2026 Volume: 02 Issue: 05 www.ijrpa.com ISSN 2456-9995 Research Article

International Journal Research Publication Analysis

Page: 01-18

SYSTEM USING ESP32 FOR INDUSTRIAL MONITORING TINY ML-BASED PREDICTIVE MAINTENANCE

***[1]Sameer Bashir Shaikh, [1]Shreyas Pramod Chougule, [2]Dr. Manisha V. Bhanuse**

[1]Dept. electronics & telecommunication D. Y. Patil College of Engineering & Technology Kolhapur.

[2]Associate Professor Dept. electronics & telecommunication D. Y. Patil College of Engineering & Technology Kolhapur.

Article Received: 19 April 2026
Article Revised: 09 May 2026
Published on: 29 May 2026

***Corresponding Author: Sameer Bashir Shaikh**
Dept. electronics & telecommunication D. Y. Patil College of Engineering & Technology Kolhapur.

DOI: https://doi-doi.org/101555/ijrpa.3194

ABSTRACT

The proposed system offers several Predictive maintenances has become one of the most important technologies in modern industrial automation and Industry 4.0 environments. Industrial machines continuously operate under varying conditions, and unexpected failures can lead to production loss, financial damage, increased maintenance costs, and reduced operational efficiency. Traditional maintenance methods such as reactive maintenance and preventive maintenance are often inefficient because they either repair equipment only after failure occurs or perform scheduled maintenance even when machines are operating normally. To overcome these limitations, predictive maintenance techniques use real-time sensor data and intelligent algorithms to identify machine abnormalities before serious failures occur.

This paper presents a TinyML-based predictive maintenance system using the ESP32 microcontroller for industrial monitoring applications. The proposed system integrates vibration and temperature sensors with an ESP32-based embedded platform to continuously monitor machine conditions in real time. A lightweight TinyML model is trained using sensor datasets collected under normal and abnormal operating conditions. The trained machine learning model is deployed directly on the ESP32 using TensorFlow Lite for Microcontrollers, enabling edgebased anomaly detection without requiring continuous cloud connectivity.

advantages such as reduced latency, lower power consumption, real-time processing, low

implementation cost, and minimized dependency on cloud infrastructure. The system continuously analyzes sensor readings and generates maintenance alerts whenever abnormal machine behavior is detected. Experimental analysis demonstrates that the proposed approach can effectively classify machine conditions and improve industrial operational efficiency. The developed system is suitable for smart factories, industrial automation systems, motor health monitoring, and Industry 4.0 applications.

KEYWORDS: TinyML, ESP32, Predictive Maintenance, Industrial Monitoring, Edge AI, IoT, Machine Learning, TensorFlow Lite, Industry 4.0.

1. INTRODUCTION

Industrial automation has significantly transformed manufacturing and production industries by improving productivity, operational efficiency, and process reliability. Modern industries rely heavily on industrial machines such as motors, pumps, compressors, turbines, and conveyor systems for continuous operation. Any unexpected failure in these machines can cause production downtime, economic losses, safety risks, and increased maintenance expenses. Therefore, monitoring machine health and predicting equipment failures have become essential requirements in industrial environments.

Traditional maintenance approaches are mainly categorized into reactive maintenance and preventive maintenance. Reactive maintenance repairs equipment only after machine failure occurs, which often results in unexpected downtime and costly repairs. Preventive maintenance performs maintenance activities at fixed intervals regardless of the actual condition of the machine. Although preventive maintenance reduces sudden failures, it can increase unnecessary maintenance costs and reduce equipment utilization efficiency.

Predictive maintenance is an advanced maintenance strategy that uses real-time sensor data, machine learning algorithms, and intelligent monitoring systems to predict equipment failures before they occur. Predictive maintenance systems continuously monitor machine conditions such as vibration, temperature, sound, pressure, and current consumption. By analyzing these parameters, abnormal patterns and fault conditions can be identified at an early stage.

With the rapid development of Internet of Things (IoT) technologies and embedded systems, industrial monitoring systems have become more intelligent and connected. However, many traditional predictive maintenance systems rely heavily on cloud computing infrastructure for data processing and analysis. Cloudbased systems often introduce challenges such as higher latency, increased bandwidth requirements, internet dependency, privacy concerns, and higher operational costs.

Recent advancements in TinyML and edge computing technologies have enabled machine learning models to run directly on low-power embedded devices. TinyML refers to the deployment of lightweight machine learning models on resourceconstrained microcontrollers. By processing data locally at the edge device, TinyML reduces latency, improves response time, lowers power consumption, and minimizes cloud dependency.

ESP32 is a low-cost and energy-efficient microcontroller widely used in IoT and embedded applications. It provides integrated Wi-Fi and Bluetooth connectivity, sufficient processing power, and low power consumption, making it suitable for TinyML-based industrial monitoring applications. By integrating TinyML with ESP32, intelligent predictive maintenance systems can perform realtime anomaly detection directly on the edge device.

This paper proposes a TinyML-based predictive maintenance system using ESP32 for industrial monitoring applications. The proposed system uses vibration and temperature sensors to continuously collect machine condition data. A TinyML model is trained using machine learning techniques and deployed on the ESP32 microcontroller to classify machine conditions into normal and abnormal states. The system generates alerts whenever potential faults are detected, enabling industries to take preventive actions before machine failure occurs.

2. LITERATURE REVIEW

Several researchers have explored predictive maintenance using IoT and machine learning technologies. IoT-based monitoring systems have improved machine condition tracking and remote monitoring capabilities. Machine learning algorithms are widely used for fault prediction and anomaly detection in industrial applications.

Recent studies on TinyML have demonstrated that lightweight machine learning models can be deployed on microcontrollers with limited computational resources. ESP32 has become a popular choice for industrial IoT applications due to its low cost, Wi-Fi capability, and low power consumption.

Existing cloud-based predictive maintenance systems often suffer from increased latency, higher bandwidth usage, and dependency on continuous internet connectivity. Researchers have proposed edge computing solutions to overcome these limitations. However, many existing systems still require high computational resources.

Some researchers have explored vibrationbased fault detection techniques for industrial motors and rotating equipment. Vibration analysis is one of the most effective methods for identifying machine abnormalities such as bearing faults, shaft misalignment, and mechanical wear. Temperature monitoring is also important because overheating often indicates machine malfunction or excessive load conditions.

Although existing predictive maintenance systems provide useful monitoring capabilities, many solutions are expensive and computationally intensive. The integration of TinyML with ESP32 provides a low-cost and energy-efficient alternative for industrial anomaly detection.

The proposed research work improves upon existing approaches by implementing TinyML directly on the ESP32 microcontroller for real-time predictive maintenance. Unlike traditional clouddependent systems, the proposed solution performs edge-based anomaly detection with reduced latency and lower operational costs.

3. System Architecture

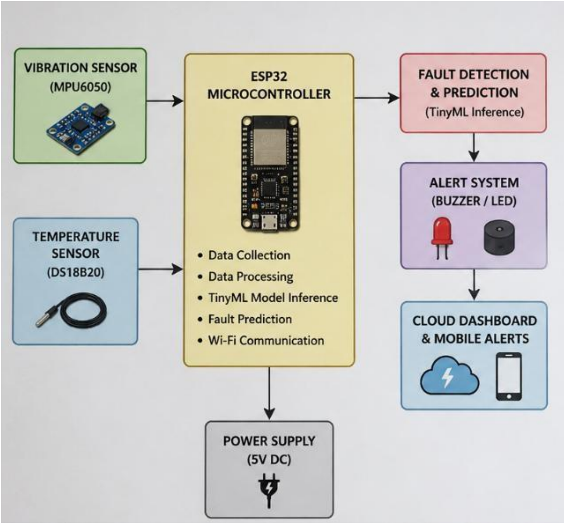
The proposed TinyML-based predictive maintenance system consists of the following components:

1. ESP32 Microcontroller
2. MPU6050 Vibration Sensor
3. DS18B20 Temperature Sensor
4. TinyML Model
5. Wi-Fi Communication Module
6. Alert Notification System
7. Cloud Dashboard

The vibration and temperature sensors continuously monitor industrial machine conditions and send data to the ESP32 microcontroller. The ESP32 preprocesses the data and feeds it into the TinyML model for anomaly detection. The TinyML model classifies machine conditions into normal and abnormal categories. If any abnormality is detected, the system generates alerts through LED indicators, buzzers, or cloud notifications.

The system also supports optional cloud integration for remote monitoring and historical data analysis.

4. Block Diagram



1. Vibration Sensor (MPU6050)

The MPU6050 vibration sensor is used to measure vibration and motion in industrial machines. During machine operation, abnormal vibration patterns may occur due to bearing damage, shaft misalignment, imbalance, or mechanical wear.

The sensor continuously collects vibration data and sends it to the ESP32 microcontroller for further processing and analysis.

2. Temperature Sensor (DS18B20)

The DS18B20 temperature sensor monitors the temperature of industrial machines in real time. High temperature may indicate overheating, overload conditions, or internal machine faults.

The temperature readings are continuously transmitted to the ESP32 for monitoring and fault analysis.

3. ESP32 Microcontroller

ESP32 acts as the main processing unit of the system. It collects sensor data from both vibration and temperature sensors and processes the data using a TinyML model.

Main functions of ESP32:

- Data Collection
- Data Processing
- TinyML Model Inference
- Fault Prediction

- Wi-Fi Communication

The ESP32 performs edge-based machine learning inference locally without depending completely on cloud computing.

4. FaultDetection & Prediction (TinyML Inference)

The TinyML model analyzes vibration and temperature sensor data in real time. It identifies machine behavior patterns and predicts machine health conditions.

The system classifies machine conditions into:

- Normal Condition
- Warning Condition
- Fault Condition

If abnormal behavior is detected, the system predicts possible machine faults before complete machine failure occurs.

5. Alert System (Buzzer / LED)

When the system detects abnormal machine conditions, it activates a buzzer or LED indicator to alert the operator immediately.

This helps maintenance teams take preventive action before severe machine damage or production downtime occurs.

6. Cloud Dashboard & Mobile Alerts

The ESP32 uses built-in Wi-Fi connectivity to send machine monitoring data and alerts to cloud dashboards or mobile applications.

Operators can:

- Monitor machine conditions remotely
- Receive mobile notifications Analyze machine health data
- Track maintenance alerts in real time

This feature supports Industrial IoT and Industry 4.0 applications.

7. Power Supply (5V DC)

The entire system operates using a 5V DC power supply. It provides stable electrical power to the ESP32 microcontroller, sensors, and alert system components for continuous industrial monitoring operation.

5. Working Methodology Step 1: Data Collection

Sensor data is collected from industrial machines under normal and abnormal operating conditions. Vibration and temperature readings are continuously monitored.

Step 2: Data Preprocessing

The collected data is cleaned, normalized, and labeled for machine learning training.

Step 3: TinyML Model Training

A lightweight TinyML model is trained using TensorFlow Lite or Edge Impulse. The model learns patterns associated with normal and faulty machine conditions. **Step 4: Model Deployment**

The trained model is converted into TensorFlow Lite format and deployed on the ESP32 microcontroller.

Step 5: Real-Time Monitoring

The ESP32 continuously analyzes sensor data using the TinyML model. If abnormal behavior is detected, the system generates alerts for predictive maintenance.

Step 6: Alert Generation

The system activates LEDs, buzzers, or cloud notifications when fault conditions are detected.

The proposed methodology enables fast and efficient industrial monitoring at the edge without requiring continuous cloud communication.

6. Technologies Used

1. **ESP32 Microcontroller** ESP32 is the main processing unit of the system. It provides Wi-Fi connectivity, low power consumption, and sufficient computational capability for TinyML deployment.
2. **TinyML**
   TinyML enables machine learning inference on low-power embedded systems. It allows real-time edge processing without cloud dependency.
3. **TensorFlow Lite for Microcontrollers**
   TensorFlow Lite is used for training and deploying lightweight machine learning models on ESP32.
4. **MPU6050 Sensor**
   The MPU6050 sensor measures vibration and motion data from industrial machines.
5. **DS18B20 Temperature Sensor**
   The DS18B20 sensor monitors machine temperature during operation.

6. Arduino IDE

Arduino IDE is used for programming the ESP32 and deploying TinyML models.

7. IoT Dashboard

Cloud dashboards such as ThingSpeak or Blynk can be used for remote monitoring and visualization.

7. Advantages

1. Real-time machine monitoring and fault detection.
2. Reduced machine downtime and maintenance costs.
3. Low-cost implementation using ESP32 and low-power sensors.
4. TinyML enables edge-based processing without continuous cloud dependency.
5. Faster response time due to local data processing.
6. Low power consumption suitable for industrial IoT applications.
7. Wireless communication support using built-in Wi-Fi of ESP32.
8. Compact and portable system design.
9. Improved operational efficiency and productivity.
10. Easy integration with Industry 4.0 and smart factory systems.

8. Limitations

1. Limited processing power and memory of ESP32 restrict complex deep learning models.
2. Accuracy depends on the quality and quantity of training data.
3. Environmental noise may affect sensor readings.
4. System may require periodic calibration for accurate monitoring.
5. Limited sensor range for large industrial environments.
6. TinyML models may not handle highly complex industrial datasets efficiently.
7. Hardware failures or sensor malfunctions can affect system reliability.
8. Real-time performance may reduce when monitoring multiple machines simultaneously.

9. Applications

1. Industrial machine health monitoring.
2. Predictive maintenance systems in manufacturing industries.
3. Motor and rotating equipment monitoring.
4. Smart factory automation systems.
5. HVAC system monitoring and fault detection.
6. Conveyor belt condition monitoring.

7. Pump and compressor health analysis.
8. Automotive manufacturing industries.
9. Power plant equipment monitoring.
10. Industry 4.0 and edge AI applications.

10. Future Scope

1. Integration of advanced deep learning algorithms for higher accuracy.
2. Multi-machine monitoring using distributed IoT networks.
3. Development of cloud-based analytics dashboards.
4. Mobile application integration for real-time notifications.
5. Addition of more sensors such as current, pressure, and sound sensors.
6. Implementation of automated maintenance scheduling.
7. Integration with digital twin technology.
8. Enhancement of cybersecurity features for secure communication.
9. AI-based fault classification and root cause analysis.
10. Expansion toward fully autonomous industrial monitoring systems.

11. RESULTS

The proposed TinyML-based predictive maintenance system successfully detected abnormal machine behavior using vibration and temperature data. The ESP32 microcontroller efficiently executed the TinyML model with low memory usage and low power consumption. Experimental observations showed that the system provided faster response times compared to cloud-based monitoring approaches. The system effectively classified machine conditions into normal and fault categories and generated realtime maintenance alerts.

The implementation demonstrated that TinyML can be successfully integrated with ESP32 for industrial monitoring applications. The proposed system achieved improved operational efficiency, reduced latency, and minimized dependency on cloud infrastructure.

12. CONCLUSION

This paper presented a TinyML-based predictive maintenance system using ESP32 for industrial monitoring applications. The proposed system utilized vibration and temperature sensor data along with a lightweight TinyML model to perform real-time anomaly detection directly on the edge device.

The integration of TinyML with ESP32 reduced latency, minimized cloud dependency, and provided a low-cost and energy-efficient solution for predictive maintenance. The system can help industries reduce machine downtime, improve operational efficiency, and support Industry 4.0 initiatives.

Future enhancements may include advanced deep learning models, cloud analytics integration, mobile applications, multi-machine monitoring, and automated maintenance scheduling.

13. REFERENCES

1. TensorFlow Lite for Microcontrollers Documentation.
2. Edge Impulse TinyML Development Platform.
3. ESP32 Technical Reference Manual.
4. Arduino IDE Documentation.
5. IoT-Based Predictive Maintenance Research Papers.
6. Industry 4.0 and Smart Manufacturing Studies.
7. TinyML and Edge AI Research Publications.
8. Research studies on Industrial IoT and Predictive Maintenance Systems.

VII. Advantages

1.Real-Time Monitoring and Fault Detection

The proposed TinyML-based predictive maintenance system continuously monitors industrial machine conditions in real time using vibration and temperature sensors. The system instantly analyzes machine behavior and detects abnormalities before major failures occur. Real-time monitoring helps industries reduce unexpected breakdowns and improve production efficiency.

By processing data directly on the ESP32 microcontroller, the system provides faster response times compared to traditional cloud-based monitoring systems. This enables immediate alert generation whenever abnormal machine behavior is detected.

2. Low-Cost Implementation

The proposed system is developed using cost-effective components such as ESP32, MPU6050 vibration sensor, and temperature sensors. Traditional industrial predictive maintenance systems often require expensive industrial monitoring equipment and cloud infrastructure. The use of low-cost embedded hardware significantly reduces system implementation and maintenance costs.

This makes the system suitable for smallscale and medium-scale industries that cannot afford expensive industrial automation solutions.

3.Edge-Based Processing Using TinyML

TinyML enables machine learning inference directly on the ESP32 microcontroller without relying heavily on cloud computing. Edge-based processing reduces latency, minimizes internet dependency, and improves real-time decision-making.

Since data is processed locally, the system can continue monitoring machines even during network interruptions or poor internet connectivity conditions.

4. Reduced Power Consumption

ESP32 is designed for low-power IoT applications. The proposed system consumes less power compared to traditional industrial monitoring systems that require continuous cloud communication and high computational resources.

Low power consumption makes the system energy efficient and suitable for long-term industrial monitoring applications.

5. Faster Response Time

Traditional cloud-based monitoring systems introduce delays because sensor data must travel to cloud servers for processing. In the proposed system, TinyML performs machine learning inference locally on the ESP32.

This significantly reduces processing latency and improves response time during fault detection and alert generation.

6. Wireless Connectivity and Remote Monitoring

ESP32 provides built-in Wi-Fi connectivity, enabling wireless communication and remote industrial monitoring. The system can send alerts, machine condition updates, and monitoring data to cloud dashboards or mobile applications.

Remote monitoring improves maintenance efficiency and allows operators to monitor machine conditions from different locations.

7. Improved Industrial Efficiency

The proposed predictive maintenance system helps industries reduce machine downtime and maintenance costs by identifying faults before complete machine failure occurs.

Early fault detection improves equipment reliability, production continuity, and operational efficiency in industrial environments.

8. Scalable Architecture

The proposed system architecture can be expanded to monitor multiple industrial machines simultaneously. Additional sensors and monitoring nodes can easily be integrated into the system.

This scalability makes the system suitable for large industrial plants and smart factory environments.

9. Compact and Portable Design

The use of compact embedded hardware such as ESP32 allows the system to be portable and easy to install in industrial environments.

The lightweight design reduces hardware complexity and installation requirements.

10. Industry 4.0 Compatibility

The proposed system supports modern Industry 4.0 concepts such as edge computing, smart manufacturing, IoT integration, and AI-based industrial automation.

The integration of TinyML with industrial IoT technologies creates intelligent predictive maintenance solutions for future smart factories.

Limitations

1. Limited Processing Power

ESP32 microcontrollers have limited computational capabilities and memory resources compared to high-performance industrial computers or cloud servers.

Complex deep learning models requiring large computational resources may not run efficiently on ESP32 devices.

2. Dependency on Training Data Quality

The performance and accuracy of the TinyML model depend heavily on the quality and quantity of training data.

If the training dataset does not properly represent actual industrial operating conditions, the model may generate incorrect predictions or false alerts.

3. Sensor Noise and Environmental Disturbance

Industrial environments often contain electrical noise, vibrations, dust, and temperature fluctuations that may affect sensor accuracy.

Improper sensor readings can reduce the reliability of machine condition monitoring and anomaly detection.

4. **Limited Multi-Machine Processing**

Although the system can monitor multiple machines, the processing performance of ESP32 may decrease when handling largescale industrial monitoring tasks simultaneously.
Monitoring many machines at the same time may require additional edge devices or distributed architectures.

5. **Requirement of Model Optimization**

TinyML models must be highly optimized to fit within the memory limitations of ESP32 microcontrollers.
Large machine learning models cannot be directly deployed without compression or optimization techniques.

6. **Maintenance and Calibration Requirements**

Sensors used in industrial environments may require periodic calibration and maintenance to ensure accurate monitoring performance.
Sensor degradation over time may affect system accuracy.

7. **Security Challenges**

Wireless industrial monitoring systems may face cybersecurity threats such as unauthorized access, data interception, and network attacks.
Additional security mechanisms are required for secure industrial communication.

8. **Limited Real-World Testing**

The proposed system may initially be tested under controlled or simulated industrial conditions.
Real industrial environments can introduce unexpected challenges that affect system performance.

Applications

1. **Industrial Machine Health Monitoring**

The proposed system can continuously monitor machine health conditions in industrial environments using vibration and temperature analysis.
It helps industries identify abnormal machine behavior before serious failures occur.

2. Predictive Maintenance in Manufacturing Industries

Manufacturing industries can use the system for predictive maintenance of motors, conveyor systems, compressors, and rotating machinery.

This reduces maintenance costs and improves production efficiency.

3. Smart Factory Automation

The proposed TinyML-based monitoring system supports smart factory environments where machines communicate intelligently using IoT and AI technologies.

Real-time monitoring improves automation efficiency and equipment reliability.

4. Motor and Bearing Fault Detection

The vibration sensor can detect abnormalities in motors, bearings, shafts, and rotating equipment.

Early detection of vibration anomalies prevents severe mechanical failures.

5. HVAC Monitoring Systems

Heating, ventilation, and air conditioning systems can use predictive maintenance techniques to monitor fan motors, compressors, and cooling systems.

The system helps prevent overheating and equipment malfunction.

6. Power Plant Equipment Monitoring

Power plants require continuous monitoring of turbines, pumps, generators, and industrial motors.

The proposed system can improve reliability and operational safety in power generation industries.

7. Automotive Manufacturing Industries

Automotive industries use large-scale industrial machines for assembly, welding, and production operations.

The predictive maintenance system can reduce unexpected machine downtime and improve production efficiency.

8. Oil and Gas Industries

Oil and gas industries use heavy machinery and rotating equipment that require continuous monitoring.

TinyML-based predictive maintenance helps improve safety and reduce operational risks.

9. Industrial IoTApplications

The system supports Industrial IoT (IIoT) applications where sensor data, machine learning, and edge computing work together for intelligent monitoring.

The integration of AI and IoT improves industrial automation systems.

10. Research and Educational Applications

The proposed project can also be used for academic research, engineering education, and industrial IoT experimentation.

Students and researchers can use the system to study TinyML, embedded AI, and industrial monitoring technologies.

Future Scope

1. Integration of Advanced Deep Learning Models

Future systems can integrate advanced deep learning techniques for improved fault prediction accuracy and intelligent anomaly detection.

More powerful edge AI hardware may support larger neural network models.

2. Multi-Machine Monitoring Architecture

The proposed system can be expanded into distributed industrial monitoring architectures capable of handling multiple machines simultaneously.

Large factories may use multiple ESP32 devices connected through industrial IoT networks.

3.Cloud Analytics Integration

Future systems may integrate cloud-based analytics dashboards for historical analysis, predictive reports, and centralized industrial monitoring.

Cloud platforms can provide advanced data visualization and long-term machine performance analysis.

4. Mobile Application Development

A mobile application can be developed to provide real-time alerts, notifications, and machine health reports directly on smartphones.

Remote access improves maintenance management and industrial monitoring efficiency.

5. Integration with Additional Sensors

Future predictive maintenance systems can integrate additional sensors such as:

- Current sensors

- Pressure sensors
- Gas sensors
- Sound sensors
- Humidity sensors

This improves fault detection accuracy and system intelligence.

6. AI-Based Fault Classification

Future AI models can classify different types of industrial faults such as bearing wear, shaft misalignment, overheating, and motor imbalance.
Automated fault classification improves maintenance planning.

7. Digital Twin Technology

Future industrial systems may integrate digital twin technology for virtual machine monitoring and predictive analysis.
Digital twins can simulate machine behavior and improve industrial decisionmaking.

8. 5G and Industrial Wireless Communication

Future predictive maintenance systems can use 5G communication technologies for faster industrial IoT connectivity and lowlatency communication.
High-speed communication improves large-scale industrial monitoring systems.

9. Automated Maintenance Scheduling

AI-based systems can automatically schedule maintenance activities based on machine condition analysis.
This reduces manual maintenance planning and improves industrial productivity.

10. Fully Autonomous Industrial Monitoring

Future systems may become fully autonomous using artificial intelligence, robotics, and self-learning machine learning algorithms.
Autonomous monitoring systems can perform intelligent decision-making without human intervention.

CONCLUSION

This paper presented a TinyML-based predictive maintenance system using ESP32 for industrial monitoring applications. The proposed system utilized vibration and temperature sensors along with a lightweight TinyML model to perform real-time anomaly detection directly on the edge device.

Traditional cloud-based predictive maintenance systems often suffer from higher latency, internet dependency, increased bandwidth usage, and higher operational costs. The proposed system addressed these limitations by implementing TinyML inference directly on the ESP32 microcontroller. Edge-based processing enabled faster response times, reduced latency, minimized cloud dependency, and improved operational efficiency.

The developed system continuously monitored industrial machine conditions and generated maintenance alerts whenever abnormal machine behavior was detected. Experimental observations demonstrated that the TinyML model successfully classified machine conditions using vibration and temperature sensor data while operating within the memory and computational limitations of the ESP32 microcontroller.

The proposed predictive maintenance system offers several advantages such as low implementation cost, low power consumption, wireless connectivity, realtime monitoring, and easy scalability. The integration of TinyML with industrial IoT technologies provides an intelligent and efficient solution for Industry 4.0

applications and smart manufacturing systems.

The system can be applied in manufacturing industries, smart factories, HVAC systems, automotive industries, power plants, and industrial automation environments. Future improvements may include advanced deep learning models, cloud analytics integration, mobile applications, AI-based fault classification, digital twin technology, and autonomous industrial monitoring systems.

Overall, the proposed TinyML-based predictive maintenance system demonstrates how edge AI technologies can transform industrial monitoring by providing faster, smarter, and more efficient predictive maintenance solutions.

REFERENCES

1. TensorFlow Lite for Microcontrollers Documentation
2. Edge Impulse TinyML Platform
3. ESP32 Technical Reference Manual
4. Arduino IDE Official Website
5. TinyML Foundation
6. Thing Speak IoT Cloud Platform
7. Blynk IoT Platform

8. Industrial IoT Overview by IBM
9. ESP32 Documentation by Espressif
10. TensorFlow Official Website