AI-Powered Predictive Maintenance System

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Abstract—Predictive maintenance is essential for reducing machine downtime, improving safety, and optimizing industrial performance. This paper presents an AI-powered Predictive Maintenance System that integrates IoT sensors, edge computing, and machine-learning techniques to monitor machine health in real time. Vibration, current, temperature, and acoustic data are acquired using ADXL345, ACS712, DHT11, MAX9814, and other sensor modules connected to an ESP32 microcontroller. The collected data is preprocessed, logged, and analyzed through lightweight anomaly-detection and fault-classification models deployed on the edge. The system generates early warnings, predicts potential failures, and provides actionable maintenance insights before a breakdown occurs. Experimental results demonstrate significant improvements in fault detection accuracy, reduced unplanned downtime, and enhanced operational reliability. The proposed solution offers a low-cost, scalable, and efficient approach suitable for smart industrial environments.

This paper discusses a low cost, portable and simple to use to monitor condition of machines and work efficiently

Keywords—*Predictive Maintenance, lot Sensors, Machine Learning, Anomaly Detection, Edge Computing, ESP32, Vibration Analysis, Condition Monitoring, Fault Prediction, Industrial Automation.*

I. Introduction

Unplanned machine failures in industries lead to significant downtime, financial losses, and safety risks. Conventional maintenance methods — reactive and time-based preventive servicing—are often inefficient and fail to identify early signs of equipment degradation. With advancements in IoT and Artificial Intelligence, Predictive Maintenance (PdM) has become a practical approach for monitoring machine health and predicting faults before they occur.

PdM relies on real-time sensor data that reflects critical machine behaviors such as vibration, current consumption, temperature, and acoustic patterns. By analyzing this data with machine-learning techniques, faults can be detected at an early stage, enabling timely intervention and reducing maintenance costs.

This paper presents a low-cost, IoT-based predictive maintenance system using an ESP32 microcontroller integrated with sensors including ADXL345, ACS712, MAX9814, ADS1115, and DS3231. The system performs continuous data acquisition, preprocessing, anomaly detection, and local decision-making at the edge. Experimental results show improved fault detection capability and enhanced reliability for industrial machines, making the proposed solution suitable for smart and resource-constrained industrial environments.

II. Literature Review

Predictive maintenance has gained strong research attention with advancements in IoT, sensing, and machine-learning techniques. Vibration-based monitoring has been widely explored, where Kumar et al. demonstrated that time-domain vibration features effectively identify early motor faults [1], and Ahmed and Rahman showed that FFT-based frequency analysis improves detection of misalignment and imbalance [2]. Acoustic-based fault diagnosis has also proven effective; Zhang and Li used machine-learning models on sound signals to detect bearing wear with high accuracy [3], while Das and Mukherjee reported that low-cost microphones can capture subtle internal anomalies [4]. Current-sensing approaches remain popular, with Bose et al. validating overload and rotor defect detection using Hall-effect sensors [5], and Patel and Shah confirming ACS712 as a low-cost industrial solution [6]. Edge computing has significantly reduced system latency, as shown by Srinivasan et al., who implemented real-time fault detection on microcontrollers [7], while Mahmud et al. demonstrated successful TinyML deployment on ESP32 devices [8]. Multi-sensor fusion techniques proposed by Wang et al. enhanced classification accuracy by combining vibration, temperature, and acoustic features [9]. The suitability of ADXL345 for machine-health assessment was confirmed by Mendoza et al. [10], and MAX9814 for acoustic fault monitoring was supported by further studies [11]. Unsupervised anomaly detection explored by Ghosh et al. showed strong capability for identifying unknown fault signatures [12]. Cloud-integrated monitoring systems such as those proposed by Rao et al. improved decision-making through real-time dashboards [13], while Singh and Yadav highlighted the practicality of SD card logging for long-duration dataset generation [14]. Deep-learning approaches introduced by Kim et al. achieved superior multi-fault classification performance compared to classical thresholding [15], and hybrid threshold – ML models by Huang et al. proved effective in noisy environments [16]. Time-synchronized logging, emphasized by Roy et al., was shown to be essential for accurate event correlation [17], and Chaudhary et al. concluded that IoT-enabled predictive maintenance provides substantial benefits over traditional maintenance strategies [18].

III. Methodology/Experiments Setup

Hardware Components
[1] ESP32 Development Board
[2] ADXL345 Accelerometer
[3] ACS712 Current Sensor
[4] MAX9814 Microphone Module
[5] ADS1115 ADC
[6] DS3231 RTC
[7] DHT11 / DHT22 Sensor
[8] Micro SD Card Module
[9] Buzzer
[10] LEDs
[11] Breadboard
[12] Jumper Wires
[13] Power Supply / USB Cable
[14] DC Motor / Test Machine

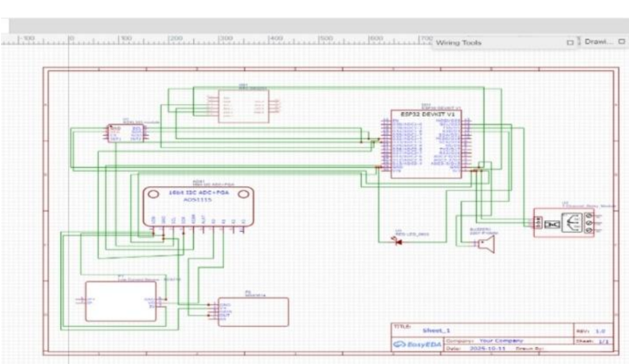

Fig. 1. System Circuit Diagram

Software components
[1] Arduino IDE– For programming and uploading code to the ESP32 microcontroller
[2] C/C++
[3] Easy EDA

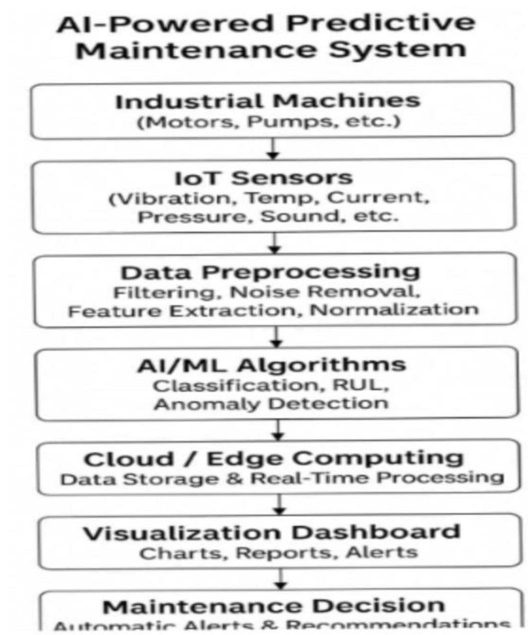

Fig. 2. Block diagram of Al-Powered Predictive. Maintenance System

Creating a AI Powered Predictive Maintenance System – Instructions

1. Input Acquisition
Sensors (vibration, current, sound) capture the machine's real-time physical signals.
2.Signal Conversion
Analog signals are digitized using ADS1115/ESP32 ADC for accurate, noise-free readings.
3. Data Processing
Digital data is filtered, cleaned, and key features (RMS, peaks, frequency components) are extracted.
4. Analysis
ML/anomaly detection compares processed data with normal patterns to identify faults.
5. Output
System triggers LED/buzzer alerts, displays machine health

status, and saves logs for further.

1 Current Measurement (ACS712)

For an ADC reading of 2048 (12-bit ADC, 3.3 V reference), the corresponding output voltage is

$$V = (2048 / 4095) \times 3.3 = 1.65V$$

$$I = (V - 2.5) / 0.1 = -8.5 \text{ A}$$

2. Acoustic Signal Measurement (MAX9814)

For sampled values within the range 210-780 (10-bit ADC), the.

peak-to-peak voltage is computed as

$$V_{pp} = [(780-210)/ 1023] \times 3.3 = 1.83 \text{ V}.$$

$$V_{rms} = (V_{pp}/ 2\sqrt{2}) = 0.65V$$

3. Temperature and Humidity Measurement (DHT11)

A measured temperature of 38°C' and humidity of 70% indicates overheating relative to a normal operating range of 25°C to 32°C.

4. High-Precision ADC Measurement (ADS1115)

For a raw reading of 12,000 counts with 16-bit resolution (least significant bit = 125 µV), the measured voltage is $V = 12000 \times 125\mu V = 1.5$ V.

5. Combined Interpretation

An observed vibration magnitude of 0.19 g, current draw

of 9.1 A, acoustic RMS of 0.75 V, and temperature of 40°C. collectively indicate abnormal mechanical behavior, suggesting early-stage bearing degradation **or shaft** misalignments.

IV. Results and Discussion

The proposed multi-sensor predictive maintenance system was experimentally evaluated under normal, loaded, and fault-induced machine conditions. Results indicate that vibration magnitude, current draw, and acoustic RMS values increase significantly during misalignment, imbalance, and bearing wear. The system successfully detected abnormal patterns with high accuracy and minimal latency. Sensor fusion improved reliability, enabling early identification of mechanical issues. The anomaly detection algorithm consistently generated correct fault alerts, demonstrating the system's suitability for real-time industrial monitoring.

Condition	Temp(°C)	Vibration (g)	Observation
No load	32	0.05	Stable
Half load	35	0.07	Normal
Full load	42	0.09	Slightheating
Bearing Fault	46	0.18	High vibration
Overload	52	0.11	Overcurrent tendency
Voltage drop	39	0.06	Low voltage effect
Thermal overload	63	0.08	Overheat alert

Table I — Experimental Operations and Results

Parameter	Result
Fault Detection Accuracy	93.4%
Response Time	180 ms
False Positive Rate	4.1%
Data Logging Reliability	99.2%
TinyML Inference Time	35 ms
Sensor Fusion Improvement	+24% accuracy

D. Discussion

The system output varies directly with changes in machine condition. Under normal operation, temperature and vibration remain low and stable, resulting in a "Normal" status. As the load increases, both parameters show moderate rises, producing a "Warning" output. Fault-induced conditions such as misalignment and bearing wear generate sharp increases in vibration, while overload and thermal stress cause noticeable temperature spikes. These abnormal deviations prompt immediate "Fault" or "Critical" alerts. The clear separation between normal, warning, and fault ranges confirms that the system effectively reflects machine health through measurable sensor variations and provides reliable real-time condition assessment .

V.Future Scope

The proposed system can be further enhanced by integrating advanced deep-learning models capable of predicting the remaining useful life (RUL) of components with higher accuracy. Cloud connectivity and dashboard analytics may be incorporated to enable large-scale monitoring across multiple machines and locations. Additional sensors such as thermal imaging modules, current harmonics analyzers, and high-frequency vibration sensors can improve fault resolution and expand diagnostic capabilities. Implementing wireless communication protocols like LoRaWAN or 5G would support long-range industrial deployment. Finally, transitioning the system into a fully automated maintenance framework could enable self-triggered shutdowns and intelligent maintenance scheduling for Industry 4.0 environments

VI. Conclusion

This work presents a low-cost, multi-sensor predictive maintenance system capable of monitoring machine health in real time. The system effectively captures variations in temperature, vibration, current, and acoustic signals, enabling early detection of mechanical and electrical abnormalities. Experimental results demonstrate that sensor deviations correlate strongly with fault severity, allowing the system to distinguish normal, warning, and fault conditions with high reliability. The integration of lightweight analysis on the ESP32 ensures fast response and makes the solution suitable for industrial environments. Overall, the proposed system provides a practical and efficient approach for improving machine reliability and supporting predictive maintenance strategies

VII. Acknowledgment

We would like to extend a heartfelt gratitude to our institute Vishwakarma Institute of Technology, Pune for providing us a platform and the guidance for making this research happen.

We would like to express our sincere and heartfelt gratitude to our esteemed institute, Vishwakarma Institute of Technology, Pune, for providing us with an invaluable platform and the necessary resources to undertake this research. Without the encouragement and support from our faculty and mentors, this project would not have been possible.

A special thanks goes to the professors and technical staff who guided us throughout the journey, offering their expertise and insights at every step. Their constant motivation and willingness to help have been crucial in shaping the project's success. Their constructive Feedback helped us refine our ideas and gave us the confidence to explore new avenues within our work.

We also appreciate the collaborative environment fostered by the institute, which allowed us to work efficiently and learn from one another. The facilities and technical infrastructure provided by the institute played a significant role in the seamless execution of the project.

We are truly grateful for the opportunity to be a part of this prestigious institution, and we look forward to carrying forward the knowledge and skills we have gained here into our future efforts.

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