AutoSentinel: Agentic AI Framework for Vehicle Fault Detection & Early Damage Prevention

IoT Project Phase 1 Review

Team D15

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Overview

Introduction

- **The Context:** Modern vehicles generate gigabytes of sensor data daily, yet diagnostic systems remain Reactive (e.g., "Check Engine" light only *after* failure).
- **The Innovation: AutoSentinel** is an **Agentic AI** framework that acts as a "Digital Mechanic."
- **Key Differentiator:** Unlike standard scanners, it analyzes **Trends** (rate of change) to predict failures before they hit critical levels.
- **Agentic Reasoning:** It leverages a Large Language Model (LLM) to translate complex numerical anomalies into plain English repair advice.

Overview

Project Objectives

1. **Universal Compatibility:** Develop a protocol-agnostic framework adaptable to both Internal Combustion (RPM-based) and Electric Vehicles (Voltage-based).

2. **True Prevention:** Shift from simple "Fault Detection" (Red State) to "Early Warning" (Yellow State) using mathematical slope analysis.

3. **Explainable AI:** Provide human-centric diagnostics (e.g., "Thermostat likely stuck") rather than cryptic error codes (P0128).

Overview

Literature Survey: Rahman et al.

Paper	A Secure and Intelligent Framework for Vehicle Health Monitoring Exploiting Big-Data Analytics
Publisher & Year	IEEE Transactions on Intelligent Transportation Systems, 2022
Technique	Proposed a central framework using IoE-driven Multi-Layer Heterogeneous Networks (HetNet) and machine learning for data handling.
Inference	• Integrates stakeholders, processes, and data via networked connections to oversee vehicle health. • Provides a taxonomy for secure data collection and analytics.
Cons	• Primarily a "conceptual framework" rather than a field-tested implementation. • Focuses on high-level architecture; lacks specific "Agentic" reasoning for driver interaction.

Literature Survey: Pérez-González et al.

Paper	An IoV-Based Real-Time Telemetry and Monitoring System for Electric Racing Vehicles
Publisher & Year	MDPI Vehicles, 2025
Technique	Integrated ESP32-based data acquisition with LoRaWAN communication and Node-RED for real-time visualization.
Inference	• Achieved 12% improvement in energy efficiency under race conditions. • Demonstrated sensor accuracy exceeding 95% and stable long-range transmission.
Cons	• Bandwidth limits of LoRaWAN restrict high-frequency signals (e.g., accelerometry). • Context is specific to racing; lacks Generative AI for general fault diagnosis.

Literature Survey: Weber, M.

Paper	Automotive OBD-II Dataset
Publisher & Year	Karlsruhe Institute of Technology, 2023
Technique	Comprehensive data logging of standard OBD-II PIDs (RPM, Speed, Throttle, Coolant Temperature) across various driving conditions.
Inference	• Provides a high-fidelity "Normal Baseline" essential for training unsupervised learning models. • Captures real-world noise and sensor fluctuations missing from simulations.
Cons	• Raw data resource only; contains no inherent anomaly detection logic. • Requires external processing (like our Isolation Forest) to extract meaning.

Overview

Problem Statement

The Problem

Vehicle diagnostics today are **Binary**: either "Good" or "Broken." There is no "Developing Fault" state.

Why this matters:

- **Safety:** A vibrating bearing is safe until it shatters at highway speeds.
- **Cost Efficiency:** Replacing a coolant hose ($20) is cheaper than replacing a warped engine head ($2000).
- **Accessibility:** Drivers cannot interpret raw sensor data (e.g., "Fuel Trim -25%") without expert knowledge.

Project Scope

In Scope (Included)

- Real-time analysis of standard OBD-II PIDs (RPM, Temp, Load).
- "Digital Twin" Simulation for Fault Injection.
- Preventive Trend Analysis (Slope Detection).
- Generative AI Diagnosis (Gemini API).

Out of Scope (Excluded)

- Automated mechanical repair (Actuation).
- Proprietary, encrypted manufacturer-specific data streams.
- Autonomous driving controls (Steering/Braking).

Overview

- **Layer 1: Perception (Data)**
  Ingests sensor data and applies **Z-Score Normalization** to make the system vehicle-agnostic.
- **Layer 2: Reflex (The Watchdog)**
  Uses an **Isolation Forest** for anomaly detection and a **Deque Buffer** for trend analysis (Prevention).
- **Layer 3: Reasoning (The Brain)**
  Sends anomalous context to the **LLM (Gemini)** to generate a "Mechanic's Report."

Overview

Progress So Far (60% Completion)

We have successfully completed the **Software Logic Core**:

- ✓ **Universal Data Pipeline:** Processed 100k+ rows of real driving data from the Weber OBD-II dataset.
- ✓ **Digital Twin Simulator:** Built a Python-based simulator to inject "Drifting Faults" (e.g., slow coolant leak) for safe testing.
- ✓ **Preventive Logic:** Implemented the "Yellow Warning." The system predicts overheating **20 seconds before** the critical limit.
- ✓ **Self-Healing Agent:** Implemented a fallback "Offline Brain" to ensure reliability even if the AI API fails.

Results: The "Matrix" Dashboard

Screenshot of our active CLI Prototype demonstrating Prevention:

```
T+15s | 2100   | 98.5C  | 0.30G |  WARNING: Rapid Temp Rise
T+16s | 2050   | 101.2C | 0.31G |  WARNING: Rapid Temp Rise

>>> TREND DETECTED. CONSULTING PREVENTIVE AI...
[PREVENTIVE ADVICE]: "Coolant temperature drift detected.
Likely thermostat failure. Reduce RPM immediately."
```

Key Result: The Agent flagged a fault at 98°C (Safe Zone) based on the *rate of change*, preventing the engine from reaching 115°C (Failure).

Overview

Challenges Risks

- **Universal Scaling:**
  Issue: A truck idles at 600 RPM, a bike at 1200 RPM. Hardcoded rules fail.
  Mitigation: Implemented Z-Score Standardization to track "Deviation from Normal" rather than raw numbers.

- **API Latency:**
  Issue: LLM calls take 1-2 seconds.
  Mitigation: We use a "Reflex Layer" (Isolation Forest) for instant safety checks, and only call the LLM for diagnosis.

- **Hardware Integration:**
  Issue: Bluetooth pairing stability with ESP32 in noisy environments.
  Mitigation: Using "Classic Bluetooth" libraries and buffering data on the Edge device.

Overview

Next Steps (Phase 2)

1. **Week 1-2: Hardware Deployment**
   Porting the Python logic to an ESP32 Microcontroller.

2. **Week 3: Physical Integration**
   Connecting the ELM327 Bluetooth Module to a real vehicle (College Bus/Personal Car).

3. **Week 4: GUI Upgrade**
   Moving from the CLI Terminal to a React/Streamlit Dashboard for the end-user app.

Overview

Conclusion

- **AutoSentinel** successfully shifts vehicle diagnostics from *Reactive* to *Preventive*.
- By combining statistical ML (Isolation Forest) with Generative AI, we provide a system that understands *context*, not just error codes.
- Phase 1 (Logic Simulation) is complete and validated.
- We are on track for Hardware implementation in the next phase.

Overview

References

📄 Md. Arafatur Rahman et al., *A Secure and Intelligent Framework for Vehicle Health Monitoring Exploiting Big-Data Analytics*, IEEE Transactions on Intelligent Transportation Systems, Vol. 23, No. 10, 2022.

📄 Andrés Pérez-González et al., *An IoV-Based Real-Time Telemetry and Monitoring System for Electric Racing Vehicles*, MDPI Vehicles, 2025, 7, 128.

📄 Marc Weber, *Automotive OBD-II Dataset*, Karlsruhe Institute of Technology, DOI: 10.35097/1130, 2023.

Overview

Questions?

Thank You