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Real-Time Advanced Vehicle Predictive Maintenance System

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Abstract: This project develops a comprehensive vehicle predictive maintenance system that leverages IoT sensors, machine learning, and cloud computing to monitor critical vehicle components and predict potential failures before they occur. The system addresses the growing need for proactive maintenance strategies in the automotive industry by monitoring real-time parameters such as brake pad pressure, gearbox usage patterns, clutch stress cycles, and environmental humidity levels using dedicated sensors connected to an ESP32/Arduino microcontroller. Data is transmitted to cloud storage via Wi-Fi for advanced analytics and machine learning-based failure prediction. The system features a web dashboard for real-time monitoring, historical data visualization, and maintenance scheduling recommendations. Multiple alert mechanisms including local buzzers, LED/OLED displays, SMS, and email notifications ensure timely maintenance interventions.

Keywords: IoT, ESP32, Brake and Pressure Sensor, Temperature sensor, Vibration sensor, Gearbox Monitoring, Clutch Health, Firebase Cloud, Machine Learning, Predictive Maintenance.

I. INTRODUCTION

The automotive industry faces significant challenges related to vehicle maintenance, with traditional reactive and scheduled maintenance approaches proving inadequate for modern transportation needs. Vehicle breakdowns due to component failures result in substantial economic losses, safety risks, and operational disruptions. Critical components like brake pads, gearboxes, and clutches often fail unexpectedly, leading to costly repairs, safety hazards, and vehicle downtime. Traditional maintenance strategies rely on fixed schedules or manual inspections, which are either too conservative (leading to unnecessary replacements). The integration of machine learning algorithms with real-time sensor data allows for accurate prediction of component failures, optimizing maintenance schedules and reducing costs. This approach is particularly crucial in fleet management, where vehicle downtime directly impacts operational efficiency and profitability.

II. PROBLEM STATEMENT AND OBJECTIVE

Modern vehicles rely on multiple mechanical and electronic components whose performance deteriorates gradually with time due to operational stress, wear, and changing environmental conditions This approach leads to critical component failures such as brake pad degradation, gearbox malfunction, and clutch wear occurring unexpectedly, posing significant safety risks and resulting in costly repairs. Breakdowns during vehicle operation also contribute to financial loss, unplanned downtime, and logistical disruptions, especially for fleet-based transportation and logistics industries. Although IoT and machine learning technologies have advanced significantly, most vehicles still lack an intelligent system capable of monitoring internal health parameters continuously and predicting failures ahead of time. Existing onboard vehicle diagnostics focus mainly on error detection rather than future forecasting and do not provide actionable insights for maintenance planning.

Objectives:

Internal health parameters continuously and predicting failures ahead of time. Existing onboard vehicle diagnostics focus mainly on error detection rather than future forecasting and do not provide actionable insights for maintenance planning.
To collect and analyze sensor data through an ESP32 microcontroller and transmit it to a cloud platform for remote accessibility.
To design and implement machine learning models that can accurately predict component failures and estimate the Remaining Useful Life (RUL) of vehicle parts.
To establish a cloud-based centralized data management system for long-term storage, analytics, and system scalability.
To provide visual insights and maintenance reports through a web dashboard for drivers, technicians, and fleet managers to monitor system status and trends.

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III. SCOPE

This project develops a comprehensive vehicle predictive maintenance system that leverages IoT sensors, machine learning, and cloud computing to monitor critical vehicle components and predict potential failures before they occur. The system addresses the growing need for proactive maintenance strategies in the automotive industry by monitoring real-time parameters such as brake pad pressure, gearbox usage patterns, clutch stress cycles, and environmental humidity levels using dedicated sensors connected to an ESP32/Arduino microcontroller. The system features a web dashboard for realtime monitoring, historical data visualization, and maintenance scheduling recommendations. Multiple alert mechanisms including local buzzers, LED/OLED displays, SMS, and email notifications ensure timely maintenance interventions. Expected outcomes include reduced maintenance costs, improved vehicle safety, extended component lifespan, and minimized unexpected breakdowns through accurate prediction of brake pad wear, gearbox failures, and clutch issues, ultimately transforming reactive maintenance practices into proactive, data -driven strategies.

IV. LITERATURE REVIEW

[1] **Shafi et al. (2025)** conducted a comprehensive review of 94 research studies focused on artificial intelligence–driven predictive maintenance in the automotive sector, emphasizing the transformative potential of machine learning and deep learning models for predicting component failures before breakdowns occur.
[2] **Sarker et al. (2024)** contributed to the literature by examining the application of artificial intelligence, digital twins, and IoT-enabled infrastructure for predictive maintenance in transportation systems. The authors emphasized that trustworthy AI and sensor-assisted digital models can mimic the behavior of physical components and detect early signatures of wear.
[3] **Jensen et al. (2023)** proposed an innovative brake-wear estimation model using fused sensor systems and statistical data processing, incorporating Bayesian linear regression and Kalman filtering to estimate the remaining useful life (RUL) of brake pads based on friction work and longitudinal vehicle dynamics.
[4] **Sathish Kumar et al. (2020)** introduced a digital-twin framework for automotive brake-pad predictive maintenance using the Thing Worx IoT platform integrated with CREO simulation models.
[5] **Theissler et al. (2021)** reviewed the role of machine learning in enabling predictive maintenance across the modern automotive industry, identifying a diverse range of use cases such as anomaly detection in transmission systems, sensor-driven diagnostics for brake wear, and prognostics for clutch plate failure
[6] **Zhang et al. (2021)** implemented an edge-computing–enabled vehicle maintenance system that performs ondevice anomaly detection using lightweight neural networks, reducing latency and dependence on cloud connectivity.
[7] **Rao and Patel (2021)** advanced multimodal sensor-fusion research by combining pressure, vibration, and humidity sensing for condition-based maintenance of automotive brake assemblies.
[8] **Martinez and Kim (2023)** developed a gearbox fault prediction system using vibration and torque sensors paired with gradient-boosting machine learning models to classify gear-mesh abnormalities.
[9] **Li et al. (2022)** investigated explainable AI (XAI) for predictive maintenance and introduced SHAPbased interpretability for component wear prediction in electric vehicle powertrains.
[10] **Zhou et al. (2022)** introduced a multi-sensor IoT diagnostic framework for vehicle clutch wear estimation using temperature, deformation force, and sliding-frequency sensors.

4.1 Gaps or Areas for Improvement

Real-time predictive maintenance systems have demonstrated strong potential in improving vehicle reliability and safety, several important gaps remain. Most existing systems are validated only through simulation or small-scale prototypes rather than extended real-world fleet trials, which limits understanding of their long-term performance under varying weather, traffic, and driving conditions. System accuracy is also highly dependent on stable and noise-free sensor data; however, practical challenges such as sensor drift, vibration, heat exposure, wiring faults, and electromagnetic interference can degrade data reliability over time. In addition, edge-AI deployment on low-power controllers such as ESP32 faces constraints related to memory capacity, thermal stress, and processing power, making it difficult to run complex predictive algorithms in real time. Continuous internet connectivity is another challenge, as vehicles may experience network dropouts in remote or obstructed environments, which affects cloud-based analytics and data synchronization.
Another major limitation is that many AI-based diagnostic models operate as “black-box” systems, providing little interpretability for technicians, which reduces trust and slows industrial adoption. Building accurate predictive models also requires large and diverse datasets, but vehicle failure data is scarce, private, and inconsistently recorded across manufacturers, resulting in bias and under-trained models. Cybersecurity and privacy concerns present further risks, since unauthorized access to vehicle telemetry could compromise safety or expose sensitive operational data. Moreover, most current systems monitor only a limited set of components such as brakes, clutch, and gearbox, rather than providing a

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holistic health-monitoring platform for all subsystems including suspension, battery systems, electronics, and emissions. Finally, although alerts are generated, many systems lack advanced decision-support features such as repair urgency ranking, cost–benefit estimation, or integration with workshop management systems.

V. SYSTEM ARCHITECTURE

The proposed real-time advanced vehicle predictive maintenance system is organized into four functional layers: the sensor layer, edge layer, cloud layer, and application layer. At the sensor layer, multiple IoT devices including a humidity sensor, brake pressure sensor, gearbox usage sensor, and clutch plate sensor continuously capture mechanical stress, environmental influence, and usage behavior from critical vehicle components. These real-time signals are transmitted to the edge layer, where an ESP32/Arduino microcontroller performs local data acquisition, preliminary analytics, and Wi-Fi-based communication. The edge device is also responsible for generating immediate in-vehicle alerts through a buzzer or OLED display whenever abnormal readings exceed defined safety thresholds.

The cloud-generated insights are consumed by the application layer, which provides multiple user-oriented interfaces. A web dashboard supports real-time monitoring, visualization of historical data trends, and predictive maintenance scheduling, enabling technicians and fleet managers to make informed decisions. In parallel, an alert system sends notifications via SMS or email when risks are detected, using configurable thresholds to tailor system responsiveness. Mobile applications further extend accessibility by allowing users to receive push notifications and maintain digital maintenance logs remotely. Overall, the architecture integrates IoT sensing, edge intelligence, cloud analytics, and user-centric applications into a unified framework capable of continuously monitoring vehicle health and supporting proactive, data-driven maintenance.

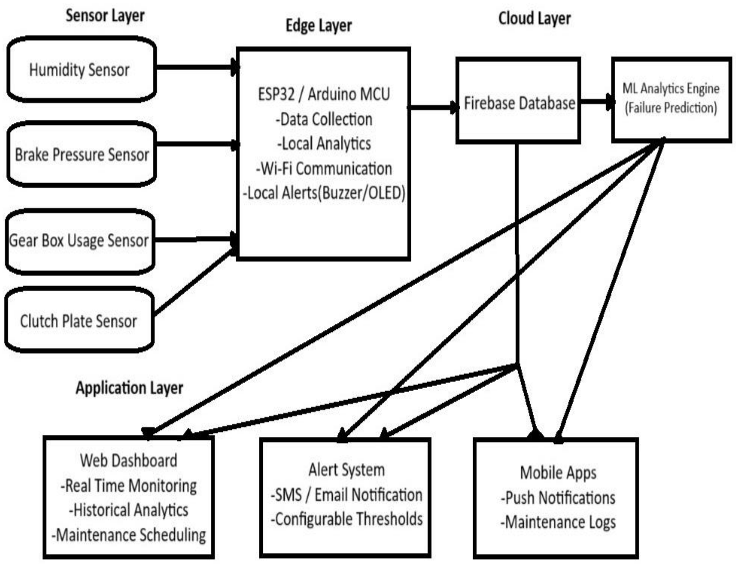

Figure 1. Proposed System Architecture of Real Time Advanced Vehicle Predictive Maintenance System

VI. METHODOLOGY

Vehicle Predictive Maintenance system capable of monitoring component health in real time and estimating remaining useful life (RUL) using IoT and machine learning.

- **Requirements Study and Component Identification:** Identification of critical vehicle components prone to failure such as brake pads, gearbox, and clutch.
- **Hardware Setup and Sensor Integration:** Integration of brake pressure sensor, gearbox usage sensor, clutch plate usage sensor, and humidity sensor with ESP32 microcontroller Design of ESP32 input– output mapping including Wi-Fi communication module.
- **Edge Processing and Data Acquisition:** Implementation of embedded firmware to capture real-time multivariate sensor readings at regular intervals. Local alert triggering (buzzer/LED) when abnormalities exceed predefined safety limits to prevent immediate risk to the driver.

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- **Cloud Storage and Data Synchronization:** Establishment of a cloud database (Firebase) to store continuous sensor readings and historical maintenance data. Development of a time stamp based logging system for long term data analysis, model training, and predictive evaluation.
- **Machine Learning Model Development:** Extraction of historical sensor datasets stored in the cloud for offline model training. Application of regression-based ML models (e.g., Random Forest) to estimate Remaining Useful Life (RUL) and predict failure probability.
- **Dashboard and Alert System Implementation:** Development of a web dashboard for visualization of live sensor data, degradation curves, analytics, and maintenance logs. Logging of all alerts and recommendations for future servicing reference

VII. IMPLEMENATION ENVIRONMENT

The implementation of the Real-Time Advanced Vehicle Predictive Maintenance System was carried out using an integrated hardware–software environment that supports continuous data acquisition, wireless communication, cloud storage, and predictive analytics. The embedded environment was based on the ESP32 microcontroller platform, programmed using the Arduino IDE, which enabled real-time interface with multiple IoT sensors including the brake pressure sensor, gearbox usage sensor, clutch plate sensor, and humidity sensor.

The ESP32 was chosen due to its built-in Wi-Fi capability, low power consumption, and suitability for edge processing tasks. Sensor data was collected through analog and digital GPIO interfaces, pre-processed locally, and transmitted securely to the cloud. The Firebase Realtime Database served as the primary cloud backend for data storage and synchronization, enabling low-latency communication between the device, server, and applications.

On the analytics side, machine learning-based predictive models were developed and executed in the cloud environment to estimate component degradation and Remaining Useful Life (RUL). The visualization and user-interaction layer consisted of a web-based dashboard and mobile application interface, developed to support real-time monitoring, historical data review, and maintenance decision-making.

Alert management was implemented via email and SMS notification services, ensuring instant communication to users when abnormal readings or failure risks were detected. The system was tested under controlled conditions to validate performance, and the hardware was powered using a regulated DC supply to replicate in-vehicle integration. Overall, the implementation environment provided a scalable, connected, and intelligent platform suitable for real-world deployment in automotive maintenance applications.

Prototype Model

The prototype developed for the Real-Time Advanced Vehicle Predictive Maintenance System represents a functional laboratory-scale model designed to simulate the behavior of critical vehicle components. The setup consists of an ESP32/Arduino-based control unit connected to multiple IoT sensors and electromechanical elements mounted on a test platform. Three simulated pedal mechanisms are installed to represent the brake, clutch, and gearbox controls. Each pedal is mechanically linked to corresponding sensing units so that variations in pressure, movement frequency, and usage intensity can be captured during operation. A humidity sensor is additionally placed near the mechanical housing to model environmental exposure and its influence on component degradation.

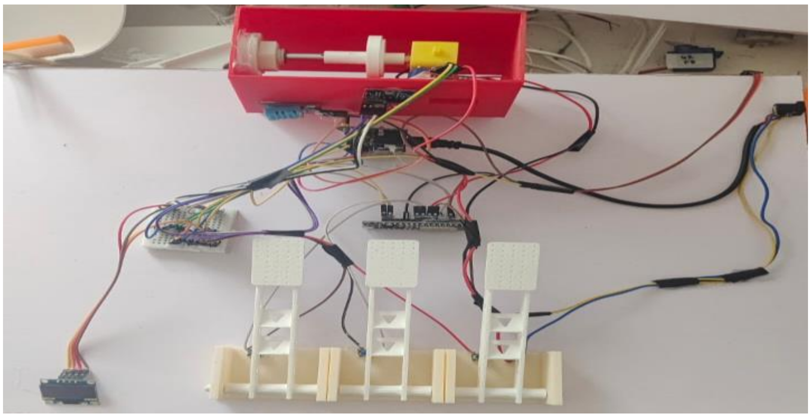

Figure 1: Vehicle Predictive Maintenance System Prototype Model

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Vehicle Predictive Maintenance System Dashboard Interface

This appendix presents the user interface of the real-time Vehicle Predictive Maintenance Dashboard. It displays critical alerts such as low oil level warnings to prevent engine damage.

The dashboard also provides key performance metrics including temperature, humidity, vibration, and oil consumption. These visual indicators help users monitor vehicle health efficiently.

Overall, the dashboard enhances early fault detection and supports proactive maintenance decisions.

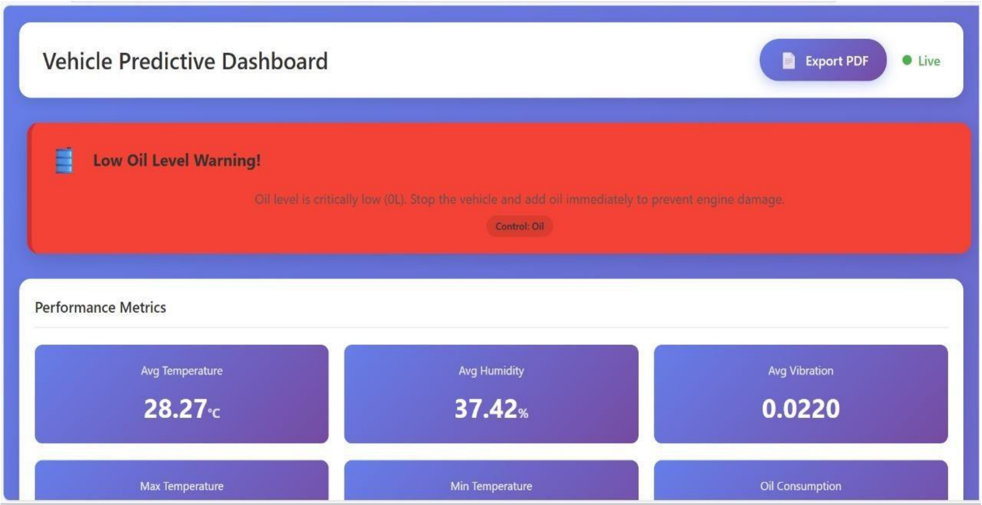

Figure 2: Vehicle Predictive Maintenance System Dashboard Interface

VIII. MODULES

1.Data Acquisition Module

The Data Acquisition Module is responsible for collecting real-time vehicle data. This module includes IoT sensors and onboard diagnostic (OBD-II) devices installed in the vehicle. Sensors continuously monitor critical parameters such as engine temperature, vibration levels, oil pressure, battery voltage, fuel consumption, brake condition, and tire pressure.

2. Onboard Processing Module

The Onboard Processing Module performs preliminary processing of sensor data before transmission. This includes data aggregation, filtering, and formatting. Basic anomaly checks are carried out to detect extreme or invalid values.

3. Communication and Telematics Module

The Communication Module handles secure and reliable data transmission from the vehicle to the cloud platform. Wireless technologies such as GSM, LTE, 4G/5G, or Wi-Fi are used to transmit data in real time.

4. Cloud Data Storage Module

The Cloud Data Storage Module stores large volumes of real-time and historical vehicle data. Scalable cloud databases are used to handle continuous data streams from multiple vehicles.

5. Data Preprocessing and Management Module

The Data Preprocessing Module cleans and prepares raw data for analysis. This includes removing noise, handling missing values, normalizing data, and detecting outliers. This module ensures high data quality, which directly impacts the accuracy of predictive models. Proper data preprocessing enables reliable pattern recognition and reduces false predictions.

6. Predictive Analytics Module

The Predictive Analytics Module is the core of the system. It uses machine learning algorithms to analyze vehicle data and predict potential component failures. The module is trained using historical vehicle data, maintenance records, and fault logs.

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7. Real-Time Monitoring and Alert Module

This module monitors live vehicle data and prediction results. When abnormal behavior or high failure probability is detected, alerts are generated automatically. Alerts include information such as affected component, severity level, and recommended maintenance action. Notifications are delivered through dashboards, mobile applications, SMS, or email, ensuring timely response.

8.Maintenance Recommendation Module

The Maintenance Recommendation Module provides actionable insights based on predictive analysis. It prioritizes maintenance tasks based on risk level, urgency, and operational impact. This module helps users schedule maintenance efficiently, reduce downtime, and optimize resource utilization. It supports condition-based maintenance planning rather than fixed schedules.

9. User Interface and Dashboard Module

The User Interface Module presents system outputs in an easy-to-understand format. Dashboards display real-time vehicle health status, alerts, historical trends, and maintenance history. Visualization tools such as graphs, charts, and tables help users interpret complex data. Role based access ensures that drivers, technicians, and managers view relevant information.

10. Security and Access Control Module

Security is a critical aspect of the system design. This module ensures data confidentiality, integrity, and availability. Authentication mechanisms, role-based access control, and encryption techniques are implemented.

IX. PERFORMANCE EVALUATION

Real-Time Advanced Vehicle Predictive Maintenance System represents a functional laboratory-scale model designed to simulate the behavior of critical vehicle components. The setup consists of an ESP32/Arduino-based control unit connected to multiple IoT sensors and electromechanical elements mounted on a test platform. Three simulated pedal mechanisms are installed to represent the brake, clutch, and gearbox controls. Each pedal is mechanically linked to corresponding sensing units so that variations in pressure, movement frequency, and usage intensity can be captured during operation. A humidity sensor is additionally placed near the mechanical housing to model environmental exposure and its influence on component degradation.

The wiring network interfaces all sensors with the microcontroller, which performs real-time data acquisition and preliminary analytics before transmitting readings to the cloud database. A small motor-driven mechanism is integrated into the assembly to generate controlled motion and simulate real driving stress conditions. The hardware is powered by a regulated DC supply, and output readings can be visualized through the web dashboard or OLED display. This prototype successfully demonstrates the end-to-end workflow of the proposed system, including sensing, data logging, cloud communication, and maintenance alert generation. It serves as a proof-of-concept platform validating that continuous monitoring can be applied to vehicle subsystems to detect abnormal wear trends before failure occurs.

X. CONCLUSION

The Vehicle Predictive Maintenance System developed in this project demonstrates that integrating IoT sensing and machine learning can transform traditional vehicle maintenance practices into a proactive and intelligent ecosystem. By continuously monitoring key automotive components such as the brake system, gearbox, clutch mechanism and environmental humidity, the system overcomes the limitations associated with periodic manual inspections and delayed fault identification. Real-time data acquisition through the ESP32 microcontroller ensures continuous visibility of the component health, thereby reducing the dependency on driver intuition alone and adding a technological safety layer to vehicular operations.

The cloud-based architecture using Firebase enables long-term storage of historical sensor data, which plays a critical role in building accurate predictive models. The trained Random Forest machine-learning model effectively analyzes live and historical information to predict failure probability and Remaining Useful Life (RUL) of components. The performance of the model during testing validates that predictive analytics can anticipate mechanical issues considerably earlier than conventional onboard diagnostics and service schedules. This facilitates systematic maintenance planning, reducing unplanned downtime and improving the operational lifespan of the vehicle.

The dashboard visualization and multilevel alert mechanisms further strengthen the usability and impact of the system. By sending warnings via buzzer, LED/OLED display, SMS and email notifications, the system ensures that drivers and fleet managers are immediately informed about high-risk conditions. This proactive intervention capability is vital, especially in high usage vehicles and fleet environments where sudden failures can lead to financial loss, safety hazards and transportation delays.

In summary, the implemented prototype successfully demonstrates that predictive maintenance significantly enhances vehicle reliability, safety and cost efficiency. The system minimizes unexpected failures by predicting component degradation in advance, allowing maintenance to be performed only when necessary instead of following fixed schedules. The findings from the project indicate that such intelligent maintenance solutions have strong potential for real-world adoption in commercial and passenger vehicle sectors, marking a major step towards smart transportation and Industry 4.0- based automotive ecosystems.

Future Work

Although the developed Vehicle Predictive Maintenance System successfully monitors and predicts the health of key mechanical components, there are several opportunities for future enhancement to expand its functionality and improve its real-world deployment potential. One important extension is the inclusion of additional sensors for vibration, temperature, speed and fuel efficiency to monitor a wider range of automotive subsystems, including the engine, suspension and transmission bearings.

Likewise, implementing deep learning models such as LSTM and Temporal Convolution Networks (TCN) can further improve prediction accuracy by learning complex time-sequence patterns in long-duration driving data. Another promising direction is the integration of a digital-twin simulation model to virtually replicate vehicle behavior and generate synthetic failure data, which would help overcome the data scarcity problem encountered during machine-learning training.

In addition, deploying the model directly on edge devices—through edge AI optimization—can reduce dependency on cloud connectivity and allow prediction processing to continue even in remote locations. For fleet-scale industrial deployment, blockchain-based data security can be implemented to ensure secure sharing of vehicle health data across service centers, manufacturers and insurance providers.
Finally, commercial adoption can be accelerated by forming collaborations with automobile workshops and transport companies to test the system on a larger sample of vehicles and evaluate its long-term economic benefits.

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