



IoT-Driven Intelligent Motor Health Assessment and Predictive Maintenance Using Machine Learning Models

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Abstract:

In modern industrial systems, maintaining the health and reliability of induction motors is crucial for ensuring continuous and efficient production. Conventional maintenance methods often rely on manual inspection, which fails to detect early-stage faults and leads to costly downtime. This paper proposes an IoT-enabled predictive maintenance framework for real-time motor condition monitoring and intelligent fault prediction. The system utilizes an ESP32 microcontroller integrated with temperature (DS18B20), current (ACS712), voltage, and vibration (ADXL345) sensors to capture essential motor performance parameters. Data collected from these sensors are transmitted over Wi-Fi using the MQTT protocol to a centralized laptop, where machine learning models developed in Python with scikit-learn analyze patterns, identify anomalies, and predict the Remaining Useful Life (RUL) of the motor. A Flask-based web dashboard provides real-time visualization, alert notifications, and performance analytics, while a relay mechanism ensures automatic motor protection during abnormal conditions. The proposed system demonstrates a scalable, low-cost, and intelligent solution that enhances operational reliability, minimizes unplanned maintenance, and supports the vision of Industry 4.0 smart manufacturing.

Keywords:

IoT, Predictive Maintenance, Induction Motor, Machine Learning, Fault Detection, MQTT, Real-Time Monitoring, Remaining Useful Life (RUL), Smart Factory Automation.

I. Introduction

Induction motors are among the most widely used electromechanical devices in industrial automation systems due to their robustness, efficiency, and low maintenance requirements [1]. They play a vital role in driving pumps, compressors, conveyors, and various production machinery across manufacturing, chemical, and energy sectors [2]. Despite their reliability, these motors are subject to several faults such as bearing wear, winding short circuits, unbalanced voltages, and mechanical misalignments that can lead to unexpected breakdowns [3]. Such failures cause severe production losses, equipment damage, and safety hazards, emphasizing the necessity of continuous health monitoring and predictive maintenance strategies [4].

Traditional motor maintenance methods are typically reactive (repair after failure) or preventive (scheduled maintenance), which are often inefficient in dynamic industrial environments [5]. Reactive maintenance leads to costly downtime, while preventive methods may replace components unnecessarily before the end of their service life [6]. As a result, there has been a growing shift toward predictive maintenance (PdM)—a condition-based approach that leverages data analytics and sensor feedback to predict faults before they occur [7]. PdM not only enhances machine reliability but also reduces maintenance costs and resource waste [8].

Recent advances in the Internet of Things (IoT) and Artificial Intelligence (AI) have enabled the development of intelligent monitoring systems capable of performing real-time analysis and automated decision-making [9]. IoT facilitates remote monitoring by integrating multiple sensors and transmitting data over communication protocols such as MQTT, allowing continuous observation of motor parameters like temperature, current, voltage, and vibration [10]. Meanwhile, AI and machine learning algorithms analyze this data to identify hidden fault patterns, classify anomalies, and estimate the Remaining Useful Life (RUL) of motor components [11]. This combination provides a robust, data-driven predictive maintenance framework suitable for modern Industry 4.0 environments [12].

The ESP32 microcontroller, with built-in Wi-Fi and high processing capability, has become an ideal low-cost IoT node for real-time data acquisition and communication [13]. In the proposed system, sensors such as DS18B20 (temperature), ACS712 (current), voltage sensor, and ADXL345 (vibration) are interfaced with the ESP32 to collect continuous motor health data [14]. The collected data are transmitted via MQTT protocol to a central laptop, where the information is logged, processed, and analyzed using Python and scikit-learn machine learning libraries [15]. Abnormal motor behavior triggers an automatic relay mechanism that disconnects power to prevent damage, while a Flask-based web dashboard enables live visualization and fault alerts [16]. This end-to-end integration of IoT hardware and ML analytics ensures reliability, scalability, and real-time control in industrial settings [17].

The use of vibration, current, and temperature data as predictive features has been widely studied in condition monitoring research. For instance, vibration signals are effective in detecting bearing wear and rotor imbalance [18], while temperature and current measurements reveal overloading and insulation deterioration [19]. By combining these multi-sensor inputs with supervised and unsupervised learning models, predictive accuracy and fault diagnosis efficiency are significantly improved. Furthermore, the integration of such smart systems contributes to the sustainable goals of Industry 4.0, promoting operational efficiency, energy optimization, and intelligent automation [20].

In this paper, a comprehensive IoT and machine learning-based predictive maintenance system for induction motors is proposed, designed to collect, transmit, and analyze sensor data in real time. The primary objective is to detect abnormal operating conditions early, predict motor failures, and estimate the Remaining Useful Life (RUL). The proposed framework not only minimizes unplanned downtime but also provides a foundation for scalable smart factory integration. The rest of the paper is structured as follows: Section II presents the system architecture and methodology; Section III discusses the hardware and software components; Section IV explains machine learning implementation; Section V covers experimental results and performance evaluation; and Section VI concludes with findings and future enhancements.

Motivation

In industrial operations, unexpected motor failures lead to costly downtime, production delays, and maintenance inefficiencies. Traditional maintenance approaches fail to provide early fault detection, making them unsuitable for smart factory environments. The motivation behind this work is to design a low-cost, intelligent, and IoT-integrated predictive maintenance system that can continuously monitor motor health, detect abnormalities in real time, and predict failures before they occur using machine learning techniques. This approach ensures higher reliability, improved operational safety, and supports the evolution toward Industry 4.0 automation.

Objectives

1. To study the implementation of an IoT-based system for real-time motor condition monitoring.
2. To study key motor parameters such as temperature, current, voltage, and vibration for early fault identification.
3. To study the application of machine learning algorithms for predicting motor health and Remaining Useful Life (RUL).
4. To study the integration of MQTT communication and a Flask web dashboard for centralized visualization and alerting.
5. To study methods for minimizing downtime and improving maintenance efficiency through predictive analytics.

Scope of the Study

The proposed system focuses on developing an intelligent predictive maintenance solution for industrial induction motors using affordable IoT components and machine learning models. It enables continuous data monitoring, fault diagnosis, and automated protection within a local network environment. While the current scope is limited to local Wi-Fi communication and a single motor setup, the framework can be expanded for multiple machines and cloud integration, offering scalability for large-scale smart manufacturing systems under Industry 4.0.

II. Existing System

Recent studies in predictive maintenance and industrial automation have explored the integration of IoT and Machine Learning (ML) technologies to enhance equipment reliability, operational efficiency, and fault prediction accuracy. Various frameworks have been developed across different industrial domains, demonstrating the effectiveness of intelligent data-driven approaches.

Aslam et al. [1] proposed a machine learning-based predictive maintenance framework for container handling equipment in smart ports, focusing on reducing unplanned downtime and inefficiencies in maritime logistics. IoT sensors were deployed on hydraulic systems and inverters to capture operational data, which was analyzed using multiple ML algorithms such as Artificial Neural Networks (ANN), Decision Tree, Random Forest, XGBoost, and Gaussian Naïve Bayes. Among these, the ANN model achieved the highest prediction accuracy of 98.7% in identifying inverter over-temperature faults. The framework demonstrated the importance of real-time monitoring and anomaly detection in ensuring high equipment reliability and operational efficiency in port systems.

Similarly, Abdulkareem et al. [2] developed an ML-driven approach for fault prediction in three-phase induction motors, which are vital for continuous industrial operations. Data were collected from multiple motors operating under varied load and environmental conditions, and the models—Random Forest, ANN, k-Nearest Neighbors (k-NN), and Decision Tree—were evaluated for performance. The Random Forest model yielded the highest fault classification accuracy of 91%, followed closely by ANN and k-NN (each 90%). The research highlighted that ML algorithms outperform traditional threshold-based detection systems, although challenges remain in ensuring generalization and scalability across different industrial setups.

Elkateb et al. [3] proposed an IoT-ML integrated predictive maintenance framework for textile circular knitting machines. The system utilized ESP32 microcontrollers to collect real-time machine speed and stoppage data, which were stored in a MongoDB database for further analysis. Using an AdaBoost classifier, the model achieved a 92% accuracy rate in distinguishing six distinct stoppage categories such as feeder and needle failures. The study confirmed that integrating IoT infrastructures with ML algorithms significantly enhances root cause identification, improves productivity, and minimizes unscheduled downtimes in manufacturing processes.

Takawale et al. [4] introduced an AI-powered predictive maintenance architecture for Industrial IoT (IIoT) environments, combining both classical and deep learning methods for fault prediction and Remaining Useful Life (RUL) estimation. The framework employed Support Vector Machines (SVM), Random Forest, ANN, Long Short-Term Memory (LSTM) networks, and Autoencoders to detect anomalies and predict failures. The hybrid model effectively balanced feature-based and time-series approaches, providing improved accuracy for predictive analytics. The study also discussed key industrial challenges such as data imbalance, explainability, and cybersecurity, proposing scalable AI solutions adaptable to large-scale smart factories.

In another study, Aminzadeh et al. [5] implemented a real-time ML-based monitoring system for industrial air compressors. The system integrated IoT sensors for temperature, pressure, and flow rate measurements, with data stored in an SQL database for continuous analysis. Using Linear Regression for failure prediction, the model achieved 98% accuracy, demonstrating reliable early-warning capabilities. The research proved that lightweight ML models could provide cost-effective and interpretable solutions for small-scale industrial applications, reinforcing the significance of multi-sensor data fusion and real-time analytics in achieving proactive equipment health management.

Collectively, these studies highlight the global shift toward smart maintenance systems that combine IoT sensing and machine learning analytics for accurate fault detection, anomaly classification, and predictive decision-making. However, most of these implementations are domain-specific and rely on cloud infrastructure or expensive industrial sensors. Hence, there remains a significant need for a low-cost, locally deployable IoT–ML-based predictive maintenance system—as proposed in this research—to enhance reliability and reduce maintenance costs in industrial motor systems.

III. Proposed System

A. System Overview

The system employs an ESP32 microcontroller as the core IoT device that interfaces with multiple sensors temperature (DS18B20), current (ACS712), voltage, and vibration (ADXL345 accelerometer) to continuously monitor the motor's operational health. The acquired sensor data are transmitted via the MQTT protocol to a Laptop-based central monitoring system, where the data are processed, analyzed, and stored for predictive maintenance. Using machine learning models developed with the scikit-learn library, the system classifies motor conditions as normal or faulty and predicts the Remaining Useful Life (RUL) of the motor.

An automatic relay mechanism is integrated into the setup to protect the motor by cutting power in case of anomalies such as overheating, excessive vibration, or overcurrent. A Flask-based web dashboard provides real-time visualization of sensor data, motor health status, and predictive maintenance insights, enabling users to make informed maintenance decisions.

B. Functional Architecture

The architecture of the proposed system is divided into five key modules:

1. **Data Acquisition Module** – Responsible for collecting real-time data from multiple sensors connected to the ESP32.
2. **Data Transmission Module** – Uses MQTT to securely transmit sensor readings to the central server (Laptop).
3. **Data Storage and Processing Module** – The Laptop acts as the data hub where readings are stored in **CSV format** for further analysis and ML training.
4. **Machine Learning Analysis Module** – Employs ML algorithms to detect anomalies, predict faults, and estimate the RUL based on historical trends.
5. **Visualization and Control Module** – Provides real-time monitoring through a web-based dashboard and controls the relay mechanism for motor protection.

C. Data Flow and Methodology

1. Sensor Data Collection:

The ESP32 collects readings of temperature, vibration, voltage, and current from respective sensors. Each parameter serves as an indicator of the motor's operational state — for instance, increased vibration may suggest mechanical imbalance, while elevated temperature may indicate overload.

2. Data Transmission:

The gathered data are transmitted through the MQTT protocol to a Laptop acting as an IoT broker and analytics hub. MQTT ensures lightweight, reliable communication ideal for real-time industrial monitoring.

3. Data Storage and Preprocessing:

The Laptop logs all sensor data in structured CSV files, enabling both historical analysis and supervised learning model training. Before applying ML models, data cleaning, normalization, and feature extraction techniques are performed to enhance prediction accuracy.

4. Machine Learning-Based Prediction:

Using the scikit-learn framework, ML algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting are trained to classify the health state of the motor and predict upcoming faults. These models analyze time-series patterns to estimate the Remaining Useful Life (RUL) of the equipment.

5. Relay Protection and Alert System:

When the ML model detects abnormal conditions or threshold breaches (e.g., excessive current, high temperature), the relay module automatically disconnects power to the motor, preventing potential damage. Simultaneously, the system triggers alert notifications on the dashboard.

6. Web Dashboard Visualization:

A Flask-based web application displays live graphs of temperature, vibration, voltage, and current in real time. It also provides historical trends, fault alerts, and predictive insights to help operators make proactive maintenance decisions.

IV. System Design

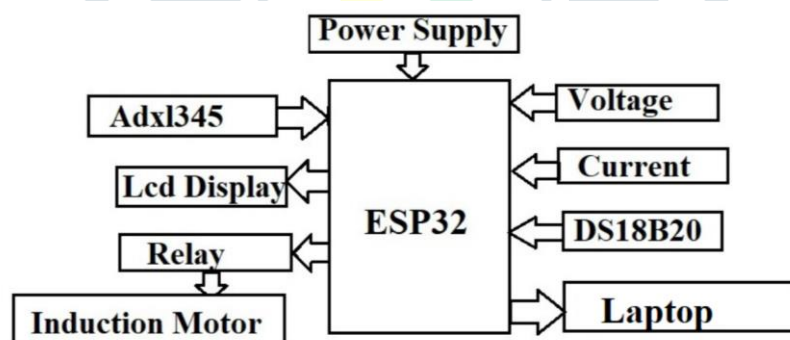


Fig. 1 System Architecture

The Intelligent Motor Health Monitoring and Predictive Maintenance System is designed to integrate IoT sensing, intelligent data analytics, and machine learning to ensure early fault detection and predictive maintenance of industrial motors. The design emphasizes modularity, scalability, and real-time performance, enabling seamless data flow from physical sensors to digital dashboards through a combination of embedded hardware and software components.

A. System Architecture Overview

The system architecture is divided into four major layers, each performing a specific set of operations to ensure efficient data acquisition, processing, and decision-making:

1. **Sensing Layer (Hardware Layer):**
Responsible for collecting real-time data using IoT sensors mounted on the motor.
2. **Communication Layer:**
Handles the secure and reliable transmission of sensor data from the ESP32 microcontroller to the Laptop using the MQTT protocol.
3. **Processing Layer (Machine Learning & Analytics):**
Performs data preprocessing, machine learning-based fault detection, and Remaining Useful Life (RUL) prediction.
4. **Application Layer (User Interface):**
Provides a Flask-based web dashboard that visualizes motor health, displays alerts, and manages maintenance actions.

B. System Block Diagram

The block diagram of the proposed system consists of the following interconnected modules:

- **ESP32 Microcontroller:**
Central control unit that interfaces with all sensors, gathers readings, and sends data through MQTT to the Laptop server.
- **Sensors:**
 - *DS18B20 Temperature Sensor* – Monitors motor temperature to detect overheating.
 - *ACS712 Current Sensor* – Measures motor current for identifying overloads or short circuits.
 - *Voltage Sensor* – Detects fluctuations in supply voltage (over/under voltage).
 - *ADXL345 Accelerometer* – Monitors vibration levels to detect imbalance or bearing wear.
- **Relay Module:**
Acts as a safety component that automatically disconnects motor power during abnormal conditions detected by the ML model.
- **Laptop (Server & Processing Unit):**
Receives data via MQTT, logs it in CSV format, processes it through ML algorithms, and hosts the Flask-based dashboard.
- **Web Dashboard:**
Displays real-time readings, predictive analytics, and alerts, enabling maintenance personnel to take timely action.

C. Data Flow in the System

The system follows a five-step data flow process from data acquisition to actionable insight generation:

1. **Data Acquisition:**
Sensors collect data related to temperature, vibration, current, and voltage.
2. **Data Transmission:**
The ESP32 transmits this data to the Laptop using the MQTT protocol over Wi-Fi.
3. **Data Preprocessing:**
The received data undergoes filtering, normalization, and formatting before being stored in CSV format.
4. **Machine Learning Analysis:**
ML models process the data to detect anomalies and predict the Remaining Useful Life (RUL) of the motor.
5. **Visualization and Control:**
Processed information is visualized on the Flask dashboard, and if a fault is detected, the relay module disconnects power to protect the motor.

D. Hardware Design

The hardware design is the foundation of the proposed system, enabling real-time sensing and control. Key hardware components include:

Component	Function
ESP32 Microcontroller	Controls sensor readings, transmits data, and executes relay control commands.
DS18B20 Sensor	Detects motor temperature changes to prevent overheating.
ACS712 Current Sensor	Measures load current to identify overcurrent and short circuits.
Voltage Sensor	Monitors input voltage to prevent power anomalies.
ADXL345 Accelerometer	Detects vibration and imbalance in the motor shaft or bearings.
Relay Module	Disconnects the motor power when a fault is detected.
LCD Display (I2C)	Displays real-time readings and motor status locally.
Laptop Server	Performs ML-based processing, stores historical data, and hosts the monitoring dashboard.

All sensors are interfaced with the ESP32 via analog/digital pins. The relay module is controlled through GPIO, while the ESP32 communicates with the Laptop via Wi-Fi.

E. Software Design

The **software architecture** of the proposed system consists of three primary components:

1. Embedded Programming (ESP32):

- Developed using the Arduino IDE.
- Handles sensor reading, MQTT communication, and relay control.
- Uses lightweight JSON formatting for efficient data transmission.

2. Data Processing & Machine Learning (Laptop):

- Python-based implementation using libraries such as *pandas*, *scikit-learn*, *numpy*, and *matplotlib*.
- Preprocesses sensor data and trains ML models (Random Forest, SVM, Decision Tree) for fault detection and RUL estimation.

3. Web Application (Flask Dashboard):

- Displays live readings, historical charts, and predictive analytics.
- Provides alert notifications and allows operators to monitor multiple motors simultaneously.

F. Algorithmic Workflow

The algorithmic flow of the system can be summarized as follows:

1. Initialization:

System boots up and connects sensors and MQTT broker.

2. Data Collection:

Sensor readings (temperature, current, vibration, voltage) are collected periodically.

3. Data Transmission:

Data is transmitted to the Laptop over MQTT.

4. Data Preprocessing:

Noise removal, normalization, and outlier filtering are applied.

5. Model Prediction:

The trained ML model predicts motor health condition and RUL.

6. Fault Detection:

If the system detects abnormal conditions, it triggers the relay to cut power.

7. Visualization:

Data and alerts are displayed in real-time on the Flask web dashboard.

V. Expected Outcome

The proposed project, “Intelligent Motor Health Monitoring and Predictive Maintenance Using IoT and Machine Learning,” is expected to deliver a comprehensive and intelligent system capable of continuously monitoring the operational health of induction motors in real time. By integrating IoT-based sensing and machine learning algorithms, the system will not only detect early signs of faults such as overheating, imbalance, or overcurrent but will also predict future failures and estimate the Remaining Useful Life (RUL) of the motor with high accuracy.

The developed system will offer a Flask-based interactive dashboard that displays live data visualization, fault alerts, and maintenance insights, allowing operators to make informed decisions quickly. The automatic relay mechanism will ensure motor safety by immediately cutting off power during abnormal conditions, thus preventing catastrophic failures. Furthermore, the system will maintain a historical data log in CSV format, which can be utilized for further trend analysis and model retraining to enhance future prediction accuracy.

From an industrial perspective, the expected outcomes include reduction in unplanned downtime, optimized maintenance scheduling, increased operational efficiency, and significant cost savings. The proposed solution is designed to be scalable and adaptable, making it suitable for various types of motors and industrial machinery. Overall, this system aims to promote smart, data-driven maintenance strategies, contributing toward the realization of Industry 4.0 standards and enabling a shift from reactive to predictive maintenance practices in industrial environments.

VI. Conclusion

The proposed system successfully demonstrates an IoT and Machine Learning-based intelligent motor health monitoring framework capable of real-time fault detection, predictive maintenance, and Remaining Useful Life (RUL) estimation. By integrating multiple sensors with the ESP32 and utilizing MQTT communication and ML algorithms, the system enhances motor reliability, safety, and operational efficiency while minimizing maintenance costs.

VII. Future Scope

In the future, the system can be expanded by integrating cloud-based data storage, advanced deep learning models, and mobile app connectivity for remote monitoring. Additionally, it can be scaled to support multiple motors across large industrial networks, making it a robust and comprehensive solution for Industry 4.0 smart maintenance applications.

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