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Design and Fabrication of Real-Time Machine Failure Prediction System

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Abstract: ***The increasing reliance on automated and connected machines in industrial and logistics environments has intensified the need for real-time machine failure detection systems that enhance reliability, safety, and maintenance efficiency. Traditional monitoring approaches are largely reactive, relying on periodic inspections or basic parameter thresholds, which limits their ability to predict failures before they occur. To address this limitation, this project presents the design and development of a Real-Time Machine Failure Monitoring and Prediction System that integrates IoT-based sensing, cloud analytics, and mechanical validation into a unified framework.***

The proposed system employs a Raspberry Pi as the central processing unit, interfaced with multiple sensors to continuously monitor critical machine health parameters. These include temperature sensors for thermal condition monitoring, Hall-effect sensors for rotational speed analysis, tire pressure and load sensors for mechanical stress evaluation, and level sensors for lubricant or fluid status detection. RFID-based authentication ensures authorized machine operation, while GPS enables asset tracking for mobile machinery. Sensor data is transmitted in real time to a cloud platform (Firebase/Blynk), where it is visualized, logged, and analyzed to detect anomalies indicative of impending machine failures.

By applying threshold-based diagnostics and trend analysis, the system generates early warnings and predictive maintenance alerts, reducing unplanned downtime and maintenance costs. Additionally, mechanical feasibility and reliability are validated through SolidWorks modeling and analytical calculations, including load distribution, torque requirements, speed estimation, and structural constraints. The developed prototype demonstrates a cost-effective, scalable, and intelligent solution for real-time machine condition monitoring and failure prevention. This work highlights the effectiveness of integrating IoT, mechatronics, and cloud computing to enable predictive maintenance systems that can be extended to industrial machinery and smart manufacturing applications.

Keywords: Real-time machine monitoring, Internet of Things (IoT), predictive maintenance, sensor-based fault detection, cloud analytics dashboard.

I. INTRODUCTION

The increasing deployment of automated and connected machines in industrial and logistics environments has created a critical need for real-time machine health monitoring systems. Unplanned machine failures can lead to production losses, safety risks, and high maintenance costs. Traditional maintenance practices are primarily reactive or time-based, offering limited visibility into actual machine conditions. These approaches lack continuous monitoring, multi-sensor integration, and predictive capabilities, making them ineffective in preventing sudden breakdowns and performance degradation.

Advancements in Internet of Things (IoT) technologies enable the development of intelligent, low-cost, and scalable machine monitoring solutions. By integrating embedded controllers, multiple sensors, and cloud connectivity, IoT-based systems allow continuous data acquisition, remote diagnostics, and early fault detection. This paper presents an IoT-based real-time machine failure monitoring system implemented on a scaled prototype using a Raspberry Pi. The system collects critical operational parameters and visualizes them through a cloud dashboard, demonstrating an effective approach for predictive maintenance and improved machine reliability.

II. LITERATURE REVIEW

Extensive research has been conducted on IoT-based machine and asset monitoring systems. Chen *et al.* presented autonomous monitoring architectures emphasizing the role of real-time data acquisition in improving operational reliability. Kumar *et al.* demonstrated that IoT-enabled condition monitoring significantly enhances system visibility and fault detection in industrial environments. These studies highlight the effectiveness of sensor integration and cloud connectivity for continuous machine health assessment.

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Predictive maintenance has emerged as a key focus in modern machine monitoring systems. Singh and Rao showed that data-driven predictive analytics can substantially reduce machine downtime and maintenance costs. Nalla proposed advanced sensing techniques for early fault detection and failure prediction in electromechanical systems. Recent research also explores digital twins, artificial intelligence, and federated learning to enhance scalability and intelligence; however, such solutions often require complex infrastructure and high implementation costs. The proposed work addresses this gap by presenting a practical, low-cost, and scalable prototype suitable for academic and small-scale industrial applications.

III. OBJECTIVE

The primary objective of this project is to design and develop a smart telematics system for fleet vehicles using IoT technologies. The system aims to monitor key operational parameters including real-time vehicle location, cargo temperature and humidity conditions, driving behavior such as sudden jerks and overspeeding, and simulated fuel consumption. Additionally, the collected data is visualized using a cloud-based platform (Firebase) and a mobile dashboard to enable real-time monitoring and effective fleet management.

IV. COMPONENTS USED

This section presents an overview of the primary components used in the real-time machine failure monitoring system. Each hardware element is carefully selected to perform specific functions such as machine condition sensing, operational parameter monitoring, fault detection, and data communication. The integrated components enable continuous acquisition of critical machine health data required for early failure identification and predictive maintenance.

The system consists of multiple sensors for monitoring parameters such as temperature, speed, pressure, load, and fluid levels, along with an embedded processing unit for data handling and decision-making. Communication modules facilitate real-time data transmission to a cloud platform for visualization and analysis. The specifications and functional roles of each component are discussed in detail to highlight their contribution to system accuracy, reliability, and overall performance.

A. Arduino UNO R3

The Arduino Uno R3 serves as the primary control and data acquisition unit in the proposed real-time machine failure monitoring system. Based on the ATmega328P microcontroller, it provides reliable real-time performance with multiple digital and analog I/O pins for interfacing sensors that monitor key machine health parameters such as temperature, speed, pressure, and vibration. The Arduino performs sensor data acquisition and threshold-based fault detection, and transmits processed data to a cloud platform via an external communication module. Its low power consumption, support for UART, SPI, and I2C protocols, and ease of programming make it a cost-effective and suitable controller for IoT-based machine condition monitoring applications.

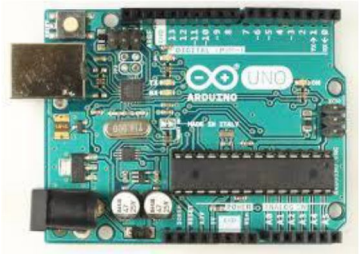


Fig 1. Arduino UNO R3

B. ESP32

ESP32 microcontroller, the driver enables precise control of motor direction, speed, and microstepping, which is essential for reproducing real-world mechanical operating conditions. The A4988 supports adjustable current limiting and multiple microstepping modes, ensuring safe motor operation and providing protection against overcurrent and thermal faults during prolonged operation.The ESP32, serving as the central control and monitoring unit, generates accurate pulse and direction signals for motor actuation through the A4988 driver while simultaneously acquiring sensor data related to vibration, temperature, current, and speed. Its high processing capability and built-in communication features allow real-time synchronization between motor control and condition monitoring. This integrated approach enables controlled stress testing of mechanical components and continuous observation of motor behavior, thereby supporting effective detection of abnormal operating patterns and early identification of potential fault conditions in predictive maintenance applications.

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Fig 2. ESP32

C. Mini Air Compressor

The mini air compressor serves as the primary electromechanical load in the proposed ESP32-based machine failure prediction system. It is used to simulate real-world industrial compressor behavior by generating controlled mechanical stress and varying load conditions during operation. The compressor converts electrical energy into compressed air, and its performance characteristics such as motor speed, temperature, vibration, and current consumption are continuously monitored for fault analysis.

In this system, the mini air compressor motor is actuated and controlled through an appropriate motor driver, enabling regulated operation under normal and abnormal working conditions. Variations in operating parameters—such as increased vibration, overheating, pressure fluctuations, or abnormal current draw—are indicative of potential mechanical or electrical faults, including bearing wear, air leakage, overload, or motor degradation.

The ESP32 microcontroller continuously acquires sensor data associated with the compressor's operation and processes it in real time. These parameters are analyzed locally or transmitted to a cloud platform for further evaluation using data analytics and machine learning techniques. Based on observed trends and deviations from normal behavior, the system predicts early failure conditions and generates alerts for preventive maintenance.

Thus, the mini air compressor acts as a practical test platform for validating the effectiveness of the machine failure prediction system, enabling real-time monitoring, fault detection, and predictive maintenance in compact and scalable industrial applications.



Fig 3 mini air compressor

D. Temperature Sensor (DHT22)

The temperature sensor is employed to continuously monitor the thermal condition of critical machine components. Abnormal temperature rise is a key indicator of mechanical faults such as excessive friction, overload, or insulation failure. The sensor provides real-time temperature data to the Arduino Uno R3, enabling early detection of overheating conditions through threshold-based analysis. Continuous thermal monitoring helps prevent severe machine damage and supports predictive maintenance by identifying potential failures before they occur.

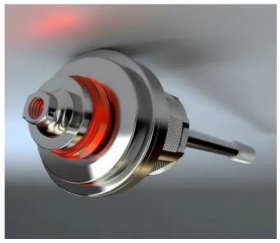


Fig 4. TEMPERATURE SENSOR

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E. Pressure Sensor

The pressure sensor is used to monitor mechanical or fluid pressure within critical machine components such as hydraulic lines, pneumatic systems, or load-bearing elements. Abnormal pressure variations often indicate faults including leaks, blockages, excessive load, or component wear. The sensor provides continuous pressure data to the Arduino Uno R3 for real-time analysis and threshold-based fault detection. Monitoring pressure levels enhances operational safety and supports early identification of failure conditions, contributing to improved machine reliability and reduced downtime.



Fig 5. Pressure sensor

F. Current Sensor

The current sensor is utilized to measure the electrical current drawn by the motor and other critical machine components during operation. Variations in current consumption are strong indicators of abnormal conditions such as mechanical overload, motor stalling, bearing wear, or electrical faults. The sensor continuously provides real-time current data to the Arduino Uno R3, enabling threshold-based monitoring and fault detection. Current monitoring enhances system safety and supports predictive maintenance by identifying abnormal operating conditions before complete machine failure occurs.

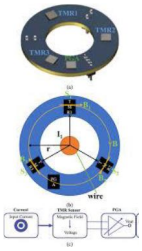


Fig 6.Current Sensor

G. Voltage Sensor

The voltage sensor is used to monitor the supply voltage of the machine and its electrical subsystems in real time. Abnormal voltage levels, such as under-voltage or over-voltage conditions, can indicate power supply faults, wiring issues, or component degradation. The sensor provides continuous voltage measurements to the Arduino Uno R3, enabling threshold-based detection of electrical anomalies. Voltage monitoring contributes to system reliability and safety by ensuring stable operating conditions and preventing damage to sensitive electronic components.



Fig 7.Voltage Sensor

H. 12V DC Battery

The 12 V DC battery serves as the primary power source for the proposed machine failure monitoring system. It supplies stable electrical power to the control unit, sensors, and actuator modules through appropriate voltage regulation circuits. A reliable power supply is essential to ensure continuous system operation and accurate data acquisition. Monitoring the battery voltage also enables detection of power-related faults, contributing to improved system reliability and uninterrupted monitoring performance.

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Fig 8.12V DC Battery

V. DESIGN CALCULATIONS

a) Airflow Conversion
35LPM=35/1000.60
=5.83*10^-4m^3/s

b) Pressure Conversion
150psi=150*6894.76≈1.034*10^6Pa(gauge)
Absolute discharge pressure:
P2=1.034*10^6 +1.034*10^5=1.135*10^6 Pa
P1=1.013*10^5 Pa
Pressure ratio:
Rp=P2/P1≈11.2.

c)Compression Work (polytropic, n=1.3)
W=1.3/0.3(1.013*10^5) (5.83*10^-4) [(11.2) ^0.23-1]
W≈188W(ideal)
Corrected for efficiency(η≈0.7):
P_ shaft=188/0.7≈268W
d)Motor Size (with safety factor 1.25)
P _motor=1.25*268≈335W(≈0.45HP)

A. Electrical Design Calculation

a) Current Draw at 12V
I=P/V
=335/12≈28A.
But spec sheet says 10A max-> means: 13
Compressor doesn't run continuously at 150psi +35LPM simultaneously.
Real average shaft power ≈ 120w, electrical ≈10-12A.
Duty cycle=10-15 minutes max.

b) Copper Loss in Motor
If winding resistance R=0.2 ohm:
Ploss=I^2R=10^2*0.2=20W.
c) Temperature Rise (natural convection h≈ 20W/m^2K, surface area≈0.01m^2):
ΔT =Ploss/h. A
=20/20*0.01=100 °C
With airflow cooling (h ≈50):
ΔT ≈40 °C

B. Sensor &Electronics Design:

a) Pressure Sensor
Range:0-16 bar (covers 150psi).
Accuracy: ±0.25%Fs.
Placement: discharge line, <50mm from port.

b) Vibration + Gyroscope Sensor
Accelerometer: ±16g, 5kHz bandwidth (bearing& piston wear).
Gyroscope: ±2000dps-> detects misalignment up to 6000rpm.
Placement:
1. One on compressor head.
2. One on motor casing near bearing.
Mounding:M4 stud with 15-20mm flat pad.
Distance between sensors:100-150mm.
Imbalance force check (2g mass at 20mm,3000 rpm):
F=mrw^2
=0.02. (314) ^2≈3.95N
->Detectable by MEMS IMU. 14

c) Temperature Sensor
Motor casing: -20 °C to 125 °C (NTC thermistor/DS18B20).
Head: 0-200 °C (K- type thermocouple)

d) Current & Voltage Monitoring
Current: Hall-effect sensor (30 A).
Voltage: Divider circuit, scaled to 0-3.3 V ADC input

C. Failure Prediction Indicators

Vibration RMS ↑ 30% ->bearing/piston wear.
FFT peaks at shaft frequency-> imbalance/misalignment failure.
Motor casing >90C-> winding degradation.
Current > 12A continuous-> motor overload.
Pressure rise > 20% slower-> valve leakage.

D. Input Data (from specifications)

•Air Flow Capacity: 35 LPM = 5.83×10^{-4} m^3/s • Max Pressure: 150 psi = 10.34 bar gauge → 11.35 bar abs • Inlet Pressure: 1.013 bar abs • Polytropic index: n = 1.3 • Efficiency: η = 0.7 • Power supply: 12 V DC, 10 A max • Weight: 400 g (portable)

E. Compressor Power Requirement

$\dot{W} = (n/(n-1))\cdot P_1\cdot \dot{V}\cdot[((P_2/P_1)^{((n-1)/n)}) - 1] = 188$ W (ideal) Corrected for efficiency → 268 W

F. Motor Size

With 1.25 safety factor → ≈335 W (≈0.5 HP) 15

G. Electrical Sizing

At 12 V DC → I = 335/12 ≈ 28 A Spec = 10 A max → short duty cycle, dual cylinder design.

H. Sensor Selection

• Vibration sensors (2x MEMS/±16 g, 5 kHz) • Pressure sensor (0–16 bar, ±0.25% FS) • Current sensor (Hall-effect, 30 A) • Voltage sensor (0–20 V divider)

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I. Sensor Spacing

• Motor casing → head: 0.1–0.15 m • Head → hose: ~0.2 m • Pressure sensor: within 50 mm of discharge • Electrical sensors: inside housing

J. Sampling Requirements

• Vibration: ≥10 kHz, 16-bit • Pressure: 10–50 Hz • Current/Voltage: 100 Hz (steady), 1 kHz (startup)

K. Failure Prediction Indicators

• Vibration RMS ↑30% → bearing/piston wear • FFT peaks abnormal → misalignment • Pressure rise delay 20% → valve leakage • Current >12 A → overload

L. Final Design Summary

• Compressor: 35 LPM, 150 psi → 0.35 kW motor • Motor: 12 V DC, 10–28 A, 0.5 HP rated • Sensors: 2× vibration, 1× pressure, 1× current, 1× voltage • Sensor spacing: 0.1–0.2 m • Electronics: ESP32/STM32 with FFT + IoT logging

VI. WORKING

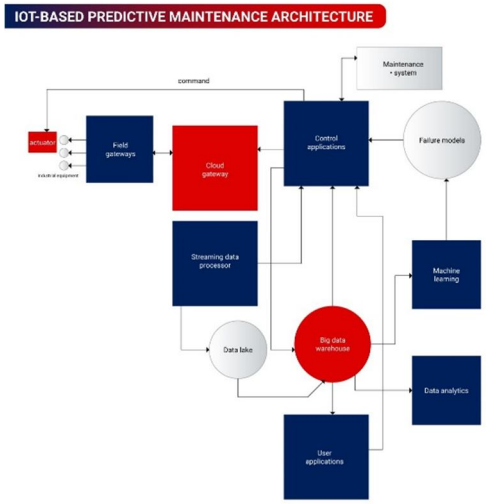


Figure 9. HARDWARE MODEL



Fig 10. SOFTWARE MODEL

The hardware architecture of the machine failure prediction system employs the ESP32 microcontroller as the central control unit, interfacing with multiple condition-monitoring sensors to continuously assess the health of industrial machinery. The system integrates vibration sensors (accelerometer) to detect imbalance, misalignment, and bearing wear, along with temperature sensors to monitor overheating of motors and mechanical components. Electrical health is evaluated using current and voltage sensors, which help identify overload conditions and abnormal power consumption. A speed or RPM sensor is included to monitor rotational performance and detect slip or degradation in mechanical motion. To simulate real operating stress and fault conditions, a motor driver and motor assembly are incorporated for controlled load variation. All hardware components are powered through a regulated power supply with appropriate protection circuitry to ensure stable and reliable operation.

On the software side, the ESP32 executes embedded firmware to acquire sensor data, perform signal conditioning and feature extraction, and transmit processed data wirelessly to a cloud platform using built-in Wi-Fi. The cloud infrastructure supports real-time data storage, visualization, and historical analysis. Machine learning algorithms analyze the collected parameters to identify abnormal patterns and predict potential machine failures. A web or mobile dashboard provides real-time visualization of machine health status, alerts, and maintenance recommendations, enabling proactive decision-making and effective predictive maintenance.

VII. CONCLUSION

This paper presented the design and development of an IoT-based real-time machine failure monitoring system using an embedded controller and multi-sensor integration. Critical machine parameters such as temperature, pressure, current, and voltage were continuously monitored to detect abnormal operating conditions indicative of potential failures. The system enables early fault detection through real-time data acquisition and threshold-based analysis, thereby improving machine safety and operational reliability. The developed prototype demonstrates a cost-effective and scalable solution suitable for academic and small-scale industrial applications. By leveraging IoT technologies and cloud-based visualization, the proposed system supports predictive maintenance and reduces unplanned downtime. Future enhancements may include the integration of advanced data analytics, machine learning algorithms, and industrial-grade communication protocols to further improve fault prediction accuracy and system robustness.

VIII. FUTURE EXPANSION

The proposed system can be further enhanced by integrating advanced predictive analytics and machine learning algorithms, such as deep learning and hybrid models, to improve failure detection accuracy and identify subtle anomalies that are difficult to detect using conventional threshold-based methods. Incorporating edge intelligence on the ESP32 can enable preliminary data processing and anomaly detection at the device level, thereby reducing latency and minimizing dependence on continuous cloud connectivity.

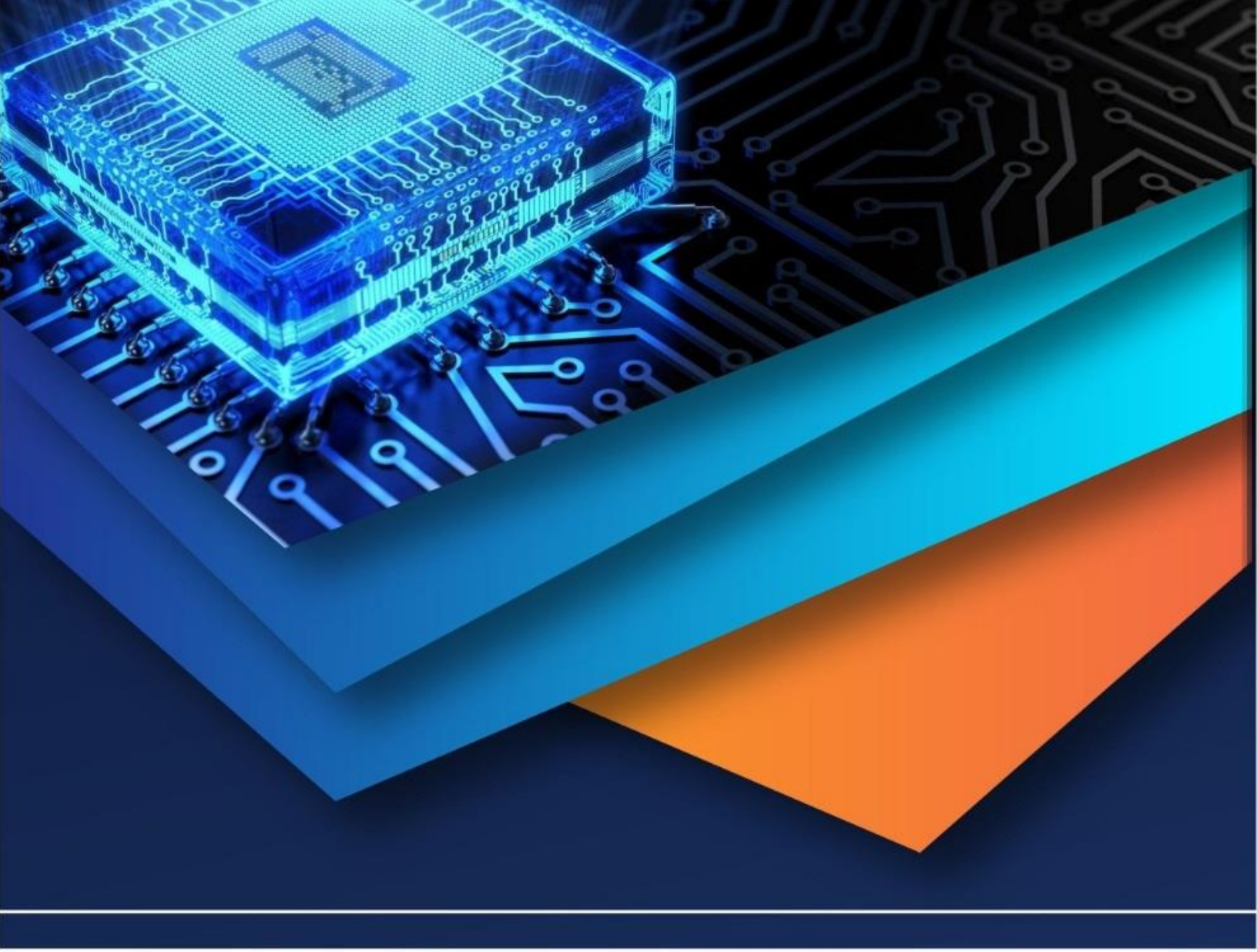
The system's robustness and industrial applicability can be significantly improved by integrating industrial-grade sensors with higher accuracy, durability, and noise immunity, enabling reliable operation in harsh environments involving vibration, temperature fluctuations, and electromagnetic interference. Support for industrial communication protocols such as Modbus, CAN, EtherCAT, or LoRaWAN would allow seamless integration with existing industrial automation systems and facilitate long-range, low-power data transmission for large-scale deployments. Additional features such as automated alert notifications through SMS, email, or mobile applications can ensure timely maintenance actions by alerting operators before critical failures occur. The incorporation of digital twin technology can provide a virtual representation of the physical machine, allowing real-time performance visualization, predictive simulations, and what-if analysis for improved decision-making. Furthermore, implementing energy-efficient power management techniques, including adaptive sampling, sleep modes, and power-aware scheduling, can enhance system sustainability and enable battery-operated or remote installations. Future enhancements may also include self-learning models that continuously adapt to changing machine behavior, secure data transmission using encryption and authentication, and scalable cloud architectures for centralized monitoring of multiple machines. These advancements would enable the system to evolve from a laboratory-scale prototype into a fully industrial-grade solution, supporting predictive maintenance, smart manufacturing, and Industry 4.0 applications with improved reliability, scalability and operational efficiency.

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