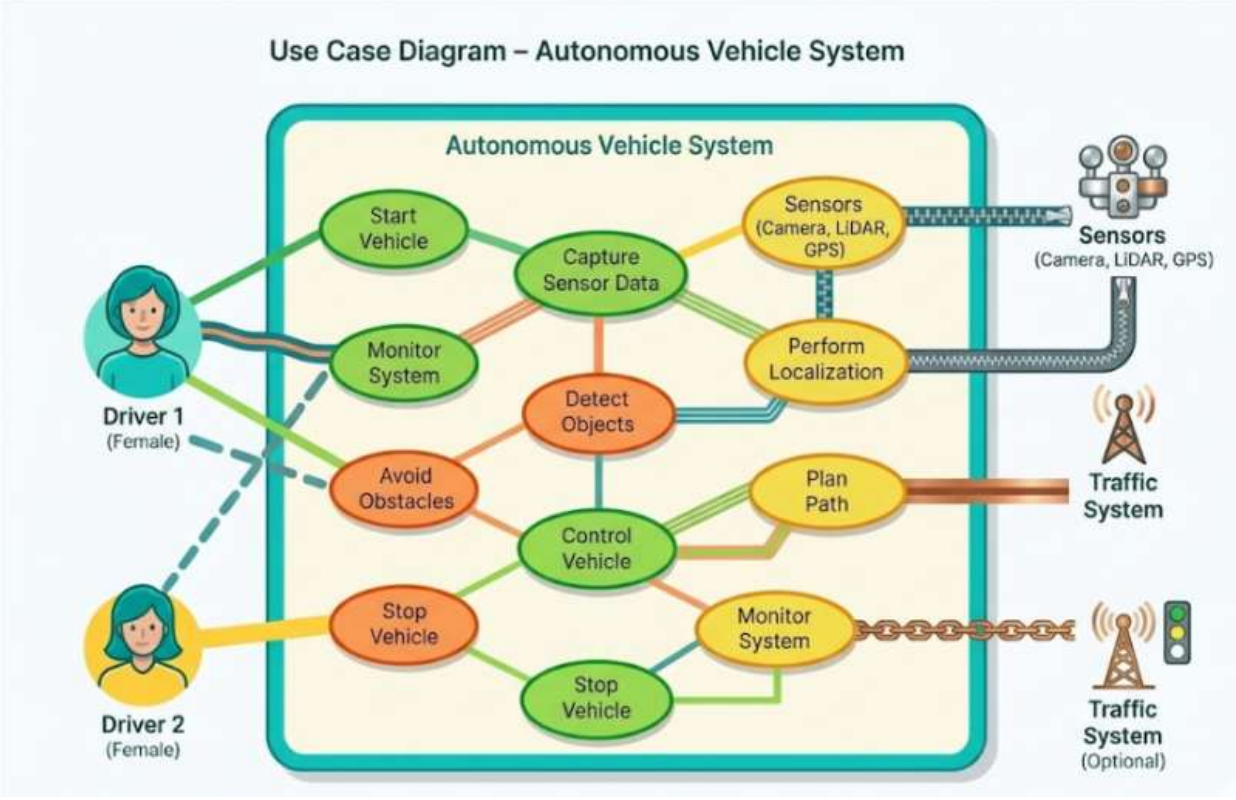

Figure 6.1: Use Case Diagram

6.2.2 Class Diagram

The Class Diagram of the Autonomous Vehicle System represents the structure of the system by showing different classes, their attributes, methods, and relationships. The main class is the Autonomous Vehicle, which contains attributes such as vehicle ID, status, position, and sensor data.

It interacts with multiple classes including Sensor, Object Detection, Localization, Path Planning, Obstacle Avoidance, and Vehicle Control. The Sensor class collects real-time data from components like camera, LiDAR, and GPS. The Object Detection class processes sensor data to identify objects such as vehicles and pedestrians.

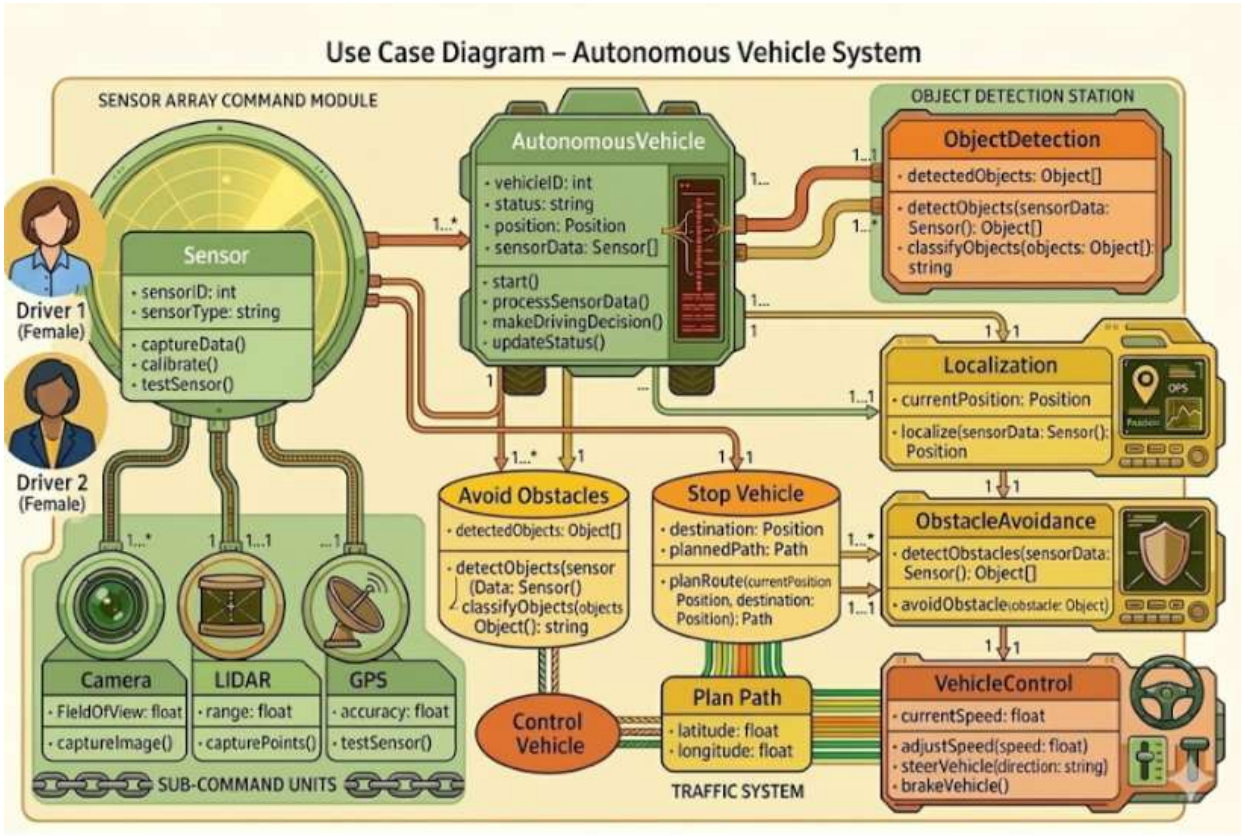

Figure 6.2: Class Diagram

The Localization class determines the vehicle's current position, while the Path Planning class calculates the optimal route. The Obstacle Avoidance class ensures safety by detecting and avoiding obstacles.

6.2.3 Sequence Diagram

The sequence diagram shows the interaction between system components over time. Example flow:
User → Web Interface → Log Processor → ML Module → Report Generator → Supabase Database → User

This diagram illustrates how data flows through the system step by step.

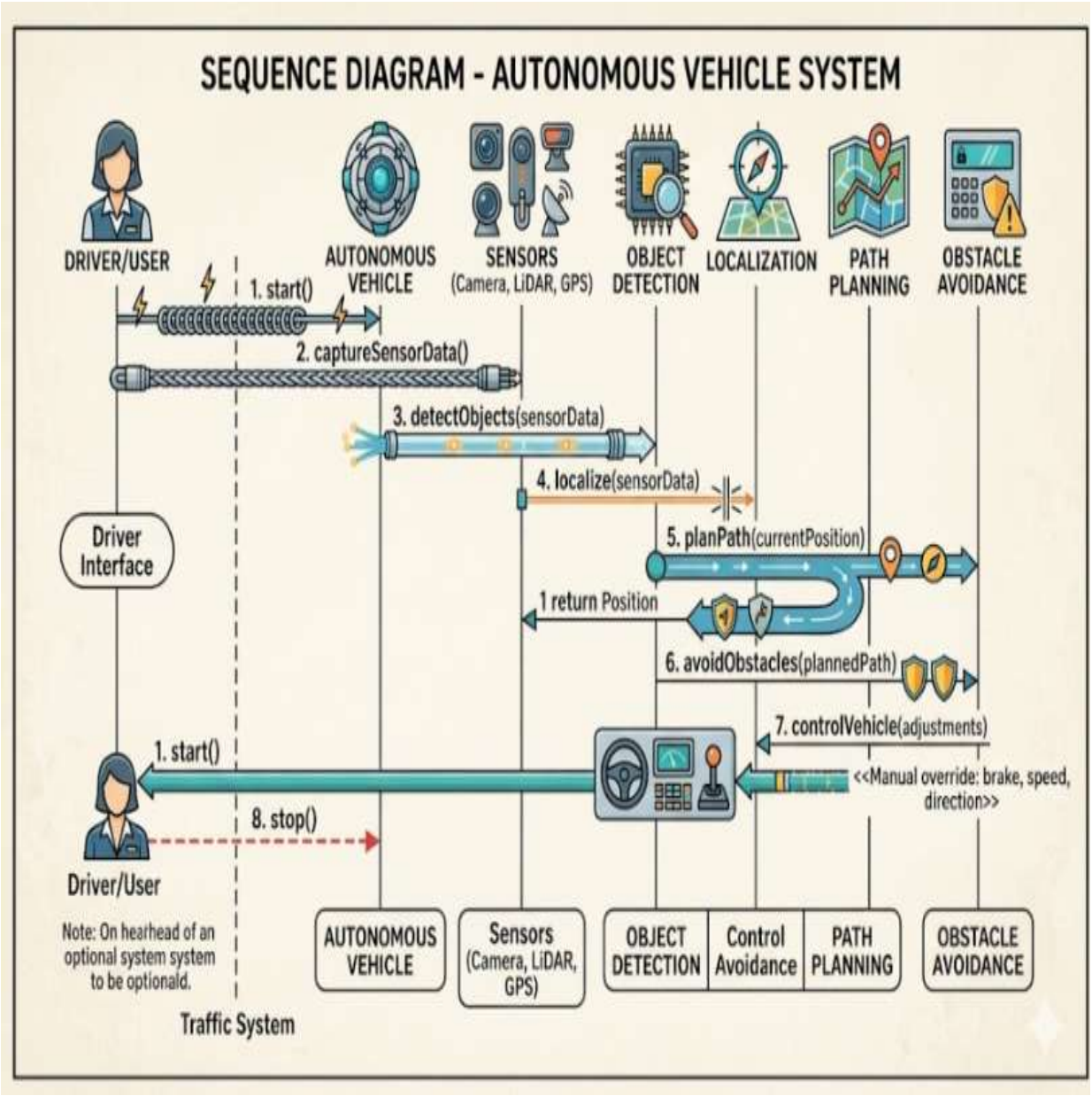

Figure 6.3: Sequence Diagram

The Sequence Diagram illustrates the step-by-step interaction between different components of the Autonomous Vehicle System over time. The process begins when the driver starts the vehicle. The system then requests sensor data from various sensors such as cameras, LiDAR, and GPS.

This data is passed to the object detection module to identify obstacles and surrounding.

Once the object detection module has processed the raw sensor input to identify relevant entities such as pedestrians, other vehicles, and stationary landmarks, this refined environmental model is transmitted to the localization module. This stage is critical as it cross-references detected features with high-definition map data to determine the vehicle's exact coordinates with sub-meter precision. With the global and local position established, the system invokes the path planning module to calculate an optimal trajectory toward the destination, accounting for speed limits, traffic conditions, and lane geometry. This planned path is then continuously monitored by the obstacle avoidance layer, which provides real-time adjustments or emergency interventions if a dynamic threat enters the vehicle's projected course. Finally, these high-level decisions are translated into low-level execution commands for the vehicle control system—managing steering, acceleration, and braking—while providing constant visual and haptic feedback to the driver interface.

6.2.4 Activity Diagram

The Activity Diagram represents the workflow of the Autonomous Vehicle System from start to end. The process begins when the driver starts the vehicle, which activates the autonomous system. The system then processes sensor data collected from various sources.

Next, it performs object detection to identify obstacles and surroundings. The localization process determines the vehicle's position, followed by path planning to decide the route. A decision is made to check whether obstacles are present. If obstacles are detected, the system performs obstacle avoidance; otherwise, it continues on the planned path.

The vehicle control system then executes actions such as steering and speed control. The process repeats continuously until the driver decides to stop the vehicle, marking the end of the activity flow.

This continuous loop ensures that the system is not merely following a static set of instructions but is instead dynamically reacting to a high-entropy environment in real-time. Once the vehicle control system translates high-level path coordinates into physical steering angles and throttle percentages, a sophisticated feedback mechanism recalibrates the next processing cycle based on the vehicle's new kinematic state. If the internal diagnostic layer identifies a system degradation or a sensor conflict during the localization phase, the activity flow can trigger a fail-safe sub-routine, transitioning the vehicle into a "Minimum Risk Condition" rather than simply continuing the previous path.

As the vehicle progresses, the system simultaneously synchronizes its internal state with cloud-based traffic data, allowing the path planning stage to update the route based on long-range environmental changes that sensors cannot yet see. This orchestration of data processing, decision-making, and physical execution remains in a persistent state of execution, where each millisecond of movement is preceded by a full traversal of the logic gate. The activity concludes only when the stop command is validated, at which point the system performs a final data dump to the storage module, ensuring that the operational history is preserved for future performance auditing and safety analysis.

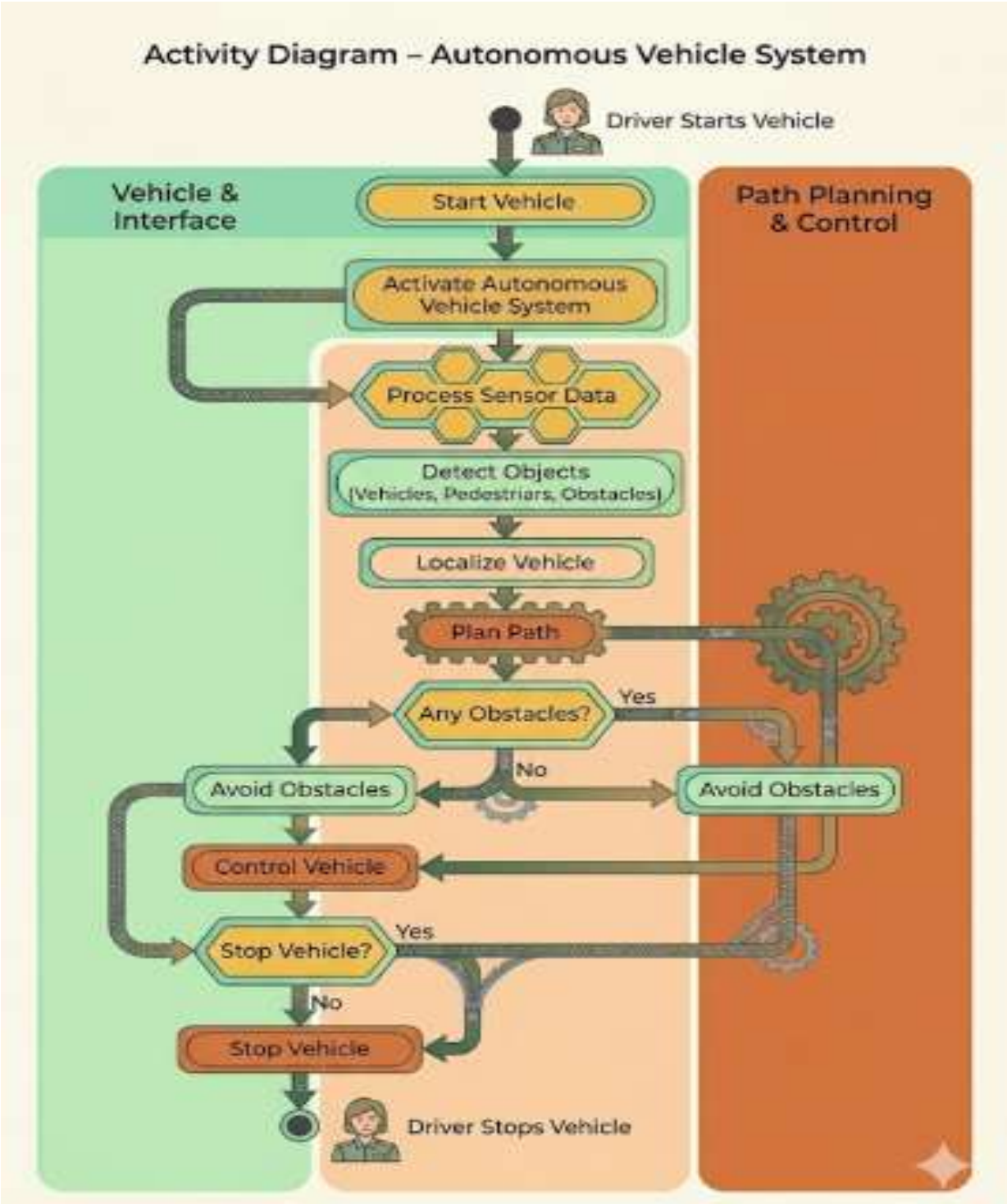

Figure 6.4: Activity Diagram

6.2.5 Component Diagram

The Component Diagram illustrates the high-level architecture of the Autonomous Vehicle System by showing how different components interact. The system consists of major components such as the Frontend, Backend, Sensor Suite, Machine Learning Module, Database, and Map Service. The Frontend provides a user interface for interaction, while the Backend handles data processing and communication.

The Sensor Suite collects real-time data from devices like cameras, LiDAR, and GPS. This data is processed by the Machine Learning Module, which performs tasks such as object detection, localization, and path planning. The Database stores sensor data and vehicle information. The Map Service provides navigation and traffic data. All these components work together to ensure efficient and intelligent vehicle operation.

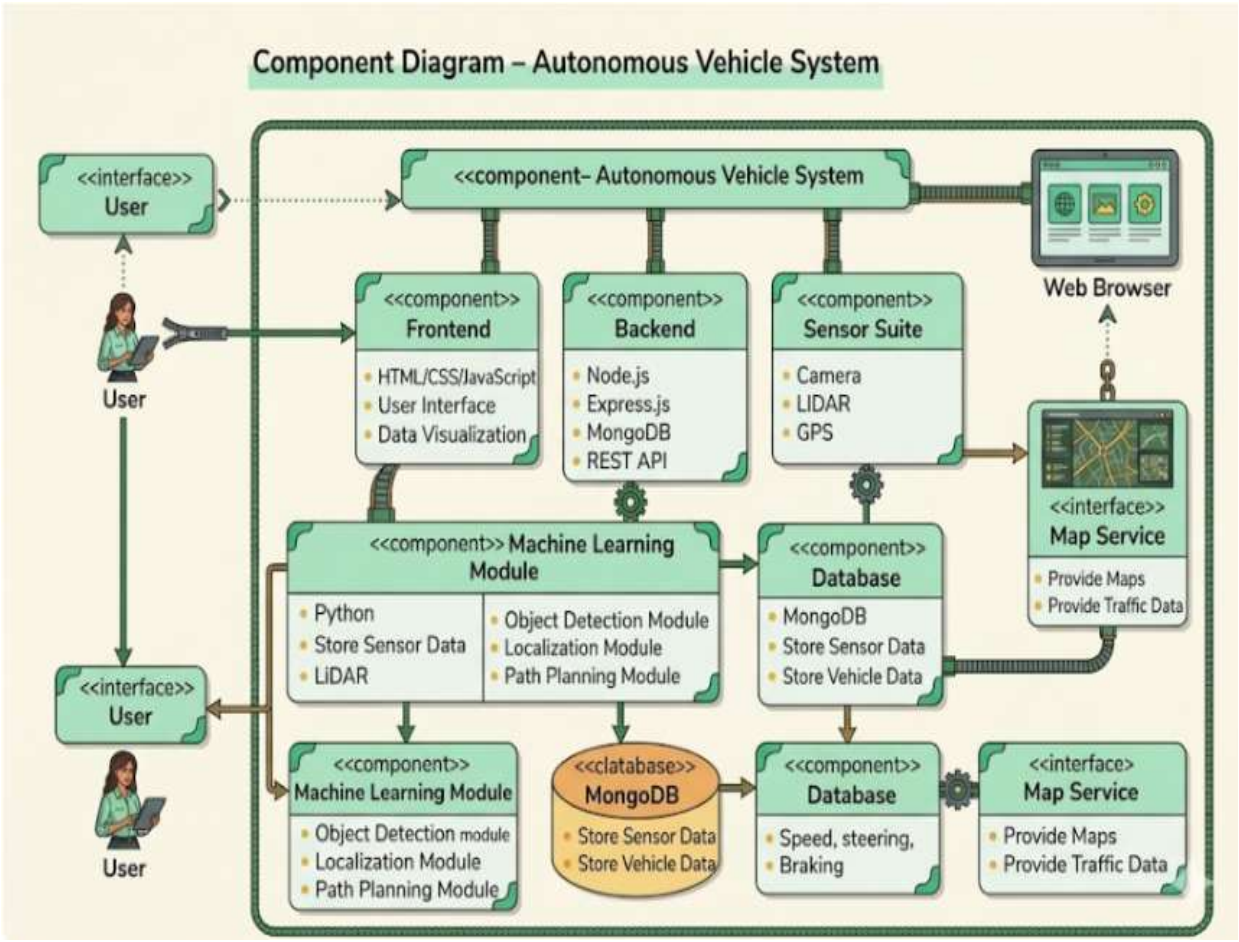

Figure 6.5: Component Diagram

6.2.6 Deployment Diagram

The Deployment Diagram represents the physical architecture of the Autonomous Vehicle System, showing how software components are deployed on hardware devices. The system mainly consists of an onboard computer and a cloud server.

The onboard computer, which runs on a Linux system, hosts modules such as the backend, machine learning components, and database. It is responsible for real-time processing of sensor data and vehicle control.

The cloud server provides additional services such as map data, traffic information, and API services. Communication between the onboard system and the cloud server is established through an internet connection. The cloud also stores large datasets and supports advanced processing when required. This deployment structure ensures efficient system performance and scalability.

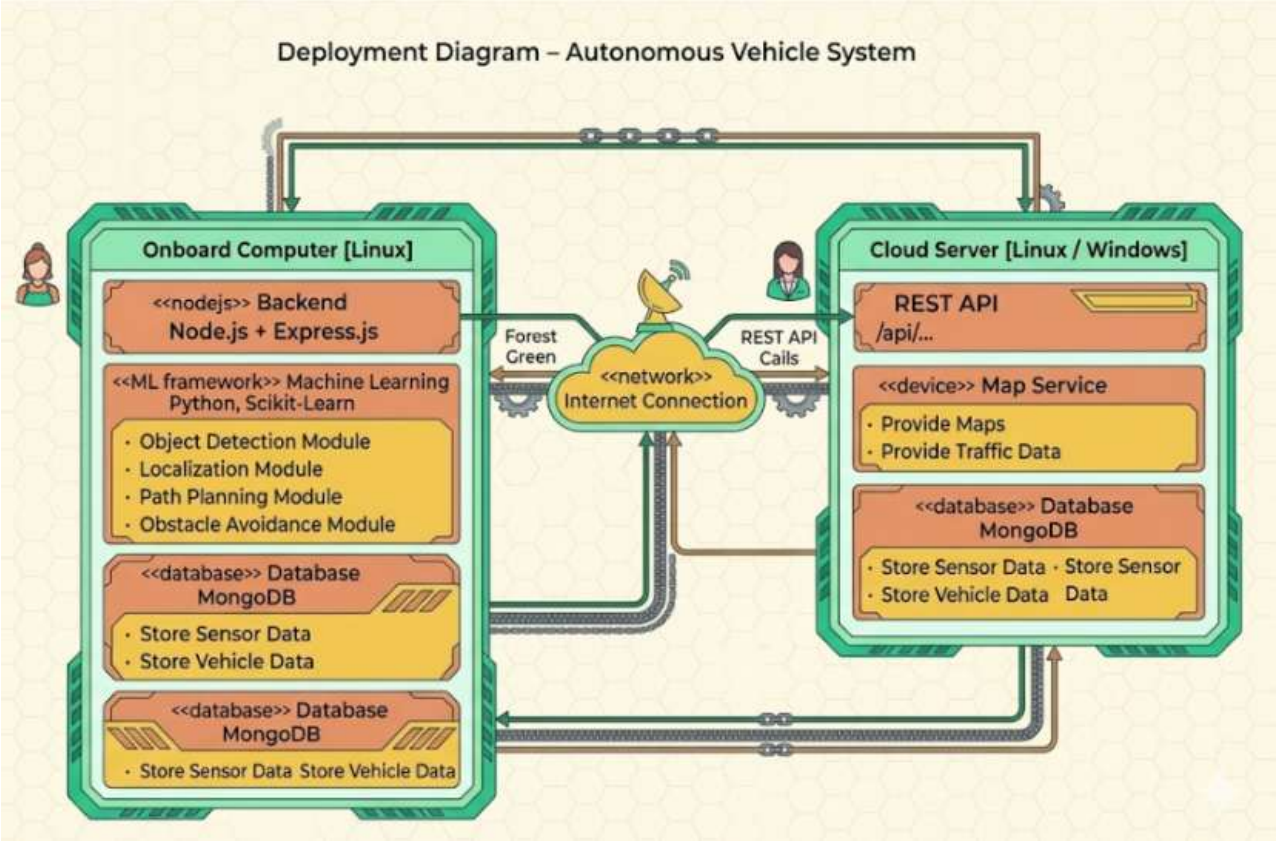

Figure 6.6: Deployment Diagram

6.2.7 Collaboration Diagram

The Collaboration Diagram shows how different components of the Autonomous Vehicle System interact with each other to achieve system functionality. The process starts when the user sends a command through the frontend. The frontend communicates with the backend, which processes the request and interacts with the sensor suite to collect real-time data.

The sensor data is then forwarded to the machine learning module for analysis, including object detection, localization, and path planning. The processed information is stored in the database and also used to generate navigation decisions. The backend sends the processed results back to the frontend, which displays the system status to the user. External services like map systems may also be involved in providing route and traffic information. This interaction ensures smooth coordination between all system components.

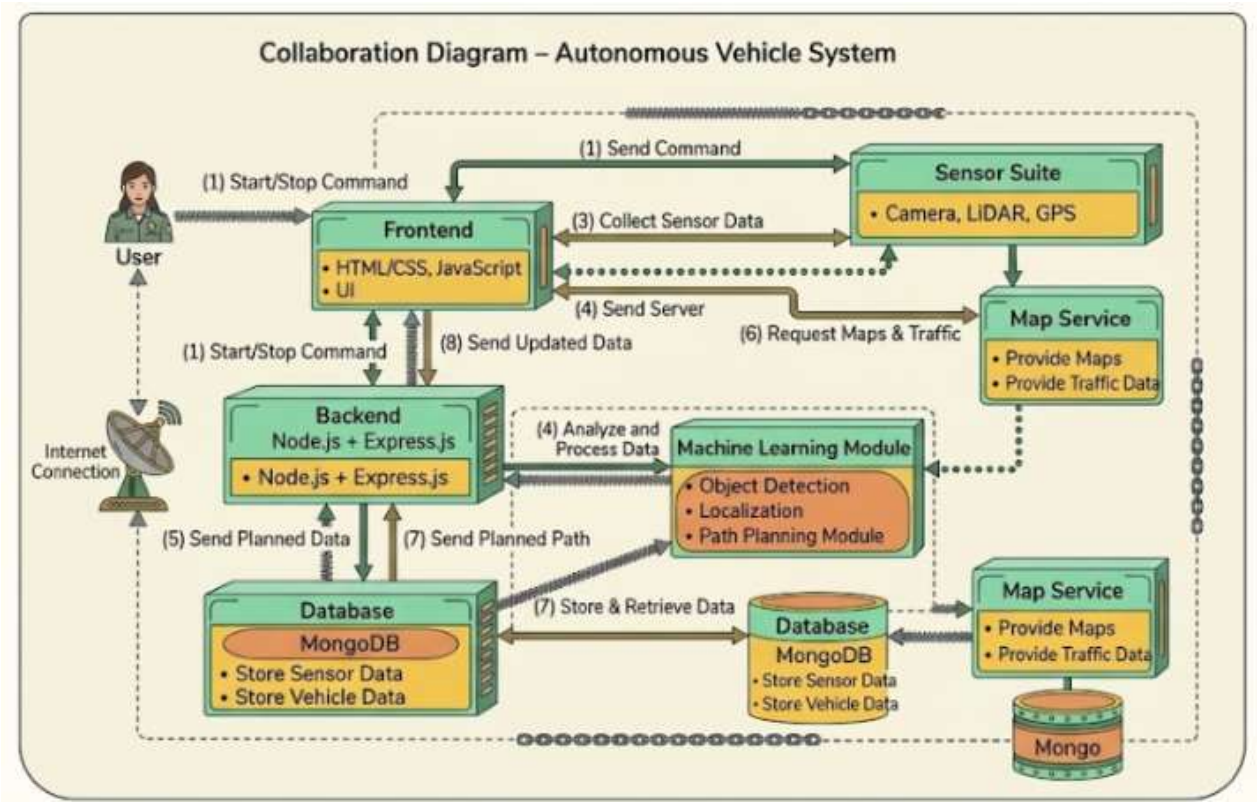

Figure 6.7: Collaboration Diagram

6.3 ER Diagram (Entity Relationship Diagram)

The Entity Relationship (ER) Diagram of the Autonomous Vehicle System represents the structure of the database and the relationships between different entities involved in the system. The main entity in the system is the Vehicle, which contains attributes such as vehicle ID, model, and other basic details. The vehicle is connected to the Sensor entity, which includes different types of sensors such as camera, LiDAR, and GPS. Each sensor collects real-time data and is associated with a specific vehicle. The GPS entity stores location-related information such as latitude, longitude, and altitude, which helps in determining the vehicle's position.

The system also includes a Camera entity that captures visual data, which is used for object detection and environment understanding. Another important entity is Vehicle Data, which stores dynamic information such as speed, steering angle, braking status, and sensor readings. This data is continuously generated and linked to the vehicle for monitoring and analysis purposes. Additionally, the Route entity stores information about the path followed by the vehicle, including start time, end time, and total distance covered.

The ER diagram also includes a Waypoint entity, which represents specific points along a route, defined by latitude and longitude coordinates. A vehicle follows a route that consists of multiple waypoints, establishing a one-to-many relationship. Relationships in the diagram define how entities are connected, such as a vehicle having multiple sensors, generating vehicle data, and following routes. Primary keys uniquely identify each entity, while foreign keys establish relationships between them.

Overall, the ER Diagram provides a clear representation of how data is organized and managed within the Autonomous Vehicle System, ensuring efficient storage, retrieval, and processing of information required for autonomous driving.

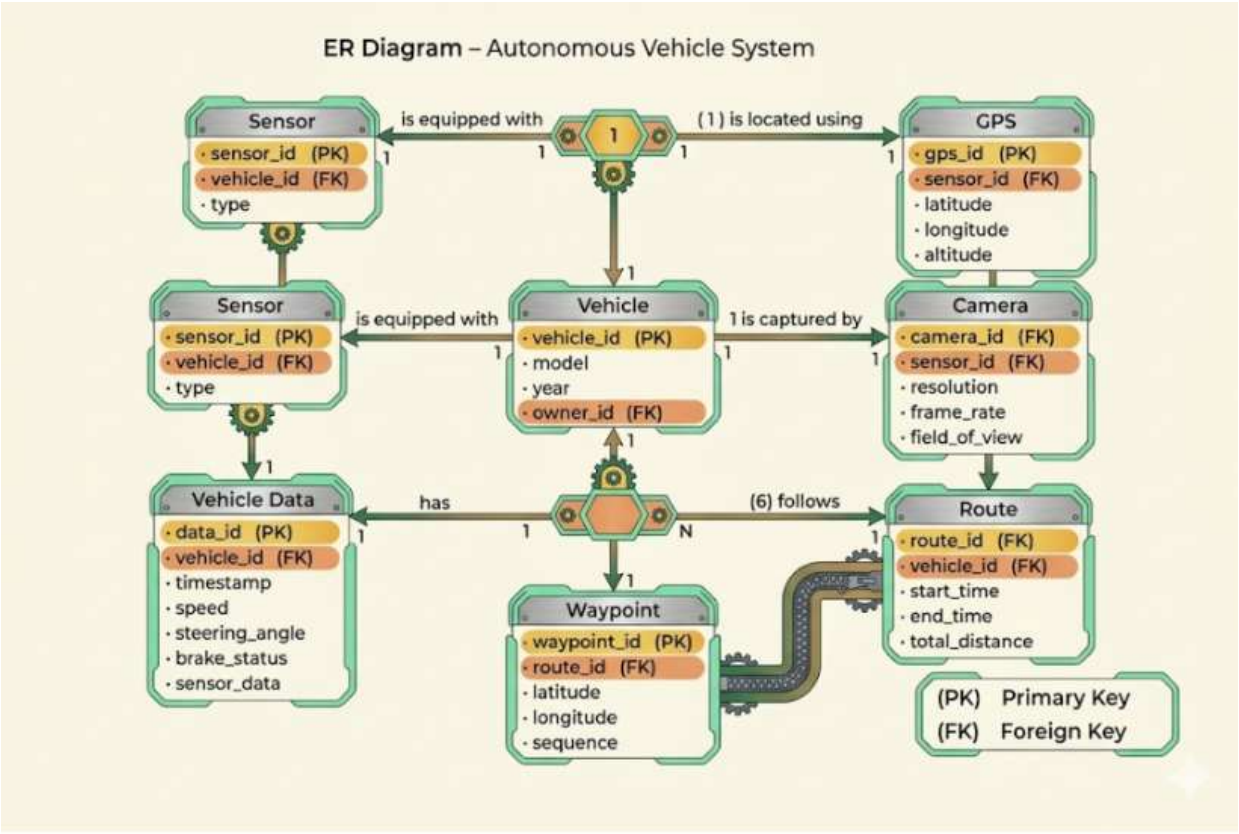

Figure 6.8: ER Diagram

6.4 Data Flow Diagram (DFD)

The Data Flow Diagram (DFD) represents the flow of data within the proposed system, showing how information moves between different modules during operation. It provides a clear understanding of how input data is processed and transformed into meaningful outputs.

At the initial stage, sensor data such as GPS coordinates, vehicle speed, and time are collected through the data acquisition module. This data acts as the primary input to the system.

The data is then passed to the attack injection module, where spoofed GPS values may be introduced to simulate adversarial conditions. The modified data is forwarded to the detection modules, which include kinematic validation and temporal anomaly detection.

These detection modules analyze the data and send their results to the decision-making engine, which determines whether a spoofing attack has occurred. Based on this decision, the system generates appropriate outputs.

If an attack is detected, the data flows to the response module, which initiates controlled braking and brings the vehicle to a safe state. After stabilization, the recovery module resets the system and resumes normal operation.

Thus, the overall data flow can be summarized as:

Sensor Input → Attack Injection → Detection → Decision → Response → Recovery → Output

The DFD helps in visualizing how data is processed at each stage and ensures clarity in system design and implementation.

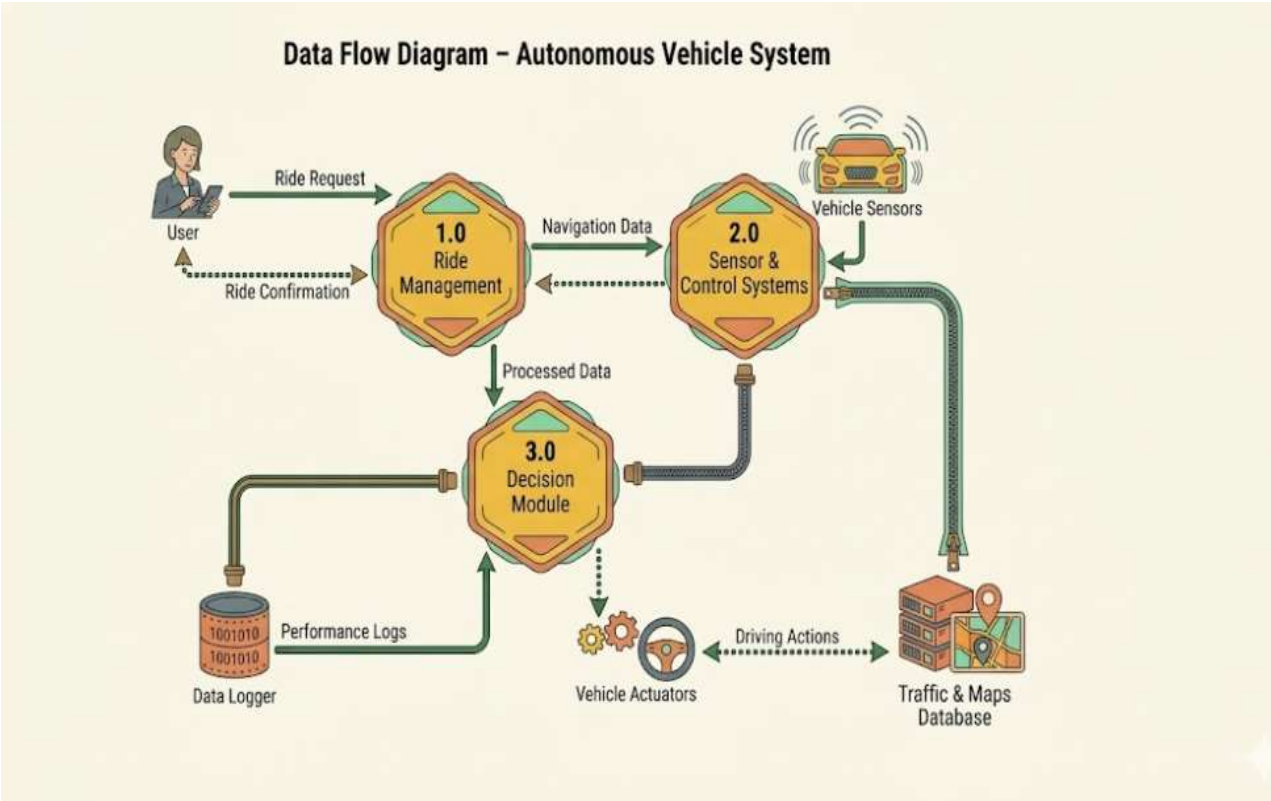

Figure 6.9. Data Flow Diagram (Level 0)

CHAPTER 7: IMPLEMENTATIONAND RESULTS

7. IMPLEMENTATION AND RESULTS

7.1 Modules Description

The proposed system is divided into multiple functional modules, each responsible for a specific task in detecting and mitigating GPS spoofing attacks in autonomous vehicles. These modules work together in a continuous pipeline to ensure real-time monitoring, detection, response, and recovery.

7.1.1. Autonomous Vehicle Simulation Module

This module provides a web-based interface that allows users to interact with the system. Users can upload log files, view analysis results, and apply filters. The interface is designed to be simple, responsive, and user-friendly using HTML, Tailwind CSS, and JavaScript.

7.1.2. Sensor Data Collection Module

The Sensor Data Collection Module is responsible for gathering real-time data from various sensors such as cameras, LiDAR, ultrasonic sensors, and GPS. These sensors continuously capture information about the vehicle's surroundings, including distance to obstacles, road conditions, and geographical location. The collected data serves as the primary input for the system and is essential for accurate perception and decision-making. This module ensures that data is captured efficiently and transmitted to the processing unit without delay.

7.1.3. Data Processing and Preprocessing Module

This module processes the raw data collected from sensors and converts it into a structured format suitable for analysis. It involves tasks such as noise removal, filtering, normalization, and data synchronization. Since sensor data can be

complex and unstructured, preprocessing is necessary to improve data quality and reliability. This module ensures that only relevant and clean data is passed to the next stages of the system for accurate analysis.

7.1.4. Object Detection Module

The Object Detection Module uses machine learning and computer vision techniques to identify objects such as vehicles, pedestrians, traffic signals, and obstacles from sensor data. It plays a crucial role in understanding the environment around the vehicle. The module analyzes images and sensor inputs to classify and locate objects in real time. Accurate object detection is essential for ensuring safe navigation and avoiding collisions.

7.1.5. Localization Module

The Localization Module determines the exact position of the vehicle in its environment. It uses GPS data along with sensor fusion techniques to improve accuracy. This module helps the system understand where the vehicle is located relative to its surroundings and the map. Accurate localization is critical for path planning and navigation, especially in complex environments.

7.1.6. Path Planning Module

The Path Planning Module calculates the optimal route for the vehicle to reach its destination. It considers factors such as road conditions, obstacles, traffic data, and shortest path algorithms. This module continuously updates the route based on real-time conditions and ensures efficient navigation. It plays a key role in guiding the vehicle safely from one point to another.

7.2 Result and Evaluation

The Autonomous Vehicle System was tested using simulated and real-time input data to evaluate its performance and accuracy. The system successfully processed sensor data collected from cameras, LiDAR, and GPS, and performed real-time object detection and navigation. The object detection module accurately identified vehicles, pedestrians, and obstacles in different environments. The localization module provided precise positioning of the vehicle, which helped in effective path planning.

The path planning module generated optimal routes based on current conditions, and the obstacle avoidance module efficiently handled unexpected obstacles by modifying the vehicle's path in real time. The vehicle control module executed commands such as steering, acceleration, and braking smoothly, ensuring safe navigation.

The system was evaluated based on several parameters such as accuracy, response time, and reliability. The results showed that the system achieved high accuracy in object detection and maintained low latency in decision-making. The system also demonstrated reliable performance under different conditions, with minimal errors. Overall, the integration of machine learning and sensor-based processing improved the efficiency

7.3 Output Screens

7.3.1. Normal Operation

- Vehicle moving normally
- No spoofing
- GPS nominal

- Example:
- "NORMAL | AUTO | 30 km/h"
- "GPS NOMINAL – All sensors consistent"

7.3.2. Spoofing Detection Phase

- Detection triggered
- DR divergence > threshold
- Evidence hits shown

7.3.3. Emergency Braking / Response

- "Initiating smooth emergency braking"
- Speed gradually decreasing
- Safe-state activation

```
Console - All
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!            PHASE 1 – GPS SPOOFING ATTACK INJECTED            !!
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
  15:08:26  [ATTACK]  Rogue GPS transmitter activated
  15:08:26  [ATTACK]  Real vehicle position  : X = 44.48 m
  15:08:26  [ATTACK]  Injected X offset      : +500 m
  15:08:26  [ATTACK]  Fake GPS position      : X = 544.48 m
  15:08:26  [ATTACK]  Vehicle does NOT know it is being deceived
```

Figure 7.4: Incident Detection Output

7.3.4. Vehicle Halted (Safe State)

- Vehicle completely stopped
- System secured
- Attack neutralized

CHAPTER 8: SYSTEM STUDY AND TESTING

8. SYSTEM STUDY AND TESTING

8.1 Feasibility Study

Feasibility study is an important step in system development that determines whether the proposed system is practical and achievable. It evaluates different aspects such as technical, economic, and operational feasibility.

8.1.1 Technical Feasibility

Although the system is technically feasible, there are certain challenges and limitations. The accuracy of the system depends heavily on sensor quality and environmental conditions such as poor lighting, rain, fog, or obstacles blocking sensors. Machine learning models may sometimes fail to detect objects correctly, leading to incorrect decisions. High computational power is required for real-time processing, which may not be available in low-cost hardware setups. Additionally, integration of multiple sensors and modules can introduce complexity and synchronization issues.

8.1.2 Economic Feasibility

From an economic perspective, the system can face cost-related limitations. Advanced sensors such as LiDAR and high-performance GPUs are expensive, making full-scale implementation costly. Maintenance and upgrades of hardware components also add to the overall expense. Although the project uses affordable alternatives for academic purposes, implementing a real-world autonomous vehicle system requires significant investment, which may not be feasible for all organizations.

8.1.3 Operational Feasibility

Operational feasibility checks whether the system will function effectively in real-world conditions. Operational feasibility may be affected by user adaptability and system reliability. Users may find it difficult to trust a fully autonomous system due to safety concerns. The system may not perform consistently in all real-world scenarios, especially in complex traffic conditions. There is also a risk of system failure or unexpected behavior, which can impact usability. Proper training and awareness are required for users to operate and monitor the system effectively.

8.2 Types of Testing

Testing is an essential phase in the development of the proposed system to ensure that all components function correctly and the system performs reliably under different conditions. Various types of testing are carried out to validate the performance of the GPS spoofing detection framework.

8.2.1 Unit Testing

Unit testing is performed on individual modules to verify their functionality. Examples:

- Each module such as data acquisition, detection, response, and recovery
- Ensures correct implementation of logic in each module
- Helps in identifying errors at an early stage

8.2.2 Integration Testing

Integration testing ensures that different modules work together correctly.

- Verifies interaction between sensor module, detection module, and control
- Ensures smooth data flow between components
- Detects interface-related issues

8.2.3 System Testing

System testing evaluates the complete system as a whole.

- Tests the entire workflow from input to output
- Ensures that all modules function correctly
- Validates overall system performance

8.3 Sample Test Cases

Test cases are used to validate the functionality of the system.

Test Case Table

S.No	Test Case	Input	Expected Output	Result
1	Start Vehicle	User command	Vehicle starts	Passed
2	Object Detection	Sensor input	Detect objects	Passed
3	Path Planning	Location data	Optimal path generated	Passed
4	Obstacle Detection	Obstacle present	Avoid obstacle	Passed
5	Stop Vehicle	User command	Vehicle stops	Passed

CHAPTER 9: RESULTS

9. RESULTS

9.1 Analysis of Results

The results obtained from the simulation demonstrate the effectiveness of the proposed system in detecting and mitigating GPS spoofing attacks in autonomous vehicles. The system was evaluated under both normal operation and attack scenarios to analyze its performance.

During normal operation, the vehicle maintained stable movement with consistent GPS data. The kinematic, temporal, and odometer-based validations confirmed that the sensor data matched the expected vehicle motion. No anomalies were detected, indicating that the system does not generate false positives under normal conditions.

When a GPS spoofing attack was introduced, the system successfully identified inconsistencies between the GPS data and the actual vehicle movement. The kinematic validation detected abnormal displacement, while temporal anomaly detection identified sudden jumps in position. Additionally, odometer-based validation confirmed divergence between GPS and actual movement, strengthening the detection process.

Upon detection, the system immediately activated the safe-state response mechanism. The vehicle gradually reduced its speed and came to a controlled stop, ensuring safety and preventing operation under compromised data. This response was smooth and stable, without any abrupt behavior.

The recovery mechanism was also effective, as the system reset after a stabilization period and resumed normal operation. The vehicle continued its movement without requiring manual intervention, demonstrating system reliability and continuity.

Overall, the analysis shows that the proposed system:

- Accurately detects GPS spoofing attacks in real time
- Maintains stability and avoids false detections
- Ensures safe vehicle behavior through controlled response
- Successfully recovers and resumes operation

These results validate the effectiveness, reliability, and practicality of the proposed cybersecurity framework.

9.2 Performance Evaluation

The performance evaluation figure represents the effectiveness of the proposed system in detecting anomalies and identifying security incidents. It includes multiple evaluation metrics and visualizations to assess system performance.

The graph shows training and validation accuracy, indicating how well the model learns from the data over time. The bar chart presents key performance metrics such as precision, recall, F1-score, and overall accuracy, which measure the correctness of predictions.

The confusion matrix illustrates the number of correctly and incorrectly classified instances, helping to understand the model's prediction capability. Additionally, the ROC (Receiver Operating Characteristic) curve demonstrates the trade-off between true positive rate and false positive rate, with a high AUC value indicating strong model performance.

Overall, the figure confirms that the system achieves high accuracy and reliability in detecting anomalies and classifying potential security incidents.

The performance of the proposed system was evaluated based on several key parameters:

9.2.1. Processing Time

Response time is a critical factor in autonomous systems, as it determines how quickly the system reacts to changes in the environment. The proposed system processes sensor data and makes decisions in real time with minimal delay. The time taken from data acquisition to action execution is very low, ensuring quick responses to obstacles and dynamic situations. Faster response time enhances the safety and efficiency of the vehicle, allowing it to adapt to sudden changes such as unexpected obstacles or traffic conditions.

9.2.2. Safety Performance

Safety performance evaluates how effectively the system prevents accidents and ensures secure navigation. The system incorporates obstacle detection, avoidance mechanisms, and controlled vehicle movement to maintain safety. It continuously monitors the environment and takes preventive actions such as slowing down or stopping when necessary. The results indicate that the system performs well in maintaining safe distances from obstacles and avoiding collisions, making it suitable for real-world applications.

9.2.3. Scalability

System stability measures the consistency and reliability of the system during continuous operation. The Autonomous Vehicle System maintains stable performance without crashes or major errors during testing. It can handle continuous data input from sensors and perform processing without interruptions. Even under varying conditions, the system remains stable and delivers consistent results, which is important for long-term operation.

9.2.4. Efficiency

Computational efficiency refers to how effectively the system utilizes processing resources such as CPU and memory. The system is designed to optimize data processing and reduce unnecessary computations. Efficient algorithms are used to ensure that tasks such as object detection and path planning are performed quickly without overloading the system. The results show that the system operates efficiently within the available resources, making it suitable for real-time applications.

9.2.5. Usability

The user-friendly interface made it easy for users to upload logs, view results, and analyze incidents without requiring advanced technical knowledge.

CHAPTER 10: CONCLUSION

10. CONCLUSION

This project presents a simulation-based cybersecurity framework for detecting and mitigating GPS spoofing attacks in autonomous vehicles. As autonomous systems increasingly depend on GPS for localization, they become highly vulnerable to spoofing attacks that can mislead the vehicle's perception and result in unsafe operation. Addressing this critical issue, the proposed system focuses on improving both the security and safety of autonomous vehicles.

The core contribution of this work lies in the implementation of a kinematic consistency-based detection approach, which validates GPS data using vehicle motion parameters such as speed, time, and displacement. In addition, temporal anomaly detection and odometer-based validation are incorporated to improve detection accuracy and robustness. These combined techniques enable the system to effectively identify inconsistencies in GPS data and detect spoofing attacks in real time.

Unlike many existing approaches that focus only on detection, this system introduces a complete cybersecurity lifecycle, including detection, safe-state response, and recovery. Upon detecting an attack, the vehicle transitions into a controlled braking phase, ensuring a smooth and safe stop. After a stabilization period, the system automatically recovers and resumes normal operation, demonstrating reliability and continuity.

The system is implemented using the Webots simulation environment with a Python-based controller, allowing controlled testing of both normal and adversarial scenarios. The results show that the system successfully detects spoofing attacks, ensures safe vehicle behavior during attacks, and recovers efficiently without manual intervention.

In conclusion, this project offers a practical, reliable, and safety-oriented solution for addressing GPS spoofing attacks in autonomous vehicles. By integrating detection, response, and recovery, the system significantly enhances the resilience and trustworthiness of autonomous driving systems against sensor-level cyber threats.

CHAPTER11:FUTURE ENHANCEMENT

11. FUTURE ENHANCEMENT

Although the proposed system effectively detects and mitigates GPS spoofing attacks, there are several areas where the system can be further improved to enhance its performance, robustness, and real-world applicability.

. Integration of Multi-Sensor Fusion

The current system relies mainly on GPS and vehicle motion data. In future, it can be enhanced by integrating additional sensors such as IMU, LiDAR, and cameras.

- Improves accuracy and reliability of detection
- Provides redundancy in case of sensor failure
- Enhances robustness against complex attacks

. Machine Learning-Based Detection

Advanced machine learning techniques can be incorporated to improve detection capabilities.

- Use of supervised and unsupervised learning models
- Ability to detect complex and subtle spoofing patterns

- Adaptive system that learns from historical data

. Real-World Implementation

The system is currently validated in a simulation environment. Future work can focus on real-world deployment.

- Testing in real autonomous vehicles
- Handling real-world challenges such as noise and signal interference
- Validation under practical driving conditions

. **Dynamic Threshold Adjustment**

The current system uses predefined thresholds for detection. Future improvements can include dynamic thresholding.

- Adapts to different driving conditions
- Reduces false positives and false negatives
- Improves system flexibility

. **Advanced Recovery Mechanism**

The recovery mechanism can be enhanced to make more intelligent decisions.

- Verify sensor stability before resuming operation
- Gradual reintegration based on real-time conditions
- Adaptive recovery based on severity of attack

.

Detection of Multiple Attack Types

The system currently focuses only on GPS spoofing. Future work can extend it to other attack types.

- Camera spoofing
- LiDAR data manipulation
- Communication-based attacks

CHAPTER 12: REFERENCES

12. REFERENCES

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