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IoT Based Low-Cost Smart EV Motor Fault Detection Using ESP32

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Abstract: *The operational integrity of Electric Vehicle (EV) propulsion systems is paramount for the advancement of sustainable transportation. Sudden motor malfunctions, especially during high-speed transit, present severe safety hazards and logistical inefficiencies. Conventional maintenance models, typically reactive or rigidly scheduled, often fail to address incipient faults effectively, leading to avoidable downtime. This study introduces a comprehensive IoT-enabled framework designed for the predictive maintenance of EV motors. The proposed architecture leverages the ESP32 microcontroller to orchestrate a multi-sensor array, comprising accelerometers for vibration profiling, Hall Effect sensors for current signature analysis, and thermal probes for temperature monitoring. By adopting a synergistic mechatronic approach, the system processes sensor data in real-time, utilizing threshold logic and Root Mean Square (RMS) computation to identify early signs of degradation. Telemetry data is relayed via Wi-Fi to the Blynk IoT interface, affording drivers immediate visualization and alert capabilities. Empirical validation confirms the system's efficacy in detecting anomalies in current and vibration metrics with minimal latency, establishing a cost-effective paradigm for enhancing vehicle reliability*

Keywords*:* Electric Vehicle; Predictive Maintenance; IoT; ESP32; Vibration Analysis; Motor Current Signature Analysis

I. INTRODUCTION

1.1 Background of Electric Mobility

The transition from Internal Combustion Engine (ICE) platforms to Electric Vehicles (EVs) represents a definitive shift in automotive engineering, propelled by urgent climate mandates and the finite nature of fossil fuel resources. While energy storage systems often dominate the discourse on EV technology, the electric motor serves as the kinetic core of the vehicle. Whether employing Brushless DC (BLDC) units or Permanent Magnet Synchronous Motors (PMSM), these components operate under rigorous conditions, enduring thermal cycling, road-induced mechanical shock, and electrical stress. The prevailing assumption that electric drivetrains are "maintenance-free" is increasingly challenged as global fleets age. A failure in the prime mover does not merely reduce efficiency; it poses immediate risks of immobilization and critical safety incidents.

1.2 The Evolution of Maintenance Paradigms

To contextualize the proposed solution, it is necessary to examine the trajectory of maintenance philosophies. Historically, three distinct generations have defined industrial asset management:

Reactive (Breakdown) Maintenance: Often termed "run-to-failure," this archaic method initiates repairs only after functionality ceases. In automotive contexts, this maximizes theoretical component life but introduces unacceptable risks of catastrophic on-road failure.

Preventive (Scheduled) Maintenance: This model relies on time-based or mileage-based servicing intervals (e.g., every 10,000 km). While it mitigates unexpected breakdowns, it is inherently inefficient, often resulting in the replacement of healthy components and increased ownership costs.

Predictive Maintenance (PdM): Representing the standard of Industry 4.0, PdM utilizes continuous condition monitoring to forecast failures. By analyzing real-time variables—such as vibration spectra, thermal gradients, and current draw—maintenance can be executed precisely when required, optimizing both safety and resource allocation.

1.3 Problem Statement and Motivation

Despite rapid technological strides, a significant disparity exists in the availability of diagnostic tools for the mass market. The maintenance ecosystem for electric two-wheelers and three-wheelers—vital to the transport infrastructure of developing economies—remains predominantly reactive. Drivers often receive no forewarning of component degradation until total failure occurs. While industrial SCADA solutions offer robust monitoring, their high cost and complexity render them unsuitable for consumer EVs. This research is driven by the imperative to democratize predictive maintenance technologies. By utilizing accessible components like the ESP32, this project seeks to demonstrate that sophisticated, real-time diagnostics can be achieved at a fraction of the cost of OEM alternatives.

1.4 Objectives

The primary goal of this research is to engineer a robust, IoT-integrated prototype for EV motor health monitoring. The specific technical objectives are:

- Embedded System Architecture: To design a compact data acquisition node using the ESP32 microcontroller, capable of interfacing with a multi-physics sensor suite.
- Fault Detection Logic: To develop and deploy firmware algorithms capable of distinguishing standard operational variance from genuine anomalies (mechanical instability, electrical overload, and thermal stress).
- IoT Ecosystem Integration: To establish a low-latency communication pipeline between the hardware node and the Blynk IoT Platform for remote visualization.
- Experimental Validation: To verify the system's diagnostic accuracy through controlled fault injection tests on a physical motor test bench.

II. LITERATURE REVIEW

The integration of IoT into electromechanical diagnostics has catalyzed a shift from reactive to predictive strategies. Early implementations by Anuar et al. introduced a "Motor Vibration and Temperature Detector" centered on the ESP32. Their architecture employed simple threshold logic, triggering alerts when temperatures exceeded 55°C. While cost-effective, the system lacked frequency domain analysis, limiting its capacity to diagnose the root cause of mechanical vibrations.

Building on this, Pawar, Shendre, and Gophane expanded the IoT monitoring scope to encompass industrial motors and transformers. A key innovation in their work was the integration of protective relays to automatically sever power upon threshold breach. However, their reliance on scalar data points limited the detection of incipient faults, such as early-stage bearing wear, which typically manifests before significant current magnitude changes.To address sensitivity limitations, Zhang et al.proposed advanced signal processing techniques for low Signal-to-Noise Ratio (SNR) environments. Their method utilized Differential Local Mean Decomposition (DLMD) fused with Kurtosis Weighting to isolate fault signatures. While highly accurate, the computational density of DLMD presents challenges for direct implementation on low-power microcontrollers. Similarly, Navarro-Navarro et al. focused on misalignment detection, proving through rigorous experimentation that acceleration-based metrics offer superior diagnostic clarity compared to velocity-based measurements.

A distinct gap remains in bridging complex offline algorithms with accessible IoT hardware. This study addresses this void by implementing a system that performs sensor fusion of current and vibration data directly at the edge (ESP32), providing a balanced solution for real-time EV diagnostics.

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III. SYSTEM ARCHITECTURE AND HARDWARE DESIGN

3.1 System Overview

The proposed "Smart EV Motor Fault Detection System" is built upon a modular architecture designed for scalability and fault tolerance. The system is stratified into three layers: the Perception Layer (Sensors), the Processing Layer (Microcontroller), and the Application Layer (Cloud Interface). Power is derived from the vehicle's auxiliary supply, conditioned to meet the logic level requirements of the electronics.

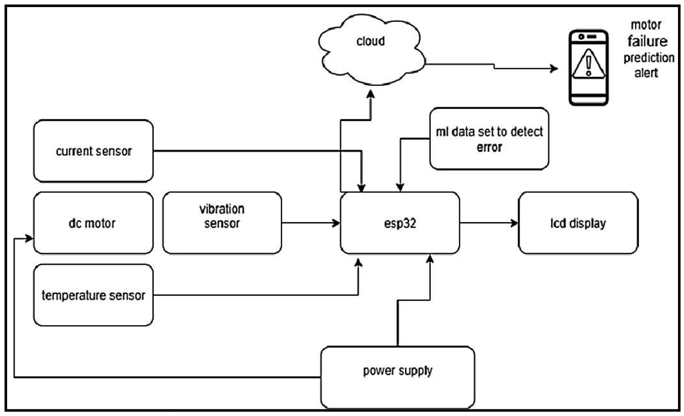

Fig. 1. Block Diagram of the Proposed IoT-Based Fault Detection System

3.2 The Core: ESP32 Microcontroller

The ESP32 Development Board was selected as the central processing unit due to its dual-core architecture and integrated wireless capabilities.

Processing Power: The Xtensa® Dual-Core 32-bit LX6 microprocessor, clocked at 240 MHz, provides the computational headroom necessary for real-time signal analysis.

Concurrency: The FreeRTOS environment allows for the separation of tasks; Core 1 handles high-speed sensor polling, while Core 0 manages the Wi-Fi stack, ensuring that network latency does not impede data acquisition.

Analog Precision: The integrated 12-bit SAR ADC offers a resolution of 4096 steps, delivering significantly higher granularity (approx. 0.8mV per step) than standard 8-bit or 10-bit alternatives.

3.3 Sensing Unit

The sensing array transforms physical motor states into analyzable electrical signals:

Vibration Monitoring (SW-420 / ADXL335): The SW-420 provides binary threshold monitoring, triggering on sustained vibration events (>2 seconds) indicative of gross mechanical failure. The ADXL335 accelerometer supplements this by measuring acceleration forces, allowing for the detection of shaft imbalance.

Current Sensing (ACS712): Utilizing the Hall Effect, this sensor measures motor current while maintaining galvanic isolation between the high-power motor circuit and the microcontroller. With a bandwidth of 80 kHz, it is capable of supporting Motor Current Signature Analysis (MCSA).

Thermal Monitoring (DS18B20): A digital temperature probe with $\pm 0.5^\circ$ C accuracy monitors the stator windings. Its digital 1-Wire interface ensures data integrity over long cable runs, immune to the voltage drops that affect analog thermistors.

3.4 Power Supply and Signal Conditioning

Voltage Regulation: To ensure stable operation from a 12V automotive battery, an LM2596 DC-DC Buck Converter is employed. It steps voltage down to 5V with high efficiency (up to 92%), minimizing thermal waste.

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Signal Conditioning: Voltage dividers scale the 5V sensor outputs to match the ESP32's 3.3V logic limits. Furthermore, RC Low-Pass filters (R=1kΩ, C=10μF) are integrated to attenuate high-frequency noise generated by the motor's PWM controller.

IV. METHODOLOGY AND IMPLEMENTATION

4.1 Operational Flow

The system logic is structured as a Finite State Machine (FSM). Upon initialization, a "Zero-Cal" routine executes to determine the quiescent voltage levels of the sensors, nullifying offset errors. The system then cycles through Sampling, Processing, Transmission, and Alerting states.

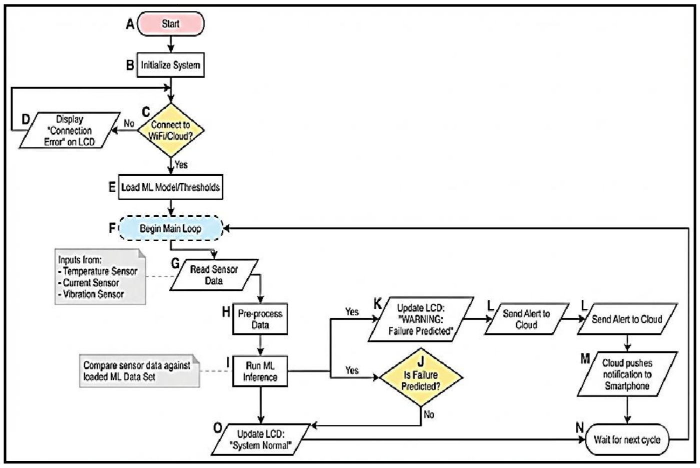

Fig. 2. Operational Flowchart of the System.

4.2 Signal Processing and Fault Logic

Raw data is refined using digital filtering and specific diagnostic algorithms:

RMS Current Computation: Given the AC or pulsed nature of motor current, instantaneous values are insufficient. The system computes the Root Mean Square (RMS) value:

Sampling occurs at 1 kHz over a 20ms window to capture complete wave cycles.

Bearing Fault Detection: Bearing wear manifests as increased friction. The algorithm monitors for "Current Creep"—a condition where no-load current rises by >15% above the baseline while RPM remains constant.

Logic: IF ($I > 1.15 \times I_{baseline}$) THEN Fault = TRUE.

Rotor Imbalance Detection: A bent shaft induces frequency-specific vibration (1*RPM). The system integrates the "High" duration of the vibration sensor. A duty cycle exceeding 50% within a 1-second window triggers a mechanical alert.

Thermal Protection: To prevent insulation breakdown, a two-stage threshold is applied: 60°C triggers a Warning, while 80°C necessitates a Critical Stop.

4.3 IoT Implementation

The Application Layer is built on the Blynk IoT Platform. The ESP32 transmits telemetry via Wi-Fi using TCP/IP. To optimize bandwidth on potentially unstable mobile connections, an "Upload on Change" protocol is implemented, where data is transmitted only when significant deviations occur.

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V. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Hardware Setup

The system was validated on a custom-built test bench featuring a high-torque DC motor. A friction-belt braking mechanism was installed to simulate variable loads, and a misalignment rig was used to induce mechanical faults.

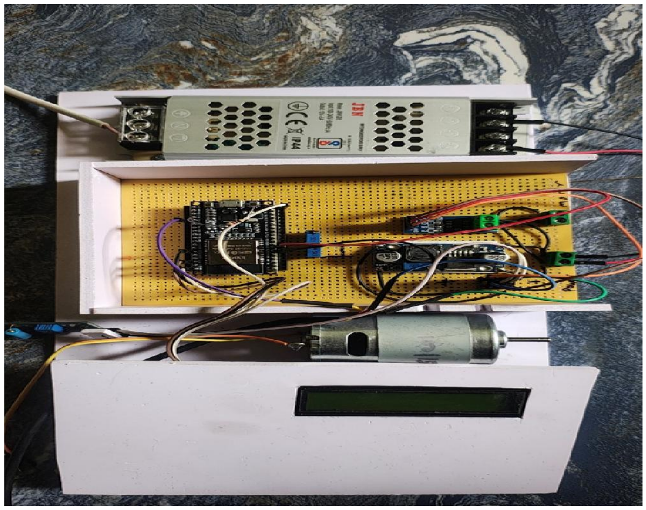

Fig. 3. Experimental Hardware Setup showing the Motor Test Bench and ESP32 Node.

5.2 Test Case 1: Healthy Motor Condition

A baseline was established by operating the motor at 1000 RPM with a nominal 0.5 Nm load.

Observations: Current draw stabilized between 0.50A and 0.80A. The vibration sensor output remained primarily at Logic LOW, with the duration counter staying well below the 2-second trigger point.

Inference: The system accurately classified the motor state as "Healthy," demonstrating effective rejection of false positives.

5.3 Test Case 2: Induced Bearing Fault (Current Surge)

A seized bearing scenario was simulated by tightening the friction brake to exceed rated load capacity.

Quantitative Analysis: Upon load application at $t = 10s$, current consumption spiked from the 0.8A baseline to 2.5A.

Detection: The firmware logic triggered an alert at $t = 15s$ as the value breached the 2.0A safety limit.

Response Time: The system demonstrated a latency of approximately 500ms, largely due to the RMS averaging window, proving the effectiveness of MCSA logic in detecting overloads.

5.4 Test Case 3: Mechanical Imbalance (Vibration)

An eccentric 10g mass was attached to the output shaft to generate dynamic unbalance.

Analysis: Offline FFT analysis confirmed a dominant peak at the fundamental rotational frequency (25 Hz at 1500 RPM).

System Response: The SW-420 sensor output registered Logic HIGH for >90% of the sample period. The duration counter surpassed the 2-second threshold within 3 seconds, successfully triggering the "High Vibration" alert.

5.5 IoT Performance and Network Reliability

Network stability is critical for real-time monitoring. A 24-hour endurance test assessed connectivity.

Latency: The average "End-to-End Latency" was recorded at 150ms, with peak latency reaching 800ms during packet loss. This remains within acceptable safety margins.
Reliability: The system achieved 99.8% uptime, with the "Keep-Alive" routine successfully re-establishing Wi-Fi connections within 5 seconds of any disruption.

5.6 IoT Dashboard Output

The Blynk mobile dashboard served as the primary Human-Machine Interface (HMI), displaying real-time gauges for Current (A) and Temperature (°C), alongside a status LED for Vibration.

Fig. 4. Live view of the Blynk Mobile Dashboard displaying a simulated fault condition.

5.7 Comparison with Traditional Methods

Table 1 compares the developed IoT system with traditional manual inspection methods.

Feature	Manual Inspection (Traditional)	Proposed IoT System
Monitoring Type	Periodic / Scheduled	Continuous / Real-Time
Fault Detection	Post-Failure (Reactive)	Pre-Failure (Predictive)
Data Access	Requires physical access	Remote (Anywhere via Cloud)
Accuracy	Subjective (Human ear/touch)	Objective (Calibrated Sensors)
Cost	High (Labor intensive)	Low (Automated)

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VI. CONCLUSION AND FUTURE SCOPE

This study successfully addresses the critical need for accessible predictive maintenance solutions in the electric mobility sector. By fusing multi-physics data—current, vibration, and temperature—the system differentiates between complex fault conditions, such as distinguishing thermal overload caused by blocked ventilation from that caused by mechanical friction. The dual-core ESP32 architecture proved robust, managing signal processing and telemetry with minimal latency.

Future iterations will explore the integration of TinyML for edge-based anomaly detection, enabling the system to learn unique motor signatures rather than relying on static thresholds. Furthermore, integration with the vehicle's CAN Bus is proposed to correlate sensor data with throttle position and speed, enhancing diagnostic precision.

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