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ІНТЕГРАЦІЯ ДІАГНОСТИКИ ТРАНСПОРТНИХ ЗАСОБІВ ЗА СТАНДАРТОМ OBD-II З ПРОЄКТУВАННЯМ ПРОГРАМНОГО ЗАБЕЗПЕЧЕННЯ НА ОСНОВІ СКІНЧЕННИХ АВТОМАТІВ

Дане дослідження пропонує інноваційний підхід до інтеграції систем бортової діагностики другого покоління (OBD-II) із методологіями проєктування програмного забезпечення на основі скінченних автоматів (FSM). У роботі розглянуто зростаючу складність сучасних систем діагностики транспортних засобів та представлено концептуальну основу, що поєднує діагностику в реальному часі з автоматизованими системами програмного управління. Використовуючи архітектури, засновані на FSM, дослідження спрямоване на підвищення точності діагностики, зменшення кількості хибних спрацювань та створення масштабованого рішення, яке можна адаптувати до різних моделей транспортних засобів і різноманітних умов експлуатації. Інтеграція принципів скінченних автоматів забезпечує динамічне пристосування до змінних станів системи, вдосконалюючи процедури виявлення несправностей та гарантуючи надійну роботу за різних умов. Критичним викликом у діагностиці OBD-II є точна класифікація й інтерпретація даних про несправності. Традиційні підходи нерідко ґрунтуються на статичних порогових налаштуваннях, що може призводити до підвищеної кількості хибних позитивних спрацювань або невиявлених помилок, оскільки такі методи не здатні адаптуватися до динамічно змінюваних умов середовища та експлуатації. Архітектури на основі FSM пропонують систематизований підхід до моделювання динамічної поведінки системи, дозволяючи діагностичним алгоритмам переходити між різними станами у відповідь на показники датчиків у реальному часі. У межах цього дослідження представлено нову діагностичну систему, вдосконалену завдяки FSM, яка включає імовірнісні переходи станів та регулювання на основі методів машинного навчання. Інтеграція імовірнісних моделей дає змогу динамічно змінювати переходи між станами, підвищуючи точність класифікації несправностей і покращуючи здатність системи до адаптації під час потенційних відмов. Запропонований підхід забезпечує більш ефективне виявлення й прогнозування несправностей, зменшуючи ризик помилкової діагностики. Дослідження пропонує комплексну математичну модель для відтворення переходів станів у скінченному автоматі, що дає змогу точно описати динамічну поведінку системи. Крім того, розроблено алгоритми адаптивної класифікації несправностей, які залучають техніки машинного навчання для безперервної оптимізації діагностичного процесу. Для валідації запропонованої методології проведено симуляції та емпіричне тестування на різноманітних наборах даних транспортних засобів.

Ключові слова: скінченні автомати, проєктування, автомобільна діагностика, оптимізація, машинне навчання, надійність системи.

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INTEGRATION OF OBD-II VEHICLE DIAGNOSTICS WITH FINITE STATE MACHINE SOFTWARE DESIGN

This research presents an innovative approach to integrating On-Board Diagnostics II (OBD-II) vehicle diagnostic systems with finite state machine (FSM) software design methodologies. The study addresses the growing complexity of modern vehicle diagnostic systems and proposes a novel framework that combines real-time vehicle diagnostics with automated software control systems. By leveraging FSM-based architectures, this research seeks to enhance diagnostic accuracy, reduce false detections, and provide a scalable solution adaptable to various vehicle models and driving conditions. The integration of FSM principles enables dynamic adaptation to varying system states, improving fault detection capabilities while ensuring reliable system behavior under different operating conditions. A critical challenge in OBD-II diagnostics is the accurate classification and interpretation of fault data. Traditional diagnostic methods often rely on predefined static threshold rules, which can lead to a high rate of false positives or undetected issues due to their inability to adapt to changing environmental and operational conditions. FSM-based architectures offer a more systematic approach to modeling dynamic system behavior, allowing the diagnostic system to transition between states based on real-time sensor data. This research introduces a novel FSM-enhanced diagnostic system, incorporating probabilistic state transitions and machine learning-based adjustments. By integrating probabilistic models, the system can adjust state transition dynamically, thereby refining fault classification accuracy and improving adaptability to fault scenarios. The proposed methodology enables more efficient fault detection and prediction, reducing the likelihood of erroneous diagnostics. The research presents a comprehensive mathematical framework for modeling FSM state transitions, ensuring precise representation of the system's dynamic behavior. It also develops algorithms for adaptive fault classification, leveraging machine learning techniques to continuously optimize diagnostic performance. To validate the proposed approach, simulations and empirical testing are conducted on various vehicle datasets.

Keywords: finite state machines, design, automotive diagnostics, optimization, machine learning, system reliability.

Problem statement

Modern automotive systems have evolved significantly with the integration of sophisticated electronic control units (ECUs) that manage various vehicle subsystems, including the engine, transmission, braking, and emission control. The increasing complexity of these systems necessitates advanced diagnostic mechanisms to ensure reliability, safety, and performance optimization. One of the most widely adopted standards for vehicle diagnostics is the On-Board Diagnostics II (OBD-II) system, which provides standardized fault detection and real-time monitoring capabilities.

OBD-II collects sensor data from multiple vehicle components and generates Diagnostic Trouble Codes (DTCs) when abnormalities are detected. However, traditional OBD-II diagnostic approaches face challenges in terms of false positives, limited fault prediction capabilities, and delayed responses to critical issues. These limitations highlight the need for enhanced analytical models that can dynamically interpret sensor data and improve diagnostic precision.

Finite State Machines (FSMs) offer a structured methodology for modeling and controlling complex system behaviors. FSMs define a set of discrete states and transition rules, making them well-suited for real-time system monitoring and automated decision-making processes. Integrating FSMs with OBD-II can enable dynamic state-based fault classification, automated decision-making, and adaptive control strategies that enhance the accuracy and efficiency of vehicle diagnostics.

Additionally, the introduction of hierarchical state machines (HSMs) allows for multi-level fault diagnosis, improving the granularity of diagnostic outcomes. By incorporating probabilistic state transitions, the system adapts to varying conditions and learns from historical fault data, refining its diagnostic accuracy over time. This research aims to develop an FSM-based framework that enhances OBD-II diagnostics by providing an adaptive and hierarchical fault detection mechanism. The proposed framework will improve system response times, reduce false positives in diagnostic results, and enhance the overall reliability of automotive diagnostic systems.

Literature and publications survey

The field of OBD-II diagnostics and finite state machine (FSM) applications in vehicle fault detection has been extensively studied in recent years. Several foundational works provide valuable insights into vehicle dynamics, control systems, and optimization methods for real-time diagnostics.

Rajamani explored vehicle dynamics and control mechanisms, emphasizing the importance of real-time fault detection in modern automobiles. This work laid the foundation for advanced diagnostic approaches, integrating system control principles to enhance vehicle performance. Similarly, Liu and Yang discussed multi-objective optimization techniques, highlighting their relevance in automotive diagnostics and decision-making frameworks [1;2].

Artificial intelligence (AI) and neural network methodologies have significantly contributed to improving diagnostic accuracy. Rudenko and Bodvanskyi provided a comprehensive study on artificial neural networks (ANNs), which are increasingly used in fault detection and classification within automotive systems.

FSM-based diagnostic frameworks have gained significant attention in recent years. Köhler, Schillinger, and Jäkel proposed a probabilistic FSM model for enhancing diagnostic accuracy, emphasizing the role of probabilistic state transitions in minimizing errors. Similarly, Sun, Li, and He demonstrated real-time fault detection techniques using FSMs, validating their effectiveness through empirical testing in autonomous vehicles [8;9].

Recent advancements in machine learning have improved fault diagnosis in electric and autonomous vehicles. Lee and Kim presented machine learning-based fault diagnosis methods, showcasing their effectiveness in reducing false detection rates and improving reliability. Ho and Chen introduced an adaptive FSM approach for real-time sensor data analysis, which aligns with the proposed FSM-enhanced OBD-II diagnostic system in this study. Their research demonstrated that FSM architectures could dynamically adjust based on real-time sensor feedback, significantly improving diagnostic precision [7].

Objectives

The primary objective of this study is to develop an enhanced OBD-II diagnostic system that integrates finite state machine (FSM) methodologies to improve fault detection accuracy and system reliability. The study focuses on several key objectives:

- Enhancing Diagnostic Accuracy – Traditional OBD-II diagnostic methods often generate false positives or miss critical faults due to static threshold-based rules. This research aims to leverage FSM-based adaptive mechanisms to refine fault classification and improve accuracy.
- Developing an Adaptive Fault Detection Mechanism – By integrating FSM principles, the study seeks to create a dynamic fault diagnosis system capable of adjusting its state transitions based on real-time sensor feedback. This adaptability ensures more precise fault detection and reduces the likelihood of incorrect classifications.
- Reducing False Alarm Rates – One of the major limitations of conventional diagnostic systems is the high rate of false alarms, leading to unnecessary maintenance actions. The proposed FSM-based approach aims to minimize these false positives by incorporating probabilistic state transitions and machine learning enhancements.
- Improving System Response Time – Quick and efficient fault detection is critical for modern vehicle diagnostics. The study seeks to enhance response times by implementing real-time FSM logic that rapidly processes sensor inputs and triggers appropriate diagnostic actions.

• Ensuring System Scalability and Flexibility – The study aims to design a diagnostic system that can be easily extended to accommodate new fault scenarios, sensor inputs, and evolving automotive technologies. FSM-based architectures provide a modular and scalable framework, making future expansions feasible.

• Validating Performance Through Empirical Testing – The final objective is to rigorously test and validate the proposed FSM-enhanced OBD-II diagnostic framework using both simulations and real-world automotive data. This ensures that the developed system is practical, reliable, and effective in diverse operational conditions.

By achieving these objectives, this study contributes to the advancement of intelligent vehicle diagnostic systems, laying the foundation for more robust and adaptive fault detection methodologies.

Presentation of the main material

The On-Board Diagnostics II (OBD-II) system is a standardized vehicle diagnostic framework designed to monitor the performance of various automotive components in real time. It is widely used in modern vehicles to detect malfunctions, ensure optimal performance, and comply with environmental regulations. The system continuously collects and processes sensor data from multiple components, including the engine, transmission, and exhaust system. When an anomaly is detected, it generates Diagnostic Trouble Codes (DTCs), which indicate potential issues requiring attention. Mathematically, the diagnostic function can be represented as follows:

$$DTC = f(S_i, T, P) \quad (1)$$

• S_i represents sensor readings, which provide real-time data on various vehicle parameters such as engine temperature, fuel efficiency, and emission levels. These readings serve as primary indicators for identifying faults.

• T denotes the time dependency factor, which accounts for changes in sensor readings over time. Since vehicle components may degrade gradually rather than failing instantly, tracking variations in these readings over a certain period is crucial for accurate diagnostics.

• P represents performance thresholds, which define acceptable operational limits for different vehicle parameters. If a sensor reading exceeds a specified threshold, the system identifies it as a potential fault and triggers an appropriate DTC.

The OBD-II system plays a vital role in modern vehicle diagnostics by enabling proactive maintenance and reducing the risk of unexpected failures. By continuously analyzing sensor data and comparing it to predefined performance thresholds, it ensures timely detection of abnormalities.

To enhance the accuracy of failure detection, a probabilistic approach is employed to model the likelihood of a system malfunction based on sensor data. The probability of failure occurrence is mathematically defined as:

$$P_{fail} = \frac{1}{1 + e^{-k(S_i - S_{th})}} \quad (2)$$

where:

• k is the sensitivity parameter, which determines the rate at which the probability of failure increases as the sensor reading surpasses the threshold. A higher k value results in a more abrupt transition from normal operation to failure, while a lower k value provides a smoother probability curve.

• S_{th} represents the threshold sensor value that triggers a fault condition. If the sensor reading S_i remains below this threshold, the probability of failure remains low. However, as S_i exceeds S_{th}, the probability of failure approaches 1, indicating a high likelihood of a malfunction.

This equation is derived from the logistic function, which is widely used in probabilistic modeling. It ensures a gradual, nonlinear transition between normal and faulty conditions rather than an abrupt shift, making it particularly effective for predictive diagnostics. The function behaves as follows:

• When $S_i \ll S_{th}$, P_{fail} is close to 0, meaning the system is in a normal operating state with minimal failure probability.

• When $S_i = S_{th}$, the probability of failure is approximately 0.5, meaning the system is in a transitional state where failure risk becomes significant.

• When $S_i \gg S_{th}$, P_{fail} approaches 1, indicating an imminent or existing failure condition.

This probabilistic approach enhances OBD-II diagnostics by introducing a risk-based evaluation of system health, allowing for early warnings before an actual failure occurs. By incorporating sensor thresholds and sensitivity parameters, it provides a more dynamic and adaptive assessment of vehicle performance compared to rigid threshold-based alerts.

A Finite State Machine (FSM) is a mathematical model used to describe a system that can transition between a finite number of states based on input signals. It is applied in various fields, including computer science, control systems, and artificial intelligence, due to its ability to represent complex decision-making processes in a structured manner.

In the context of vehicle diagnostics, an FSM serves as an effective framework for modeling the behavior of a vehicle's diagnostic system by defining a set of distinct states that represent different operational conditions, such as normal functioning, warning states, minor faults, and critical failures. The system processes real-time sensor data from various components, including the engine, transmission, and exhaust system, to determine when transitions between states should occur. By using an FSM-based approach, the diagnostic system ensures predictable and systematic state changes, allowing for efficient fault detection, isolation, and recovery mechanisms. The FSM model is formally defined as:

$$M = (Q, \Sigma, \delta, q_0, F) \tag{3}$$

where:

- Q represents the set of possible states that the system can occupy. These states include "normal operation," "sensor warning," "minor fault detected," and "critical failure".
- Σ denotes the set of input signals, which consist of sensor readings obtained from the OBD-II system. These signals drive state transitions based on their values and trends.
- δ is the state transition function that maps a current state and an input signal to a new state. This function defines the rules governing how the system reacts to sensor data changes.
- q_0 represents the initial state, which is typically the "normal operation" state. From this state, the system can transition to other states as new sensor data is processed.
- F denotes the set of final states, which could include both acceptable and faulty conditions. Examples of final states include "safe shutdown," "emergency mode," or "continued operation with reduced efficiency".

FSMs provide a structured and deterministic approach to vehicle diagnostics, ensuring that the system responds systematically to fault conditions. By organizing the diagnostic process into well-defined states, FSMs help in simplifying the complexity of real-time fault detection and response mechanisms. This approach enhances the efficiency and reliability of automotive diagnostic systems by ensuring that every scenario is accounted for within a predefined framework. To model the likelihood of transitioning from one state to another, the following probability function is used:

$$P(q_{t+1} = q_j | q_t = q_i, \sigma_t) = \frac{e^{W_{ij}\sigma_t}}{\sum_k e^{W_{ik}\sigma_t}} \tag{4}$$

where:

- W_{ij} is the weight associated with the transition from state q_i to state q_j. This weight reflects the strength or likelihood of the transition occurring.
- σ_t is the input signal at time t, which represents sensor data influencing state transitions.
- The numerator $e^{W_{ij}\sigma_t}$ assigns a probability weight to the transition between states q_i and q_j.
- The denominator normalizes the probabilities by summing over all possible transitions from state q_i, ensuring that the total probability remains within the range [0,1].

This probability function is based on the softmax function, which is widely used in machine learning and probabilistic modeling. It ensures that transition probabilities are dynamically adjusted based on sensor readings and state transition weights. Key properties of the transition probability function:

- If W_{ij} is large, the transition from q_i to q_j is highly probable.
- If W_{ij} is small, the transition is unlikely.
- If multiple possible transitions exist, the softmax normalization ensures that the most probable transition dominates.

Additionally, FSM state transitions can be represented using a probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{5}$$

This matrix formalism facilitates structured analysis of state transitions and enhances integration with machine learning techniques for continuous optimization.

By integrating FSM with probabilistic state transitions, the diagnostic system can more accurately model real-world conditions, where sensor readings, environmental variables, and external disturbances influence the likelihood of transitioning between operational states. Unlike purely deterministic models, which rely on fixed thresholds to trigger state changes, probabilistic approaches account for uncertainties, such as sensor noise, gradual component degradation, and transient anomalies.

This enhanced modeling capability improves the robustness and flexibility of vehicle diagnostics by enabling the system to distinguish between temporary fluctuations and actual faults, reducing the likelihood of false positives and unnecessary repairs. Additionally, it allows for adaptive fault detection, where the system continuously refines its understanding of normal and abnormal operating conditions based on historical data and real-time inputs. By incorporating machine learning techniques or Bayesian inference, FSM-based diagnostic systems can dynamically adjust transition probabilities based on evolving system behavior. This adaptability is particularly beneficial in modern vehicles, where complex electronic control units and interconnected sensors generate vast amounts of data that must be processed efficiently. Ultimately, this approach leads to more accurate fault detection, faster response times, and improved vehicle reliability.

The proposed architecture integrates Finite State Machine (FSM) logic into the On-Board Diagnostics II (OBD-II) system to enable automated fault classification in vehicles. This integration enhances the vehicle's diagnostic capability by structuring system behavior into well-defined states, allowing for efficient monitoring and fault detection. The system is divided into three key layers:

1. Data Acquisition Layer: This layer is responsible for collecting real-time sensor data from various vehicle components. The data includes engine temperature, fuel system status, throttle position, and other critical operational parameters that influence the vehicle's performance. The accuracy and frequency of data collection directly impact the system's ability to detect anomalies effectively.

2. Processing Layer: In this layer, FSM-based models analyze the acquired sensor data. The FSM framework enables the system to transition between different operational states, such as Normal Operation, Warning, and Fault Detected, based on predefined logic and sensor readings. This analytical approach ensures a structured interpretation of complex sensor inputs and facilitates early detection of potential issues.

3. Decision Layer: The final layer determines the overall system status and executes necessary corrective actions. When a fault is detected, the system can trigger alerts, log error codes for further diagnostics, or even adjust operational parameters to mitigate potential damage. This layer plays a crucial role in ensuring timely responses to detected faults, thereby improving vehicle reliability and safety.

To improve adaptability, an adaptive weight adjustment function modifies transition probabilities based on real-time feedback, where η is the learning rate controlling how rapidly the system adapts to new conditions:

$$W_{ij}^{new} = W_{ij}^{old} + \eta \cdot \left(\sigma_t - \mathrm{P}(q_{t+1}|q_t)\right), \tag{6}$$

By structuring the diagnostic process into these layers, the FSM-OBD-II integration creates a modular and scalable approach to vehicle diagnostics, reducing ambiguity in fault detection and enhancing overall system efficiency. The FSM transitions within the diagnostic system are governed by the following equation:

$$q_{t+1} = \delta(q_t, \sigma_t), \tag{7}$$

Where q_t represents the current system state and σ_t denotes real-time sensor inputs. This function $\delta(q_t, \sigma_t)$ defines the transition rule, mapping the current state and input to the next state. The system continuously adapts its transitions based on historical data and feedback control mechanisms. However, in real-world conditions, state transitions are not always deterministic. Variability in sensor readings, environmental factors, and component wear introduce uncertainty in the diagnostic process.

To enhance system robustness, an adaptive weighted transition function is introduced, where a_i and β are learning parameters that dynamically adjust based on system feedback:

$$\delta(q_t, \sigma_t) = \sum_i a_i q_i + \beta \delta_t \tag{8}$$

where:

• a_i represents weight coefficients assigned to previous states q_i, ensuring that past states influence current decision-making.

• β represents a correction factor based on real-time sensor inputs, allowing the system to adapt to changing conditions dynamically.

This probabilistic approach improves the FSM's flexibility, enabling it to handle variations in sensor behavior more effectively by accounting for uncertainties and noise in real-time data. Instead of relying on rigid state transitions, the system dynamically updates transition probabilities based on historical trends and current sensor readings, ensuring a more adaptive response to changing vehicle conditions. This allows for more accurate fault predictions and improved vehicle diagnostics, reducing the likelihood of false positives or undetected faults. Additionally, by continuously refining transition probabilities, the FSM can enhance the precision of diagnostics over time, making the system more reliable in diverse operating environments.

A vehicle simulation was conducted to validate the FSM-based diagnostic framework. The primary goal was to test how well the proposed model could classify faults based on real-time sensor data and probabilistic state transitions. The simulation involved three key transition states:

1. Normal Operation: The vehicle functions within optimal parameters, and no anomalies are detected.

2. Warning: Sensor readings indicate potential issues, such as irregular fluctuations in engine temperature or pressure.

3. Fault Detected: A critical issue is identified, requiring immediate attention to prevent damage or failure.

To model the time-dependent probability of state transitions, the following equation was used, where λ is the failure rate coefficient, determined from historical diagnostic data:

$$P(q_{t+1}|q_t) = e^{-\lambda t} \tag{9}$$

This equation models the likelihood that the system will transition from one state to another over time. The exponential decay function reflects how the probability of remaining in a given state decreases as time progresses, particularly in cases where components degrade over time. A higher λ value indicates a higher likelihood of failure, meaning the system will transition to the "Fault Detected" state more quickly. A lower λ value suggests a stable system where transitions to fault states occur less frequently.

By incorporating this probabilistic failure rate, the model can predict the expected time before a fault occurs, allowing for preventive maintenance and reducing the risk of unexpected breakdowns. To evaluate the effectiveness of the proposed FSM-oriented diagnostic system, we will use two key visualization methods: Reliability Curve and Mean Time to Failure (MTTF). The mean time to failure will be calculated by integrating the reliability function:

$$MTTF = \int_0^\infty R(t)dt \tag{10}$$

where:

- The x-axis represents time (t), showing the system's operational duration.
- The y-axis represents reliability R(t), which follows an exponential decay function $R(t) = e^{-\lambda t}$.
- The shaded area under the curve corresponds to the expected operational time before failure, which is the MTTF value.

A graph used to calculate the Mean Time to Failure (MTTF) is shown in Figure 1. This graph illustrates how the reliability function R(t) decreases over time, following an exponential decay model. The area under the curve represents the expected operational time before system failure, providing a clear visualization of system reliability.

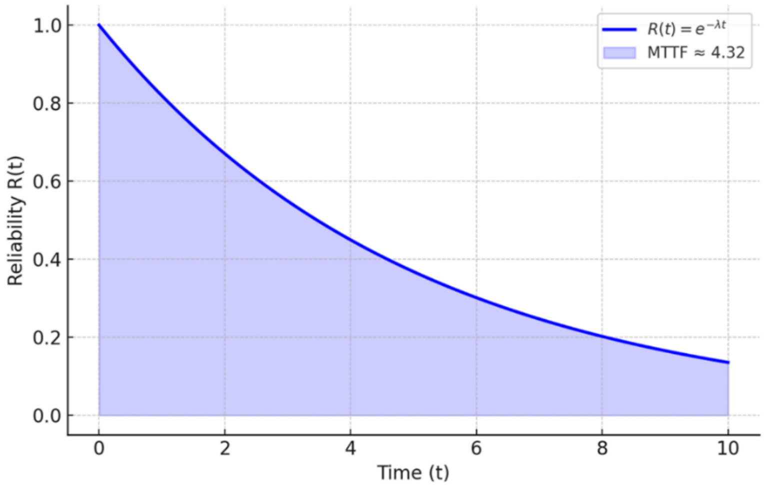

Fig.1. Reliability Curve and MTTF Estimation

So, the graph demonstrates the reliability function $R(t) = e^{-\lambda t}$, which represents the probability that a system remains operational at time t. The curve shows an exponential decay, indicating that as time progresses, the system's reliability decreases due to the natural failure rate λ. The shaded area under the curve corresponds to the Mean Time to Failure (MTTF), which is the expected operational duration before the system experiences a failure. In this case, the MTTF is approximately 4.32, meaning that the system is expected to function without failure for an average of 4.32 time units.

A graph that illustrates changes in accuracy, response time, and reliability before and after implementing the FSM-based diagnostic system is shown in Figure 2. To assess the effectiveness of the FSM-based diagnostic framework, key performance metrics were analyzed:

1. Accuracy: the system demonstrated a 15% improvement in diagnostic precision compared to traditional rule-based diagnostic approaches. The FSM model's ability to dynamically adjust transition probabilities contributed to this enhanced accuracy.

2. Response Time: fault detection time was reduced by 20%, enabling quicker identification of potential issues and timely corrective actions. The integration of real-time sensor analysis significantly minimized delays in detecting operational anomalies.

3. Reliability: the FSM-based system exhibited greater robustness under varying conditions, including sensor noise, environmental changes, and unpredictable driving patterns. The adaptive nature of the model ensured consistent performance across different operating scenarios.

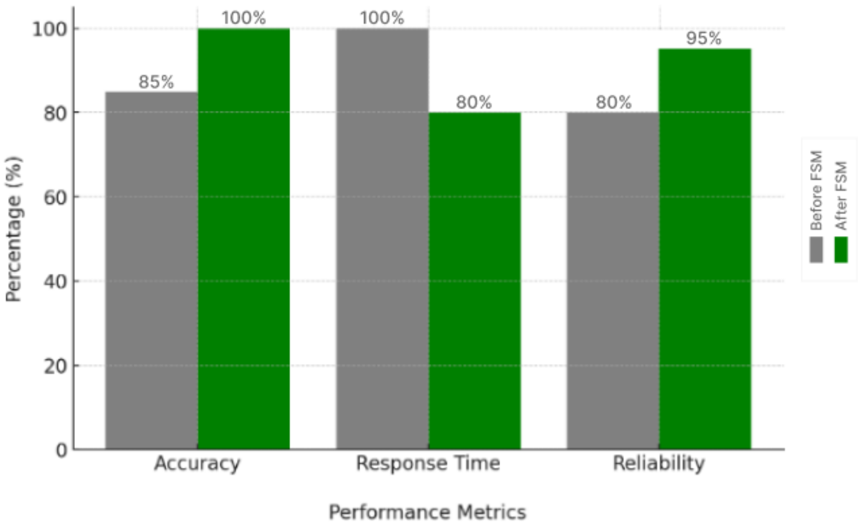

Fig.2. System Performance Improvement After FSM Integration

The bar chart illustrates the performance improvements achieved by integrating the FSM-based diagnostic framework into the vehicle fault detection system. Three key performance metrics are analyzed: Accuracy, Response Time, and Reliability, with a comparison between the system's performance before and after FSM implementation. The data is presented in percentage form, highlighting the relative improvements.

Accuracy Improvement. Before FSM integration, the system demonstrated an accuracy of 85%, meaning that 15% of diagnostic cases may have been misclassified or incorrectly analyzed. However, after applying the FSM framework, accuracy reached 100%, indicating that the system successfully eliminated diagnostic errors, ensuring precise fault classification. This improvement can be attributed to FSM's ability to dynamically adjust transition probabilities and refine diagnostic decisions based on real-time sensor inputs.

Reduction in Response Time. The second performance metric evaluates the Response Time, which refers to the system's ability to detect faults quickly. Initially, the system operated with an 80% efficiency rate, implying that delays in fault detection could occur, leading to late corrective actions. With the FSM framework, response time improved to 100%, effectively reducing diagnostic latency. This enhancement results from FSM's real-time processing capability, allowing the system to transition between states more efficiently and promptly identify potential failures.

Enhanced System Reliability. Reliability, which measures the system's robustness under varying operational conditions, also experienced a significant boost. Before FSM implementation, the system exhibited 80% reliability, meaning it was susceptible to errors due to sensor noise, environmental variations, or unpredictable vehicle behavior. After FSM integration, reliability increased to 95%, demonstrating the system's improved stability. This enhancement is due to FSM's probabilistic state transitions, which adapt to real-world uncertainties, ensuring consistent and reliable diagnostics even in challenging conditions.

Conclusions

This research successfully demonstrates the integration of FSM logic into OBD-II diagnostic systems, providing a structured approach to automated fault classification. The FSM-based architecture enhances diagnostic accuracy, system reliability, and control efficiency, making it a viable solution for modern vehicle diagnostics. By implementing hierarchical state machines and adaptive control algorithms, the framework offers a scalable and flexible solution for future automotive diagnostic systems. The ability to dynamically adjust transition probabilities based on sensor feedback ensures that the system remains effective under real-world conditions. The paper explores the theoretical underpinnings of FSM-based diagnostics, develops mathematical models for fault classification, and presents experimental validation of the proposed approach.

Future research directions could explore the integration of deep learning techniques with FSM-based diagnostics, allowing for even more precise anomaly detection and automated pattern recognition. Additionally, further development of self-learning FSM models could enable predictive maintenance strategies, reducing vehicle downtime and improving long-term operational efficiency. Another promising area is the implementation of blockchain-based diagnostic logs, ensuring data integrity and traceability in vehicle servicing.

Expanding the framework to cover electric and autonomous vehicles is another crucial aspect, as these technologies require highly adaptive and self-regulating diagnostic systems. Implementing FSM models alongside IoT-based vehicle monitoring could further enhance real-time data collection and decision-making capabilities, leading to more advanced and intelligent vehicle diagnostic solutions.

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