

AI-Based Predictive Maintenance System for Electric Motor Fault Detection

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Abstract:

The proposed work develops a cost-effective IoT and artificial-intelligence-based predictive maintenance system for electric motor fault detection. A BO geared DC motor is monitored using an ESP32 microcontroller integrated with DHT11, INA219, and MPU9250 sensors to measure temperature, current, voltage, and vibration parameters. The collected sensor data are processed using time-domain statistical features and transmitted through Wi-Fi to a local server for analysis. Machine learning models, including Decision Tree, Random Forest, and XGBoost, are employed and combined using a soft-voting approach to improve fault classification. The system categorizes the motor condition into normal, high-current, and maintenance-required states. In addition, vibration, current, and temperature trends are analyzed to provide early warnings before critical thresholds are reached. Blynk IoT is used for remote monitoring, while automatic email notifications are generated when abnormal conditions persist. The study demonstrates the feasibility of implementing an affordable real-time predictive maintenance solution suitable for laboratories, small industries, and academic applications.

Keywords — Predictive maintenance, condition monitoring, electric motor fault detection, Internet of Things, ESP32, XGBoost, ensemble learning, decision tree, vibration analysis, MPU9250, INA219, DHT11, Blynk, Industry 4.0.

I. INTRODUCTION

Electric motors are widely used in industrial applications such as pumps, fans, compressors, conveyors, and machine tools, making their reliable operation essential for plant productivity. Common motor faults include bearing degradation, winding insulation failure, rotor defects, shaft misalignment, and rotor unbalance. These faults generally develop gradually and produce measurable changes in

vibration, electrical, and thermal parameters, making condition monitoring and predictive maintenance effective approaches for early fault detection. Traditional corrective and preventive maintenance methods can result in unexpected downtime or unnecessary maintenance. Recent advances in low-cost IoT devices, wireless microcontrollers such as ESP32, MEMS sensors, and machine-learning techniques have enabled

affordable real-time predictive maintenance systems.

IoT platforms further support continuous data transmission, remote monitoring, visualization, and automatic fault notifications. Therefore, integrating sensor-based condition monitoring with machine learning provides a practical and cost-effective solution for detecting abnormal motor conditions at an early stage. The proposed work combines ESP32-based sensing, machine-learning-based fault classification, IoT monitoring, and automated alerts into a single predictive maintenance platform suitable for small industries, laboratories, and academic applications.

II. LITERATURE SURVEY

The literature related to this project covers classical motor condition monitoring, machine-learning-based predictive maintenance, deep-learning methods for rotating machinery, and IoT-based industrial monitoring. Nandi, Toliyat and Li reviewed electrical motor condition monitoring and fault diagnosis, identifying bearing, winding and rotor faults along with their electrical and mechanical signatures, and established vibration and motor-current analysis as important diagnostic techniques. Lee and co-workers developed a systematic prognostics and health-management framework covering data acquisition, signal processing, diagnosis and prognosis, which provides a conceptual foundation for the proposed system. Smith and Randall demonstrated the importance of vibration-based bearing diagnosis and highlighted the influence of experimental procedures on classification accuracy.

Choudhary and colleagues compared thermal, vibration, acoustic and current-based monitoring techniques and reported that vibration provides a faster indication of mechanical faults, whereas temperature changes more slowly. These findings support the use of vibration, current and temperature sensors in the proposed system. Carvalho and co-authors reviewed machine-learning methods for predictive maintenance and identified Random Forest, Support Vector Machines and neural networks as widely used approaches.

Zhang, Yang and Wang described predictive maintenance as a pipeline involving data acquisition, preprocessing, feature engineering, modelling and decision support. Breiman's Random Forest, Quinlan's decision-tree approach and Chen and Guestrin's XGBoost provide important foundations for the machine-learning models considered in this project. Studies by Cinar, Ran and Zonta highlighted the importance of integrating machine-learning predictions with maintenance decisions and identified limited labelled data as a major challenge. Recent studies by Achouch and Ucar and their co-workers further emphasised real-time implementation, robustness and explainability, while Lundberg and Lee's SHAP framework provides a practical method for interpreting tree-based model predictions. Zhang and co-authors reviewed deep-learning techniques such as convolutional neural networks, autoencoders and recurrent networks for bearing fault diagnosis. Although these methods can achieve high accuracy on benchmark datasets, they generally require large labelled datasets and greater computational resources.

Hoang and Kang reported similar limitations and noted that raw-signal deep-learning approaches often require high-quality, high-frequency sensor data, making lightweight and interpretable machine-learning models more suitable for low-cost and resource-constrained applications. In the area of IoT-based industrial monitoring, Sahal, Breslin and Ali studied IoT and big-data architectures for Industry 4.0 predictive maintenance and established a layered approach involving sensing, edge processing, communication, analytics and application layers. Existing ESP32- and Arduino-based motor monitoring systems using platforms such as ThingSpeak and Blynk demonstrate the feasibility and low cost of IoT-based monitoring. However, many existing systems mainly focus on visualization and fixed-threshold alerts. The proposed work extends these approaches by integrating ESP32-based sensor data acquisition, machine-learning-based fault classification, IoT monitoring and automated notifications into a single predictive maintenance platform for early detection of motor faults.

III. COMPARISON OF EXISTING STATE

TABLE I
COMPARISON OF EXISTING STATE

Ref No.	Paper Title	Year	Key Idea	Limitation
[1]	Signal Based Condition Monitoring Techniques for Fault Detection and Diagnosis of Induction Motors: A State-of-the-Art Review	2020	Reviews vibration and current signal analysis for detecting electrical and mechanical induction-motor faults.	Conventional signal-processing methods can require expert interpretation and may be affected by operating conditions.
[2]	Machine Learning-Based Fault Detection and Diagnosis of Faulty Power Connections of Induction Machines	2021	Applies machine-learning techniques for detecting and diagnosing faults in induction-machine power connections.	Focuses mainly on specific power-connection faults rather than comprehensive multi-fault monitoring.
[3]	Recent Developments Towards Industry 4.0 Oriented Predictive Maintenance in Induction Motors	2021	Reviews AI, deep learning and intelligent approaches for predictive maintenance of induction motors.	Mainly a review; practical low-cost embedded implementation is limited.
[4]	A Two-Phase Machine Learning Approach for Predictive Maintenance of Low Voltage Industrial Motors	2022	Uses vibration sensors and ML in two stages: abnormal-behaviour detection followed by specific fault identification.	Requires sensor data and machine-learning processing; real-time low-cost edge implementation is not fully addressed.
[5]	Application of ANN in Induction-Motor Fault-Detection System Established with MRA and CFFS	2022	Uses multiresolution analysis, feature selection and ANN for detecting bearing, inter-turn and broken-rotor-bar faults.	ANN training requires suitable labelled data and computational resources.
[6]	Artificial Intelligence of Things Based Approach for Anomaly Detection in Rotating Machines	2023	Combines IoT, machine learning and vibration monitoring for real-time remote anomaly detection using an edge device.	Uses Raspberry Pi-based edge processing rather than a very low-cost microcontroller such as ESP32.
[7]	Machine Learning-Based Explainable Stator Fault Diagnosis in Induction Motor Using Vibration Signal	2023	Uses vibration features and Random Forest with explainable AI for stator-fault detection and severity prediction.	Mainly concentrates on stator faults rather than multiple motor fault categories.
[8]	Advancements in Predictive Maintenance Modelling for Industrial Electrical Motors: Integrating Machine Learning and Sensor Technologies	2024	Integrates vibration and temperature sensing with ML for industrial motor predictive maintenance and IoT-based data collection.	Requires industrial sensor infrastructure and centralized data-processing systems, increasing implementation complexity.
[9]	Prediction of Induction Motor Faults Using Machine Learning	2025	Compares RF, ANN, k-NN and Decision Tree models for classifying healthy and faulty induction-motor conditions.	Dataset and experimental conditions are limited; further validation with diverse real-world motor data is required.
[10]	AI-Based Multi-Signals Fault Diagnosis of Induction Motor	2025	Combines vibration, current, sound and thermal signals with ML and CNN for multi-sensor motor-fault diagnosis.	Multi-sensor deep-learning implementation has higher computational and hardware requirements.

IV. PROPOSED METHODOLOGY

The proposed system is a five-layer, closed-loop predictive maintenance platform for a single electric motor. A BO geared DC motor driving a controllable mechanical load is instrumented with three sensors that together capture its thermal, electrical and mechanical state. An ESP32 microcontroller acquires these signals, condenses each one-second observation window into a statistical feature frame, and transmits the frame

over Wi-Fi to a local server. The server stores the frame, renders it on a live dashboard, and classifies it with a trained ensemble of tree-based machine-learning models. The resulting class label and confidence are returned to the ESP32, mirrored to a Blynk IoT dashboard for remote continuous monitoring, and, when a non-normal state is confirmed, escalated automatically by electronic mail to a designated point of contact.

V. BLOCK DIAGRAM

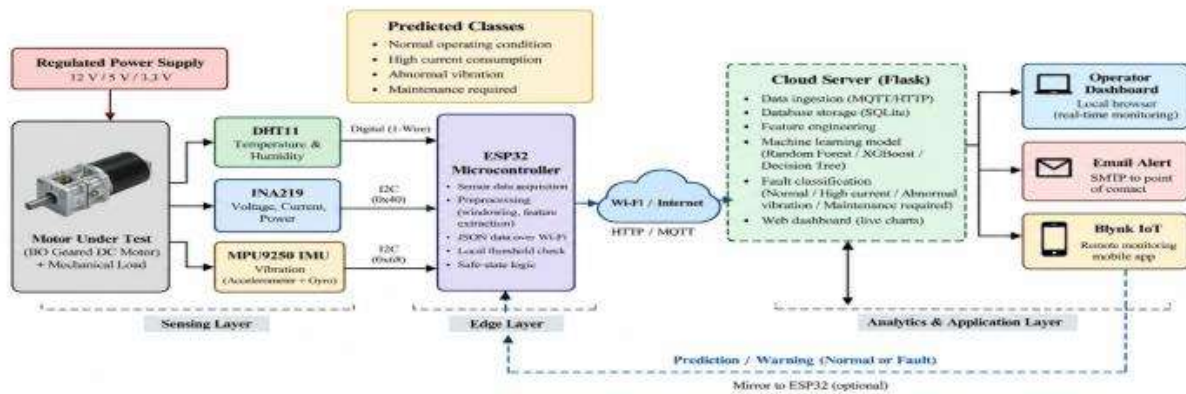


Fig. 1. Block diagram of AI-based predictive maintenance system

VI. HARDWARE AND SOFTWARE REQUIREMENTS

A. Hardware Requirements

- ESP32 DevKit V1 is used as the main controller for sensor data acquisition, feature extraction, processing, and wireless communication in the predictive maintenance system.
- BO Geared DC Motor is used as the experimental machine under test for monitoring motor operating conditions and generating different fault conditions.
- DHT11 Temperature and Humidity Sensor is used to measure the motor-body and ambient temperature for monitoring thermal conditions and identifying slow temperature-based degradation.
- INA219 Current and Voltage Sensor is used to measure the motor supply voltage, load current, and power consumption for identifying abnormal electrical conditions and overloads.
- MPU9250 Nine-Axis IMU Sensor is used to measure three-axis acceleration and angular-rate variations for detecting abnormal vibration and mechanical faults such as unbalance and misalignment.
- Regulated DC Power Supply is used to provide a stable power supply to the motor, ESP32 controller, and sensor modules. A 12 V,

2 A adaptor with an LM2596 buck converter is used to obtain the required regulated voltage.

- Mechanical Load Assembly consisting of an acrylic disc, shaft coupler, adjustable friction pad, eccentric masses, motor bracket, and base plate is used to apply controlled load and unbalance conditions for dataset generation.
- Local Server Host such as a laptop, desktop, or Raspberry Pi is used for sensor-data ingestion, storage, machine-learning model inference, dashboard hosting, and email alert generation.
- Wi-Fi Router or Access Point is used to provide 2.4 GHz wireless connectivity between the ESP32 edge controller and the local server.
- Status Indicators and Passive Components including green and red LEDs, 330 Ω resistors, a 5 V buzzer with an NPN driver, 4.7 k Ω pull-up resistor, breadboard/perfboard, and jumper wires are used for visual and audible fault indication and sensor interfacing.
- Digital Multimeter is used for independent verification and calibration of the INA219 voltage and current measurements.

B. Software Requirements

- Arduino IDE or PlatformIO with ESP32 Board Package is used for developing, compiling, and flashing the firmware to the ESP32 controller. Arduino IDE 2.x with ESP32 Core 3.x is used for programming the

sensor-acquisition and communication functions.

- DHT Sensor Library (Adafruit) is used to interface with the DHT11 sensor and obtain temperature and humidity measurements through the single-wire communication protocol.
- Adafruit INA219 Library is used to communicate with the INA219 sensor through the I²C interface for measuring bus voltage, load current, and power consumption.
- MPU9250 / MPU6500 Library (Bolder Flight or equivalent) is used to configure and communicate with the inertial measurement unit through I²C for acquiring acceleration and angular-rate data.
- ArduinoJson Library is used for serializing sensor features into JSON format and parsing prediction responses received from the server.
- WiFi and HTTPClient Libraries provided with the ESP32 core are used for Wi-Fi network connection and HTTP-based data transmission between the ESP32 and the local server.
- Blynk Library for ESP32 is used to publish real-time sensor values, motor condition, and prediction results to the Blynk IoT platform for remote monitoring.
- Python 3.10 or Later is used as the main server-side programming environment for data processing, machine-learning analysis, prediction, and system integration.
- Flask is used to develop the REST prediction endpoint and host the local web dashboard for real-time motor-condition monitoring.
- NumPy and pandas are used for numerical processing, dataset preparation, data manipulation, feature extraction, and feature engineering.
- scikit-learn is used for implementing Decision Tree, Random Forest, soft-voting ensemble models, preprocessing, cross-validation, performance evaluation, and classification metrics.
- XGBoost is used to implement the gradient-boosted tree classifier for accurate motor-condition and fault classification.
- joblib is used for saving, serializing, and loading the trained machine-learning model and preprocessing pipeline.
- SQLite is used for local storage of time-series sensor data, model predictions, motor conditions, and generated alerts.
- Plotly.js or Chart.js is used to create interactive live and historical charts for displaying sensor readings and motor-condition trends on the dashboard.
- smtplib and Python Email Library are used to send SMTP-based email notifications for abnormal motor conditions, fault detection, and recovery events.
- Matplotlib and Seaborn are used to generate confusion matrices, ROC curves, feature-importance graphs, and other visualization plots required for model evaluation and report preparation.
- SHAP (SHapley Additive exPlanations) is used to provide per-prediction feature attribution and explain which sensor features contribute to individual fault predictions.
- Blynk IoT Cloud Platform is used for continuous remote monitoring of sensor values, motor status, and machine-learning predictions through mobile and web interfaces.
- Jupyter Notebook or Visual Studio Code (VS Code) is used for exploratory data analysis, dataset processing, machine-learning model training, testing, visualization, and experiment documentation.

VII. APPLICATIONS

The proposed AI-based predictive maintenance system can be applied to various rotating electrical machines where continuous and low-cost condition monitoring is required:

- Small and medium manufacturing: Monitoring motors used in conveyors, mixers, lathes, drilling and packaging machines.
- Agricultural pumping: Monitoring borewell and irrigation pumps for overload, dry running and abnormal conditions.
- Building and HVAC systems: Monitoring fans, pumps and cooling systems for bearing wear and unbalance.

- Water and wastewater systems: Remote monitoring of booster, dosing and sludge pumps.
- Electric vehicles and battery systems: Monitoring traction and auxiliary motors using current, voltage and vibration data.
- Renewable energy systems: Monitoring solar pump drives, solar trackers and small wind-turbine actuators.
- Robotics and CNC machines: Detecting vibration, bearing wear, belt problems and abnormal current consumption.
- Domestic and commercial appliances: Monitoring washing machines, fans, compressors and water pumps.
- Academic laboratories: Providing an Industry 4.0 platform for learning and research in IoT, sensors and machine learning.
- Multiple-motor monitoring: The system can be extended to monitor several motors simultaneously using individual device identifiers.

VIII. RESULT

The developed predictive maintenance system provides real-time monitoring and fault prediction of the motor using sensor data collected through the ESP32. Temperature, humidity, voltage, current, power, and vibration parameters are continuously measured and displayed on the local dashboard. The machine-learning model classifies the motor condition into three categories: Normal Operation, High Current Consumption, and Maintenance Required due to Abnormal Vibration. The sensor readings and prediction results are also transmitted to the Blynk IoT platform, enabling remote monitoring through mobile and web applications. When an abnormal motor condition is detected, automatic email alerts are generated with the predicted fault and relevant sensor information. The collected sensor data, predictions, and alert information are stored in a SQLite database for further analysis, model retraining, and performance assessment. The performance of the Decision Tree, Random Forest, XGBoost, and soft-voting ensemble models is evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curves, and feature-importance analysis. SHAP

analysis is additionally used to explain the contribution of individual sensor features to the model predictions. Overall, the system demonstrates the integration of sensor-based condition monitoring, machine-learning-based fault classification, IoT visualization, data storage, and automated alerts into a low-cost predictive maintenance platform.

IX. CONCLUSION

This report presented an AI-based IoT predictive maintenance system for early detection of electric motor faults. The proposed system uses a DHT11, INA219, and MPU9250 sensors with an ESP32 to collect temperature, current, voltage, power, and vibration data. The extracted features are analysed using Decision Tree, Random Forest, and XGBoost-based soft-voting ensemble models to classify the motor condition as normal, high current consumption, or maintenance required. The results are displayed through a local dashboard and Blynk IoT platform, while automatic email alerts provide timely notification of abnormal conditions. Although the DHT11 is limited to slow thermal monitoring and the MPU9250 is more suitable for low-frequency vibration detection, the system demonstrates that a low-cost, real-time, closed-loop predictive maintenance solution can be effectively developed for small industries, laboratories, and academic applications.

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