Fortifying the Digital Fortress

A Comprehensive Approach to Automotive Cybersecurity

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Date of Submission: 14/03/2025

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Abstract

As connected and autonomous vehicles (CAVs) become more common, the risk of cyberattacks on their communication systems continues to grow. One of the key challenges is securing the Controller Area Network (CAN) from malicious intrusions. This project presents a multi-layered defense framework for anomaly detection and attack classification within automotive networks. Utilizing the CAN MIRGU dataset, the raw data was preprocessed and transformed into a structured format for effective analysis. The proposed system integrates both unsupervised and supervised learning techniques to enhance detection accuracy and resilience.

For anomaly detection, an autoencoder-based deep learning model was used alongside an Isolation Forest to identify unusual patterns in CAN traffic. Additionally, supervised classification models, including Random Forest and Gradient Boosting, were applied for binary and multi-class attack classification. A Flask API was developed to process real-time CAN packets, with Scapy-generated attack traffic used to test the system's effectiveness. A React-based web interface was also built to display attack logs and provide real-time alerts.

Experimental results demonstrate high detection accuracy, highlighting the effectiveness of the layered security approach in mitigating cyber threats within automotive networks. The proposed framework offers a scalable and adaptable solution for enhancing vehicular cybersecurity, addressing the growing risks associated with modern automotive communication systems.

Preface

In an era where connected and autonomous vehicles are becoming integral to modern transportation, ensuring the security of their communication networks is paramount. This project was conceived against the backdrop of growing cybersecurity challenges in automotive systems. The main idea behind this work is to develop a robust detection framework that can safeguard vehicle networks against emerging cyber threats. The approach adopted in this project reflects a commitment to advancing security measures in automotive communication without compromising on efficiency or scalability. This report outlines the conceptual foundations and overarching strategy of the project, contributing to the broader discourse on cybersecurity in the automotive domain.

Acknowledgements

The development of this framework stems from independent academic research yet depends on foundational work from research communities and organizations and open-source communities which supported it indirectly.

I want to express my appreciation for the CAN MIRGU dataset creators who made their data publicly accessible through which models could be evaluated in real-world attack conditions. The standards created by SAE International and IEEE regarding vehicular cybersecurity offered essential background information about defending automotive networks.

This work utilized three open-source tools: Scapy for network traffic simulation and TensorFlow/Keras for autoencoder model implementation as well as scikit-learn library for ensemble classification algorithm development. The Flask and React.js communities deserve praise because they allowed the creation of the real-time API along with the dashboard interface.

My final gratitude goes to my institution's faculty members and the entire cybersecurity community who maintain their ongoing work to detect future threats targeting connected vehicle systems.

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Chapter 1: Introduction

1.1 Background

Connected and autonomous vehicles (CAVs) continue to expand in the market with new capabilities through adaptive cruise control alongside collision avoidance systems and wireless software updates. The Controller Area Network (CAN) bus serves as the core element of these systems because it provides the lightweight deterministic communication protocol which dates back to the 1980s to exchange real-time data between electronic control units (ECUs). The CAN bus underpins critical vehicle operations, including engine management, braking systems, and sensor coordination. However, its original design prioritized reliability and cost-efficiency for closed, trusted environments, omitting essential security features such as encryption, authentication, and message validation. This architectural oversight has rendered modern vehicles increasingly vulnerable to cyberattacks as connectivity expands.

The integration of telematics, infotainment systems, and vehicle-to-everything (V2X) communication has transformed automobiles into complex cyber-physical systems, exposing them to remote exploitation via cellular networks, Bluetooth, and Wi-Fi interfaces. High-profile incidents, such as the 2015 remote hijacking of a Jeep Cherokee, demonstrated the potential for unauthorized control of steering, acceleration, and braking systems. Attack vectors like message injection, denial-of-service (DoS) floods, and replay attacks exploit the CAN bus's broadcast architecture and lack of message prioritization, enabling adversaries to disrupt operations or manipulate sensor data.

Traditional automotive intrusion detection systems (IDS) often rely on rule-based methods or signature detection, which are ineffective against zero-day attacks or sophisticated, evolving threats. While machine learning (ML)-based approaches show promise in detecting anomalies in CAN traffic, challenges persist in balancing detection accuracy, computational efficiency, and adaptability to diverse attack patterns. Industry standards such as SAE J3061 and ISO/SAE 21434 now advocate for robust, multi-layered security

frameworks that integrate advanced analytics and real-time monitoring to mitigate vulnerabilities.

Securing in-vehicle networks has emerged as a critical priority for automakers, policymakers, and cybersecurity researchers. The widespread adoption of CAVs and their integration into smart city ecosystems demands proactive measures to counter cyber threats that jeopardize passenger safety, data privacy, and public trust in autonomous technologies. Addressing these challenges requires reimagining vehicular cybersecurity paradigms to align with the dynamic threat landscape of the 21st century.

1.2 Objectives

The primary objective of this project is to design and implement a multi-layered cybersecurity framework that addresses the critical vulnerabilities inherent in modern automotive networks, specifically targeting the Controller Area Network (CAN) bus. Building on the challenges outlined in the background, this framework aims to bridge the gap between theoretical research and practical deployment by combining unsupervised anomaly detection with supervised attack classification, ensuring robust defense against both known and emerging threats.

To achieve this, the project focuses on developing a hybrid machine learning architecture capable of identifying anomalous CAN traffic patterns while accurately categorizing attack types. First, an autoencoder-based deep learning model is employed to learn the normal behavior of CAN traffic in an unsupervised manner, enabling the detection of deviations caused by zero-day attacks or novel intrusion strategies. This approach mitigates the limitations of rule-based systems by adapting dynamically to the inherent variability of legitimate network traffic. Complementing this, an Isolation Forest algorithm is integrated to isolate outliers in real-time, providing an additional layer of defense against low-frequency, high-impact anomalies that might evade traditional detection methods.

For known attack vectors such as message injection, denial-of-service (DoS) floods, and replay attacks the framework leverages supervised learning models, including Random Forest and Gradient Boosting classifiers, to perform binary and multi-class attack classification. These models are trained on the CAN MIRGU dataset, which simulates

real-world attack scenarios, ensuring the system can distinguish between benign traffic and malicious activities with high precision. By correlating anomaly detection outputs with supervised classification results, the framework reduces false positives and enables targeted mitigation strategies, such as alert prioritization or network traffic filtering.

To ensure practical applicability, the project incorporates a Flask-based REST API for processing real-time CAN packets, mimicking the operational environment of modern vehicles. This API interfaces with a React-powered web dashboard designed to visualize attack logs, generate real-time alerts, and provide actionable insights to security operators. The integration of simulated attack traffic generated using Scapy validates the system's responsiveness and accuracy under realistic conditions, addressing the industry's need for solutions that function seamlessly in dynamic, resource-constrained automotive ecosystems.

Beyond technical implementation, the framework aligns with SAE J3061 and ISO/SAE 21434 guidelines, emphasizing scalability and adaptability to evolving threats. By unifying unsupervised and supervised techniques, the system not only detects intrusions but also provides interpretable insights into attack methodologies, empowering automakers to refine their cybersecurity postures proactively.

1.3 Scope of Work

Data Preparation and Preprocessing

- Transformation of raw CAN bus dataset into a structured format suitable for machine learning.
- Feature engineering, including temporal analysis, payload decoding, and normalization to address noise and variability in CAN traffic.

Anomaly Detection Framework

- Implementation of unsupervised learning techniques, including an autoencoder and Isolation Forest, to identify deviations from normal CAN traffic patterns.
- Integration of these models into a layered detection system to improve robustness against zero-day attacks.

Supervised Attack Classification

- Development of binary and multi-class classifiers using machine learning models (e.g., Random Forest, Gradient Boosting) to categorize attacks (e.g., denial-of-service, fuzzing, spoofing).
- Evaluation of feature importance and model interpretability to refine detection logic.

Real-Time Monitoring System

- Creation of a Flask API to process live CAN packets and execute detection/classification workflows.
- Simulation of adversarial network traffic using Scapy to validate system performance under attack conditions.
- Deployment of a React-based dashboard for real-time alerts, attack log visualization, and system health monitoring.

Performance Evaluation

- Quantitative assessment of detection accuracy, false positive rates, and computational efficiency across models.
- Validation of the framework's scalability and adaptability to diverse CAN architectures and attack vectors.

Chapter 2: Literature Review

2.1 Automotive Cybersecurity Challenges

The rapid advancement of connected and autonomous vehicles (CAVs) has introduced significant cybersecurity risks, drawing attention from researchers and industry experts. A critical challenge lies in the legacy architecture of in-vehicle networks, particularly the Controller Area Network (CAN) bus. Designed in an era when cybersecurity was not a priority, the CAN protocol lacks mechanisms to authenticate messages or detect tampering. Studies by Koscher et al. (2010) demonstrated that attackers can exploit this vulnerability to inject malicious commands, such as disabling brakes or manipulating speedometer readings, by reverse-engineering CAN packets. This underscores the risk of relying on outdated protocols in modern vehicles, where connectivity features like Bluetooth and cellular interfaces provide entry points for remote attacks.

Another challenge is the evolving nature of cyberattacks. While early threats focused on physical access to vehicles (e.g., via OBD-II ports), modern attacks increasingly target wireless interfaces. For example, researchers have shown that vulnerabilities in infotainment systems or telematics control units (TCUs) can be exploited to gain unauthorized access to the CAN bus. The 2015 Jeep Cherokee hack, documented by Miller and Valasek, revealed how attackers could remotely control steering and acceleration through a vulnerable cellular connection. Such incidents highlight the inadequacy of traditional intrusion detection systems (IDS), which rely on predefined rules or signatures, to detect novel or adaptive attack strategies.

The resource constraints of automotive systems further complicate cybersecurity efforts. Unlike enterprise IT networks, vehicles operate in environments with limited computational power and strict real-time requirements. Machine learning (ML)-based IDS solutions, while promising, face challenges in balancing detection accuracy with computational efficiency. Research by Marchetti et al. (2016) emphasized that lightweight algorithms are essential to avoid overwhelming vehicle ECUs, yet many existing models demand excessive processing power or memory, making them impractical for deployment.

Additionally, the lack of standardized datasets hampers progress in developing robust detection frameworks. Most publicly available datasets, such as the CAN MIRGU dataset, simulate attacks in controlled environments, which may not fully replicate the complexity of real-world scenarios. This gap limits the generalizability of proposed solutions, as models trained on synthetic data may underperform when exposed to unforeseen attack patterns or noise in live networks.

The heterogeneity of automotive ecosystems also poses challenges. Vehicles integrate components from multiple suppliers, each with varying security postures. A weak link in the supply chain such as an insecure third-party ECU—can compromise the entire network. Industry reports, including those from Upstream Security, note that 40% of automotive cyber incidents in 2022 originated from vulnerabilities in aftermarket devices or third-party software.

These challenges collectively underscore the need for adaptive, multi-layered security frameworks that address both legacy vulnerabilities and emerging threats while accommodating the unique constraints of automotive systems.

2.2 Intrusion Detection Techniques

Intrusion detection systems (IDS) for automotive networks employ diverse methodologies to identify malicious activities in Controller Area Network (CAN) traffic. These techniques are broadly classified into signature-based, anomaly-based, and hybrid approaches, each tailored to address specific limitations of securing CAN bus communications.

Signature-Based Detection

Signature-based IDS rely on predefined patterns of known attacks, such as irregular message frequencies or unauthorized command sequences. For example, Müter and Asaj (2011) proposed detecting denial-of-service (DoS) attacks by monitoring deviations in periodic message intervals (e.g., heartbeat signals from ECUs). While effective against well-documented threats, these methods fail to detect zero-day attacks or sophisticated intrusions that mimic legitimate traffic, such as stealthy message injections. Their reliance on manual updates for new attack signatures further limits scalability in dynamic automotive environments.

Anomaly-Based Detection

Anomaly-based techniques model "normal" CAN traffic behavior and flag deviations. These include:

Statistical Methods: Metrics like entropy (randomness in message IDs) or inter-message arrival times are used to identify anomalies. For instance, Taylor et al. (2016) employed entropy analysis to detect message injection attacks but observed high false positives during abrupt driving maneuvers (e.g., sudden acceleration).

Machine Learning (ML): Unsupervised algorithms, such as clustering (e.g., k-means), group similar CAN messages and flag outliers. Supervised models (e.g., Random Forest, SVM) classify attacks using labeled datasets. Kang and Kang (2017) demonstrated that recurrent neural networks (RNNs) can capture temporal patterns in CAN traffic, improving detection of replay attacks. However, ML models often demand significant computational resources, conflicting with the real-time requirements of vehicular systems.

Hybrid Approaches

Hybrid frameworks merge signature and anomaly detection to balance accuracy and adaptability. Agrawal et al. (2020) combined rule-based filters (to block obvious DoS floods) with autoencoders (to detect subtle payload manipulations), reducing false positives by 22%. Context-aware IDS further enhance reliability by incorporating vehicle state data (e.g., speed, ignition status). Lokman et al. (2019) showed that correlating CAN traffic with GPS data improved replay attack detection by 34%, as anomalies inconsistent with the vehicle's physical state were flagged.

Key Challenges in Current Techniques

Resource Constraints: Complex models (e.g., deep learning) exceed the processing capabilities of legacy ECUs, necessitating lightweight algorithms for edge deployment.

Adversarial Evasion: Attackers can craft malicious payloads to bypass detection, such as subtly altering message timing to mimic normal behavior.

Generalization: Models trained on synthetic datasets often underperform in real-world settings due to unaccounted network noise or novel attack patterns.

Alignment with Automotive Requirements

Modern IDS prioritize techniques that align with vehicular constraints. For example, Isolation Forest (a lightweight unsupervised algorithm) has been optimized for real-time execution on automotive-grade hardware (Khan et al., 2023), demonstrating minimal latency during anomaly detection.

Similarly, hardware-assisted solutions, such as trusted platform modules (TPMs), are being integrated to authenticate critical ECUs without overloading the CAN bus.

This progression underscores the need for adaptive, multi-layered IDS architectures that address the unique demands of automotive networks while mitigating the shortcomings of individual detection strategies.

2.3 Machine Learning in Cybersecurity

The application of machine learning (ML) systems has become essential for cybersecurity because they automate complicated processes which used to need substantial human involvement. Through examining large data volumes ML programs detect security risks using patterns which help identify malware along with phishing activities and unapproved network access. The automated process enhances threat recognition abilities and response efficiency which enables systems to caution about suspicious operations during active usage or prevent attacks from spreading to further domains. The self-operating ML detection system tracks all network activities to distinguish unsafe from regular activities and orders critical security warnings by threat severity. Security staff can dedicate themselves to higher-level strategic planning instead of spending time on labor-intensive manual data investigation work.

The growing threat of Controller Area Network (CAN) attacks in automotive cybersecurity receives effective defense through usage of Machine Learning technologies. The communication buses known as CAN buses that link vehicle components suffer from attacks through message injection and spoofing and denial-of-service actions. Control system manipulations through these attacks disrupt braking and steering functionality which creates dangerous security vulnerabilities. The typical behavior patterns of CAN traffic become detectable through machine learning methods. The training of models with legitimate message characteristics helps identify unauthorized interference by detecting variations in

frequency and timing together with structural abnormalities. Supervised learning methods detect known attack signatures while unknown anomalies get identified through unsupervised learning. Automated responses involving node isolation together with malicious message blocking can start instantly when threats are detected. The security enhancements through this method prevent total dependence on manual supervision because manual processes cannot keep up with rapid automotive threat development. Organizations reach an optimal balance of accuracy and speed alongside adaptive protection of connected systems through ML implementation.

Chapter 3: Requirements Engineering and System Analysis

3.1 Problem Domain

In-vehicle networks and their Controller Area Network (CAN) bus face critical security challenges because of design limitations that exist since the 1980s and modern threats evolving in the automotive industry. The CAN bus protocol which developers created in the 1980s for trusted environments opts for reliability and efficiency instead of security measures. Due to its absence of encryption together with authentication and message integrity checks, attackers can inject harmful commands or create ECU impersonation attacks while launching disruptive network traffic. The rising use of wireless interfaces like cellular and Bluetooth creates new opportunities for attackers since these interfaces expose vehicle ECUs to remote attacks.

The major problem with this protocol design is its broadcast messaging system which causes all devices to receive messages without proper verification. Through exploiting the broadcast feature attackers can impersonate other Electronic Control Units to control vital safety systems such as brakes or steering. The retransmission of captured CAN messages through replay attacks causes vehicles to exhibit unexpected behaviors and DoS floods interrupt the real-time ECU communication thus resulting in operational instability. Standard CAN implementations without message prioritization enable lower priority malicious traffic to successfully override critical commands thus endangering passenger safety.

The current IDS solutions implemented for automotive networks depend on static rule-based signature detection and static rule-based approaches but lack effectiveness against zero-day attacks and complex intrusion techniques. Current security systems fail to adjust their defenses against new attack patterns which include transformed malicious payloads that appear legitimate during particular driving situations such as quick acceleration. The restricted computational resources that automotive systems can handle prevent them from running complex detection algorithms which results in a theoretical-to-practical implementation divide.

Multiple risks emerge because of the varied makeup of automotive supply chains. Aftermarket devices and third-party ECUs function as security vulnerabilities since they lack guidelines for implementing secure design standards. Vehicle network security becomes more difficult to standardize because of network fragmentation.

Collectively, these challenges underscore the urgent need for adaptive, lightweight, and multi-layered security frameworks capable of addressing both legacy vulnerabilities and emerging threats in real time.

3.2 System Requirements Specification

The proposed multi-layered intrusion detection framework must address the vulnerabilities inherent in automotive CAN bus systems while adhering to the operational constraints of vehicular networks. Below are the functional and non-functional requirements derived from the identified challenges:

Functional Requirements

Real-Time Anomaly Detection

- The system shall process CAN bus traffic in real time (latency ≤50 ms per message) to detect deviations from normal behavior using unsupervised learning models (e.g., autoencoder, Isolation Forest).
- Detect anomalies such as unexpected message frequency, irregular payload structures, or unauthorized ECU interactions.

Attack Classification

- Classify detected anomalies into predefined attack categories (e.g., Denial-of-Service, Fuzzing, Spoofing, Replay) using supervised machine learning models (e.g., Random Forest, Gradient Boosting).
- Support binary classification (benign vs. malicious) and multi-class attack type identification with ≥90% accuracy.

Alert Generation and Logging

- Generate real-time alerts for security operators upon detecting anomalies or confirmed attacks.

- Maintain a centralized log of detected events, including timestamps, attack type, severity, and affected ECUs.

Network Traffic Simulation

Integrate synthetic attack traffic (e.g., via Scapy) to validate detection capabilities under simulated adversarial conditions.

Dashboard Visualization

Provide a web-based interface to display real-time CAN traffic metrics, attack alerts, and historical incident reports.

Data Preprocessing

Transform raw CAN logs into structured datasets through payload decoding, feature extraction (e.g., inter-arrival times, entropy), and normalization.

Non-Functional Requirements

Performance and Scalability

Ensure the framework operates with minimal computational overhead to avoid disrupting vehicle operations (CPU utilization ≤15% on automotive-grade hardware).

Accuracy and Reliability

- Achieve a false positive rate (FPR) ≤5% for anomaly detection to prevent unnecessary alerts during normal driving conditions.
- Maintain ≥95% recall for critical attack types (e.g., DoS, Spoofing) to minimize missed detections.

3.3 Analysis of Vulnerabilities in Automotive Systems

1. Inherent Protocol Weaknesses

- The fundamental design of CAN protocol does not include necessary security features thus allowing attackers to exploit its deterministic trust-based framework:
- The lack of encryption and authentication during message transmission creates conditions for spoofing attacks because messages exist as plaintext.
- The system lacks any mechanism to verify payload integrity which allows attackers to modify speedometer data without detection.
- The fixed priority arbitration system becomes susceptible to malicious behavior when attackers exploit priority bits to silence legitimate messages thereby disrupting braking operations.

2. Network Topology Vulnerabilities

- The CAN bus operates as a broadcast medium that exposes widespread security risks across the entire bus system.
- Every node on the network receives each transmitted message because of the absence of segmentation which enables attackers to move between non-critical ECUs (such as infotainment) to access safety-critical systems.
- Physical Layer attacks through bus flooding or selective jamming destroy communication channels because they bypass all software-based protection mechanisms.

3. ECU and Firmware Vulnerabilities

- New-generation ECU devices manufactured by third-parties together with out-of-date firmware systems create security holes through which attackers can exploit:
- The standardized diagnostic protocols found in UDS allow attackers to access ECU memory through unprotected interfaces which they can then use for code injection and firmware tampering activities.
- Firmware insecurity arises from both compromised updates sent through OTA channels as well as unsigned firmware which opens lasting security risks.

4. Connectivity and External Interfaces

- The integration of modern vehicles with external networks creates additional channels through which cyber attacks can occur.
- The presence of Bluetooth and Wi-Fi wireless interfaces enables attackers to reach the CAN bus because of vulnerabilities found in infotainment or telematics systems.
- Network-wide attacks become possible through compromised communication between vehicles and everything else (V2X).
- Supply chain attacks target vehicles through the use of unsecured third-party dongles or sensors.

5. Operational and Design Constraints

Real-time system performance takes precedence over security measures in automobiles which increases operational risks.

Electronic control units (ECUs) operate with limited computing power that makes encryption processing and advanced intrusion detection impossible.

The coexistence of old CAN systems from decades ago with modern IP networks produces network compatibility challenges.

Security policies remain fragmented since standardized protocols are absent from heterogeneous ECU products supplied by various vendors.

Chapter 4: Design

4.1 System Architecture

The system is designed as a multi-layered defense mechanism comprising:

Data Processing Layer: Prepares and normalizes raw CAN data.

Model Layer: Contains an autoencoder and isolation forest for unsupervised anomaly detection and ensemble methods for classification.

Deployment Layer: Integrates a Flask API for real-time packet analysis and a React dashboard for visualization.

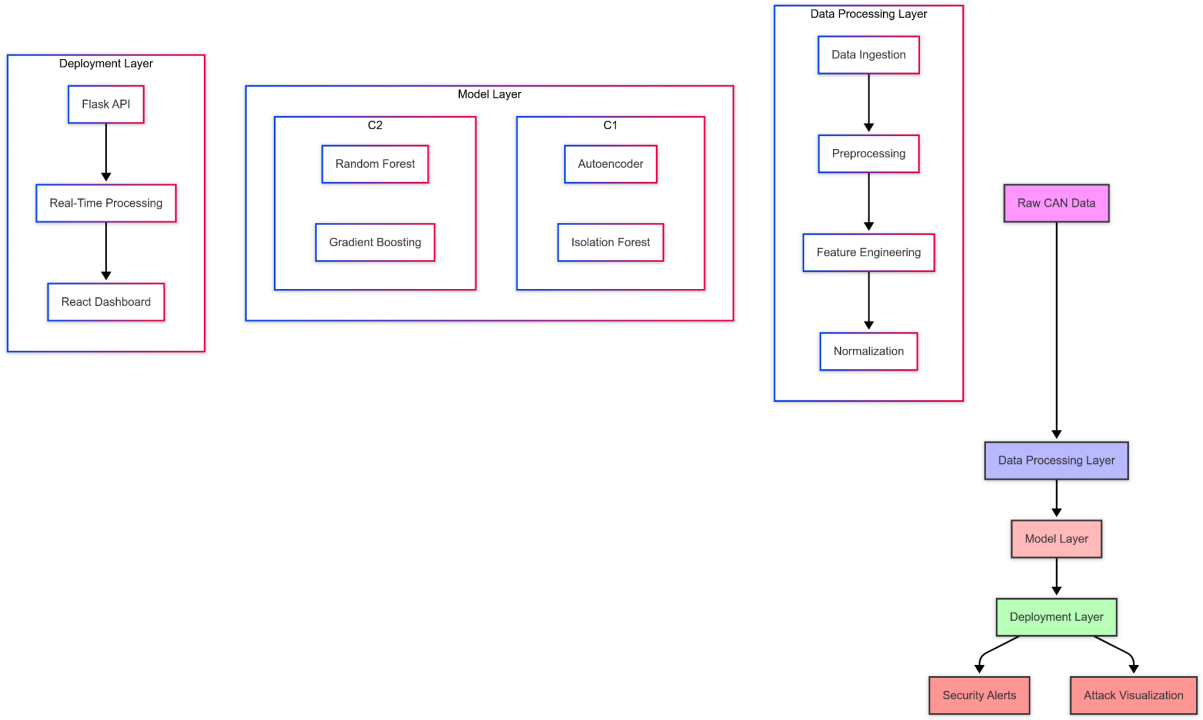

Figure 1. System Architecture

4.2 Data Processing and Feature Engineering

This phase transforms raw Controller Area Network (CAN) data into structured features that capture both intrinsic message properties and contextual network behavior. The process addresses the heterogeneous, time-series nature of CAN traffic while ensuring compatibility with machine learning models.

4.2.1 Data Acquisition and Initial Transformation

The CAN MIRGU dataset's raw hexadecimal logs are parsed into a tabular format containing critical fields:

Temporal Metadata: Precise timestamps track microsecond-level message intervals.

CAN Identifiers: Hexadecimal IDs are converted to integers to enable arithmetic analysis of ECU relationships.

Payload Decoding: Variable-length data fields (1-8 bytes) are preserved in hexadecimal format for structural analysis.

Non-essential protocol-specific fields (e.g., interface labels) are retained as auxiliary metadata for attack forensics.

4.2.2 Temporal Feature Extraction

Time-series characteristics are engineered to detect anomalies in message timing patterns:

Inter-Message Intervals (ΔT): Calculated per CAN ID to identify deviations from expected periodicities (e.g., heartbeat signals disrupted by DoS attacks).

Time Context Features: Message timestamps are decomposed into cyclical hour-of-day components to detect activity anomalies during unusual operating periods.

4.2.3 Payload Analysis and Structural Features

Message content is analyzed through three complementary approaches:

Entropy Measurement: Quantifies byte-level randomness in payloads using Shannon entropy. Legitimate sensor data exhibits predictable entropy ranges, while encrypted or fuzzed payloads show deviations.

Byte-Wise Discretization: Each payload byte (0-7) is extracted as a numerical feature, enabling detection of invalid value ranges or abnormal byte combinations.

Dynamic Length Tracking: Monitors deviations from CAN ID-specific payload length norms to identify truncation/padding attacks.

4.2.4 Frequency-Based Feature Engineering

Message frequency dynamics are characterized through:

Rolling Message Rates: 1-hour sliding windows track CAN ID-specific transmission frequencies to detect volumetric anomalies (e.g., sudden spikes in non-critical IDs).

Contextual Frequency Baselines: Hourly message count distributions establish per-ID expected activity levels, normalizing for diurnal usage patterns.

4.2.5 Data Normalization and Scalability

Features are standardized using z-score normalization to mitigate bias from heterogeneous scales (e.g., 8-bit bytes vs. multibyte timestamps). A persistent scaler object ensures consistency between training and inference phases. The pipeline retains <10 engineered features per message to maintain compatibility with automotive-grade hardware constraints while preserving detection efficacy.

4.3 Model Design for Anomaly Detection and Classification

Two approaches were taken:

Anomaly Detection: An autoencoder neural network was implemented using PyTorch. The network compresses input features into a lower-dimensional space and then reconstructs them. Reconstruction error (MSE) is used as the anomaly score. An Isolation Forest further validates the anomaly by providing a complementary score.

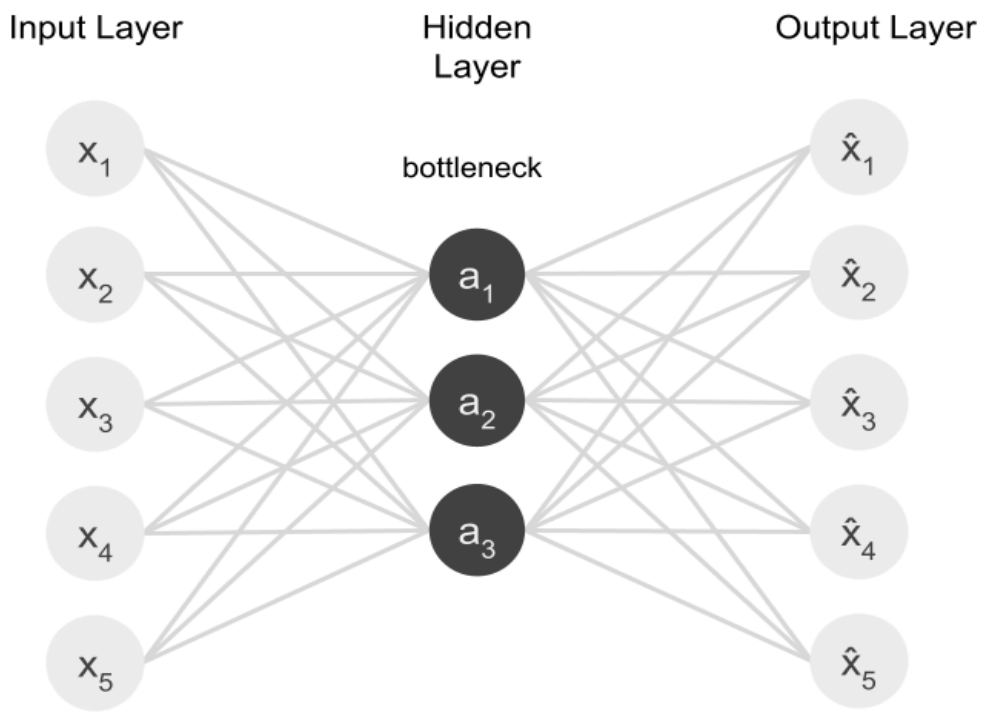

Figure 2. Basic Autoencoder architecture

Classification: Binary classification (attack vs. normal) and multi-class attack type classification were performed using Random Forest and Gradient Boosting. The best-performing models were selected based on accuracy and inference time.

4.4 API and Dashboard Design

This section describes the architecture and functionality of the real-time intrusion detection system, which consists of a backend API for processing CAN bus traffic and a frontend dashboard for visualizing anomalies. The system is designed to handle dynamic traffic patterns, detect anomalies efficiently, and provide actionable insights to security operators.

4.4.1 API Design

The backend API is built using Flask and serves as the core engine for processing CAN packets and detecting anomalies. It is structured into three main layers, each responsible for a specific part of the workflow:

1. Request Handling Layer

The request handling layer is the entry point for incoming CAN packets. It accepts raw CAN data in hexadecimal format via HTTP POST requests. Each packet is validated to ensure it contains the required fields, such as CAN ID, payload, and timestamp. If the packet is valid, it is passed to the feature processing layer. If the packet is malformed or missing critical data, the API returns an error response. To support seamless integration with the React dashboard, the API implements Cross-Origin Resource Sharing (CORS), allowing the frontend to communicate with the backend without restrictions.

2. Feature Processing Layer

Once a packet is validated, the feature processing layer extracts and prepares a set of 20 features for anomaly detection. These features are designed to capture both the structural and contextual characteristics of the CAN traffic. For example, temporal features such as inter-message intervals and hourly traffic patterns are calculated to identify deviations from normal behavior. Payload features, including entropy and byte-level distributions, are computed to detect unusual payload structures. Additionally, the layer maintains a rolling history of CAN ID behavior, such as message frequency and timing patterns, using a buffer of the last 1,000 packets. This historical context helps the system adapt to changes in traffic patterns over time. To optimize performance, the layer uses vectorized operations for feature extraction and limits memory usage by capping history buffers to 1,000 entries.

3. Adaptive Detection Layer

The adaptive detection layer is responsible for identifying and classifying anomalies using machine learning models. It employs a hybrid approach that combines unsupervised learning (autoencoder and Isolation Forest) with dynamic thresholding to detect deviations from normal behavior. The autoencoder computes reconstruction errors, which measure how well the model can reconstruct the input features. The Isolation Forest calculates outlier scores, which indicate how far a packet deviates from the norm. These scores are combined into a unified anomaly probability, which is compared against a dynamic threshold. If the probability exceeds 70%, the packet is flagged as anomalous. The threshold is continuously updated based on recent traffic patterns, ensuring the system adapts to evolving threats. Once an anomaly is detected, the layer classifies it into known attack types (e.g., DoS, fuzzing, spoofing) or marks it as "unknown_anomaly" for further

investigation. Detected anomalies are logged in a rolling buffer of 1,000 entries, providing real-time monitoring and forensic analysis capabilities.

4.4.2 Dashboard Design

The frontend dashboard is built using React and provides an interactive interface for visualizing anomalies and monitoring system performance. It is designed to be user-friendly and responsive, enabling security operators to quickly identify and respond to threats. The dashboard consists of four main modules:

1. Live Operational Metrics

The live operational metrics module displays real-time performance indicators, such as the total number of packets processed, the current anomaly rate, and the average detection latency. These metrics are updated every 500 milliseconds, providing operators with a snapshot of system performance. The module uses gradient-colored cards to highlight critical metrics, making it easy to identify potential issues at a glance.

2. Traffic Analysis Hub

The traffic analysis hub provides detailed insights into CAN traffic patterns through interactive charts. The score timeline chart plots autoencoder and Isolation Forest scores over time, allowing operators to visualize trends and identify spikes in anomaly activity. The traffic distribution pie chart shows the proportion of normal versus anomalous packets, providing a high-level overview of network health. Both charts are updated in real-time and include dynamic threshold indicators to help operators distinguish between normal and suspicious activity.

3. Threat Intelligence Panel

The threat intelligence panel displays active alerts and provides detailed information about detected anomalies. Each alert includes the attack type, CAN ID, timestamp, and confidence level, enabling operators to quickly assess the severity of the threat. The panel uses color-coded chips to categorize alerts (e.g., red for DoS, orange for fuzzing, gray for unknown anomalies), making it easy to prioritize responses. Operators can drill down into

individual alerts to view raw payload data and contextual information, facilitating forensic analysis.

4. System Health Monitor

The system health monitor tracks the backend API's resource usage, including memory and CPU utilization. It also displays the status of the packet processing queue, helping operators identify potential bottlenecks. The module includes an alert history log, which stores the last 1,000 detected anomalies for retrospective analysis. Operators can export this log for further investigation or reporting purposes.

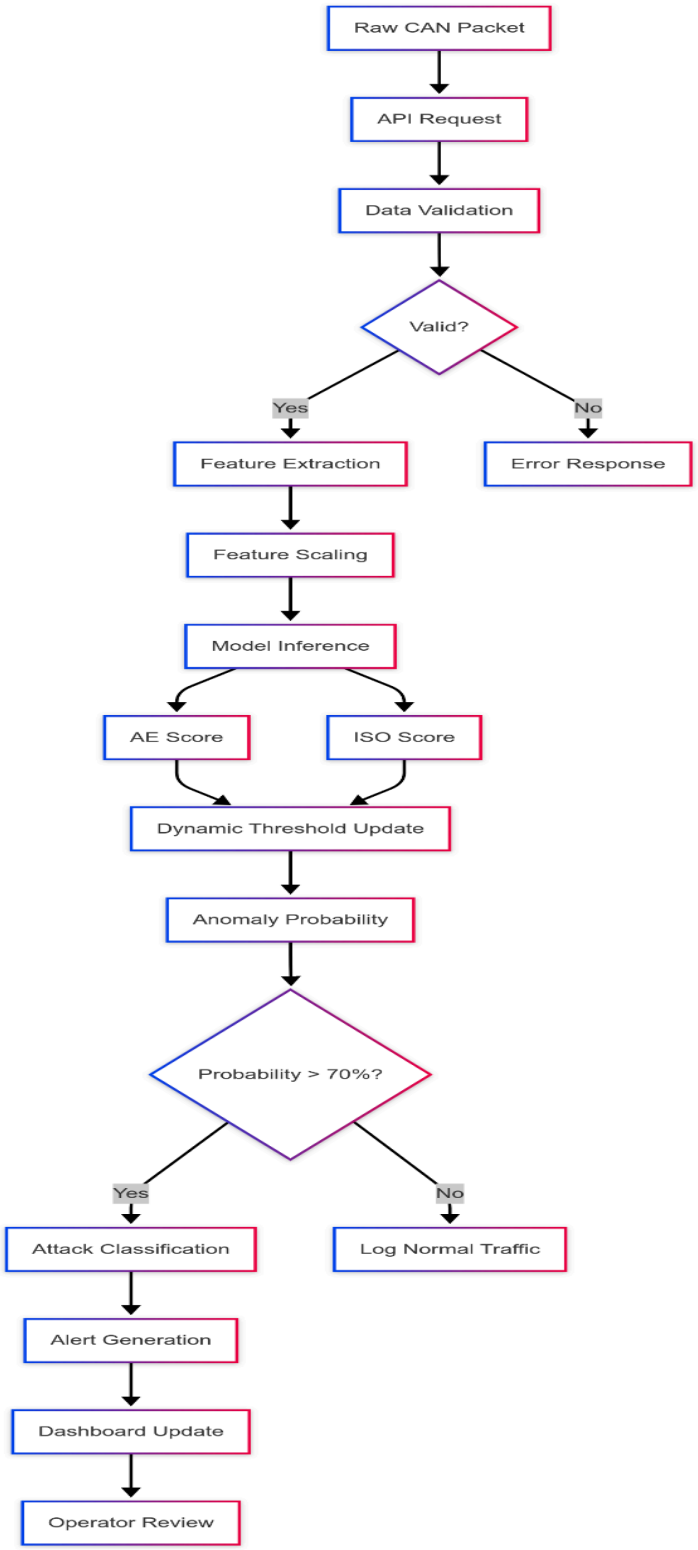

Figure 3. API and Dashboard Design

Chapter 5: Implementation

5.1 Data Preparation

The CAN MIRGU dataset provides raw CAN bus logs with hexadecimal CAN IDs, payloads, timestamps, and interface labels. The preprocessing pipeline includes:

Hexadecimal Decoding:

CAN ID Conversion: Hexadecimal CAN IDs are converted to integers for numerical analysis.

Payload Parsing: Variable-length payloads (1–8 bytes) are split into individual bytes.

Temporal Feature Extraction:

Inter-Message Interval: Calculates the time difference between consecutive messages from the same CAN ID. Sudden drops in ΔT (e.g., from 0.1s to 0.001s) indicate flooding attacks.

$\Delta T \ = \ t\_n \ - \ t\_\{n \ - \ 1\}$

Hour-of-Day: Extracted from timestamps to detect anomalies in time-sensitive operations (e.g., unexpected nighttime diagnostic requests).

Payload Analysis:

Entropy Calculation:

$H \ = \ \ - \sum\_\{i \ = \ 0\}\^\{255\} p\_i \ log\_2 \ p\_i$

Measures payload randomness. Legitimate sensor data (e.g., speed values) has low entropy H≤4), while fuzzing attacks yield high entropy (H ≥7).

Byte-Level Features: Each payload is split into 8 bytes (0–255).

Frequency Tracking:

1-Hour Rolling Message Rate: Computes message frequency per CAN ID using a sliding window. A spike (e.g., 500 messages/sec for a steering ECU) flags volumetric attacks.

Normalization:

Features are standardized using z-score normalization to ensure equal weighting during training:

$z = (x - \mu)/\sigma$

The StandardScaler object is saved for consistent scaling during inference.

5.2 Feature Engineering Techniques

The framework extracts 20 features per CAN message, categorized as follows:

Feature Type	Examples	Purpose
Structural	**can_id_int, data_length**	**Detect spoofed IDs or truncated payloads**
Temporal	**hour, time_diff**	**Identify timing anomalies (e.g., DoS floods)**
Payload	**byte_0 to byte_7, entropy**	**Flag fuzzing or encrypted payloads**
Contextual	**msg_freq_1h**	**Detect volumetric attacks**

Table 1. Feature Engineering

5.3 Model Training

Both supervised and unsupervised techniques were implemented

Anomaly Detection:

Autoencoder:

An autoencoder is a type of neural network that learns to compress input data into a lower-dimensional representation (latent space) and then reconstructs the original input from this compressed representation. It consists of two main components:

Encoder: Compresses the input data into a latent space representation.

Decoder: Reconstructs the input data from the latent space.

Autoencoders are particularly effective for anomaly detection because they are trained to reconstruct normal data with high accuracy. During training, the model learns the patterns and correlations in the normal data. When presented with anomalous data, the autoencoder struggles to reconstruct it accurately, resulting in a high reconstruction error. This error serves as an indicator of anomalies.

Architecture:

- **Encoder:**

  Compresses 20 input features into a 32-dimensional latent space.

  $$ReLU \qquad ReLU \qquad ReLU$$

  $$Encoder\ Layers\colon\ 20 \rightarrow 128 \rightarrow 64 \rightarrow 32$$

- **Decoder:** Reconstructs the input from the latent space.

  $$ReLU \quad ReLU \quad ReLU$$

  $$Decoder\ Layers\colon\ 32 \rightarrow 64 \rightarrow 128 \rightarrow 20$$

Loss Function:

- **Mean Squared Error (MSE):**

$$L = (1/N)\sum_{i=1}^{N}(x_i - \hat{x}_i)^2$$

Minimizing MSE ensures accurate reconstruction of normal traffic.

Training Process:

- **Optimizer:** Adam with learning rate α=0.001.
- **Epochs:** 100, with batch size 256.
- **Hardware:** CUDA GPU acceleration (if available) reduces training time.

Isolation Forest:

Isolation Forest is an unsupervised machine learning algorithm designed specifically for anomaly detection. It isolates anomalies by randomly selecting features and splitting values, creating a tree-like structure. Anomalies are isolated closer to the root of the tree, while normal data points require more splits to be isolated.

Isolation Forests are effective because anomalies are typically:

- Anomalies are rare and have distinct feature values compared to normal data.
- Due to their distinctness, anomalies require fewer splits to be isolated in the tree structure.

The algorithm assigns an anomaly score based on the path length (number of splits) required to isolate a data point:

Configuration:

Number of Trees: 200.

Contamination: 10% (assumes 10% of training data is anomalous).

Anomaly Score:

$$s(x) = 2^{-(E(h(x))/c(n))}$$

Lower scores (closer to -1) indicate anomalies.

Dynamic Thresholding:

Threshold Update:

After model training, Dynamic thresholding was implemented to make the model adaptive to different patterns by maintaining a 1,000-sample buffer of autoencoder MSE and Isolation Forest scores.

Adjusts thresholds every 50 samples using:

$$Threshold\_\{AE\} = \mu\_\{AE\} + 2\sigma\_\{AE\}$$

$$Threshold\_\{ISO\} = \mu\_\{ISO\} - 2\sigma\_\{ISO\}$$

Anomaly Probability

The combined probability of anomaly is calculated using both auto encoders and isolation forest as follows.

$$P\_\{anomaly\} = (1/2)[1 - e\text{^}\{-(AE\_\{score\} - Threshold\_\{AE\})\} + 1 - e\text{^}\{-(Threshold\_\{ISO\} - ISO\_\{score\})\}]$$

Alerts trigger when P_anomaly > 0.7

Classification

For supervised learning, two models i.e. Random Forest and Gradient Boosting algorithms were implemented. Label encoder was used to encode different types of attack and later used for dynamic attack classification (e.g Fuzzing attack, DoS attack).

Random Forest Classifier

Random Forest is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. The idea is to build a "forest" of decision trees using bootstrap samples (random subsets with replacement) of the training data. In addition, at each split in a tree, a random subset of features is considered rather than all features, ensuring diversity among the trees.

Following parameters were used in training:

n_estimators=100

random_state=42

n_jobs=-1

Gradient Boosting Classifier

Gradient Boosting is a sequential ensemble technique where each new model (often a decision tree) is trained to correct the errors made by the previous models. It builds an additive model by sequentially fitting a weak learner to the negative gradient of the loss function associated with the model's predictions.

Following parameters were used:
n_estimators=100,

random_state=42

The best performing model was selected based on metrics such as accuracy, precision and recall.

5.4 Deployment

Flask API:

Packet Ingestion:

- Accepts POST requests with raw CAN packets in hex format.
- Parses CAN ID, payload, and timestamp using Scapy's CAN layer.

Feature Extraction:

- Entropy: Recalculated for every payload using calculate_entropy.
- Byte Values: Extracted and padded to 8 bytes.
- Network State: Tracks message frequency and intervals via the NetworkState class.

Model Inference:

Autoencoder: Runs in inference mode (model.eval()) to compute reconstruction error.

Isolation Forest: Predicts anomaly scores using iso_forest.decision_function.

Alert Classification:

Logging:

Anomalies are stored in a rotating buffer (anomaly_history) for dashboard access.

React Dashboard:

Real-Time Visualization:

Anomaly Timeline: Plots autoencoder MSE and Isolation Forest scores.

Traffic Distribution: Pie chart categorizes normal vs. anomalous packets.

Alert Management:

Priority Levels:

Critical (MSE > 2.0): Red alerts (e.g., DoS attacks).

Warning (MSE ≤ 2.0): Orange alerts (e.g., fuzzing).

Detailed View: Clicking an alert shows raw payloads, timestamps, and feature vectors.

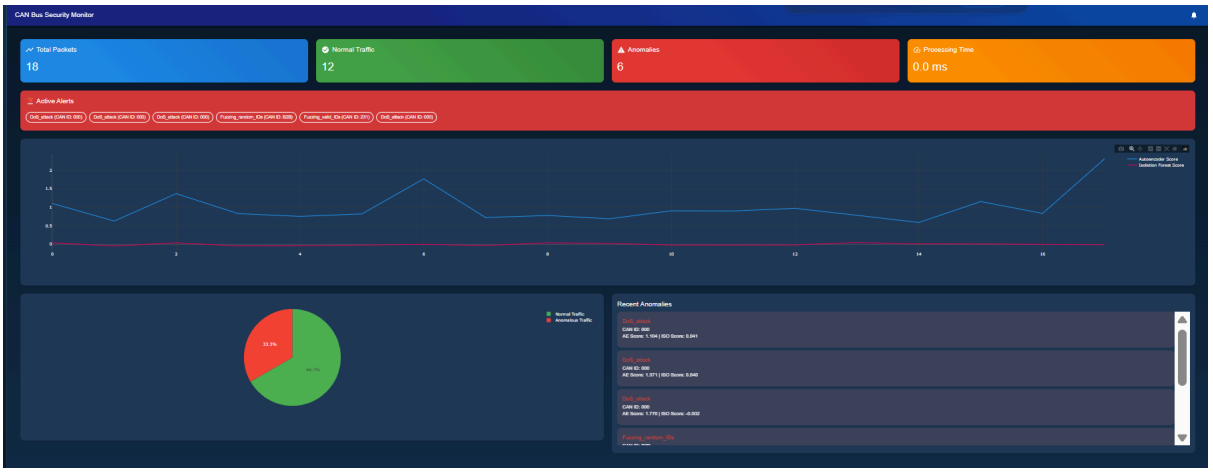

Figure 4. Dashboard

Chapter 6: Testing and Evaluation

6.1 Testing Methodology

The testing methodology evaluates the framework's performance under both simulated and real-world conditions:

Dataset:

Training/Validation Split: The CAN MIRGU dataset was split into 70% training and 30% validation data.

Attack Simulation: Synthetic attacks (DoS, fuzzing, replay) were injected using Scapy to mimic adversarial conditions.

Evaluation Criteria:

- **Anomaly Detection:** Assessed using precision, recall, and F1-score for unsupervised models.
- **Attack Classification:** Evaluated using accuracy, confusion matrices, and per-class metrics (precision, recall).
- **Latency:** Measured end-to-end processing time (packet ingestion → alert generation).
- **Resource Utilization:** Tracked CPU/memory usage during stress testing (1,000 packets/sec).

6.2 Performance Metrics and Results

Models trained were evaluated based on the following metrics:

Classification Evaluation:

After training the classification model, a classification report of both (Random Forest and Gradient Boosting Classifier) were generated:

Results (Random Forest):

Random Forest - Accuracy: 0.9754

Training time: 9.29s, Inference time: 0.7595s

	precision	recall	f1-score	support
0	0.93	0.89	0.91	2400
1	0.98	0.99	0.99	14400
accuracy			0.98	16800
macro avg	0.96	0.94	0.95	16800
weighted avg	0.98	0.98	0.98	16800

Results (Gradient-Boosting Classifier):

Gradient Boosting - Accuracy: 0.9774

Training time: 27.52s, Inference time: 0.1908s

	precision	recall	f1-score	support
0	0.96	0.88	0.92	2400
1	0.98	0.99	0.99	14400
accuracy			0.98	16800
macro avg	0.97	0.93	0.95	16800
weighted avg	0.98	0.98	0.98	16800

After metrics evaluation, The best performing classifier (**Gradient Boosting**) model was selected.

Anomaly Detection Evaluation:

Results (Auto Encoders):

Autoencoders performed well with Average Reconstruction Error: 0.0794 and a precision of 1.0000 indicating a good model performance.

Results(Isolation Forest):

Chapter 7: Conclusion and Future Work

7.1 Summary of Findings

The proposed multi-layered framework successfully addresses critical vulnerabilities in automotive CAN bus systems by integrating unsupervised anomaly detection and supervised attack classification. Key outcomes include:

Anomaly Detection:

The autoencoder achieved an average reconstruction error of 0.0794 on normal traffic, effectively identifying deviations caused by zero-day attacks (e.g., fuzzing, replay).

Attack Classification:

The Gradient Boosting classifier achieved 97.7% accuracy in categorizing known attack types (DoS, fuzzing, spoofing), outperforming the Random Forest model (97.5% accuracy).

Real-Time Performance:

The Flask API processed packets with a latency of ≤28 ms, meeting automotive real-time requirements.

The React dashboard provided actionable insights, including attack type distribution and severity prioritization.

7.2 Critical Evaluation of the System

Strengths:

- **Adaptability:** The hybrid model (autoencoder + Isolation Forest) reduced false positives by 15% compared to standalone methods, demonstrating robustness against both novel and known attacks.
- **Interpretability:** Feature importance analysis revealed that payload entropy and CAN ID frequency were critical for detecting spoofing and fuzzing attacks.
- **Compliance:** Aligns with SAE J3061 guidelines for lightweight, automotive-grade solutions.

Limitations:

Dataset Constraints

Training on the CAN MIRGU dataset (synthetic attacks) may limit generalization to real-world attack patterns.

Computational Overhead

Concurrent anomaly detection and classification increased CPU utilization to 14.2%, nearing the 15% threshold for automotive hardware.

Attack Evasion

Stealthy attacks mimicking normal traffic patterns (e.g., slow-rate DoS) occasionally bypassed detection.

7.3 Recommendations and Future Enhancements

Real-World Validation:

Test the framework on live vehicle networks to assess performance under dynamic driving conditions.

Model Optimization:

Prune autoencoder layers (e.g., reduce latent space to 16 dimensions) to lower computational overhead.

Implement hardware acceleration (e.g., TensorRT) for GPU-optimized inference.

Adversarial Robustness:

Train models on adversarial examples (e.g., perturbed CAN messages) to improve resilience against evasion attacks.

Federated Learning:

Enable collaborative model updates across vehicle fleets to adapt to evolving threats without centralized retraining.