Indian Journal of Computer Science and Technology
Volume 5, Issue1 (January-April 2026), PP: 404-408.
www.indjcst.com
ISSN No: 2583-5300

Design and Implementation of an Integrated Approach to Predictive Maintenance Using IoT & Machine Learning in Manufacturing Industries

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To Cite this Article: *T.Jansirani[*1], K.Gopika[*2], S.Padmaanjali [*3], S.P.Sujitha[*4], "Design and Implementation of an Integrated Approach to Predictive Maintenance Using IoT & Machine Learning in Manufacturing Industries", Indian Journal of Computer Science and Technology, Volume 05, Issue 01 (January-April 2026), PP: 404-408.*

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Abstract: *In modern manufacturing industries, unexpected equipment failures lead to increased downtime, maintenance costs, and reduced productivity. To address these challenges, this paper presents an integrated approach to predictive maintenance using Internet of Things (IoT) and Machine Learning (ML) techniques. The proposed system continuously monitors critical parameters such as temperature, voltage, and current of industrial equipment using embedded sensors. These sensor data are collected and processed by a microcontroller, which transmits real-time information to a cloud platform through an IoT module. The collected data are analyzed using machine learning algorithms to identify patterns and predict potential failures before they occur. An LCD display provides on-site monitoring, while a buzzer alerts operators during abnormal conditions. The system enables remote monitoring, data logging, and intelligent decision-making, thereby reducing unplanned downtime and improving operational efficiency. This integrated solution enhances reliability, optimizes maintenance schedules, and minimizes operational costs in manufacturing environments. The proposed model demonstrates a scalable and cost-effective framework for smart industrial maintenance aligned with Industry 4.0 standards.*

Key Words: *Predictive Maintenance, Internet of Things (IoT), Machine Learning, ESP32, Microcontroller, Industrial Induction Motor, Fault Prediction.*

I. INTRODUCTION

In today's rapidly evolving industrial landscape, manufacturing systems are becoming increasingly complex and automated. Ensuring the reliability and continuous operation of machinery is critical for maintaining productivity and reducing operational losses. Traditional maintenance strategies such as reactive maintenance — repair after failure — and preventive maintenance — scheduled servicing — often result in unnecessary downtime, increased costs, and inefficient resource utilization. These limitations have led to the growing adoption of predictive maintenance techniques.

Predictive maintenance leverages advanced technologies such as the Internet of Things (IoT) and Machine Learning (ML) to monitor equipment health in real time and predict potential failures before they occur. IoT-enabled sensors, including temperature, voltage, and current sensors, continuously collect data from industrial machines. This data is transmitted to a centralized system where it is analyzed to detect anomalies and performance degradation.

The integration of machine learning algorithms allows the system to learn from historical and real-time data, enabling accurate fault prediction and decision-making. By identifying early warning signs, maintenance activities can be scheduled only when necessary, thereby reducing downtime and extending equipment lifespan. The system employs a microcontroller-based architecture integrated with IoT modules for real-time monitoring and cloud connectivity.

Traditional maintenance methods lack real-time monitoring and predictive capabilities, leading to unexpected machine failures, increased downtime, and higher maintenance costs. There is a pressing need for an intelligent system that can continuously monitor equipment conditions and predict failures in advance to improve efficiency and reliability.

II.LITERATURE REVIEW

Predictive maintenance in industrial environments has been extensively studied in recent literature. A number of works demonstrate the effectiveness of combining IoT sensor data with machine learning models for early fault detection and proactive maintenance scheduling. The following subsections summarize key contributions in this domain.

1. Predictive Maintenance in Industrial IoT Using Machine Learning Approach (2024)

S. Pani, O. Pattnaik and B. K. Pattanayak presented the integration of machine learning with Industrial IoT for predictive maintenance applications. The authors emphasized real-time monitoring using sensors to collect operational data such as vibration, temperature, and pressure. Machine learning models are applied to predict equipment failures before they occur, thus reducing downtime and maintenance costs. The study highlights how predictive maintenance improves operational efficiency and extends machine life. Results show improved fault detection compared to traditional maintenance strategies and the approach supports proactive decision-making in industries.

2. Predictive Maintenance Using Machine Learning in Industrial IoT Systems (2024)

A. Suphalakshmi et al. focused on applying ML algorithms to industrial IoT environments for predictive maintenance. The system collects real-time data from machines and processes it using ML models to identify anomalies. Various ML techniques such as classification and regression are used to analyze equipment health. The authors emphasize reduced maintenance costs, increased productivity, and early fault detection. The research shows that predictive maintenance systems outperform traditional maintenance methods and that IoT and ML integration is essential for Industry 4.0.

3. IoT-Based Predictive Maintenance Using AI/ML: A Systematic Review (2024)

Rohit Raj, Kishor Kolhe, and Vitthal Gutte provided a comprehensive review of predictive maintenance using AI and ML techniques in IoT environments. The study discusses various algorithms such as neural networks and deep learning for fault detection and highlights the role of IoT sensors in collecting continuous machine data. The paper emphasizes real-time monitoring and cloud-based analytics and reviews challenges like data security, scalability, and model accuracy. It concludes that AI-driven predictive maintenance is key to smart industry development.

III.PROPOSED SYSTEM AND METHODOLOGY

System Overview

The proposed system is a microcontroller-based predictive maintenance platform that integrates IoT connectivity and machine learning-based analytics. It continuously monitors critical industrial parameters — temperature, voltage, and current — of manufacturing equipment using embedded sensors. The system provides on-site alerts through an LCD display and buzzer, while transmitting real-time data to a cloud platform for remote monitoring, historical logging, and intelligent fault prediction.

Data Acquisition and Processing

IoT-enabled sensors are deployed directly on industrial machinery to collect real-time operational data. A temperature sensor monitors thermal conditions, a voltage sensor tracks electrical supply levels, and an ACS712 current sensor measures current draw. These analog signals are digitized and processed by the microcontroller, which applies preprocessing algorithms to filter noise and normalize the data before transmission to the cloud platform. Feature engineering extracts indicators such as rate of temperature rise, voltage fluctuation amplitude, and current surge frequency.

IoT-Based Cloud Integration

The ESP8266 Wi-Fi module enables seamless transmission of sensor data to a cloud platform. The I2C (Inter-Integrated Circuit) communication protocol is used for inter-chip communication between the microcontroller and peripheral modules. Cloud storage allows historical data logging and enables remote monitoring through web or mobile interfaces. The collected datasets are used to train and update the machine learning model continuously, ensuring the system adapts to changing equipment behavior over time.

Machine Learning-Based Prediction

Machine learning algorithms analyze both real-time and historical data to detect patterns indicative of equipment degradation or impending failure. Classification models are trained on labeled datasets of normal and fault conditions. The system identifies early warning signs by comparing current operational patterns with learned baselines, enabling timely intervention before failures occur. Classification algorithms including Random Forest, Support Vector Machine, and Gradient Boosting are evaluated for optimal fault classification performance.

User Interface and Alert Mechanism

An LCD 16x2 display provides operators with immediate on-site feedback on system status, including current sensor readings and fault conditions. A buzzer module provides audible alerts when abnormal conditions are detected. The system categorizes conditions into Normal, Warning, Fault Likely, and Critical states based on threshold values derived from training data, enabling tiered responses from maintenance teams. Remote alerts can also be dispatched via cloud notifications to maintenance personnel.

Components Required

The hardware components of the proposed system include: ESP32/Arduino Microcontroller for central processing, LM35 Temperature Sensor for thermal monitoring, Voltage Sensor Module for electrical supply tracking, ACS712 Current Sensor for load measurement, ESP8266 IoT Wi-Fi Module for cloud connectivity, I2C LCD Display (16x2) for on-site output, Buzzer for audible alerts, Industrial Induction Motor as the test subject, SMPS (Switched Mode Power Supply), and LM7805 Voltage Regulator for stable power delivery.

IV.MODELING AND ANALYSIS

System Architecture

The proposed predictive maintenance system is built on a three-tier architecture. The first tier is the Sensing Layer, where IoT sensors continuously collect machine parameters including temperature, voltage, and current at defined sampling intervals. The second tier is the Processing Layer, where the microcontroller preprocesses and transmits data via the ESP8266 module to the cloud platform.

Sensor Data Collection and Preprocessing

Raw sensor data is collected at defined sampling intervals and transmitted to the cloud platform. Preprocessing involves noise filtering using moving average filters, normalization to a 0-1 scale, and handling of missing or corrupted values through interpolation. Feature engineering extracts relevant indicators such as rate of temperature rise, voltage fluctuation amplitude, and current surge frequency — all of which serve as input features to the prediction model and significantly improve classification accuracy.

Machine Learning Model Training

The predictive model is trained using labeled datasets comprising both normal operation records and known fault scenarios. The dataset includes readings collected across five operational states: Healthy, Slight Degradation, Warning, Fault Likely, and Critical. Multiple algorithms are compared — Random Forest achieved the highest accuracy at 97.4%, followed by Gradient Boosting at 96.8% and SVM at 94.2%. The final deployed model uses Random Forest due to its superior performance and interpretability.

Power Supply and Voltage Regulation

The system uses a Switched Mode Power Supply (SMPS) to convert AC mains supply to DC power for all components. The LM7805 voltage regulator ensures a stable 5V output for the microcontroller and sensor modules, protecting sensitive electronics from voltage fluctuations. The power management design ensures continuous operation even during brief supply interruptions, which is critical for uninterrupted industrial monitoring applications.

V.RESULTS AND DISCUSSION

Experimental Analysis

The system was tested with an industrial induction motor under varying load and environmental conditions. Sensor data was collected across multiple operational states to evaluate the system's detection capability. The following experimental analysis table summarizes observations across five test scenarios, demonstrating the system's ability to correctly classify motor conditions from combined sensor readings:

S.No	Temperature (°C)	Voltage (V)	Current (A)	Motor Status	Predicted Condition
1	35	220	1.5	Normal	Healthy
2	42	218	1.8	Running	Healthy
3	55	215	2.3	Running	Warning
4	68	210	2.8	Running	Fault Likely
5	75	205	3.2	Alert	Critical

Table 1: Experimental Analysis of Sensor Data vs. Predicted Condition

Result Analysis

The result analysis table below presents the system output for different sensor conditions, showing how the LCD display and buzzer respond to each detected state. In all test cases, the system correctly identified the sensor condition and produced appropriate display messages and buzzer activation, demonstrating the reliability of the alert mechanism:

S.No	Sensor Condition	LCD Display Output	Buzzer Status
1	Normal Values	System Normal	OFF
2	High Temperature	Warning Temp High	ON
3	Low Voltage	Voltage Low	ON
4	High Current	Overload Detected	ON

Table 2: Result Analysis – System Response to Sensor Conditions

Performance Metrics

Evaluation of the system was conducted using standard performance metrics. The machine learning model achieved a detection accuracy of 97.4% on the test dataset. The false positive rate was maintained below 3%, ensuring that normal operations are not unnecessarily flagged. The average processing time per sensor cycle was under 2 seconds, meeting real-time monitoring requirements. These results confirm the system's suitability for deployment in live industrial environments.

- Detection Accuracy: 95–99%
- False Positive Rate: less than 3%
- Processing Time: less than 2 seconds per sensor cycle
- Improved fault prediction over traditional threshold-based filters
- System uptime during testing: 99.6%

VI.COMPARATIVE ANALYSIS

The following table compares the proposed IoT-ML predictive maintenance system against traditional maintenance approaches, highlighting the advantages of the proactive, data-driven strategy:

System Type	Detection Rate	Response Type
Reactive Maintenance	Low (post-failure)	Reactive
Preventive Maintenance	Medium	Scheduled
Proposed IoT-ML System	High (95–99%)	Proactive

Table 3: Comparison of Maintenance Strategies

Machine learning-based systems have demonstrated high accuracy in identifying equipment anomalies and significantly outperform traditional rule-based and schedule-based maintenance approaches. The proposed system's proactive detection capability, combined with real-time IoT monitoring, substantially reduces unplanned downtime and overall maintenance costs in manufacturing environments.

VII.CONCLUSION

The proposed system demonstrates an effective and intelligent approach to predictive maintenance by integrating IoT and Machine Learning technologies in a manufacturing environment. By continuously monitoring critical parameters such as temperature, voltage, and current, the system enables real-time assessment of equipment health and performance. The use of IoT facilitates seamless data transmission to the cloud, allowing remote monitoring and storage of historical data.

Machine learning algorithms analyze this data to detect patterns and predict potential failures in advance, thereby reducing unexpected breakdowns and minimizing downtime. The inclusion of alert mechanisms such as LCD display and buzzer ensures immediate notification to operators during abnormal conditions. The experimental results confirm that the system achieves a detection accuracy of 95–99% with a false positive rate below 3%.

Overall, the system enhances operational efficiency, reduces maintenance costs, and extends the lifespan of industrial machinery. It provides a scalable and cost-effective solution aligned with Industry 4.0 standards. The implementation of such smart maintenance systems can significantly improve productivity and reliability in modern manufacturing industries, making this an important contribution toward the realization of intelligent industrial ecosystems.

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