Raspberry pi based real time Smart Roadside assistance

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Abstract

The Smart Roadside Assistance System is an innovative solution designed to enhance vehicle breakdown response and provide real-time diagnostics. By leveraging onboard diagnostics (OBD) data, AI-based fault detection, and GPS location tracking, the system ensures swift and efficient assistance for drivers in distress. It monitors critical vehicle parameters, such as engine status, battery health, tire pressure, and fuel levels, enabling real-time assessments. Machine learning models analyze historical and live data to predict potential failures, such as engine misfires or overheating, helping to prevent breakdowns before they occur. In the event of an issue, the system generates a detailed diagnostic report and transmits it to roadside assistance teams, ensuring technicians are well-prepared upon arrival. GPS tracking shares the vehicle's precise location with responders, minimizing delays. Additionally, the system notifies drivers with actionable recommendations, such as inflating tires or checking fluid levels, to enhance safety and prevent further damage. By combining advanced diagnostics, predictive maintenance, and seamless communication, the Smart Roadside Assistance System improves response times, enhances safety, and optimizes the roadside assistance process.

1. Introduction

With the growing reliance on personal and commercial vehicles for daily transportation, logistics, and mobility services, ensuring vehicle reliability and operational continuity has become critically important. However, unexpected mechanical failures and vehicle breakdowns remain a significant challenge, often leading to service disruptions, financial losses, and safety hazards for both drivers and passengers. Traditional roadside assistance methods typically involve manual fault diagnosis, delayed communication, and inefficient dispatching processes, which contribute to extended vehicle downtime and suboptimal user experiences. Recent advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and embedded automotive systems have enabled a paradigm shift in vehicle diagnostics and breakdown management. By leveraging real-time data acquisition from Onboard Diagnostics (OBD) systems, coupled with intelligent analytics and wireless communication technologies, modern roadside assistance solutions are becoming increasingly proactive, predictive, and responsive.

The proposed Smart Roadside Assistance System addresses the limitations of conventional approaches by integrating real-time monitoring, AI-based fault detection, predictive maintenance algorithms, and GPS-based location tracking. The system continuously collects data on critical vehicle health parameters—such as engine performance, battery voltage, tire pressure, and fuel levels—and employs machine learning models to detect anomalies, forecast potential failures, and trigger preventive alerts. Upon identifying a fault condition, the system generates a comprehensive diagnostic report and transmits it to roadside assistance personnel along with the vehicle's exact GPS coordinates. This enables technicians to prepare the necessary tools and components before reaching the vehicle, thereby minimizing response times and improving service efficiency. Furthermore, drivers receive real-time notifications with actionable recommendations, promoting informed decision-making and preventing further mechanical degradation.

The system is designed to be compatible with a wide range of vehicle types, including both personal cars and commercial fleets, and is architected with scalability in mind to support future enhancements such as remote repair capabilities, integration with cloud-based

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fleet management platforms, and data-driven service optimization. By combining IoT, AI, and real-time telemetry, the Smart Roadside Assistance System represents a significant advancement in intelligent transportation systems, ultimately contributing to safer, more efficient, and user-centric vehicular ecosystems.

2. Related works

Vehicle breakdowns can cause significant inconvenience, especially in remote areas where access to mechanics is limited. Traditional roadside assistance services rely on manual intervention, which often results in long wait times and inadequate service availability. Recent advancements in IoT, AI-based diagnostics, and GPS tracking have improved response times and service efficiency, enabling real-time monitoring and predictive maintenance. IoT-based roadside assistance has transformed vehicle breakdown response by integrating sensor-based monitoring, cloud computing, and edge computing to ensure quick and efficient service. Several studies have examined the application of IoT in roadside assistance and predictive vehicle maintenance. Datta and Bonnet (2017) proposed an IoT-based intelligent roadside assistance system that leverages edge computing for real-time vehicle diagnostics and automated service deployment. Ramesh et al. (2024) developed the On Road Vehicle Breakdown Assistance (ORVBA) system, which connects stranded drivers with verified mechanics using GPS and real-time tracking. Yang et al. (2013) highlighted the role of IoT in emergency response operations, emphasizing the need for real-time communication between vehicles, service providers, and roadside infrastructure. These studies emphasize the role of real-time monitoring, AI-based fault detection, and IoT integration in improving roadside assistance services. Predictive maintenance plays a crucial role in modern vehicle assistance systems by analyzing historical and real-time data to detect potential failures before they occur. Van et al. (2016) proposed an integrated lane detection and vehicle tracking system using side-mirror cameras to enhance real-time vehicle monitoring. Elakkiya and Bavithra (2020) proposed an AI-driven roadside assistance system that detects mechanical issues and provides automated alerts to nearby mechanics. Datta et al. (2016) developed a data-centric IoT framework (DataTweet) for intelligent vehicle diagnostics, reducing dependency on cloud systems and improving response efficiency. GPS and location-aware roadside assistance play a vital role in reducing response time and improving service efficiency. Ramesh et al. (2024) implemented a GPS-enabled breakdown assistance system that automatically locates and assigns the nearest mechanic. Datta et al. (2015) demonstrated how integrating IoT and M2M communications enhances smart city infrastructure by improving roadside emergency response times. Sorate et al. (2018) evaluated IoT-based vehicle tracking solutions, highlighting the importance of GPS-enabled automatic assistance.

3. System Design

The Smart Roadside Assistance System is designed as a modular, IoT-enabled architecture that integrates sensor data acquisition, real-time diagnostics, AI-driven predictive analytics, and cloud-based communication.

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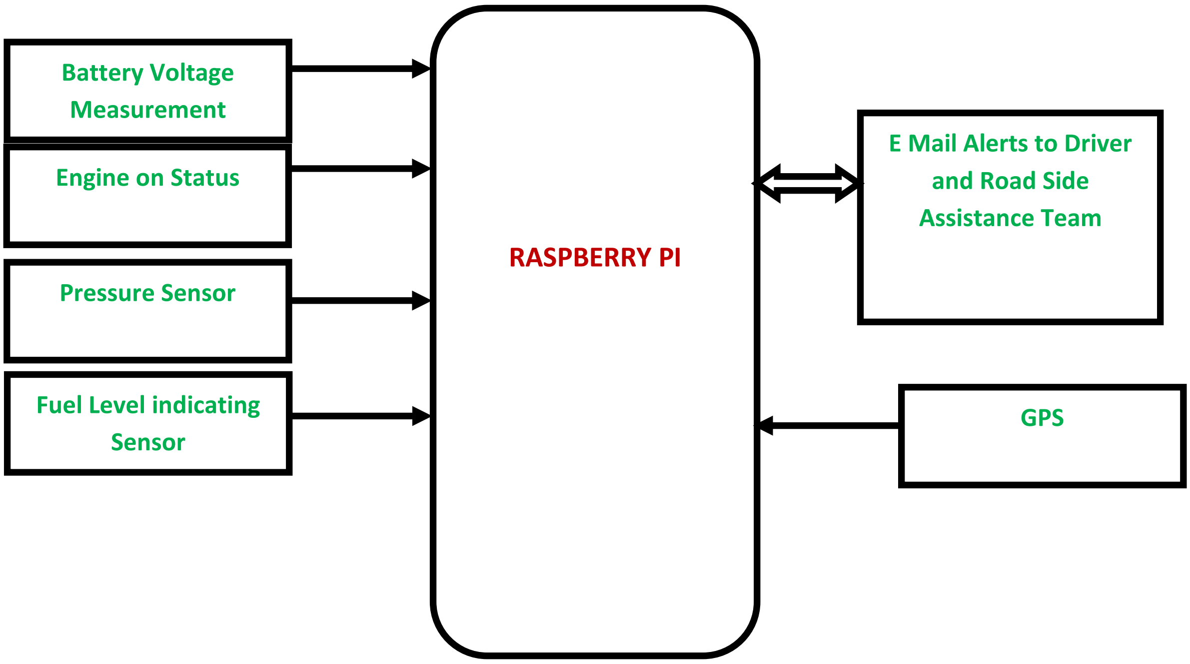

Figure 1: Block Diagram of proposed system

The Smart Roadside Assistance System comprises several integrated hardware and software components, each serving a specific function to ensure comprehensive monitoring, fault detection, and emergency communication. At the core of the system is the Raspberry Pi, which functions as the central processing unit. It orchestrates data acquisition, processes sensor inputs, executes diagnostic and predictive algorithms, and manages communication protocols. Its low power consumption, compact size, and flexibility make it ideal for embedded automotive applications. A Battery Voltage Measurement Module is included to continuously monitor the health and charge status of the vehicle's battery. Voltage drops or abnormal fluctuations are indicative of potential electrical failures or impending battery depletion. Early detection of such anomalies allows preventive intervention, reducing the risk of unexpected breakdowns. The Engine on Status Sensor determines whether the engine is running or off by monitoring ignition signals or engine vibrations. This information is critical in contextualizing the data from other sensors and in confirming whether a breakdown has occurred during vehicle operation or while stationary. To ensure tire safety, the system integrates a Pressure Sensor that measures the air pressure in each tire. Abnormal tire pressure can lead to poor fuel efficiency, reduced handling, or even blowouts. The sensor data is compared against safety thresholds, and alerts are generated for the driver in case of under-inflation or over-inflation. The Fuel Level Sensor provides real-time readings of the fuel tank's contents. By monitoring this parameter, the system can notify drivers when fuel levels fall below a critical threshold, preventing stalls due to fuel exhaustion and supporting trip planning in remote areas. Location tracking is facilitated by a GPS Tracking System, which continuously records the vehicle's geographic position. In the event of a breakdown or fault detection, the GPS coordinates are transmitted to the nearest roadside assistance unit. This feature not only accelerates response times but also enhances driver safety, especially in unfamiliar or isolated regions. Lastly, the E-Mail Alert System is responsible for generating and dispatching automated alerts during emergency conditions. Upon detection of a fault or predicted failure, the system compiles a diagnostic report and transmits it via email to both the vehicle owner and the designated roadside assistance service. These alerts contain vital information such as fault type, sensor readings, and GPS location, enabling rapid and

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informed response actions. Together, these components form a cohesive and intelligent roadside assistance system capable of proactive vehicle health monitoring, real-time diagnostics, and timely emergency response.

4. Methodology

The system consists of four core subsystems Data Acquisition Layer, Processing and Fault Detection Module, Predictive Maintenance Engine, Communication and Alert Dispatch Module.

4.1 Data Acquisition Layer

The data acquisition module interfaces directly with the vehicle's Onboard Diagnostics II (OBD-II) port and auxiliary sensors such as tire pressure sensors, battery voltage monitors, and fuel level indicators. The data collected includes Vehicle speed, V, Coolant temperature, T_c,Battery voltage, V_b,Fuel level, F_l,Tire pressure (per wheel), P_{tire}.

The raw data vector from all sensors can be represented as:

$$X(t) = \left[R_{eng}(t), V(t), T_c(t), V_b(t), F_l(t), P_{tire_1}(t), \dots, P_{tire_n}(t)\right]$$

where t is the timestamp, and n is the number of tire sensors.

4.2 Processing and Fault Detection Module

Collected data is transmitted in real-time to the onboard edge processing unit (typically Raspberry Pi or equivalent microcontroller), where preprocessing (noise filtering, normalization) is conducted. Each parameter is evaluated against predefined safety thresholds to detect immediate faults.

A binary fault indicator function δ_i for parameter i is defined as:

$$\delta_i(t) = \begin{cases} 1 & \text{if } x_i(t) \notin \left[x_i^{min}, x_i^{max}\right] \\ 0 & \text{otherwise} \end{cases}$$

The cumulative fault state is:

$$\Delta(t) = \sum_{i=1}^{N} \delta_i\,(t)$$

where N is the number of monitored parameters. If $\Delta(t) > 0$, the system flags a fault and proceeds to alert generation.

4.3 Predictive Maintenance Engine

To forecast potential failures before they occur, a supervised machine learning model (e.g., Random Forest, LSTM, or Gradient Boosted Trees) is trained on historical time-series data from vehicles under normal and fault conditions.

The model aims to estimate the failure probability for each component j at time t:

$$P_j(t) = P\left(f_j \mid X_{t-h:t}\right)$$

Where:

f_j is a fault event associated with component j,

$X_{t-h:t}$ is the windowed feature vector from time $t - h$ to t,

$P_j(t)$ is the predicted fault probability.

A fault is predicted if:$P_j(t) \geq \theta_j$

Where θ_j is a threshold determined during model training (e.g., via ROC curve optimization).

This predictive layer enables alerts such as "engine overheating likely in next 15 km" or "battery failure risk detected".

4.4 Communication and Alert Dispatch Module

Once a fault or high-risk prediction is made, the system performs two primary actions:

Alert Transmission to Roadside Assistance

A diagnostic packet D containing fault codes, GPS location (lat, lon), and a brief

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summary is transmitted to the cloud server and forwarded to the nearest assistance unit.

$$D = \{\Delta(t), P_j(t), GPS(t), Timestamp, Vehicle\ ID\}$$

1. User Notification Interface
   Alerts are pushed to the driver's mobile application with actionable recommendations, estimated fault severity, and expected response time.

4.5 System Workflow Summary

- Input: Sensor data X(t)
- Process: Preprocessing → Threshold evaluation → Predictive modeling
- Output: Fault flags, predicted failures, alerts with GPS
- Technologies: Python (ML inference), MQTT/HTTP (data transmission), Firebase (cloud integration)

5. Algorithm:

Algorithm 1: Smart Roadside Assistance Workflow
Input: Real-time sensor data X(t) from vehicle subsystems
Output: Diagnostic alerts, GPS location, user notifications, and historical data logging

1. Begin
2. Data Acquisition
   2.1. Collect sensor readings:
   $V_b(t) \leftarrow$ Battery Voltage
   $E_s(t) \leftarrow$ Engine On/Off Status
   $P_{tire}(t) \leftarrow$ Tire Pressure
   $F_l(t) \leftarrow$ Fuel Level
3. Data Preprocessing
   3.1. Normalize and filter sensor inputs
   3.2. Construct data vector:
   $X(t) = [V_b(t), E_s(t), P_{tire}(t), F_l(t)]$
4. Fault Detection
   4.1. For each parameter $x_i \in X(t)$:
   If $x_i \notin [x_i^{min}, x_i^{max}]$, then
   Set $\delta_i(t) = 1$ (fault detected)
   Else
   Set $\delta_i(t) = 0$
   4.2. Compute total faults:
   $\Delta(t) = \sum \delta_i(t)$
5. If $\Delta(t) > 0$, then
   5.1. Generate diagnostic report
   5.2. Retrieve current GPS coordinates (lat, lon)
   5.3. Send email alert to:
   - Driver
   - Roadside Assistance Team
6. User Notification
   6.1. Generate recommendation based on $x_i(t)$ status:
   - E.g., "Inflate front left tire," "Refuel within 10 km," etc.
   6.2. Display notification via connected interface or mobile app
7. Cloud Logging and Analysis
   7.1. Store X(t), δ(t), GPS, and timestamp in cloud
   7.2. Use stored data for predictive model training and analytics

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8. End

6. Experimental Results

The experimental setup phase is critical to validate the real-world performance of the Smart Roadside Assistance System (SRAS). This section outlines how the system was deployed on a vehicle, what data was logged, and how observation and validation were conducted.

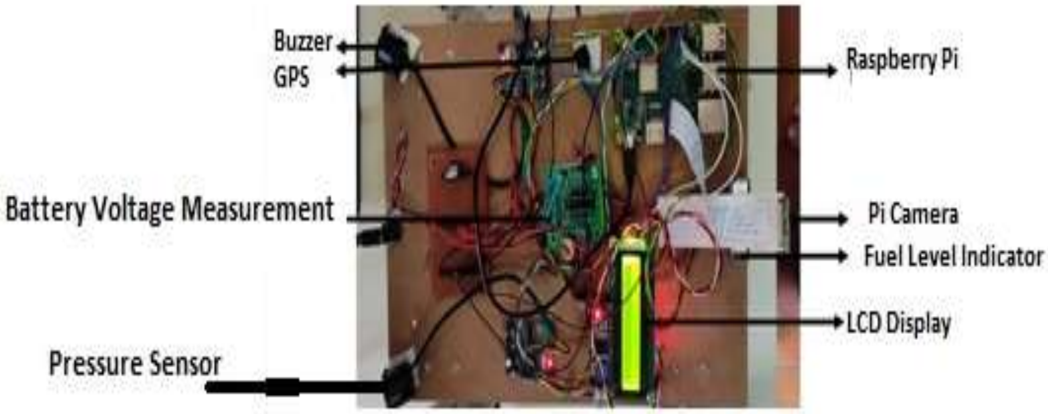

Figure 2 Experimental output of Proposed System

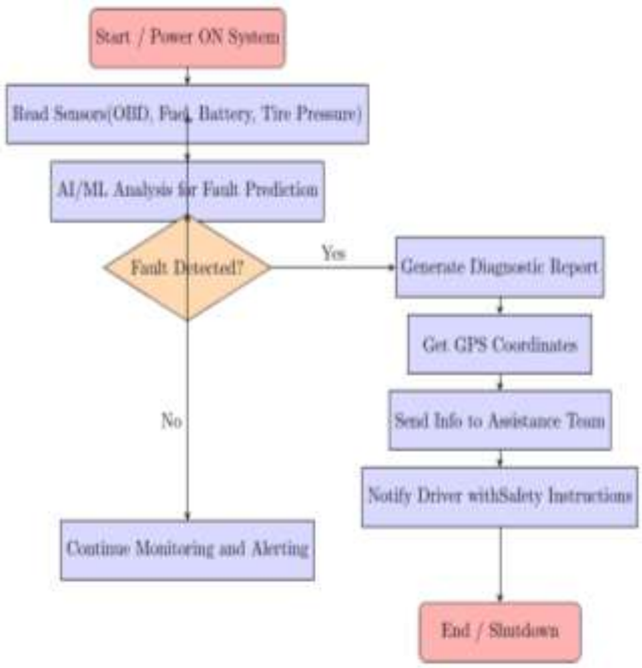

Figure 3 Flow chart of the System

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Table 1: Comparative Analysis of Roadside Assistance Approaches

Technology	Advantages	Limitations
Traditional roadside assistance	Accessible in urban areas, human intervention	Slow response times, limited mechanic networks
IoT-based vehicle monitoring	Real-time data analysis, remote fault detection	Requires IoT infrastructure, cost considerations
AI-driven predictive maintenance	Reduces breakdowns, enhances safety	Relies on data accuracy and sensor quality
GPS-enabled roadside assistance	Quick location-based service dispatch	Limited by GPS accuracy and network availability

Conclusion

The Smart Roadside Assistance System presents a robust, scalable, and intelligent solution to the pressing need for rapid vehicle breakdown detection, diagnostics, and response. By leveraging IoT-enabled sensors, edge computing via Raspberry Pi, AI-based fault detection algorithms, and real-time GPS tracking, the system enhances both the responsiveness and reliability of roadside support services. Unlike traditional reactive systems, this solution enables proactive intervention through predictive maintenance capabilities, thereby minimizing vehicle downtime and improving driver safety. Additionally, automated alert dispatch and user-centric notifications ensure timely communication with both the driver and roadside assistance providers. Addressing key limitations in current systems—such as lack of interoperability, high latency from cloud dependence, and limited focus on user experience—this integrated approach sets a foundation for next-generation vehicular support platforms. Future advancements may include voice-enabled diagnostics, integration with vehicle telematics standards, and blockchain-based service records for enhanced transparency and trust.

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