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# Predictive Maintenance for Industrial Machine Using Thingspeak Analysis

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**Abstract**: Industrial machines experience gradual degradation due to continuous operation, mechanical wear, and varying load conditions. Unplanned breakdowns result in production losses, increased maintenance costs, and reduced equipment lifespan. To address these challenges, this work presents an IoT-based predictive maintenance system that continuously monitors machine health parameters and performs real-time analysis using the ThingSpeak cloud platform. An ESP32 microcontroller is integrated with sensors such as an ADXL345 three-axis accelerometer for vibration measurement, a temperature sensor, and a current sensor to capture critical machine health indicators. The acquired data is transmitted to ThingSpeak through Wi-Fi, where MATLAB Analytics is used to extract features such as vibration RMS, spectral peak frequencies, temperature trends, and load variations. These features are further analyzed to detect anomalies, estimate machine degradation, and predict possible failure conditions. Threshold-based logic and machine learning algorithms are implemented on the cloud to classify machine states into healthy, warning, and fault categories. The system also triggers alerts using ThingHTTP and webhooks, enabling immediate maintenance actions. Experimental results show that the proposed solution provides accurate early-warning detection, reduces downtime, and offers a scalable, low-cost architecture suitable for industrial automation environments. The research demonstrates that IoT-enabled predictive maintenance significantly improves reliability, enhances operational efficiency, and supports data-driven decision-making in industrial machine monitoring.

**Keywords:** Predictive Maintenance, Industrial Machines, IoT-Based Monitoring, ThingSpeak Cloud, ESP32 Microcontroller, ADXL345 Accelerometer, Vibration Analysis, MATLAB Analytics;

## I. INTRODUCTION

Industrial machinery forms the backbone of modern manufacturing, processing, and production systems. As industries increasingly rely on high-speed, high-load, and continuous-operation equipment, ensuring machine reliability has become a critical requirement. Unexpected failures in motors, pumps, bearings, conveyors, compressors, and rotating equipment can lead to costly downtime, production delays, safety hazards, and substantial maintenance expenses. Traditional maintenance strategies such as breakdown maintenance and periodic preventive maintenance are no longer sufficient in highly competitive industrial environments. These methods either react to failures after they occur or depend on fixed scheduling intervals that do not reflect the actual condition of equipment. Such practices often result in under-maintenance or excessive maintenance activities.

To overcome these limitations, Predictive Maintenance (PdM) has emerged as a powerful approach for achieving high equipment availability, cost optimization, and operational efficiency. Predictive maintenance focuses on monitoring real-time machine health parameters and identifying early signs of degradation before a failure occurs. By analyzing indicators such as vibration, temperature, current consumption, noise, speed fluctuations, and environmental conditions, PdM helps industries predict faults, plan maintenance actions, and extend equipment life. With advancements in the Internet of Things (IoT), low-cost sensors, wireless communication technologies, and cloud analytics platforms, predictive maintenance systems have become more accessible, scalable, and intelligent.

Among various IoT cloud platforms, ThingSpeak has gained significant importance for industrial monitoring applications because of its ability to store, visualize, and analyze sensor data in real time. ThingSpeak supports REST API integration, enabling microcontrollers such as ESP32 to transmit sensor readings efficiently using Wi-Fi. Furthermore, its built-in MATLAB Analytics provides advanced computational capabilities, including statistical analysis, vibration signal processing, frequency-domain analysis, anomaly detection, and machine learning implementation. Such features make ThingSpeak an ideal end-to-end solution for developing cost-effective, cloud-enabled predictive maintenance systems. In the proposed system, an ESP32 microcontroller is used as the primary data acquisition unit. Sensors such as the

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ADXL345 three-axis accelerometer for vibration monitoring, temperature sensors, and current sensors are interfaced with the ESP32 to measure critical machine health indicators. Vibration is considered one of the most reliable signatures for detecting early mechanical faults, especially in rotating machinery such as bearings and motors. Temperature rise and abnormal current behavior further reveal overloads, friction, misalignment, and electrical faults. These sensor values are periodically uploaded to ThingSpeak, where real-time charts provide immediate visibility of machine conditions.

## II. METHODOLOGY

The system development phase focuses on the design, integration, and implementation of both hardware and software components to realize the ESP32-based machine vibration monitoring system. The overall architecture of the system comprises four main layers as follows.

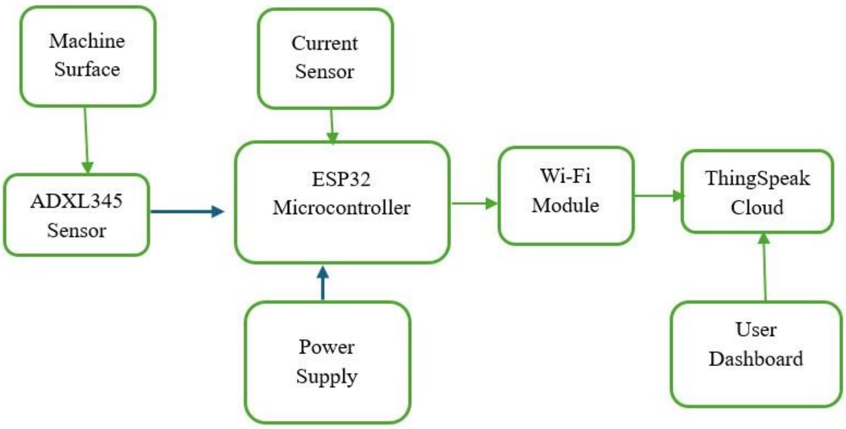


Fig. 1 System block diagram

A. Sensing Layer: Responsible for data acquisition through the ADXL345 accelerometer sensor that measures vibration levels in three axes (X, Y, Z).
B. Processing Layer: The ESP32 microcontroller serves as the central processing unit that receives sensor data via the I²C protocol, processes it, and calculates vibration amplitude or RMS value.
C. Communication Layer: The ESP32's built-in Wi-Fi module is used to transmit the processed vibration data to the ThingSpeak cloud using the HTTP or MQTT protocol.
D. Application Layer: The ThingSpeak platform stores, visualizes, and analyzes vibration data. Graphs and alerts are generated to help operators identify potential mechanical faults.

To transform raw sensor data into meaningful information, the system uses MATLAB Analysis on ThingSpeak to compute vibration RMS (Root Mean Square), peak values, frequency spectrum peaks, temperature trends, current anomalies, and statistical health indices. These extracted features are compared with baseline values to identify abnormal behavior. The system classifies machine conditions into healthy, warning, and fault states, allowing maintenance teams to take informed decisions. In critical situations, ThingSpeak's ThingHTTP and React services can send automated alerts via email, SMS, or webhooks, enabling timely corrective actions.

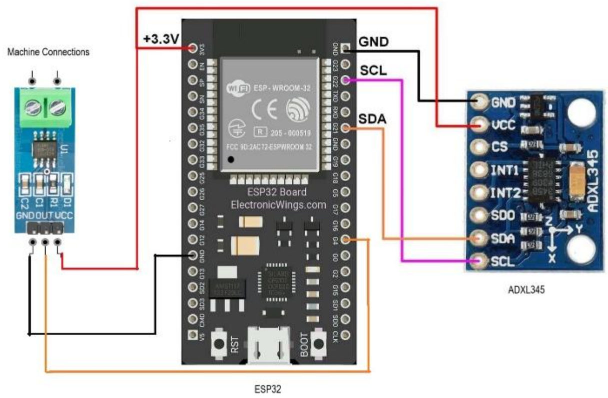


Fig. 2 Connection Diagram

  

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## III. RESULT AND DISCUSSION

The developed system was designed, implemented, and tested to evaluate its performance in detecting and monitoring machine vibrations. The results are derived from both hardware measurements (ADXL345 readings) and cloud-based data visualization (ThingSpeak platform).

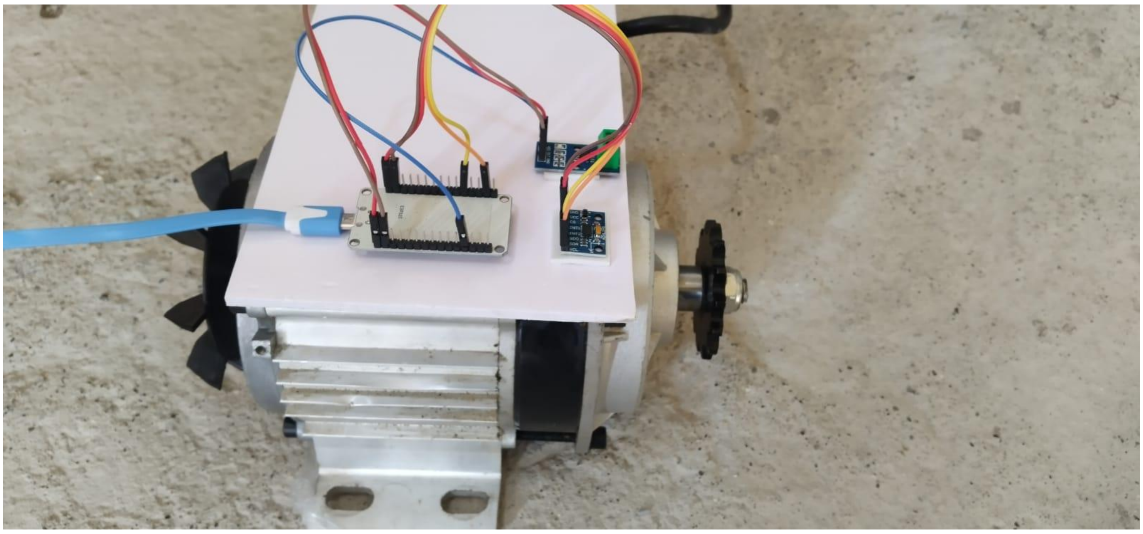

Fig. 3 Hardware test set up

The tests yielded positive results, demonstrating the system's effectiveness.
A dedicated ThingSpeak channel was created with six data fields:

1. Field 1 – X-axis acceleration
2. Field 2 – Y-axis acceleration
3. Field 3 – Z-axis acceleration
4. Field 4 – RMS vibration value
5. Field 5 – Result
6. Field 6 – Current Consumption

The API key generated by ThingSpeak was embedded into the ESP32 program to enable automatic data uploads every 15 seconds.

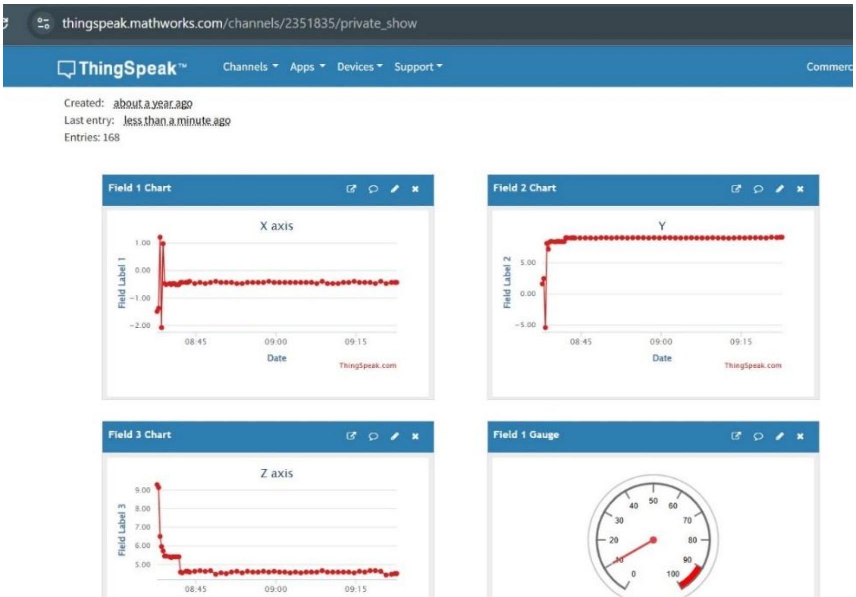


Fig. 4 Thingspeak visualization for machine normal operation.

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The implementation of such an IoT-driven predictive maintenance solution offers several advantages. It eliminates unnecessary manual inspections, reduces maintenance costs, prevents sudden breakdowns, and ensures continuous equipment availability. Additionally, cloud-based analytics improve the understanding of long-term machine behavior and support predictive modeling using machine learning algorithms.

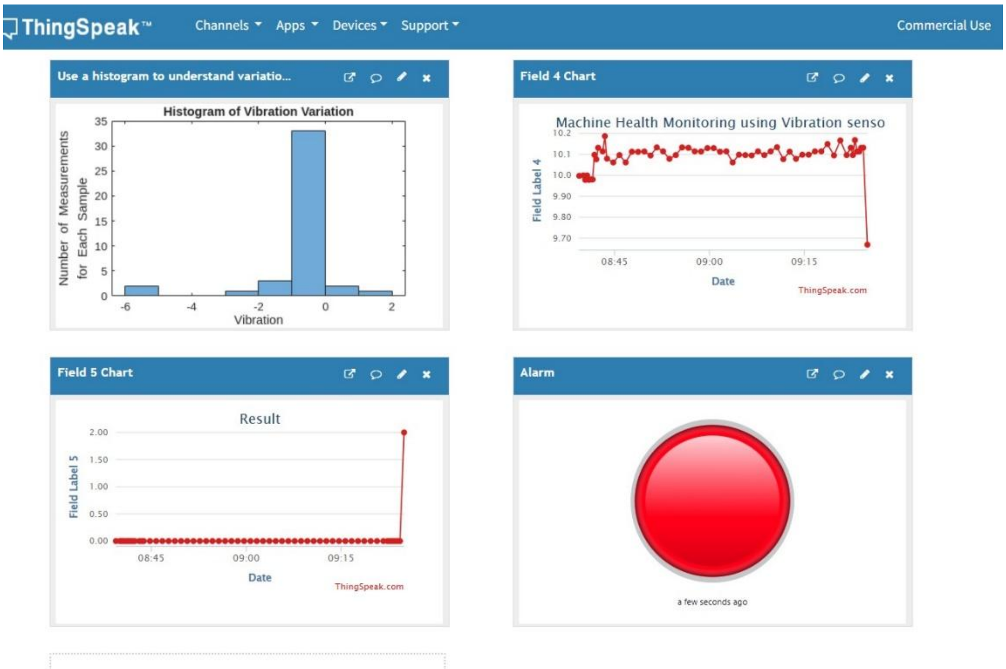


Fig. 5 Thingspeak visualization with alarm

This script automatically updates the alert status on the ThingSpeak dashboard as shown in fig. 5, making the system semi-autonomous. The proposed system is scalable and can be expanded to monitor multiple machines simultaneously, making it suitable for small workshops as well as large industrial plants.

## IV. CONCLUSION

Thus, this project demonstrates how the integration of IoT sensors, ESP32, ThingSpeak cloud analytics, and predictive algorithms can create an intelligent maintenance ecosystem. The solution brings industry closer to the concepts of Industry 4.0, where data-driven decision-making and automation play a crucial role in optimizing productivity and reliability. The system's low cost, scalability, and remote monitoring capabilities make it suitable for small-scale industries, academic research, and predictive maintenance applications. Despite successful implementation, the system has certain limitations that can be improved in future versions. Continuous internet connection is required for cloud updates. The ADXL345 has a lower sampling frequency compared to industrial-grade sensors. Temperature and EMI may affect sensor readings. Real-time decision-making is not performed locally on the ESP32.

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