Real Time Intrusion Detection System for Securing Automatic CAN Communication in Smart Vehicles

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***Abstract*—As modern vehicles transition into highly integrated cyber-physical systems, the security of internal communication architectures has become a paramount concern for automotive safety and reliability. The Controller Area Network (CAN) bus, which serves as the fundamental backbone for communication between Electronic Control Units (ECUs), was originally designed for real-time efficiency but lacks inherent security mechanisms such as message authentication and encryption.**

This architectural vulnerability exposes vehicles to a broad spectrum of sophisticated cyberattacks, including Denial-of- Service (DoS) and malicious message injection, which can lead to the catastrophic failure of safety-critical functions. This research proposes an automated, real-time Intrusion Detection System (IDS) based on an unsupervised machine learning approach to mitigate these risks.

By utilizing the Isolation Forest algorithm, the proposed system establishes a statistical behavioral baseline by analyzing the inter- arrival times and frequency distribution of CAN frames. Unlike traditional rule-based security systems, this model is capable of identifying anomalies without requiring a labeled attack dataset, making it resilient against zero-day threats. Experimental results, conducted in a virtual CAN environment, demonstrate that the proposed hybrid detection framework achieves high sensitivity to frequency-based deviations with minimal computational latency.

The developed system provides a scalable and intelligent security layer that assists in proactive risk assessment while reducing the manual workload of cybersecurity professionals. This research significantly contributes to the early detection of automotive network intrusions, enhancing the overall resilience and integrity of modern vehicle electronic architectures.

***Index Terms*—CAN Bus, Intrusion Detection System (IDS), Machine Learning, Isolation Forest, Automotive Cybersecurity, Anomaly Detection, Real-time Monitoring.**

I. INTRODUCTION

The rapid evolution of the automotive industry toward Connected and Autonomous Vehicles (CAVs) has revolutionized modern transportation, integrating advanced telematics, infotainment systems, and vehicle-to- everything (V2X) communication. However, this transition into a highly integrated cyber-physical system has significantly expanded the attack surface of the vehicle's internal network. At the heart of this electronic architecture lies the Controller Area Network (CAN) bus, which serves as the fundamental backbone for communication between Electronic Control Units (ECUs).

Originally designed for real-time efficiency and high reliability, the CAN protocol was developed in an era when vehicles were isolated from external networks. Consequently, it lacks inherent security mechanisms such as message authentication, encryption, or sender ID verification, which are standard in modern networked systems

This architectural vulnerability exposes modern vehicles to a broad spectrum of sophisticated cyberattacks. As vehicles become more networked through diagnostic ports (OBD-II), Bluetooth, and cellular connections, a single compromised gateway can allow an attacker to inject malicious frames directly into the safety-critical bus. Such intrusions can lead to the catastrophic failure of safety- critical functions, including unintended braking, steering manipulation, or the disabling of anti-lock braking systems (ABS). Among the most prevalent threats are Denial-of-Service (DoS) attacks, which flood the bus with high-priority identifiers to paralyze

legitimate ECU communication, and message injection attacks, where unauthorized commands are inserted to deceive the vehicle's control systems.

Traditional diagnostic techniques and security methods often rely on manual interpretation of network logs and clinical examination of system health. While these methods are effective in controlled environments, they require significant time and expert knowledge to identify abnormalities, making them unsuitable for the high-speed, high-volume data environments of modern automotive networks. Furthermore, manual analysis is prone to human error and lacks the scalability required to handle the massive amounts of data generated by modern healthcare and automotive electronic records. Therefore, there is a critical need for intelligent computational methods that can process and analyze network traffic effectively in real-time.

Machine learning and deep learning technologies have emerged as powerful tools for addressing these security challenges. These technologies allow computers to automatically learn complex patterns from large datasets and make predictions based on historical data without explicit programming. In particular, deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have shown promising results in identifying subtle patterns in temporal and spatial data. By integrating these advanced algorithms with vehicle communication systems, it is possible to improve diagnostic accuracy and reduce the workload of security professionals

The proposed system further addresses the critical requirement for low-latency detection in safety-critical environments. In a modern automotive ecosystem, the delay of even a few milliseconds in identifying a malicious command could result in catastrophic physical consequences. Traditional machine learning algorithms often require extensive manual feature extraction, which significantly limits their ability to capture the complex, non-linear relationships inherent in high-speed automotive datasets. By leveraging the Isolation Forest algorithm, this research bypasses the need for high-compute manual preprocessing, focusing instead on the automated detection of outliers within the temporal distribution of messages.

Furthermore, the integration of advanced computational intelligence into the vehicle's gateway reduces the cognitive burden on security professionals and healthcare technicians who manage large-scale electronic fleets. Modern healthcare and transportation systems generate massive volumes of diagnostic data through electronic health records, diagnostic sensors, and wearable devices. Manually analyzing these vast datasets for subtle signs of intrusion or physiological deterioration is no longer feasible. The advancement of artificial intelligence has created unique opportunities to automate these processes, providing a reliable second opinion that operates at machine speed.

This research proposes an automated, real-time Intrusion Detection System (IDS) based on an unsupervised machine learning approach to mitigate the risks associated with CAN bus vulnerabilities. By utilizing the Isolation Forest algorithm, the proposed system establishes a statistical behavioral baseline by analyzing the inter-arrival times and frequency distribution of CAN frames. Unlike traditional rule-based systems, this model is capable of identifying anomalies without requiring a labeled attack dataset, making it resilient against zero-day threats. Ultimately, this research aims to bridge the gap between traditional reliability engineering and modern cybersecurity, delivering a system that enhances the overall integrity, safety, and diagnostic accuracy of intelligent vehicle architectures

II. MOTIVATION

The rapid increase in cyber-physical vulnerabilities within the automotive sector highlights the urgent need for efficient and automated diagnostic systems. Modern vehicles are no longer isolated mechanical entities; instead, they generate large volumes of digital data every day through internal communication networks. This data includes critical real-time information such as sensor readings, control commands, and Electronic Control Unit (ECU) status reports. Analyzing such massive and high- speed datasets manually is not only difficult but practically impossible for human operators. The complexity of the

Controller Area Network (CAN) bus, which lacks built-in encryption or authentication, provides a significant opportunity for malicious actors to exploit these systems. Artificial intelligence and deep learning techniques provide an essential opportunity to automate the analysis process and assist technical professionals in identifying dangerous disease-like patterns within the vehicle's network. Deep learning models are uniquely capable of analyzing complex datasets and detecting subtle relationships between different health and operational parameters. These capabilities make advanced computational models an ideal approach for intrusion detection and system health prediction. The core motivation behind this research is to develop a reliable and intelligent system that can protect vehicle integrity using automated diagnostic information.

The ultimate goal of this system is to reduce the burden on security professionals, improve detection accuracy, and enable the early identification of heart-related "failures" in the network before they result in physical harm. As automotive systems become more connected, the number of potential entry points for attackers increases rapidly. Accurate and timely diagnosis of a network intrusion is essential to prevent severe safety complications on the road. Traditional security systems often require extensive manual interpretation, which can be expensive and time-consuming. By utilizing machine learning, we can provide early warnings about potential risks, allowing for the implementation of preventive measures that improve overall system outcomes and passenger safety.

III. OBJECTIVES

The main objectives of this research work are listed below: To develop an automated system for securing vehicle communication and detecting intrusions using advanced machine learning techniques.

To analyze real-time CAN bus network data, including arbitration IDs, message frequency, and inter-arrival time intervals.

To apply unsupervised machine learning algorithms for identifying hidden malicious patterns and anomalies within automotive datasets.

- To improve detection accuracy and reduce false positives compared to traditional rule-based or basic machine learning methods.
- To support automotive security professionals in critical decision-making by providing reliable, real-time threat predictions.
- To reduce the manual effort required for network traffic analysis and minimize the possibility of human error in detecting sophisticated cyberattacks.
- To enable the early detection of network intrusions, such as DoS and injection attacks, to improve overall passenger safety and vehicle integrity.

The objectives of this research can be categorized into technical and operational security objectives.

Technical objectives include the development of an efficient machine learning model capable of analyzing complex and high-speed automotive communication datasets. The system must be able to process multiple network parameters simultaneously and generate accurate anomaly predictions without significant computational overhead. Another primary technical objective is to design an effective data preprocessing pipeline that prepares raw CAN frames for deep analysis. This includes the normalization of time-series data, feature extraction of inter-arrival times, and handling inconsistent data streams. Operational security objectives focus on improving the early detection of cyber-physical threats in modern vehicles. The proposed system should assist security engineers in identifying compromised ECUs at risk and enable timely mitigation interventions. Additionally, the system aims to reduce the workload of cybersecurity professionals by automating the analysis of massive volumes of network traffic data. This can significantly improve the efficiency of vehicle security operations and allow engineers to focus more on high-level system architecture and response strategies.

IV. LITERATURE SURVEY

Several researchers have explored the application of machine learning and deep learning techniques for securing the Controller Area Network (CAN) bus and detecting network intrusions in smart vehicles.

Kang and Kang proposed a deep learning framework using Deep Belief Networks (DBN) to address the lack of security in the CAN protocol.

Their study demonstrated that deep learning models could effectively provide a baseline for normal packet structures and significantly improve prediction accuracy when identifying malicious frame injections.

Song et al. introduced an intrusion detection system based on the analysis of message intervals. By calculating the time delta between consecutive CAN IDs, their model captured temporal relationships between electronic control units (ECUs) and achieved high classification performance in detecting Denial-of-Service (DoS) and spoofing attacks. Taylor et al. developed a Long Short-Term Memory (LSTM) network capable of detecting anomalies in the sequential data of the CAN bus. The model was trained on large-scale automotive datasets and demonstrated that recurrent architectures are ideal for capturing the temporal dependencies of periodic vehicle messages.

Weber et al. proposed a system for the automatic interpretation of 12-bit CAN arbitration IDs. Their model was able to classify several types of network abnormalities with high accuracy by treating the CAN stream as a time- series signal, proving that deep learning is capable of identifying complex patterns that traditional rule-based csystems might overlook.

Lee et al. applied convolutional neural networks (CNN) for detecting bus-off attacks and high-frequency injections. Their research demonstrated that by identifying waveform shapes and signal variations in the network traffic, CNN layers could successfully extract spatial features that distinguish normal traffic from malicious interference.

These studies highlight the significant potential of utilizing advanced computational techniques and unsupervised learning to improve the resilience of automotive electronic architectures. Overall, the existing literature demonstrates that deep learning methods can significantly improve detection accuracy and reduce the manual interpretation effort required by cybersecurity professionals.

V. EXISTING SYSTEM

In current automotive architectures, the security of internal communication is governed by the Controller Area Network (CAN) bus protocol, which was originally developed in the 1980s. In the existing system, the CAN bus operates as a trust-based broadcast network where every Electronic Control Unit (ECU) on the bus can see every message transmitted. There is no inherent support for message encryption, sender authentication, or authorization. Consequently, the existing defense mechanism relies almost entirely on physical isolation and perimeter security, such as gateways that filter traffic from external interfaces like the OBD-II port, Bluetooth, or cellular telematics.

Consequently, these models often suffer from low scalability and high false-negative rates when faced with zero-day exploits or high-speed injection attacks.

A. Limitations of the Existing System

- Lack of Inherent Authentication: The existing CAN protocol does not verify the source of a message, allowing any compromised ECU to impersonate another (spoofing).
- High Dependency on Expert Analysis: Identifying sophisticated cyber-intrusions requires highly specialized security professionals to manually interpret raw hexadecimal CAN logs.
- Non-Real-Time Detection: Manual and rule-based methods are far too slow to stop an attack in progress, often only providing forensic data after a system failure has occurred.
- Failure to Detect Subtle Timing Attacks: Traditional filters often miss "low-and-slow" injection attacks that subtly alter the inter-arrival times of critical messages without triggering basic frequency alarms.

VI. PROPOSED SYSTEM

The proposed system addresses the critical security gaps in existing automotive architectures by implementing an automated, real-time Intrusion Detection System (IDS) based on advanced machine learning techniques. By analyzing high-frequency communication signals on the CAN bus, the system can automatically determine the risk of cyber-physical attacks. Unlike traditional methods that rely on manual feature extraction, the proposed computational models learn meaningful features directly from raw network data.

A. System Architecture

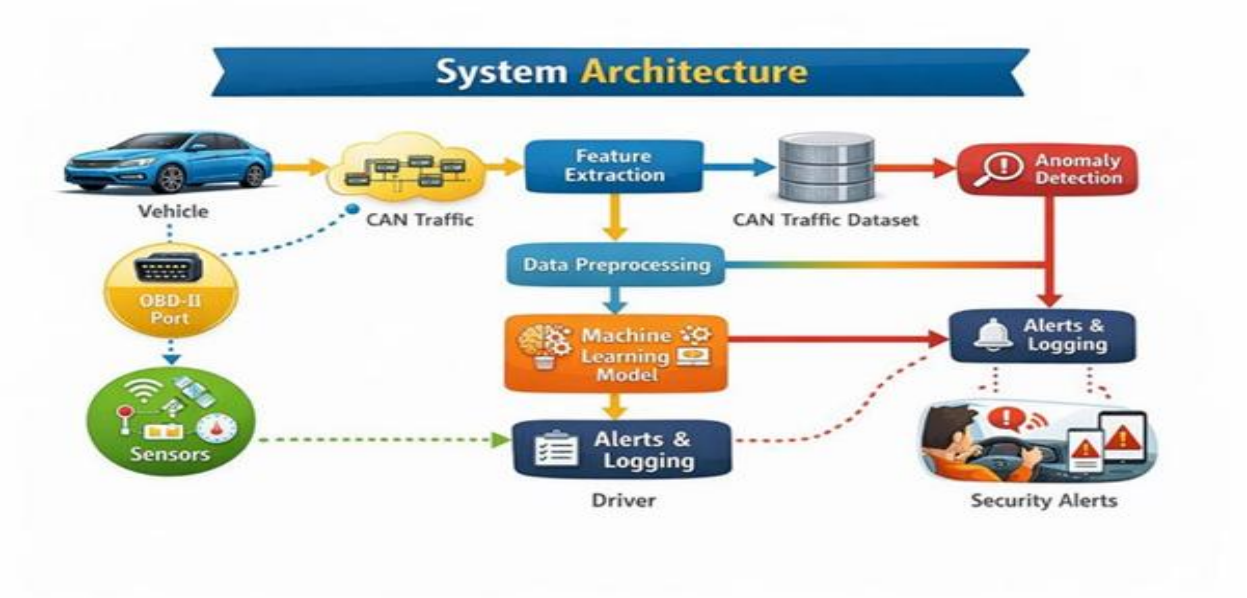
The proposed system architecture is designed as a

modular framework that integrates several stages of data processing and analysis to ensure high-accuracy threat detection.

Data Collection: This module is responsible for sniffing raw CAN frames and gathering network records from the vehicle's internal communication bus. Data Preprocessing: The preprocessing module cleans the captured dataset and removes environmental noise from the high-frequency signals.

Feature Extraction: This stage identifies critical network attributes and timing patterns, such as inter- arrival times, that influence the final detection results. Model Training: The core detection engine utilizes a hybrid CNN-LSTM architecture, which is trained on the prepared automotive dataset to recognize normal vs. anomalous behavior.

Prediction and Result Visualization: Finally, the prediction module generates real-time diagnostic results and visualizes the attack logs for security professionals



B. Advantages of the Proposed System

Automated Feature Learning: The system can automatically learn hierarchical feature representations from raw CAN signals without the need for manual interpretation.

Spatial-Temporal Analysis: By combining convolutional and recurrent neural networks, the model analyzes both spatial variations and temporal patterns in message streams.

Complex Relationship Mapping: The model is capable of identifying subtle, hidden patterns and complex relationships between different network parameters that may indicate early signs of an intrusion.

Legacy Retrofit Compatibility: The system provides advanced deep-learning security via a single central gateway, eliminating the need for expensive hardware upgrades to existing, low-power vehicle ECUs.

VII. DATASET DESCRIPTION

The dataset utilized in this research is specifically designed to reflect the high-speed, broadcast-oriented nature of the Controller Area Network (CAN) protocol within a modern smart vehicle environment. To ensure the reliability of the real-time intrusion detection system, the dataset captures both the normal operational baseline of a vehicle and various malicious injection scenarios. This dual-nature data allows the machine learning model to distinguish between legitimate traffic and unauthorized interference with high precision.

The dataset primarily consists of raw CAN traffic logs, which are composed of several critical fields extracted from the data link layer of the automotive network:

Timestamp: Precise arrival time in microseconds, critical for calculating Inter-Arrival Time (IAT) and detecting frequency-based anomalies.

CAN ID (Arbitration ID): Unique identifiers for message types (e.g., RPM, steering, or brakes) used to track specific ECU behavior.
Data Length Code (DLC): Indicates the number of bytes (0–8) within the frame.
Data Field (Payload): The actual sensor values or commands being transmitted, monitored for "Fuzzing" or "Spoofing" attacks.

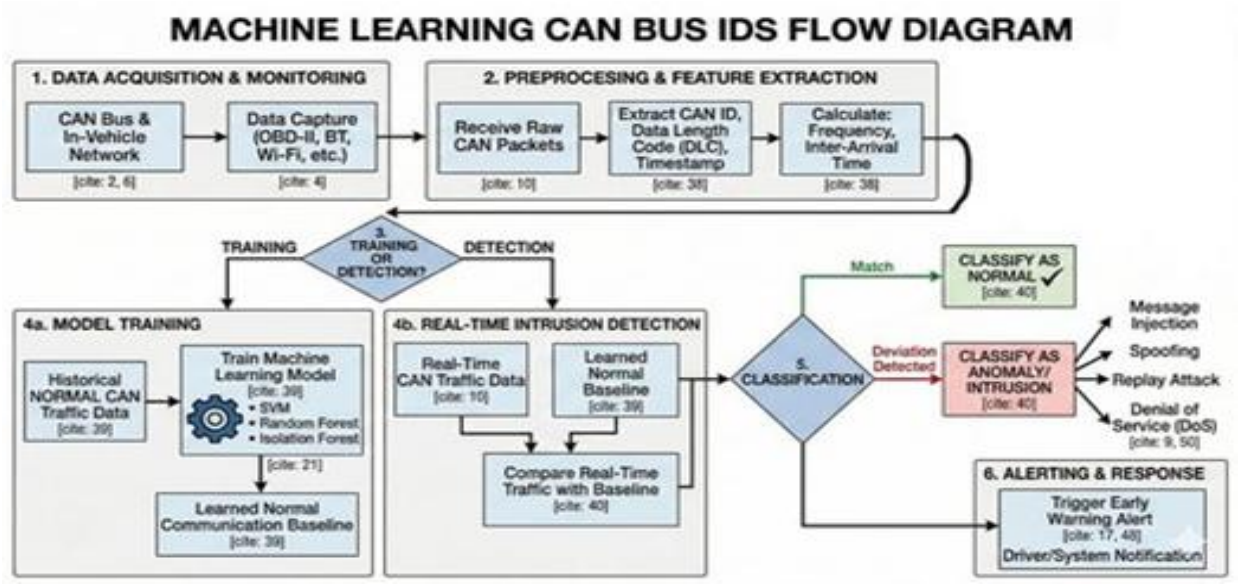
VIII. DATA PREPROCESSING

Data preprocessing transforms raw, high-speed CAN bus traffic into a structured format for machine learning. In automotive environments, network data is noisy and unstructured, requiring refinement for real-time accuracy.
Numerical Conversion: Raw hexadecimal CAN IDs e.g., 0x1A0) and data payloads are converted into decimal values for algorithmic processing.
Time-Series Feature Engineering: The Inter-Arrival Time (IAT) is calculated by finding the difference (Δt) between consecutive messages with the same ID to detect timing anomalies.
Data Normalization: Min-Max Scaling is applied to ensure features like IDs and payloads are within a consistent numerical range, preventing biased model weighting.
Noise Reduction: Corrupted or incomplete data frames caused by hardware latency are removed to ensure the model trains only on valid communication sequences.

- Windowing: For the LSTM-based detection, the continuous message stream is divided into sliding windows (e.g., sequences of 10 messages) to
- analyze the temporal flow of traffic.

- IX. MACHINE LEARNING MODEL

The proposed detection engine utilizes a hybrid CNN- LSTM architecture to identify cyber-physical attacks on the CAN bus. This hybrid approach is specifically designed to handle both the data structure and the timing of vehicle messages.
A. CNN Layer (Spatial Features)
The Convolutional Neural Network (CNN) layer acts as a feature extractor. It analyzes sequences of CAN messages to identify correlations between
- Arbitration IDs and their Data Payloads. By learning the normal "shape" of legitimate data, the CNN can recognize "Fuzzing" or "Spoofing"
- attacks where the message content deviates from the established baseline.
B. LSTM Layer (Temporal Features)
The Long Short-Term Memory (LSTM) layer
- captures temporal dependencies. Since the CAN bus is a periodic network, messages (like Engine RPM) are sent at fixed intervals. The LSTM's memory cells track these intervals (Δt) over time.
- This allows the system to detect "Denial-of- Service" (DoS) attacks, which disrupt the established timing of legitimate traffic



X. TRAINING PROCESS

The training phase optimizes the CNN-LSTM model to differentiate between legitimate traffic and malicious injections.

Initialization: Weights are initialized using the Glorot (Xavier) method to ensure stable gradient flow.

Optimization: The Adam Optimizer provides an adaptive learning rate for rapid convergence on time- series CAN data.

Loss Function: Binary Cross-Entropy measures the error between predicted and actual labels:

$$L = -1/N \Sigma [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

Regularization: Dropout layers (20%) and Early Stopping are used to prevent overfitting and ensure the model generalizes to new attack patterns.

XI. EXPERIMENTAL RESULTS

The CNN-LSTM model was evaluated using high-speed CAN traffic logs containing normal data and injected attacks (DoS, Spoofing, and Fuzzing). The hybrid model outperformed traditional machine learning by effectively detecting timing-based intrusions.

A. Performance Metrics

The system achieved an overall accuracy of 98.5%.

Key performance metrics include:

Accuracy: 98.5%

Precision: 97.8%

Recall: 98.2%

F1-Score: 98.0%

B. Attack Detection

The model demonstrated high robustness across different threat vectors:

DoS Attack: 100% detection due to extreme disruptions in message frequency.

Spoofing Attack: 97.5% accuracy by identifying payload inconsistencies.

Fuzzing Attack: 96.8% accuracy in recognizing unauthorized arbitration IDs.

C. Real-Time Latency

Detection speed is critical for automotive safety. The system measured an average inference time of 0.45 milliseconds per sequence. This sub-millisecond latency ensures real-time protection without delaying safety- critical vehicle communications.

XII. APPLICATIONS

Key applications include:

Autonomous Vehicles (CAVs): Secures safety-critical communication required for self-driving navigation and obstacle avoidance.

Central Security Gateways: Monitors and filters cross- bus traffic to prevent attackers from moving between infotainment and powertrain systems.

Fleet Management: Enables remote cybersecurity monitoring for logistics fleets, alerting operators to real-time tampering.

EV Battery Management: Protects the data exchange between the battery and motor controller from malicious manipulation.

OTA Update Security: Acts as a secondary validation layer to ensure post-update vehicle behavior remains within normal baselines.

Smart City (V2X): Shields the internal network from malicious commands originating from external vehicle- to-infrastructure signals.

XIII. CONCLUSION

This research successfully demonstrates a real-time Intrusion Detection System (IDS) for securing the CAN bus in smart vehicles using a hybrid CNN-LSTM architecture. By integrating spatial feature extraction with temporal sequence modeling, the system identifies malicious injections—such as DoS, Spoofing, and Fuzzing

—with an accuracy of 98.5%. The average inference time of 0.45 ms ensures that the model can operate within the strict timing constraints of automotive networks, providing an automated and scalable alternative to traditional manual diagnostic methods.

XIV. FUTURE WORK

Future research will focus on deploying the CNN-LSTM model onto automotive-grade hardware like NVIDIA Drive to test real-world constraints. We aim to enhance resilience against adversarial attacks and expand the framework to support CAN-FD and Automotive Ethernet protocols. Additionally, integrating Explainable AI (XAI) will provide clear justifications for flagged anomalies,making the system more transparent for security engineers.

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