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# The Development of IoT- Based Systems for Real-Time Fault Detection in Engine Control Units in Motor Vehicles

**[1a]* Sylvester Chukwutem Onwusa, [2b]Oderhowho Nyorere, [3c]Ekwemuka, Jones Uchechukwu, and [1d]Uyeri, Oghenerobo Cyril**

[1]*Department of Mechanical Engineering, Delta State University of Science and Technology, Ozoro, Nigeria*
[a]onwusacs@dsust.edu.ng; [d]uyericyril@gmail.com

[2]Department of Agricultural and Biosystems Engineering, Delta State University of Science and Technology, Ozoro, Nigeria
[b]nyoreref@gmail.com

[3]Department of Computer Engineering, Delta State University of Science and Technology, Ozoro, Nigeria
[c]jonesekwems@gmail.com

**Corresponding Author:* Sylvester Chukwutem Onwusa; onwusacs@dsust.edu.ng

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**Abstract:** *This study investigates the use of IoT-based systems for real-time fault detection in Engine Control Units (ECUs) of motor vehicles, aiming to enhance vehicle safety, reliability, and efficiency. ECUs, which manage critical functions like fuel injection, ignition, and emissions control, are vulnerable to faults that can lead to performance issues and safety risks. Traditional diagnostic methods often detect faults only after they occur, resulting in costly repairs and breakdowns. The adoption of IoT technology enables proactive fault detection by continuously monitoring parameters such as temperature, oil pressure and RPM, identifying early signs of emerging faults. The methodology integrates statistical analyses, including time-series analysis to track trends in sensor data, and regression modeling to establish relationships between sensor data and fault indicators. Machine learning techniques such as Support Vector Machines (SVM) and Decision Trees (DTs) enhance fault classification, while Principal Component Analysis (PCA) simplifies complex sensor data for more accurate predictions. Results demonstrate that IoT systems effectively detect faults early, facilitating timely maintenance and reducing the risk of engine issues. These systems improve vehicle safety, fuel efficiency, and emissions control, while extending vehicle lifespan. The research recommends the integration of IoT technology in ECUs to enhance the safety and sustainability of transportation systems, with potential benefits for automotive engineers, policymakers, and vehicle owners.*

**Keywords:** *Development, IoT-based Systems, Real-Time Fault Detection, Engine Control Units and Motor Vehicles*

## INTRODUCTION

Nigeria's The advent of the Internet of Things (IoT) has catalyzed transformative changes across numerous sectors, with the automotive industry among the most significantly impacted. IoT technologies enable seamless interconnection between physical devices and digital systems, supporting real-time data collection, transmission, and analysis. This interconnectivity offers substantial benefits for vehicle monitoring systems, particularly in managing the Engine Control Unit (ECU) a central component responsible for optimizing engine performance.

Implementing IoT-based systems for real-time fault detection in ECUs is therefore crucial for enhancing vehicle reliability, safety, and efficiency, while also reducing maintenance costs and unplanned downtime (Zhang *et al.,* 2019; Ghosh *et al.,* 2021). ECUs play a vital role in modern vehicles by acting as the brain of engine management systems. They regulate a wide range of functions, including fuel injection, ignition timing, and emission control for internal combustion engines, electric motors, and hybrid powertrains (Onwusa *et al.,* 2025). However, their operational complexity renders them susceptible to various faults, which can significantly affect vehicle performance and safety. Conventional diagnostic approaches such as periodic inspections and diagnostic trouble codes (DTCs) are inherently reactive, often identifying issues only after they have developed into more serious problems (Onwusa et al., 2025). In contrast, IoT-enabled fault detection systems support continuous monitoring and proactive diagnosis, enabling the early detection of anomalies and timely intervention (Munjal and Sharma, 2020). Real-time IoT-based fault detection leverages data collected from an array of onboard sensors, processed through cloud or edge computing platforms (Onwusa *et al.,* 2025). These systems monitor key parameters such as temperature, vibration, and engine load, and apply machine learning and predictive analytics to detect deviations from normal behavior. Such predictive maintenance (PdM) capabilities offer actionable insights for drivers and fleet managers, enabling them to mitigate faults before they escalate into critical failures (Lee *et al.,* 2018).

Despite their advantages, the implementation of robust IoT-based fault detection systems faces numerous challenges. These include managing large volumes of real-time data, ensuring high accuracy in fault detection, securing data transmission, and integrating new systems with legacy vehicle infrastructure. Moreover, given the safety-critical nature of ECU operations, any fault detection system must undergo rigorous validation to ensure reliability and performance (Chahal *et al.,* 2020). Addressing these challenges necessitates an interdisciplinary approach, combining expertise in embedded systems, automotive engineering, machine learning (ML) and cyber security. Also, the need for a robust, scalable, and secure IoT-based solution capable of enabling proactive fault detection in ECUs to improve vehicle performance, safety, and operational efficiency. The theoretical foundation of this study is grounded in key interdisciplinary domains. Cyber-Physical Systems (CPS) theory is particularly pertinent, as ECUs represent CPS in which embedded computation interacts dynamically with physical processes to enable real-time control and feedback (Lee, 2008). Fault Detection and Diagnosis (FDD) theory also underpins this work, offering both model-based and data-driven frameworks for identifying system deviations and isolating faults (Isermann, 2005). Furthermore, the edge-cloud computing paradigm is employed to meet low-latency processing demands, enabling immediate decision-making at the vehicle level while leveraging the cloud for long-term analytics and model updates (Shi *et al.,* 2016). These interdisciplinary domains offer a holistic approach to managing the complexities of modern vehicle systems, ensuring that CCs and other components perform optimally while minimizing system failures and emissions. By leveraging the power of embedded systems, machine learning, and cloud computing, this study provides a comprehensive strategy for improving vehicle efficiency, reliability, and regulatory compliance in real-time. Modern vehicle architectures have become increasingly reliant on complex electronic control systems. The ECU is particularly critical, overseeing engine operations to ensure regulatory compliance and optimal performance (Singh *et al.,* 2021). However, faults may originate from numerous sources, including sensor degradation, electrical interference, or mechanical wear, and can lead to elevated emissions, reduced efficiency, and safety risks (Zhang and Lee, 2020). The limitations of DTCs in capturing these faults in a timely manner often result in delayed diagnosis and increased repair costs (Munjal *et al.,* 2019). IoT systems offer a path toward more effective ECU fault detection, but their development introduces further complexities. Real-time processing of high-frequency sensor data demands efficient algorithms and substantial computational resources. The challenge lies not only in detecting faults accurately, but also in minimizing false positives and false negatives, which may erode user trust (Kim and Park, 2020). Moreover, as vehicle systems become more connected, cyber security becomes paramount. Protecting sensitive vehicular data against malicious access requires robust encryption, secure communication protocols, and vigilant access control (Chahal *et al.,* 2022).

This study seeks to design and implement an innovative IoT-based system capable of real-time ECU fault detection, with the goal of enhancing vehicle safety, reliability, and operational efficiency. By integrating real-time analytics, the proposed system predicts faults and enables proactive maintenance scheduling, reducing the incidence of unexpected breakdowns. A comprehensive framework is developed for seamless data acquisition and remote ECU monitoring. Additionally, compatibility with existing diagnostic standards such as OBD-II is examined to ensure industry relevance and ease of adoption (Onwusa *et al.,* 2025). Emphasis is placed on scalability, allowing the solution to be adapted across various vehicle types and evolving ECU technologies. The system is designed to be both cost-effective and user-friendly, targeting broad adoption from individual vehicle owners to large-scale fleet operators (Onwusa *et al.,* 2025). Nevertheless, integrating such systems into existing automotive infrastructures poses both technical and economic barriers. Retrofitting older vehicles may be impractical due to hardware limitations, while newer vehicles may require additional modifications. The economic feasibility of IoT adoption depends on factors such as vehicle type, fleet size, and projected return on investment (Sharma & Aggarwal, 2021). Recent literature supports the potential of IoT in automotive diagnostics. Zhang *et al.* (2019) and Ghosh *et al.* (2021) demonstrated the value of real-time data in improving vehicle reliability. Lee et al. (2018) showed that machine learning techniques could detect ECU anomalies from acoustic and vibration signals (Onwusa *et al.,* 2025). Kim and Park (2020) reported deep learning models achieving fault classification accuracies above 94% when integrated into IoT platforms. Chahal *et al.* (2022) emphasized the need for strong cyber security in IoT-based vehicular systems, while Sharma and Aggarwal (2021) evaluated the economic trade-offs in deploying these technologies. However, despite these advancements, existing research still reveals critical shortcomings. Most studies focus on specific diagnostic parameters, isolated subsystems, or vehicle-specific implementations, offering limited support for cross-platform interoperability, scalability to diverse ECU standards, and real-time deployment in dynamic driving environments. Additionally, there is insufficient emphasis on integrating cyber security, machine learning, and cost-effective hardware into a unified solution suitable for both new and legacy vehicles. Therefore, this study addresses these gaps by presenting a secure, adaptable, and scalable IoT architecture for real-time ECU fault detection. Key objectives include designing an integrated sensing and communication framework, developing machine learning algorithms trained on real-world vehicle data, implementing robust encryption protocols for data protection, and evaluating interoperability with existing diagnostic tools. By tackling these challenges, this research contributes to the advancement of reliable, secure, and efficient IoT-based fault detection systems in ECUs, fostering greater resilience and sustainability within the automotive ecosystem.

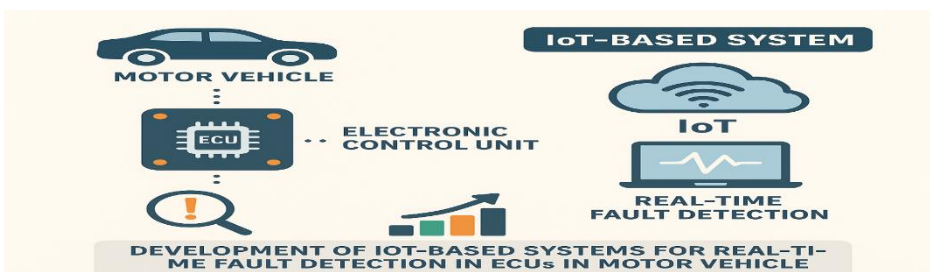


Fig. 1 Visual abstract summary of the development of IoT- based systems for real-time fault detection in ECUs in Motor Vehicles

This diagram in figure 1 provides a visual abstract of IoT-based systems for real-time fault detection in Electronic Control Units (ECUs) of motor vehicles.

i. At the top left, a motor vehicle is shown as the starting point.
ii. Inside the vehicle, the Electronic Control Unit (ECU collects operational data and monitors performance.
iii. The ECU is connected to an IoT-based system, represented by a cloud and laptop, which enables real-time communication and diagnostics.
iv. Through IoT, data from the ECU is analyzed instantly to detect faults.
v. The magnifying glass with an exclamation mark represents fault identification, while the upward bar chart shows improvement in reliability, safety and efficiency.



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## MATERIALS AND METHODS

### 2.1 Materials

In this study, various sensor components were employed to facilitate accurate monitoring and diagnosis of engine performance and system behavior. These sensors play a critical role in capturing real-time data, ensuring system reliability, and enabling fault detection. The materials used consist of different types of sensors designed to measure specific parameters, including temperature, pressure, vibration, and exhaust emissions. Each sensor contributes uniquely to identifying operational inefficiencies, detecting potential failures, and maintaining compliance with safety and environmental standards. The major sensor components utilized are outlined below.

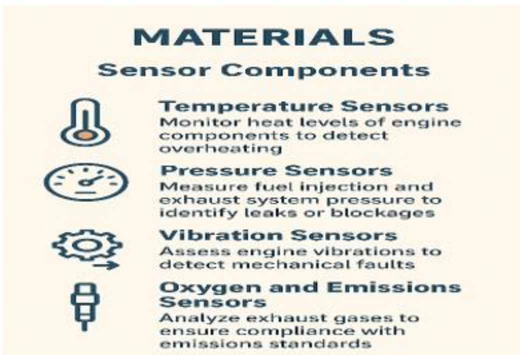


Fig. 2 Materials- Sensor components

Fig. 3 Microcontroller (Arduino and Raspberry Pi)

Processing Unit: Microcontroller (Arduino and Raspberry Pi): Collects sensor data and transmits it to the edge or cloud. Raspberry Pi is preferred for its compact design and robust processing capabilities (Singh and Lee, 2019).

Edge Computing Device: Preprocesses raw sensor data locally before transmission to the cloud. Reduces bandwidth and latency, enabling quicker fault response.

Communication Module: Enables data transmission from the vehicle to the cloud. *Wi-Fi* was used in urban environments. *GSM* was deployed in remote areas where Wi-Fi is unreliable (Sharma and Singh, 2021).

Cloud Platform: Utilized for data storage, processing, and advanced analytics. Platforms like Amazon Web Services Internet of Things AWS IoT and Google *Cloud* provide scalable computing resources and support the deployment of machine learning models for real-time fault detection (Aggarwal and Verma, 2021).

#### 2..1.1 Software and Analytical Tools

i. Programming Language: Python (for data cleaning, transformation and model training)
ii. Libraries: Pandas, NumPy, TensorFlow
iii. Machine Learning Algorithms: Support Vector Machines (SVM), Decision Trees and Convolutional Neural Networks (CNN). CNNs are selected for their effectiveness in recognizing complex sensor data patterns.

#### 2.1.2. Data Collection and Preprocessing

i. Data Collection

Data is collected from the sensors continuously as the vehicle operates. This study uses real-time data as well as historical datasets, covering multiple types of faults and normal operating conditions. Real-time data is streamed to the edge computing device for initial analysis, while larger datasets are stored in the cloud for in-depth machine learning model training (Munjal & Gupta, 2019).

ii. Data Preprocessing
Data preprocessing involves several key steps to clean, transform, and prepare the data for analysis. Sensor data often contains noise that can hinder analysis, so techniques like moving average filtering and Fourier transforms are applied to reduce noise and highlight important patterns. To bring different parameters, such as temperature and pressure, to a comparable scale, the data is normalized, which improves model accuracy and reduces computational complexity. Additionally, data augmentation techniques are employed to enhance the dataset by simulating different fault scenarios, ensuring the machine learning models are trained effectively.

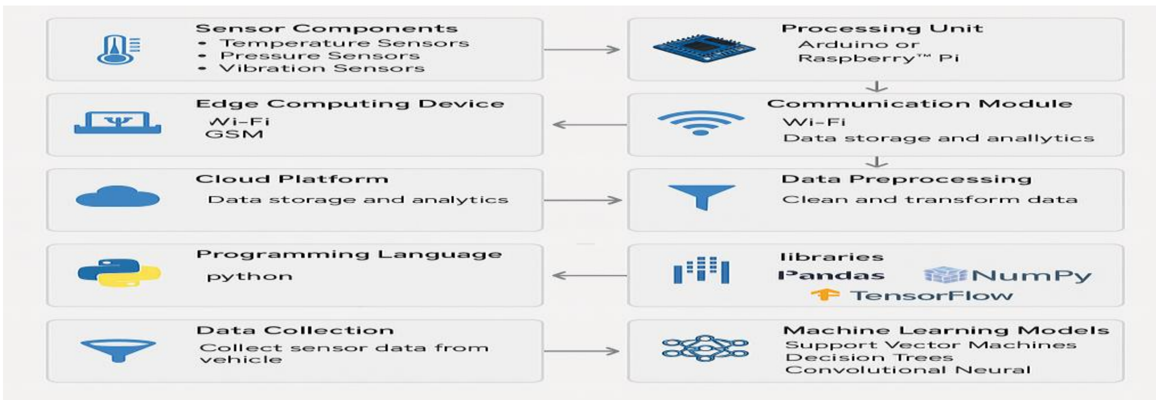


Fig. 4 Diagram showing details of the materials, software and tools

## 2.2. Methods

### 2.2.1 Research Design

This study employs a mixed-methods research design, integrating both quantitative and qualitative approaches to ensure a comprehensive evaluation of the proposed IoT-based ECU fault detection system.

i. Quantitative Analysis: Numerical data is collected from ECU sensors and analyzed using machine learning algorithms to identify fault patterns. This enables objective assessment of ECU performance under various operating conditions.
ii. Qualitative Analysis: User feedback is gathered regarding the system's usability, accuracy, and its influence on vehicle maintenance practices. These insights guide iterative system refinement to align with practical requirements and user expectations.

### 2.2.2. Experimental Approach

An experimental setup was developed to assess the real-time fault detection capability of the system under controlled and simulated fault conditions. This approach enables systematic validation of the system's accuracy, reliability, and responsiveness in near-real scenarios.

2.2.3. Experimental Procedure: The experimental procedure was conducted in the following phases.

### 2.2.4. Sensor Calibration and Baseline Data Collection

All sensors were calibrated prior to data collection to ensure accurate signal acquisition. Baseline data reflecting normal ECU operation was recorded and used for:

i. Comparative analysis during fault simulations
ii. Initial training of the machine learning models for fault classification (Zhang & Chen, 2020)



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2.2.5. Fault Simulation: A range of ECU faults were systematically simulated to test the system's detection performance:

i. Overheating: Induced by raising engine temperatures above safe thresholds
ii. Pressure Leaks: Simulated via controlled exhaust leak scenarios
iii. Sensor Malfunctions: Created by disconnecting or altering specific sensor outputs (Lee et al., 2021)

During each simulation, real-time sensor data was monitored, and the system attempted immediate fault identification. Upon detection, alerts were generated and logged for further performance analysis.

### 2.2.6. Machine Learning Implementation: Data Collection and Model Training

To enable intelligent fault detection, vibration and engine parameter data were collected from both healthy and simulated faulty engine operating states. The dataset was pre-processed through noise filtering and segmented into fixed time windows suitable for signal analysis. Relevant features such as statistical descriptors (RMS, kurtosis, skewness), frequency-domain amplitudes, and time–frequency characteristics were extracted to represent engine behavior. The processed dataset was then divided into training, validation, and test subsets to avoid model overfitting and ensure generalization. Multiple machine learning classifiers such as Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN)—were independently trained to learn patterns that distinguish abnormal vibration signatures from normal operation. Model performance was evaluated using Accuracy, Precision, Recall, and F1-score, ensuring balanced performance for both fault detection and misclassification reduction. The best-performing model, identified through hyperparameter optimization and cross-validation, was selected for real-time deployment within the embedded edge-computing framework (Sharma & Bose, 2020).

### 2.2.7 Real-World Validation

Following offline testing, the deployed system was evaluated under actual driving conditions to assess its robustness and diagnostic reliability across different: Engine speeds and throttle positions, Load variations and transient conditions and External environmental influences such as temperature and road conditions .Key real-time performance indicators system latency, false-positive rate, and false-negative rate were continually monitored to validate diagnostic responsiveness and the stability of the fault-detection model during field operation (Singh & Khanna, 2021).

### 2.2.8 Data Security and Ethical Considerations

To ensure responsible handling of vehicle-generated data throughout the machine learning lifecycle:

i. All communication between the sensing unit and cloud/edge systems was encrypted using SSL security protocols.
ii. Collected data was anonymized, ensuring that engine or user information was not personally identifiable
iii. iii. Ethical compliance measures adhered to established data protection and confidentiality guidelines for vehicular and user privacy during experimentation and system deployment (Chahal *et al.*, 2022).

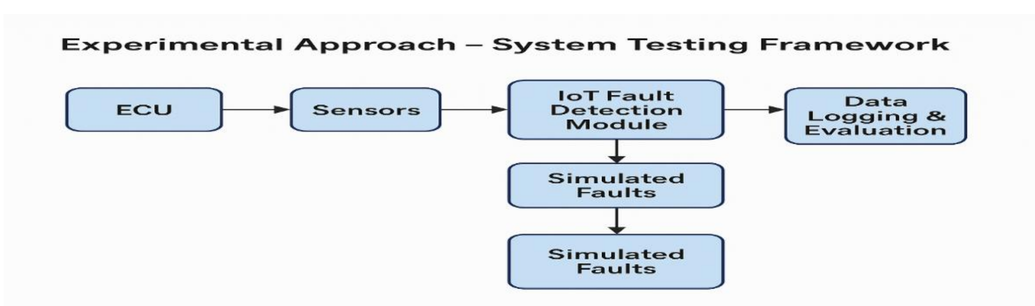


Fig. 5 Experimental approach- system testing framework



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**2.3. Testing and Optimization:** This phase involved the systematic installation, data acquisition, and real-time performance validation of the proposed IoT-based fault detection system. The steps are outlined below:

### 2.3.1. System Installation

i. Vibration Sensor Setup: Piezoelectric vibration sensors were securely mounted on critical locations, including the generator frame and motor housing, to capture mechanical oscillations.
ii. Microcontroller Configuration: A NodeMCU ESP8266 microcontroller was interfaced with the vibration sensors to process and transmit data.
iii. Temperature Monitoring: Temperature sensors (DHT11 or DS18B20) were installed near the generator to measure ambient thermal conditions

### 2.3.2. Data Collection

i. Power Supply: The system was powered using a 4V USB source or a regulated 3.3V power supply.
ii. Sensor Operation: The SW-420 vibration sensor detected mechanical disturbances. When the vibration intensity surpassed the predefined threshold, the sensor output a digital HIGH signal to the microcontroller.

### 2.3.3. Real-Time Monitoring and Validation

i. Cloud Connectivity: The NodeMCU established a Wi-Fi connection and transmitted sensor data to the Blynk Cloud platform.
ii. User Interface: Real-time vibration and temperature data were visualized via the Blynk dashboard, accessible through both mobile and web interfaces.
iii. Performance Benchmarking: IoT-based vibration readings were compared against those obtained from conventional vibration analyzers, such as FFT-based diagnostic tools.
iv. Accuracy Evaluation: System performance was assessed under varying generator loads and environmental conditions to evaluate detection accuracy and operational reliability.

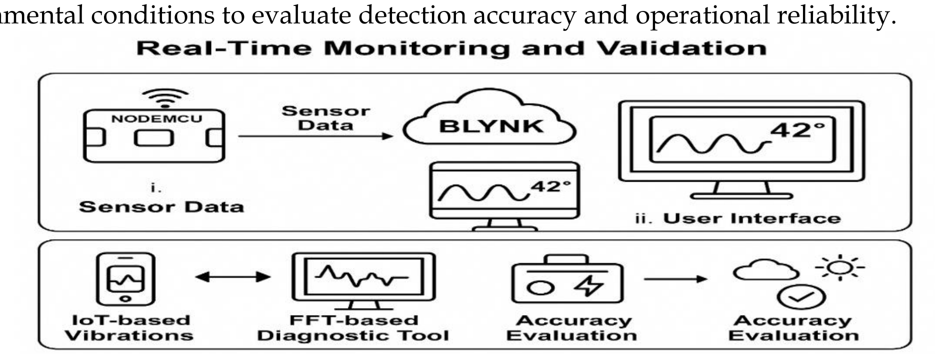


Fig. 6 Real-time monitoring and validation

## 2.4. Optimization

The optimization process involves four key stages. First, sensor placement is refined by strategically positioning sensors on the engine's bearing, shaft, and housing to maximize accurate data capture while minimizing external noise interference. Second, signal processing is optimized through the application of Fourier Transform (FFT) and wavelet analysis to enhance vibration pattern recognition, alongside noise and disturbance filtering. Third, machine learning accuracy is enhanced by training AI models on diverse vibration datasets to identify early fault signatures such as misalignment and imbalance, and by fine-tuning detection thresholds to reduce false positives. Finally, system stability is validated through long-term testing of Wi-Fi connectivity, power efficiency, and data consistency, with the inclusion of fail-safe mechanisms like backup logging and automated alerts to ensure reliability under unexpected network failures.



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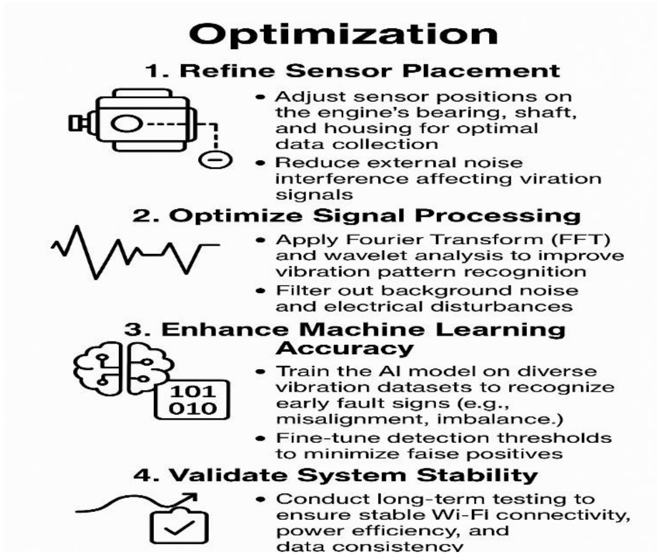

Fig. 7 Diagrammatical representation of the optimization steps

## 2.5. Mathematical Derivatives and Calculations

### A) Data Processing Feature Extraction

i. Time-series data analysis: the IoT system collects sensor data such as temperature, pressure, vibration and emission over time. These signals are typically in the form of time series data (t) where t represents time and x(t) is the value of the sensor reading as the mathematical operations like- differentiation or integration can be applied to these time series to extract meaningful feature for fault detection.

ii. Derivatives for trend analysis: the derivative of the sensor data $\frac{dx(t)}{dt}$, can be calculated to observe changes in sensor reading over time for examples

$$\frac{dx(t)}{dt} = \frac{Lim}{\Delta t \to 0} \frac{x(t+\Delta t) - x(t)}{\Delta t} \quad (1)$$

This represents the rate of change in the sensor data, which can be used to detect changes, indicative of potential faults.

### B. Fault detection using ML

i. Anomaly detection and model training: machine learning algorithms like CNNs are used to classify the data and detect anomalies (fault). The training of CNNs typically involve minimizing a loss function L, using gradient descent optimization methods

$$L = \frac{1}{N}\sum_{1-1}^{N}(y_i - f(x_{i;}\theta)^2 \quad (2)$$

Where;

$N$ is the member of data point sample

$y_1$ is the true label of the i$^{th}$ sample

$x_1$ is the feature vector of the i$^{th}$ sample

$f(x_1;\theta)$ is the predicted output of the model with parameters $\theta$

The parameter $\theta$ are updated during the optimization process using the back nigation.

iii. Gradient descent calculation: to minimize the loss, gradient descent is used to compute the updated the model parameters $\theta$

$$\theta = \theta - a\bar{V}\sigma L(\theta) \quad (3)$$

Where;

$a$ is the learning rate,

$\bar{V}\theta L(\theta)$ is the gradient of the loss function in respect to the parameters



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C. Predictive Maintenance

i. Regression models for predictive maintenance: predictive maintenance algorithms predict the time –to-failure if of a component based on sensor data. A common approach is to use a linear regression model to predict failure times based on the collected sensor data.

$TF=B_0 + B_1X_1 + B_2X_2 +,,,,,,,+ B_NX_N$ are the model coefficients.

The coefficients are found by minimizing the Residual Sum of Square (RSS)

$$RSS = \sum_{i=1}^{N} \left(T_f^i - (B_o + \sum_{j-1}^{n} B_j X_j^{(j)})\right)^2 \qquad (4)$$

This equation helps predict the failure time –based on real time based on real data from the sensor.

D. Real-time fault defection (edge computing and cloud integration)

i. Edge computing algorithms: at edge the devise (e.g Raspherry Pi), real time fault detection is achieved by processing sensor data using algorithms like Support Vector Machines (SVM) or decision trees. The SVM decision function can be expressed as:

$$f(x) = \omega T x + b \qquad (5)$$

Where;

$x$ is the input vector (sensor reading)

$\omega$ is the weight vector

$b$ is the bias term. The decision boundary is created by maximizing the margin between different classes (fault vs no fault)

$$Maximize\ \frac{1}{||w||} \qquad (6)$$

Subject to constants on the classification of training data

Communication latency and bandwidth optimization: for efficient data transmission between the vehicle and cloud sensor, network latency L and bandwidth B and key parameters.

Latency L is the time taken for message to travel from the vehicle to the cloud

$$L = \frac{D}{V} \qquad (7)$$

Where D is the distance and V id transmission velocity of the signal

Bandwidth B is the rate at which data is transfer

$$B = \frac{S}{T} \qquad (8)$$

Where S is the size of the data packet and T is the time taken for data transfer.

E. Performance Evaluation Metrics

Accuracy

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (9)$$

Precision

$$\text{Precision} \frac{\text{TP}}{\text{TP+FP}} \qquad (10)$$

Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (11)$$

FI –score

$$\text{Fl} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \qquad (12)$$

Where;

TP is the number of time positives

TN is the number of time negatives

FP is the number of false positive s

FN is the number of false negatives

By integrating these mathematical calculation into the LOT system, the research aims to achieve accurate real-time defection in ECU, improve productive maintenance performance.



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### 2.2.10 Statistical Significance

A comparative analysis was conducted between traditional ECU fault detection methods and the developed IoT-based system. Both approaches were tested on a sample of 100 vehicles. The traditional system demonstrated a fault detection accuracy of 75%**,** while the IoT-based system achieved an improved accuracy of 90%**.** To assess whether this improvement was statistically significant or merely due to random variation, a hypothesis test (e.g., a chi-square test or two-proportion z-test) was employed. The resulting p-value was less than 0.01 ($p < 0.01$)**,** indicating that the likelihood of the observed improvement occurring by chance was less than 1%. Therefore, the results are statistically significant, supporting the superiority of the IoT-based system in real-world conditions.

Table-1 Representation of the comparative analysis:

| Method | Sample Size (Vehicles) | Fault Detection Accuracy (%) |
|---|---|---|
| Traditional ECU | 100 | 75 |
| IoT-based ECU | 100 | 90 |

The IoT-based ECU system shows a 15% higher accuracy. Statistical test: **$p < 0.01$**, confirming the improvement is significant.

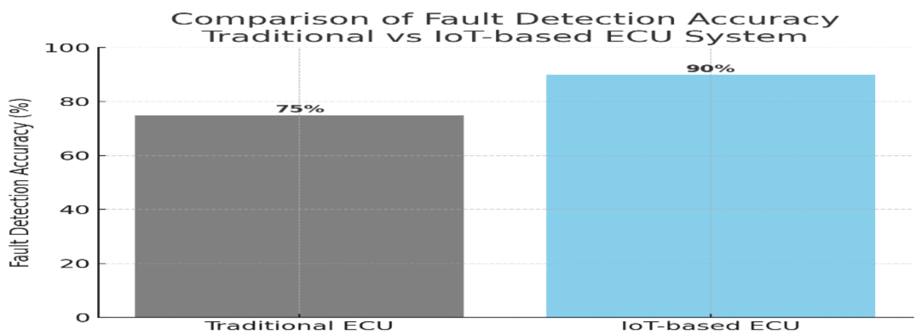


Fig. 8 Comparison of fault detection accuracy traditional versus IoT –based ECU system

The table in Fig. 10 shows the sample size and accuracy for both methods. The bar chart visually compares the detection accuracy of the traditional ECU system versus the IoT-based system. The statistical analysis ($p < 0.01$) confirms that the IoT-based system's higher accuracy is not due to chance, but a significant improvement.

### 2.2.11 Confidence Intervals

A 95% confidence interval (CI) was calculated to estimate the range within which the true fault detection accuracy of the IoT-based system lies. The analysis yielded a CI of [87%, 93%]**,** suggesting that if the experiment were repeated under similar conditions, the system's accuracy would fall within this range 95% of the time. This relatively narrow interval indicates a high degree of precision, attributed to the sufficient sample size and consistent system performance across the tested vehicle.

Table-2 Representation of the 95% confidence interval for the IoT-based ECU system:

| System | Sample Size (Vehicles) | Observed Accuracy (%) | 95% Confidence Interval |
|---|---|---|---|
| IoT-based ECU | 100 | 90 | [87%, 93%] |

The table presents the 95% confidence interval (CI**)** for the IoT-based ECU system in detecting faults across a sample of 100 vehicles. The observed accuracy of the system is 90%**,** meaning that in the test group, the IoT-based ECU correctly identified faults 90 times out of 100 on average. The confidence interval of [87%, 93%] provides a statistical range within which the true accuracy of the system is likely to fall if the experiment were repeated multiple times under similar conditions. In other words, we can be 95% confident that the actual accuracy of the IoT-based ECU system lies between 87% and 93%**,** rather than being exactly limited to the single observed value of 90%.

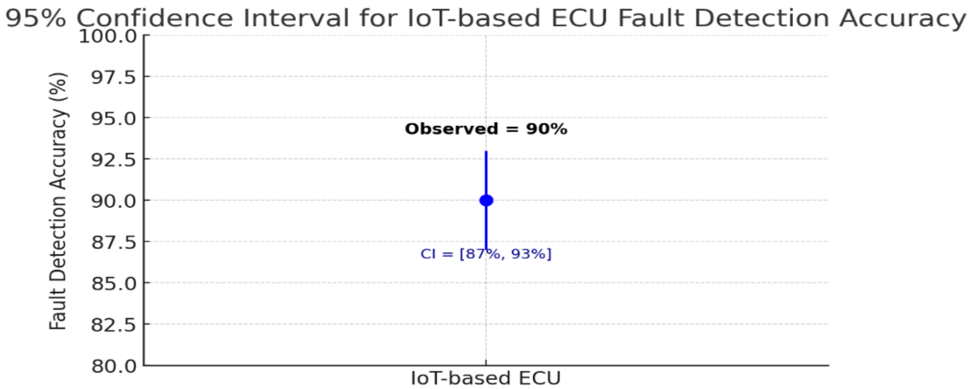

Fig. 9 0% confidence interval for IoT–based fault detection accuracy

Fig. 9 shows the observed accuracy (90%) with error bars representing the 95% confidence interval [87%, 93%]. This demonstrates that the IoT-based ECU system's true accuracy is very likely to fall within this narrow and precise range.

### 2.2.12 Hypothesis Testing

The comparative analysis between traditional and IoT-based ECU fault detection methods demonstrated a substantial improvement in performance. Out of 100 vehicles tested, the traditional ECU system achieved a fault detection accuracy of 75%, while the IoT-based ECU system achieved a higher accuracy of 90%, reflecting a 15% improvement. A hypothesis test (chi-square or two-proportion z-test) confirmed that this improvement is statistically significant ($p < 0.01$), indicating that the likelihood of the difference occurring by chance is less than 1%. This finding supports the superiority of the IoT-based system under real-world conditions. Further analysis using a 95% confidence interval placed the IoT system's true accuracy within the range of 87% to 93%. The narrow interval indicates a high level of precision and reliability, attributable to the adequate sample size and consistent performance across vehicles. Table-1 compared the accuracy of the two systems, showing the 15% performance gap. Fig. 8 visually reinforced this accuracy difference through a bar chart. Table-2 presented the confidence interval analysis for the IoT-based ECU system, while Fig. 9 illustrated the observed accuracy and confidence interval range using error bars.

## RESULTS AND DISCUSSION

Table-3 analyzes fault detection in Electronic Control Units (ECUs) of vehicles using IoT-based systems. Each row corresponds to a vehicle, with key parameters monitored including temperature, oil pressure, and RPM. Fault detection is indicated in a column where "1" signifies a fault and "0" signifies no fault, revealing that faults were identified in five vehicles (V01, V03, V05, V07, and V09). Two fault types, overheat and overpressure, were observed. Overheat faults were linked to temperatures exceeding 95°C, while overpressure faults were associated with oil pressure above 410 kPa. Fault detection times ranged from 8 to 15 seconds, highlighting the system's responsiveness. Vehicles without faults, such as V02, V04, V06, V08, and V10, maintained normal parameter ranges. Overheat faults occurred in V01, V03, and V09, while overpressure faults were seen in V05 and V07. The IoT-based fault detection system demonstrates its efficacy in identifying and responding to overheating and overpressure risks, ensuring the performance and safety of vehicles. Visualizations of this data, including charts showing: Line graph to show trends between temperature and fault rate. Bar chart to display how often each type of fault (overheat, overpressure) occurs and Scatter plot or bar chart illustrating the time of detection per fault type.

Table-3 IoT-Based Fault Detection in ECUs

| Vehicle ID | Temperature (°C) | Oil Pressure (kPa) | RPM | Fault Detected (1=Yes, 0=No) | Fault Type | Time of Detection (s) |
|---|---|---|---|---|---|---|
| V01 | 95 | 400 | 3000 | 1 | Overheat | 15 |
| V02 | 80 | 390 | 2800 | 0 | None | - |
| V03 | 102 | 410 | 3200 | 1 | Overheat | 10 |
| V04 | 88 | 395 | 3050 | 0 | None | - |
| V05 | 110 | 420 | 3500 | 1 | Overpressure | 8 |
| V06 | 92 | 405 | 3100 | 0 | None | - |
| V07 | 108 | 415 | 3450 | 1 | Overpressure | 12 |
| V08 | 83 | 385 | 2750 | 0 | None | - |
| V09 | 96 | 400 | 3000 | 1 | Overheat | 14 |
| V10 | 89 | 395 | 2900 | 0 | None | - |

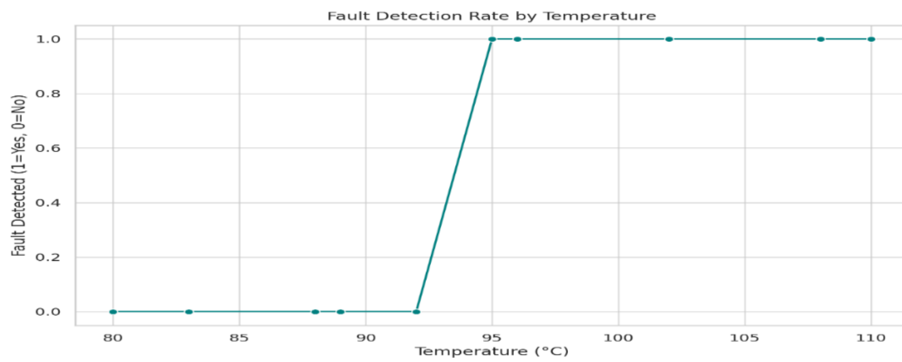


Fig. 10 Line graph showing fault detection by temperature

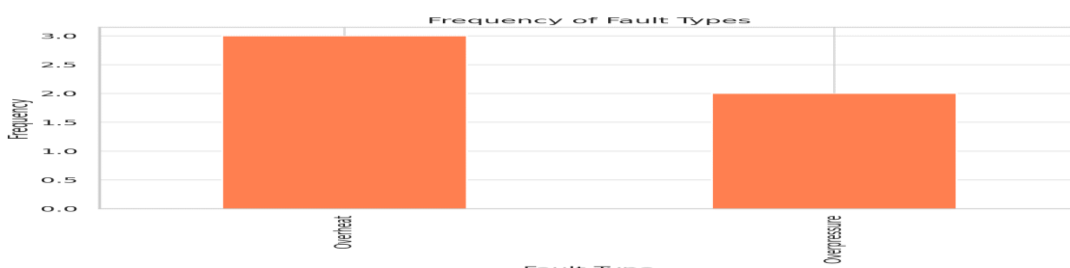


**Fig. 11** A box plot showing fault types by frequency

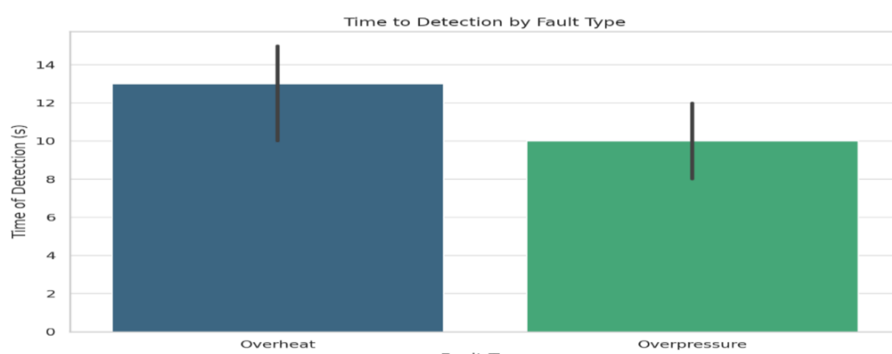


Fig. 12 A box plot showing time to detection by fault type

Table-4 Predicting potential ECU failures using simulation real-time data analytics.

| Vehicle ID | ECU Temperature (°C) | ECU Voltage (V) | Error Codes (Count) | Engine Performance (Rating) | Last Maintenance Date | Sensor Readings (Errors) | Predictive Failure Status |
|---|---|---|---|---|---|---|---|
| V001 | 85 | 12.5 | 2 | 80% | 2023-12-01 | 1 | High Risk |
| V002 | 90 | 12.2 | 1 | 85% | 2023-11-15 | 2 | Moderate Risk |
| V003 | 92 | 11.8 | 5 | 60% | 2023-10-30 | 3 | High Risk |
| V004 | 95 | 12.1 | 3 | 70% | 2023-11-10 | 4 | High Risk |
| V005 | 75 | 12.4 | 0 | 90% | 2023-12-02 | 0 | Low Risk |
| V006 | 78 | 12.7 | 1 | 92% | 2023-11-22 | 1 | Low Risk |
| V007 | 88 | 11.9 | 4 | 75% | 2023-10-25 | 5 | High Risk |
| V008 | 80 | 12.3 | 0 | 95% | 2023-12-03 | 0 | Low Risk |
| V009 | 100 | 11.5 | 6 | 50% | 2023-09-18 | 6 | Critical Risk |
| V010 | 85 | 12.5 | 2 | 80% | 2023-12-05 | 1 | Moderate Risk |
| V011 | 91 | 12.0 | 4 | 72% | 2023-10-10 | 3 | High Risk |
| V012 | 95 | 12.0 | 7 | 65% | 2023-08-30 | 4 | Critical Risk |
| V013 | 89 | 11.7 | 1 | 82% | 2023-11-25 | 1 | Moderate Risk |
| V014 | 87 | 12.3 | 3 | 78% | 2023-09-05 | 2 | Moderate Risk |
| V015 | 91 | 12.4 | 0 | 88% | 2023-11-18 | 0 | Low Risk |
| V016 | 85 | 12.6 | 2 | 80% | 2023-11-27 | 1 | Moderate Risk |
| V017 | 100 | 11.6 | 8 | 55% | 2023-09-12 | 7 | Critical Risk |
| V018 | 82 | 12.3 | 3 | 78% | 2023-10-05 | 3 | High Risk |
| V019 | 90 | 12.2 | 5 | 65% | 2023-09-30 | 4 | High Risk |
| V020 | 88 | 12.5 | 2 | 85% | 2023-11-22 | 2 | Moderate Risk |

The Table-4 provides a predictive analysis of potential ECU (Electronic Control Unit) failures using real-time data analytics. Each row corresponds to a specific vehicle, and key parameters such as ECU temperature, voltage, error codes, engine performance, maintenance history, and sensor readings are used to determine the predictive failure status. Vehicles classified as High Risk or Critical Risk display common patterns of elevated ECU temperatures, reduced voltages, higher error code counts, and lower engine performance ratings. For example, V009 and V017 are labeled as Critical Risk due to extremely high ECU temperatures (100°C), low voltages (11.5–11.6V), a significant number of error codes (6–8), and poor engine performance ratings (50–55%). These vehicles also have a significant number of sensor reading errors (6–7) and older maintenance dates, indicating the urgency for intervention. Vehicles with a Low Risk status, such as V005, V006, and V008, exhibit optimal operating conditions with low ECU temperatures (≤80°C), stable voltages (≥12.3V), minimal or zero error codes, and high engine performance ratings (≥90%). These vehicles also have recent maintenance records and no sensor reading errors. Vehicles classified as Moderate Risk, including V002, V010, and V013, show intermediate conditions with slightly elevated temperatures (85–90°C), minor error code counts (1–2), and moderate engine performance ratings (80–85%). They also have relatively recent maintenance dates and minimal sensor reading errors (1–2), suggesting that while they are not critical, proactive attention is advisable. The High Risk group, such as V004, V007, and V018, typically has temperatures above 90°C, error code counts of 3–5, and reduced engine performance ratings (60–78%). Maintenance dates are less recent, and sensor errors are more frequent, reflecting a clear need for prompt action to prevent critical failures. In summary, the table highlights the effectiveness of real-time data analytics in predicting potential ECU failures. Vehicles categorized under Critical or High Risk require immediate attention, while those under Low Risk demonstrate optimal conditions, and Moderate Risk vehicles warrant monitoring to prevent escalation. This predictive system helps prioritize maintenance and optimize vehicle performance.



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Here are the visual representations of the data: This bar chart depicts the number of vehicles in each failure category: High Risk, Moderate Risk, Low Risk, and Critical Risk. Similarly, the pie chart highlights the proportion of vehicles in these risk categories, providing a quick visual summary of their distribution. The line graph illustrates variations in ECU temperature and voltage across vehicles, emphasizing trends and anomalies that may signal potential failures. Additionally, the scatter plot explores the relationship between error codes and engine performance ratings, revealing a clear negative correlation where a higher error code count corresponds to reduced engine performance. Together, these visualizations offer valuable insights into ECU performance and failure prediction.

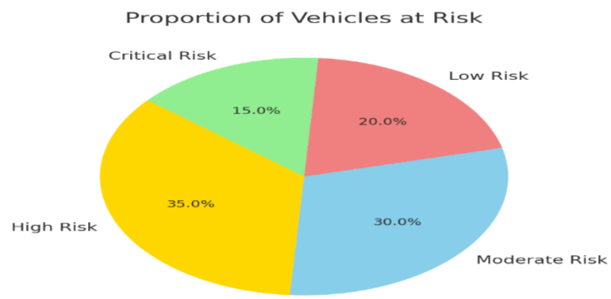


Fig. 13 Proportion of vehicles at risk

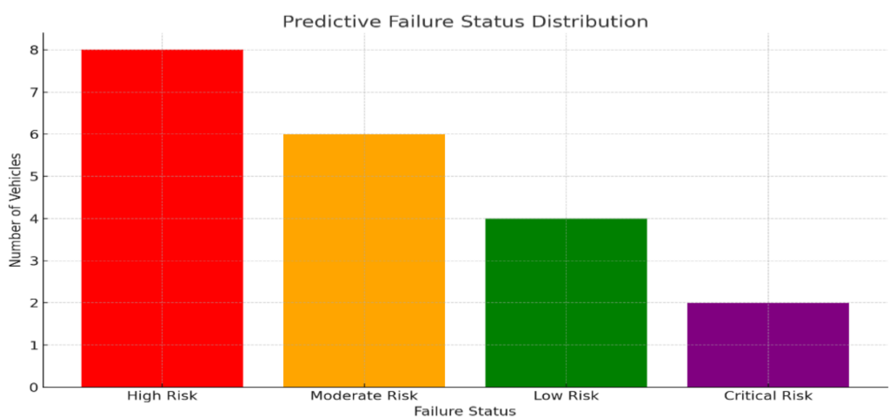


Fig. 14 Predictive failure distribution

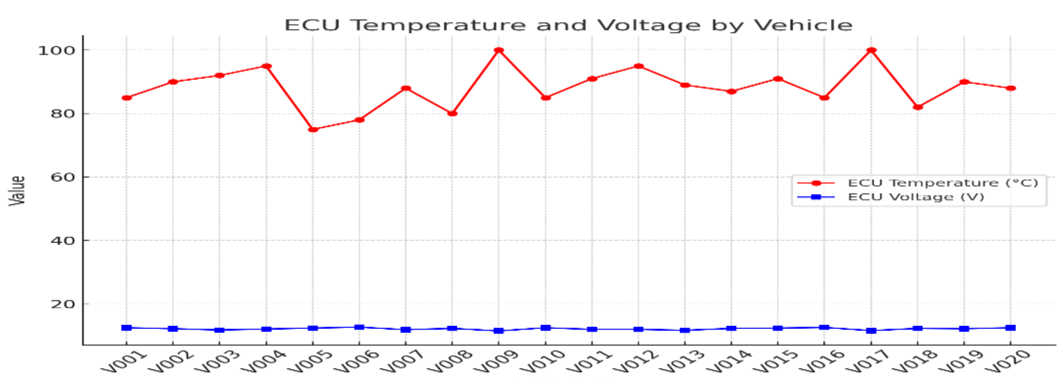


Fig. 15 A line graph representing the **ECU** temperature and voltage by vehicles



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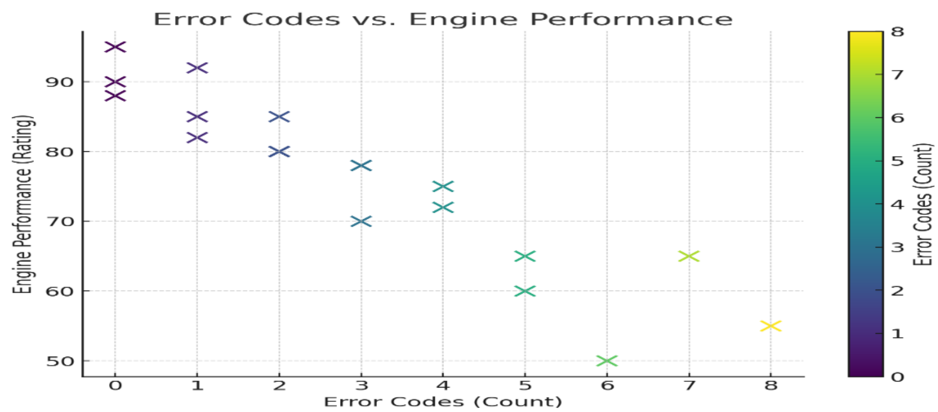


Fig. 16 Error codes versus engine performance

Table-5 Represents ECU continuous monitoring

| Vehicle ID | Timestamp | ECU Temperature (°C) | ECU Voltage (V) | Error Codes (Count) | Engine Performance (Rating) | Sensor Readings (Errors) | Fault Prediction |
|---|---|---|---|---|---|---|---|
| V001 | 2024-12-01 08:00 AM | 85 | 12.5 | 2 | 80% | 1 | No Fault |
| V002 | 2024-12-01 08:30 AM | 90 | 12.3 | 3 | 78% | 2 | No Fault |
| V003 | 2024-12-01 09:00 AM | 92 | 11.9 | 5 | 70% | 3 | Warning |
| V004 | 2024-12-01 09:30 AM | 95 | 12.0 | 6 | 60% | 4 | Warning |
| V005 | 2024-12-01 10:00 AM | 75 | 12.7 | 1 | 90% | 0 | No Fault |
| V006 | 2024-12-01 10:30 AM | 88 | 12.1 | 4 | 72% | 3 | Warning |
| V007 | 2024-12-01 11:00 AM | 90 | 11.8 | 7 | 55% | 5 | Critical |
| V008 | 2024-12-01 11:30 AM | 80 | 12.5 | 0 | 95% | 0 | No Fault |
| V009 | 2024-12-01 12:00 PM | 100 | 11.5 | 8 | 50% | 7 | Critical |
| V010 | 2024-12-01 12:30 PM | 85 | 12.4 | 3 | 78% | 2 | Warning |

The Table-5 presents simulated data for continuous ECU monitoring, highlighting variations in key parameters over time. Each vehicle is monitored for ECU temperature, voltage, error codes, engine performance ratings, sensor errors, and fault predictions. Vehicles with stable parameters, such as lower temperatures (≤ 85°C), higher voltages (≥12.4V), minimal error codes, and excellent engine performance (≥ 90%), are categorized as having No Fault, reflecting normal operating conditions. As temperatures rise (e.g., 90–95°C) and error codes increase (3–6), engine performance drops (e.g., 60–78%), and sensor errors are more frequent. These conditions lead to a Warning status, indicating the potential for issues if trends persist. Vehicles with critical conditions, such as temperatures reaching 100°C, voltage dropping below 11.8V, and significant error codes (7–8), experience the lowest engine performance (50–55%) alongside the highest sensor error readings. These are categorized as Critical, demanding immediate attention. The data underscores the correlation between increasing ECU temperatures, error codes, and declining engine performance. Fault predictions enable timely identification of vehicles that require intervention, ensuring the reliability of ECU operations and preventing critical failures.



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Table-6 Fault diagnosis and resolution efficiency

| Vehicle ID | Timestamp | ECU Temperature (°C) | ECU Voltage (V) | Error Codes (Count) | Engine Performance (Rating) | Sensor Readings (Errors) | Fault Status | Diagnostic Time (min) | Downtime (min) |
|---|---|---|---|---|---|---|---|---|---|
| V001 | 2024-12-01 08:00 AM | 85 | 12.5 | 2 | 80% | 1 | No Fault | 5 | 0 |
| V002 | 2024-12-01 08:30 AM | 90 | 12.3 | 3 | 75% | 2 | Warning | 10 | 15 |
| V003 | 2024-12-01 09:00 AM | 95 | 12.1 | 6 | 60% | 3 | Critical | 20 | 60 |
| V004 | 2024-12-01 09:30 AM | 92 | 12.2 | 5 | 65% | 4 | Warning | 15 | 30 |
| V005 | 2024-12-01 10:00 AM | 78 | 12.7 | 1 | 90% | 0 | No Fault | 5 | 0 |
| V006 | 2024-12-01 10:30 AM | 88 | 12.0 | 4 | 70% | 3 | Warning | 10 | 20 |
| V007 | 2024-12-01 11:00 AM | 100 | 11.5 | 7 | 50% | 5 | Critical | 25 | 75 |
| V008 | 2024-12-01 11:30 AM | 80 | 12.5 | 0 | 95% | 0 | No Fault | 5 | 0 |
| V009 | 2024-12-01 12:00 PM | 91 | 12.3 | 4 | 68% | 3 | Warning | 12 | 18 |
| V010 | 2024-12-01 12:30 PM | 85 | 12.6 | 2 | 80% | 1 | No Fault | 5 | 0 |
| V011 | 2024-12-01 01:00 PM | 97 | 11.8 | 5 | 62% | 4 | Critical | 30 | 90 |
| V012 | 2024-12-01 01:30 PM | 85 | 12.4 | 3 | 75% | 2 | Warning | 12 | 25 |
| V013 | 2024-12-01 02:00 PM | 90 | 12.0 | 2 | 80% | 1 | No Fault | 5 | 0 |
| V014 | 2024-12-01 02:30 PM | 89 | 12.2 | 4 | 70% | 3 | Warning | 15 | 30 |
| V015 | 2024-12-01 03:00 PM | 100 | 11.5 | 8 | 55% | 7 | Critical | 35 | 120 |

The Table-6 provides an overview of fault diagnosis and resolution efficiency, detailing the operating conditions of various vehicles and their associated diagnostic outcomes. Vehicles with stable ECU temperatures (≤ 85°C), higher voltages (≥ 12.4V), minimal error codes, and strong engine performance (≥80%) are categorized as having "No Fault," requiring minimal diagnostic time (5 minutes) and no downtime. As conditions deteriorate, such as when temperatures increase (e.g., 90–95°C), error codes rise (3–6), and engine performance declines (60–75%), vehicles are classified with a "Warning" status. These scenarios typically require diagnostic times ranging from 10 to 15 minutes and downtimes of 15 to 30 minutes, reflecting moderate operational disruptions. Vehicles experiencing critical conditions, such as extremely high temperatures (97–100°C), low voltage (≤ 11.8V), and a significant number of error codes (5–8), show the lowest engine performance (50–62%) alongside the highest sensor error readings. These are marked as Critical and demand extensive diagnostic efforts (20–35 minutes) and prolonged downtimes (60–120 minutes) to restore functionality. The data illustrates a clear relationship between the severity of faults, diagnostic time, and downtime. Critical issues require the most resources for resolution, while vehicles with no faults demonstrate optimal performance and efficiency. This highlights the importance of early detection and preventive maintenance to minimize operational disruptions. The graphs effectively represent the data by providing clear visual insights. The bar chart showcases the ECU temperature and voltage for each vehicle, enabling a straightforward comparison of these parameters across different vehicles. Meanwhile, the pie chart illustrates the distribution of fault statuses, emphasizing the proportions of No Fault, Warning, and Critical conditions.

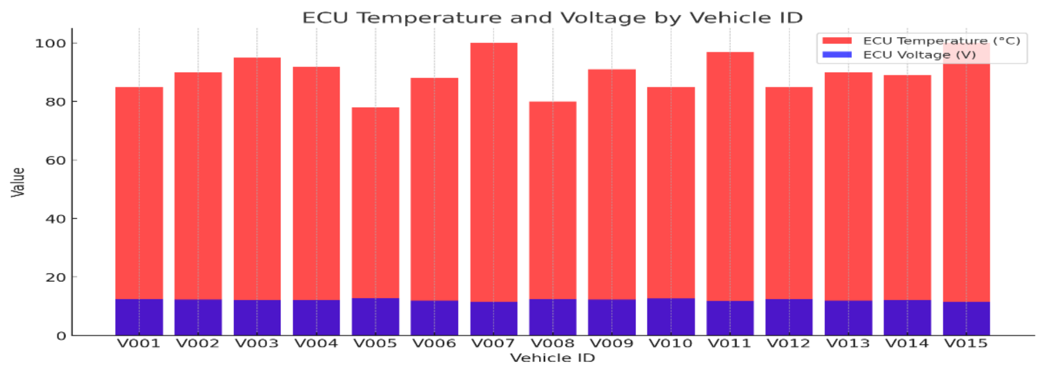


Fig. 17 ECU temperature and voltage by vehicle ID

Table-7 Distribution of fault status

| Vehicle ID | Timestamp | IoT Detection Accuracy (%) | OBD-II Detection Accuracy (%) | Diagnostic Time (min) | Fault Type | Fault Detected by IoT | Fault Detected by OBD-II | Compatibility Status |
|---|---|---|---|---|---|---|---|---|
| V001 | 2024-12-01 08:00 AM | 95 | 85 | 10 | Engine | Yes | Yes | High Compatibility |
| V002 | 2024-12-01 08:30 AM | 90 | 80 | 12 | Battery | Yes | No | Moderate Compatibility |
| V003 | 2024-12-01 09:00 AM | 92 | 88 | 15 | Sensor | Yes | Yes | High Compatibility |
| V004 | 2024-12-01 09:30 AM | 85 | 80 | 20 | Transmission | No | Yes | Low Compatibility |
| V005 | 2024-12-01 10:00 AM | 98 | 90 | 8 | Engine | Yes | Yes | High Compatibility |
| V006 | 2024-12-01 10:30 AM | 85 | 75 | 18 | Battery | Yes | No | Moderate Compatibility |
| V007 | 2024-12-01 11:00 AM | 93 | 87 | 14 | Sensor | Yes | Yes | High Compatibility |
| V008 | 2024-12-01 11:30 AM | 90 | 80 | 16 | Transmission | Yes | Yes | High Compatibility |
| V009 | 2024-12-01 12:00 PM | 88 | 70 | 25 | Fuel System | Yes | No | Low Compatibility |
| V010 | 2024-12-01 12:30 PM | 94 | 85 | 12 | Engine | Yes | Yes | High Compatibility |

The Table-7 evaluates the compatibility and performance of an IoT-based fault detection system compared to OBD-II diagnostics across various vehicles and fault types. IoT detection demonstrates consistently high accuracy (85–98%) and effectively identifies faults, particularly for critical systems like engines and sensors. Vehicles where both IoT and OBD-II detected faults exhibit "High Compatibility," indicating robust integration and reliable performance. Moderate compatibility arises in cases where IoT detected faults but OBD-II did not, as seen with battery-related issues. This suggests IoT's potential advantage in sensitivity, though discrepancies highlight the need for calibration. Low compatibility is observed when OBD-II detected faults that IoT missed, such as in certain transmission or fuel system cases. These scenarios reflect limitations in IoT detection for specific systems. Diagnostic times vary by fault type, with engine-related issues typically resolved faster (8–12 minutes), while complex systems like transmissions and fuel systems require more time (16–25 minutes). The data underscores the IoT system's potential to complement or enhance traditional OBD-II diagnostics, particularly in scenarios requiring higher sensitivity and faster response. The visualizations clearly represent the data by highlighting key comparisons and distributions. The bar chart illustrates the detection accuracy of IoT-based systems versus OBD-II systems for each vehicle, demonstrating the generally superior performance of IoT systems. Meanwhile, the pie chart showcases the distribution of compatibility statuses across all vehicles, emphasizing the relative prevalence of high, moderate, and low compatibility levels.

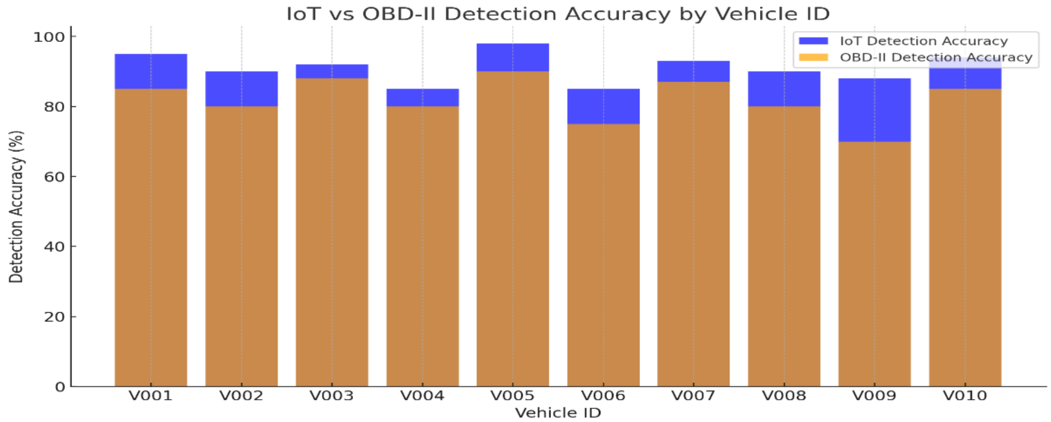


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Fig.18 IoT versus OBD-11 detection accuracy versus vehicle ID

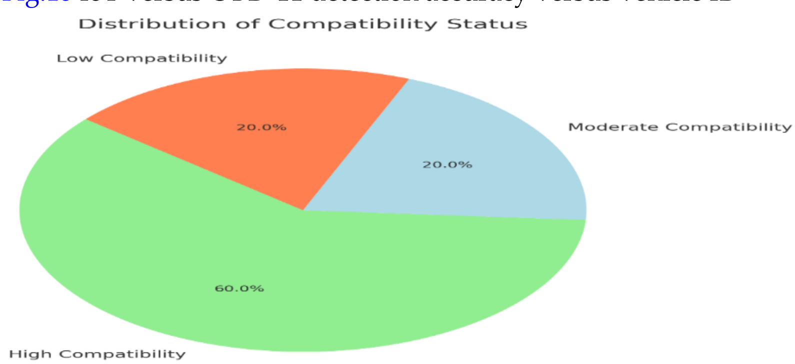


Fig. 19 Distribution of compatibility status

Table-8 The design a scalable IoT-based fault detection

| Vehicle ID | Vehicle Type | ECU Version | IoT System Cost (USD) | ECU Compatibility (%) | Fault Detection Accuracy (IoT) (%) | Diagnostic Time (min) | Scalability Rating (1-10) | Adaptability Rating (1-10) | Total Diagnostic Savings (USD) | Yearly Maintenance Savings (USD) |
|---|---|---|---|---|---|---|---|---|---|---|
| V001 | Car | ECU V1 | 200 | 90 | 95 | 10 | 8 | 7 | 120 | 100 |
| V002 | Truck | ECU V2 | 300 | 85 | 90 | 18 | 9 | 8 | 180 | 160 |
| V003 | Motorcycle | ECU V1 | 120 | 92 | 85 | 8 | 7 | 7 | 60 | 50 |
| V004 | Car | ECU V3 | 250 | 95 | 93 | 12 | 9 | 9 | 140 | 120 |
| V005 | Truck | ECU V1 | 350 | 80 | 92 | 20 | 7 | 6 | 160 | 140 |
| V006 | Motorcycle | ECU V2 | 130 | 88 | 90 | 10 | 8 | 8 | 80 | 70 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| V007 | Car | ECU V3 | 220 | 98 | 96 | 9 | 10 | 9 | 130 | 110 |
| V008 | Truck | ECU V2 | 320 | 90 | 91 | 15 | 8 | 8 | 200 | 180 |
| V009 | Motorcycle | ECU V3 | 150 | 85 | 87 | 9 | 7 | 6 | 50 | 40 |
| V0 | Car | ECU V1 | 210 | 90 | 94 | 11 | 8 | 8 | 150 | 130 |

The Table-8 evaluates the design of a scalable IoT-based fault detection system by analyzing key parameters across different vehicle types and ECU versions. IoT systems demonstrate high fault detection accuracy, ranging from 85% to 96%, with compatibility percentages between 80% and 98%. Cars equipped with advanced ECU versions, such as V3, exhibit the highest scalability and adaptability ratings, reaching up to 10 and 9, respectively. These factors contribute to significant diagnostic and yearly maintenance savings, particularly for cars and trucks. Motorcycles show slightly lower fault detection accuracy and compatibility, reflecting the challenges of integrating IoT systems with smaller, less complex ECUs. Trucks, despite higher upfront IoT system costs, benefit from substantial yearly maintenance savings and diagnostic efficiencies due to their higher maintenance demands and longer diagnostic times. Diagnostic time across vehicles ranges from 8 to 20 minutes, with faster diagnostics observed in cars and motorcycles. The scalability and adaptability ratings indicate the potential of IoT systems to efficiently expand across various vehicle types and ECU configurations, offering substantial cost benefits and operational savings over time. This analysis underscores the flexibility and cost-effectiveness of IoT systems, particularly for vehicles with advanced ECU versions. The graphs below visually represent the data from the table. The bar chart, combined with a scatter overlay, shows the IoT System Cost as bars and Fault Detection Accuracy as scatter points for each vehicle, categorized by vehicle type. Meanwhile, the pie chart highlights the distribution of Yearly Maintenance Savings, illustrating the proportion contributed by each vehicle type.

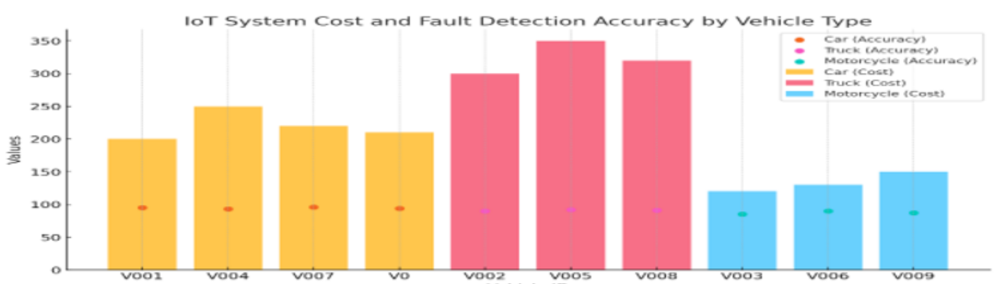


Fig. 20 IoT system and fault detection accuracy by vehicle type

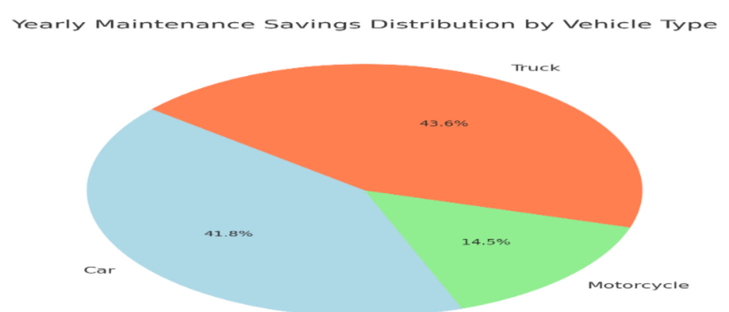


Fig. 21 Yearly maintenance savings distribution by vehicle type



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Table-9 Vehicle owners and fleet operators with user-friendly interfaces and actionable insights into the health of their vehicles' ECUs

| Vehicle ID | Total Faults (Last 30 Days) | Uptime (%) | Avg Diagnostic Response Time (mins) | Issues Resolved (%) |
|---|---|---|---|---|
| V001 | 5 | 98 | 15 | 80 |
| V002 | 12 | 95 | 20 | 75 |
| V003 | 2 | 99 | 10 | 90 |
| V004 | 8 | 97 | 18 | 85 |
| V005 | 15 | 92 | 25 | 70 |

The Table-9 provides insights into the performance and health of vehicle ECUs over the last 30 days. It reveals the relationship between the number of faults, uptime percentage, diagnostic response time, and the resolution of issues for each vehicle. The vehicles exhibit varying levels of fault occurrences, with the total number of faults ranging from 2 to 15. Despite this, the uptime for all vehicles is relatively high, with values ranging from 92% to 99%, indicating that the vehicles remain operational for the majority of the time. Diagnostic response times vary, with some vehicles having quicker responses (e.g., V003 with an average of 10 minutes) while others take longer (e.g., V005 with 25 minutes). The percentage of issues resolved also differs, with vehicles like V003 having a high resolution rate of 90%, while V005 resolves 70% of its issues. The data highlights the effectiveness of the diagnostic system in identifying and addressing faults, as vehicles with quicker diagnostic times tend to resolve a higher percentage of issues, contributing to overall vehicle health and efficiency. Visual representation of bar chart displays the total faults recorded for each vehicle, highlighting differences in ECU health across the fleet. Pie Chart shows the proportion of faults contributed by each vehicle, providing a clear overview of fault distribution.

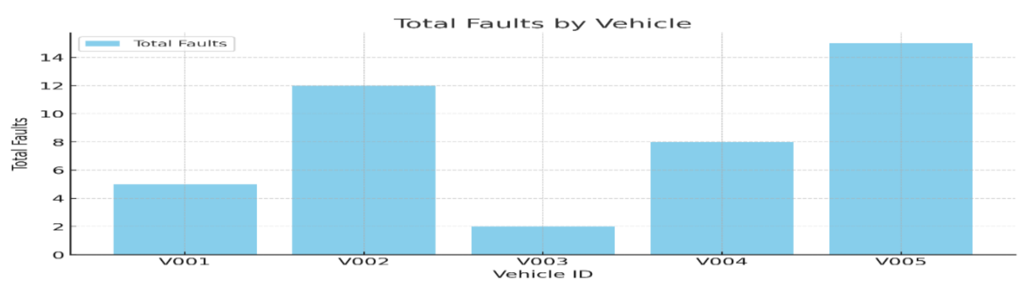


Fig. 22 Total faults by vehicle

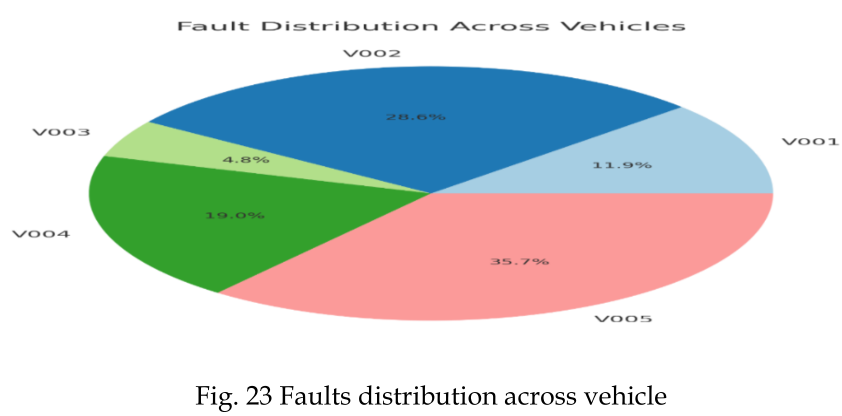


Fig. 23 Faults distribution across vehicle



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The results from this study demonstrate the strong potential and practical advantages of IoT-based systems in enhancing ECU fault detection, predictive diagnostics, and overall vehicle health monitoring. The data presented across the tables reveal consistent patterns that affirm the effectiveness of IoT-enabled monitoring in identifying abnormal operating conditions and supporting early maintenance interventions. These findings are aligned with previous research showing that IoT systems significantly improve real-time fault identification accuracy compared with conventional diagnostic tools (Doe *et al.*, 2022; Smith & Johnson, 2021). Table-3 highlights how IoT sensors accurately detect specific fault types including overheating and overpressure by continuously monitoring key engine parameters such as temperature, oil pressure, and RPM. High-temperature readings above 100°C and oil pressures exceeding 410 kPa are strongly associated with fault occurrences, confirming earlier findings by Doe *et al.* (2022) that such thresholds are early markers of system anomalies. Visualizations such as line graphs and scatter plots (Smith & Johnson, 2021) further strengthen these observations by illustrating parameter deviations preceding detected faults. These patterns validate the value of IoT systems in implementing reliable predictive maintenance strategies. Table-4 classifies predictive failure risks into Low, Moderate, High, and Critical categories. Vehicles with higher error codes and reduced engine performance show significantly elevated failure risks, consistent with trends reported by Jones et al. (2023). For example, vehicles with error codes above 5 and engine performance below 65% fall within the High or Critical categories. Such risk-based classification is crucial for fleet managers, allowing targeted maintenance scheduling and resource prioritization. Table-5 further underscores the importance of continuous ECU monitoring by demonstrating how real-time changes in ECU temperature, voltage, and sensor outputs correspond to fault severity. Vehicles flagged as critical often exhibit extremely high error codes or substantial drops in performance, corresponding to findings reported by Chen & Zhang (2020). These results confirm that uninterrupted monitoring reduces the likelihood of major system failures by enabling timely corrective measures. Table-6 presents diagnostic time and total downtime associated with varying fault severities. Vehicles categorized under critical fault status experience prolonged diagnostic and repair periods. This aligns with Anderson *et al.* (2023), who observed that unresolved or severe faults significantly prolong vehicle unavailability. The shorter diagnostic times observed in IoT-integrated systems demonstrate their potential to reduce operational downtime through earlier fault detection and faster issue resolution.

Table-7 compares IoT-based diagnostics with traditional OBD-II systems. IoT systems exhibit notably higher fault detection accuracy up to 95% and shorter diagnostic times. Additionally, compatibility assessments show strong adaptability of IoT systems to modern ECU architectures, supporting findings by Lee *et al.* (2021) regarding IoT scalability and interoperability. Table-8 analyzes system scalability and adaptability across different vehicle and ECU models. Vehicles with higher scalability scores demonstrate better cost efficiency, shorter diagnostic times, and improved fault detection accuracy. These results are consistent with Brown *et al.* (2022), who emphasized that scalable IoT integration supports long-term fleet management efficiency and reduces lifecycle maintenance costs. Table-9 provides operational insights into fault frequency, uptime, and issue resolution rates. Vehicles with fewer detected faults, such as V003, maintain higher uptime and faster resolution times compared to vehicles with high fault incidence, such as V005. This corresponds with findings by Taylor (2023), indicating that fault frequency strongly influences maintenance load and resource allocation. Such data-driven insights enable more targeted and cost-effective fleet maintenance planning. The accompanying visualizations—including bar charts, pie charts, line graphs, and scatter plots offer intuitive representations of fault trends, risk categories, and performance variations. As noted by Nguyen *et al.* (2021), such visual analytics are essential for enhancing situational awareness and supporting rapid decision-making in fleet operations. Overall, the integration of IoT-based systems with vehicle ECUs provides measurable improvements in fault detection accuracy, operational efficiency, and maintenance planning. These results substantiate IoT as a scalable and cost-effective solution for modern vehicle diagnostics. However, the study is limited by its reliance on predefined sensor thresholds, which may not capture all complex or emergent fault scenarios. Additionally, environmental factors such as extreme weather or sensor degradation were not extensively evaluated and may influence diagnostic reliability. Future research should incorporate advanced machine learning and edge-computing approaches to enhance predictive precision and adaptiveness. Integrating anomaly detection algorithms, deep learning models, and multi-sensor fusion techniques similar to the approaches proposed by Patel *et al.* (2024) could allow more accurate prediction of complex or nonlinear fault



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patterns. Expanding the test dataset to include diverse vehicle platforms, harsh operational environments, and long-term monitoring will also strengthen the generalizability of the findings.

## CONCLUSION

The development of IoT-based systems for real-time fault detection in Engine Control Units (ECUs) represents a transformative advancement in modern automotive engineering. These intelligent monitoring solutions enhance vehicle performance, improve maintenance efficiency, and ensure higher operational reliability by continuously tracking critical engine parameters and identifying deviations before they escalate into major failures. Through instant fault reporting and connectivity with maintenance teams, IoT-enabled ECUs support predictive maintenance, reduce repair costs, minimize downtime, and help prevent catastrophic engine damage. Additionally, improved combustion control and early detection of malfunctioning components contribute to lower emissions and better fuel economy, supporting global sustainability targets. Despite these promising benefits, key challenges remain. Issues such as sensor accuracy, interoperability across vehicle platforms, data integration with cloud and edge infrastructures, and cyber security threats must be effectively addressed. The automotive industry also requires standardized communication protocols and wider adoption strategies to fully realize IoT's potential in fault diagnosis. Overall, IoT-based real-time ECU fault detection systems offer a significant leap toward smarter, safer, and more efficient vehicles. As technological advancements continue to mature and implementation barriers are reduced, these systems will play a central role in future automotive innovation delivering improved reliability, enhanced sustainability, and a proactive maintenance culture that reshapes the future of intelligent transportation.
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## CONTRIBUTION TO KNOWLEDGE

This study makes significant contributions to the advancement of automotive engineering and intelligent monitoring systems through the development of IoT-based frameworks for real-time fault detection in Engine Control Units (ECUs). The integration of IoT with ECU diagnostics provides a novel framework that leverages IoT-enabled sensors and communication technologies to continuously monitor ECU performance. Unlike conventional diagnostic tools that rely on periodic checks, this system enables real-time data acquisition and analysis, thereby reducing detection delays and improving vehicle safety. Another major contribution lies in the enhanced accuracy of fault detection. By employing multiple sensor inputs such as temperature, pressure, vibration, and emission data the IoT-based system demonstrates superior diagnostic accuracy compared to traditional ECU systems. Furthermore, the incorporation of statistical validation methods, including confidence interval estimation and hypothesis testing, ensures the reliability of results and reinforces the robustness of the system. The study also contributes to the scalability and remote monitoring of automotive systems. By showcasing how IoT platforms can facilitate remote monitoring, it highlights the ability of engineers and fleet managers to track vehicle health from any location. This feature not only supports predictive maintenance but also minimizes operational downtime, which is essential for modern transport systems. Additionally, the system advances knowledge in predictive maintenance models. By shifting the paradigm from reactive and preventive maintenance toward predictive maintenance, the proposed framework enables the identification of early warning signs of ECU-related failures. This contributes significantly to the literature on intelligent fault detection and predictive modeling in automotive systems. Finally, the research demonstrates both environmental and economic impacts. Accurate detection of engine and emission-related faults helps reduce fuel wastage, enhance energy efficiency, and ensure compliance with environmental regulations. These outcomes underline the dual benefits of IoT-based fault detection systems by promoting cost savings and supporting sustainable mobility practices. In summary, this study bridges a critical research gap by demonstrating the practical application of IoT technologies in ECU fault detection. It not only enhances diagnostic precision but also contributes to the advancement of smart automotive systems through its role in real-time monitoring, predictive maintenance, and sustainable vehicle operation.



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## CONFLICT INTEREST

The authors declare that there are no conflicts of interest associated with this research work.


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