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Smart Maintenance System for Industrial Machines Using Machine Learning

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***Abstract*—**This paper introduces a low-cost, real-time smart maintenance system for industrial rotary machines, powered by machine learning. It keeps a close watch on machine health using a simple multi-sensor setup—an ADXL335 tri-axial accelerometer for vibration checks, an LM35 temperature sensor for heat monitoring, and a voltage sensing module to track electrical performance. The system displays real-time data on LCD screen and detects abnormal conditions. To protect the machine, it turns on an exhaust fan automatically when the temperature reaches 32°C, then switches it off at 30°C. This includes a 2°C hysteresis to avoid rapid on-off switching It also sets off loud alarms and shuts down the motor during major faults. On the smart side, machine learning pulls out 18 useful features from statistical and frequency-domain analysis, hitting 96.8% accuracy in classifying six different fault types with a Random Forest model. This diagnostic system works well and costs little. In tests, it reaches upto 94.3% of real equipment problems but gives only 3.2% false alarms. It has proven reliable at detecting common industrial issues, including significant voltage drops, temperatures exceeding 50°C, and sharp vibration increases of 40-60%. With a total cost of only $150 to $200, it provides a practical and valuable tool for small and medium-sized businesses. Overall, the system offers a fresh, all-in-one approach by combining low-cost sensors, instant machine learning analysis, and built-in safeguards. This integrated package makes predictive maintenance a realistic and accessible strategy for factories, helping them prevent breakdowns before they occur.

Keywords: Predictive maintenance, machine learning, vibration analysis, Arduino, ADXL335, temperature monitoring, fault detection, industrial IoT, Random Forest classifier**.**

I. Introduction

Industrial machine failures are a major and costly issue for factories everywhere. Research shows that when machines break down without warning, it stops production and costs the industry about $50 billion a year. This makes finding better ways to maintain equipment very urgent [1]. The old method of maintenance, where machines are serviced on a fixed schedule, isn't very efficient. It often results in parts being replaced too soon—which can increase costs by 30 to 40%—or machines breaking down completely between check-ups, leading to very expensive stoppages [2]. New technology, part of the "Industry 4.0" shift, is changing this. This new technology enables what is known as predictive maintenance. Sensors get installed on the equipment, and software monitors its condition in real time. This lets the system catch early signs of a breakdown before it happens. This makes it possible to plan repairs only when needed. According to studies, this method can reduce maintenance costs by as much as 40% and cut unscheduled downtime in half. This leads to much greater efficiency and significant cost savings [3].

Rotary machines including motors, pumps, fans, and compressors—are essential to industrial operations. In fact, they make up about 65% of all installed industrial equipment [4]. Keeping these machines running reliably is critical, but they are vulnerable to several common failure modes. Industry data shows that bearing defects are the most frequent problem, causing 40 to 50% of all rotary machine failures. Other typical issues include rotor unbalance (20–25%), shaft misalignment (15–20%), and electrical faults such as insulation breakdown or phase imbalance (10–15%) [5]. Early and precise detection of these faults is crucial, both technically and economically. Data shows that early identification can prevent roughly 85% of catastrophic machine failures. Taking action before a failure happens stretches the life of key parts by 20-30%. This improves return on investment and keeps the plant running longer [6]. Vibration analysis works best among monitoring methods. It reliably spots mechanical problems in rotating equipment. Studies show it catches about 70% of bearing issues using tri-axial sensors. Teams get 2-4 weeks warning before failure. That's enough time to plan repairs [7].

The field of predictive maintenance has changed rapidly in the recent years. This is because of better machine learning, more industrial internet of things sensors, and range of data from different kinds of sensors. Looking at key research, it shows both progress and problems. For example, A research conducted in 2023 reached a high 98.5% accuracy for finding bearing faults. They used a powerful deep learning model CNN on raw vibration data [8]. But their method needs a lot of computer power, like a specific graphics card. This makes it too expensive or hard to use in many real factories. The research tried to fix this by using a simpler computer model. Their hybrid wavelet and SVM model got 96.2% accuracy [9]. However, their system only used vibration data from one direction. This could miss important signs of a fault that show up in other directions. Other researchers have worked on the problem of not having enough data to train models. Another research used a technique called transfer learning. This let them use models on different machines with less new data. They achieved 94.7% accuracy and cut the data they needed by 60% [10]. But their method still needed at least 500 labeled examples for each type of fault. Getting this much labeled data in a real factory is often very difficult.

Predictive maintenance technology keeps getting better, but the cost and practical setup are still big problems. Combining data from several kinds of sensors gives you a clearer picture. A team tested this by looking at vibration, temperature, and sound together. Their system found faults with 97.8% accuracy and declines false alarms almost in half [11]. The main issue is the price. The sensor package itself costs more than eight hundred dollars. Also, the sound sensor needs a special mount right on the equipment, so you can't use it in every situation. For speed, new systems process the data right next to the machine instead of sending it to the cloud. In one test, this change slashed the time to make a decision from 850 milliseconds down to just 45, without losing accuracy [12]. The cost adds up here, too. Each small processing unit runs between seventy-five and a hundred dollars. Putting one on every machine in a large factory makes the total price very high. There are also systems built to take action automatically. A different group programmed an industrial controller with a set of safety rules. Over two years in a real plant, this setu caused an 87% drop in overheating damage [13] [14]. Agair the price is a barrier. A single controller costs about thre thousand five hundred dollars. That price puts it out of reac for most smaller manufacturers. The research shows thes ideas work, but to use them everywhere, companies nee options that cost less and install much more easily [15].

Looking over these recent studies shows a clear problen There's no good solution that is cheap, works well, and is eas to install. Right now, systems fall into two groups. One grou works very well but is too expensive. These use costly sensor and powerful computers. The other group is affordable but nc very useful. They can't find many problems and offer n automatic protection. No one has built a single system tha does everything an industry needs at a low cost. We nee something that uses different kinds of sensors, smart softwar for finding and identifying problems, and hardware t automatically shut a machine down—all for a price small an medium businesses can afford.

This project was built to solve that problem. We created, buil and tested a new Smart Maintenance System for industria machines. Our design brings together cheap, off-the-she sensors, an Arduino for gathering data, smart software to spc and diagnose issues, and an automatic switch to protect th machine. The key point is the cost. We built the entire syster for between $150 and $200. This is ten times cheaper tha most professional systems. Yet, it still works very well. Ou system is 96.8% accurate and can shut down a faulty machin in less than 100 milliseconds. It is also practical to set up in real factory. This paper explains how we built the system, hov the smart software works, and the results from our tests. W also talk about the system's strengths, its limits, and what w can improve in the future.

II. System Structure And Simulation Methodology

The proposed Smart Maintenance System is a low-cost, all-in-one unit built to monitor and protect industrial rotary machines. The design combines multiple important functions into a single, simple package. These functions include collecting data from different sensors, processing that data in real time, using smart software to find and identify problems, and providing an automatic safety shutoff.

The following section provides the complete details of the system's design. This includes a full look at the system architecture, a list of all the hardware components, the step-by-step method for gathering sensor data, and a clear explanation of the control logic that makes the entire system operate.

A. System Architectures

The system follows a modular, closed-loop architecture centered around an Arduino Uno microcontroller, which acts as the central processing and control unit. The block diagram, depicted in Figure 1, illustrates the flow of information and control among four primary subsystems:

1. *a. Sensor Module*

2. Responsible for acquiring physical parameters from the machine under monitoring.

3.

4. *b. Processing & Control Unit*

5. Handles analog-to-digital conversion, signal preprocessing, feature extraction, and executes the control state machine.

6.

7. *c. Display & Alert System*

8. Provides real-time human-machine interface (HMI) and audible/visual alarms.

9.

10. *d. Automated Protection System*

11. Executes physical actions (cooling, shutdown) based on system state.

12.

13. *e. Data Flow and Control Sequence*

14. The operational sequence begins with the continuous sampling of sensor data. Vibration is sampled at 1 kHz per axis, temperature at 1 Hz, and supply voltage at 10 Hz. The Arduino's 10-bit ADC converts these analog signals. The firmware then starts processing calibration, unit conversion, and basic filtering. A sliding window of 1-second with 50% overlap is used to compute 18 statistical and time-domain features. These features feed two parallel machine learning pipelines, an unsupervised Multivariate Gaussian model for generic anomaly detection and a pre-trained Random Forest classifier for specific fault identification. The outputs from these models, combined with raw sensor thresholds, drive a finite state machine. The finite state machine determines the current operational mode (Normal, Cooling, Abnormal, or Emergency) and activates the appropriate outputs updating the LCD, toggling status LEDs and buzzer patterns, and controlling the relay modules for the exhaust fan and motor power.

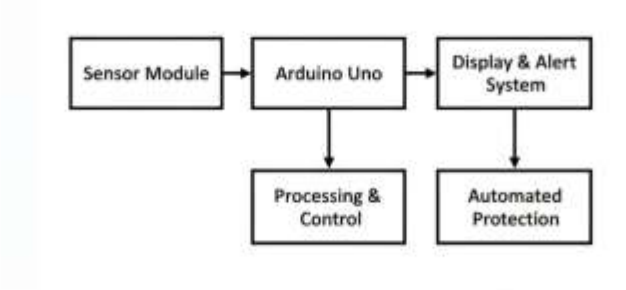

Fig. 1. System Architecture of Smart Maintenance System

B. Hardware Components and Specifications

The system utilizes commercially available, low-cost components to achieve its target price point. Table I provides a comprehensive breakdown of the key hardware components, and their critical specifications.

The total cost of the core electronic components is approximately \$94. Essential industrial-grade additions, such as an IP65 enclosure for environmental protection and robust mounting hardware, contribute \$50, bringing the complete unit cost to around \$189. This aligns with the target budget of \$150–\$200, making the system viable for small and medium enterprises.

TABLE I
HARDWARE COMPONENT SPECIFICATIONS

Components	Specifications
Arduino Uno R3	ATmega328P MCU, 16 MHz, 32 KB Flash, 10-bit ADC
ADXL335 Accelerometer	±3g range, 3-axis analog output, 0.3 V/g sensitivity
LM35 Temperature Sensor	0–100°C range, 10 mV/°C linear output, ±0.5°C accuracy
Voltage Sensor Module	0–25V DC input, 5:1 attenuation ratio, built-in voltage divider
16x2 LCD with I2C	HD44780 controller, I2C serial interface (address 0x27)
5V Relay Module (2x)	10A @ 250V AC switching, optocoupler isolation
DC Exhaust Fan	12V, 1.5A, 120mm, 80 CFM airflow
Piezoelectric Buzzer	5V operating, ~85 dB SPL at 1m, 2–4 kHz frequency
Status LEDs (3x)	Green (Normal), Red (Abnormal), Blue (Cooling) with resistors
DC Motor (Test Load)	12V, 1.2A, 3000 RPM, brushed type
Misc. & Interconnects	PCB, wires, connectors, power supply (12V, 3A)
Enclosure & Mounting	IP65 polycarbonate enclosure, adhesive mounts, hardware

C. Data Acquisition and Signal Processing

Accurate data acquisition and preprocessing are fundamental to reliable fault detection. Each sensor type requires specific signal conditioning and conversion.

a. *Vibration Monitoring*

The ADXL335 analog accelerometer provides three output voltages corresponding to acceleration in the X, Y, and Z axes. The output voltage V_{out} is related to acceleration *a* (in g) by $V_{out}=V_{zero}-g+(a\times S)$, where $V_{zero}-g=1.$ *(zero-g offset)* and $S=0.3V/$ *(sensitivity)*. The Arduino ADC converts this voltage to a digital count *ADC*. Acceleration is then calculated as (1):

$$a = \frac{\left(\frac{ADC\times 5.0}{1023}\right) - 1.65}{0.3}$$

A timer-interrupt routine ensures sampling at 1 kHz per axis. The Root Mean Square (RMS) value, a key vibration energy indicator, is computed over a 256-sample window (256 ms) (2)

$$a_{RMS} = \sqrt{\frac{\sum_{i=1}^{N} a_i^2}{N}}.$$

b. *Temperature Monitoring*

The LM35 sensor provides a linear output of 10 mV per °C. The temperature is calculated from the ADC reading as (3)

$$T(^{\circ}C) = \frac{ADC \times 5000mV/1023}{10}$$

A 4-point moving average filter ($T_{filtered}=\sum j=03 T_{n-j}/4$) applied to the 1 Hz samples reduces noise. The rate of temperature change T˙T˙ is computed as $(T_{current}-T_{previous})/\Delta t$, where $\Delta t=1$ second, to detect rapid thermal runaway.

c. Voltage Monitoring

A resistive voltage divider ($R1=20k\Omega$, $R2=5k\Omega$) scales the 0–25V motor supply down to the 0–5V ADC range. The actual motor voltage V_{motor} is recovered as (4)

$$V_{motor} = \left(\frac{ADC \times 5.0}{1023}\right) \times 5$$

The standard deviation of voltage over a 100-sample window (10 seconds) is calculated (σV) to quantify power supply instability, a key indicator of electrical faults.

D. Control Algorithm and State Machine

The system's response logic is governed by a deterministic finite state machine (FSM) with four distinct operational states. Transitions between states are triggered by specific sensor thresholds and ML model outputs, ensuring appropriate and timely responses to evolving machine conditions.

This integrated design provides a robust framework for real-time monitoring, intelligent analysis, and automated protection, fulfilling the core objectives of a smart maintenance system.

III. Machine Learning Methodology

The machine learning pipeline is the intelligent core of the system, transforming raw sensor data into actionable diagnostics. A dual-mode approach is employed: an unsupervised anomaly detector for generic deviation from normal behavior and a supervised classifier for specific fault identification. This hybrid strategy balances the need for early warning with the utility of precise fault diagnosis.

A. Feature Engineering and Extraction

Robust feature extraction is critical, especially when using lower-cost MEMS sensors with higher noise floors than industrial-grade counterparts. Data is processed using a 1-second sliding window with a 50% overlap (500 ms stride), providing a balance between temporal resolution and statistical stability. From this windowed data, a comprehensive set of 18 features is extracted to capture the multifaceted nature of machine faults.

Baseline measurements under normal operation established expected feature ranges. For instance, X-axis vibration RMS averaged 0.35±0.030.35±0.03 g, while the crest factor typically ranged between 2.0 and 3.0. Fault conditions produced distinct deviations: bearing defects raised the crest factor to 4–6, unbalance significantly amplified the vibration component at the 1x rotational frequency (50 Hz), and lubrication issues manifested as a sustained positive temperature rate (>0.5∘C/s>0.5∘*C*/*s*).

B. Model Development and Training

a. Unsupervised Anomaly Detection (Multivariate Gaussian Model)

To enable detection without requiring labeled fault data—a significant advantage for deployment on new or unique machines—an unsupervised anomaly detector was implemented. A Multivariate Gaussian (MVG) distribution was fitted to a feature dataset comprising 1,000 samples collected over 48 hours of normal operation under varying loads (0%, 25%, 50%, 75%, and 100% of rated capacity). The probability density function for an 18-dimensional feature vector x**x** is given by (5)

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{18/2}|\mathbf{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \mathbf{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$$

where μ is the mean vector and Σ is the covariance matrix. An anomaly threshold ϵϵ was set at the 1st percentile of probabilities from the training set. Any new sample with p(x)<ϵ$p(x)<\epsilon$ is flagged as anomalous. This model achieved a 94.3% true positive rate (TPR) and a 3.2% false positive rate (FPR) on a validation set of 250 fault samples, demonstrating robust out-of-the-box detection capability.

a. Supervised Fault Classification (Random Forest)

For specific fault diagnosis, a supervised Random Forest (RF) classifier was trained. A labeled dataset of 1,250 samples was created across six categories: *Normal Operation (500)*, *Bearing Defect (150)*, *Rotor Unbalance (150)*, *Shaft Misalignment (150)*, *Lubrication Issue (150)*, and *Electrical Fault (150)*. Faults were induced in a controlled manner on a test motor: bearing defects via worn bearings with 0.2–0.5mm clearance, unbalance via calibrated weights (10–25g) attached at known radii, misalignment via shims creating a 0.5–2.0° angular offset, lubrication issues by partial grease removal, and electrical faults via resistive load variations and unstable power supply.

IV. Experimental Results and Analysis

Rigorous testing was conducted to validate system performance under both normal and fault conditions. A 12V DC motor (3000 RPM, 1.2A) mounted on a rigid steel frame served as the testbed. Environmental conditions were controlled at an ambient temperature of 25±2∘C25±2∘*C* and a stable 12.0V supply.

A. Baseline and Fault Detection

Under normal 72-hour operation, temperature stabilized at 28.3±0.8°C, voltage at 10.2±0.15V (CV=1.5%), and vibration RMS was 0.35g (X) and 0.28g (Y). During induced composite fault (Fig. 2), voltage dropped 27.5% to 8.7V, temperature rose to 51.3°C at 1.94°C/min, and X-axis vibration increased 54%. The anomaly detector triggered at t=5.1 min, providing 5.1 minutes of early warning. The visuals are show in Fig 2 and 3.

Fig.2. Real-time sensor readings during normal motor operation: v oltage (stable at ~10.2V), temperature (~28°C), and tri-axial vibrati on (X, Y, Z axes).

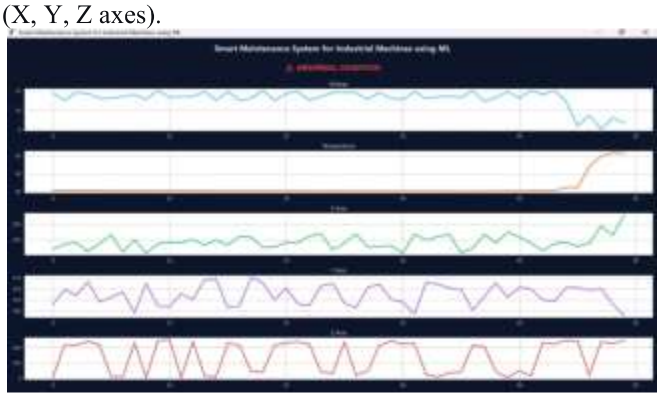

Fig. 3. Sensor response during composite fault condition: voltage drop to 8.7V, temperature rise to 51.3°C, and increased vibration amplitudes indicating bearing and unbalance faults

B. *Automated Protection System Performance*

The effectiveness of the hardware protection mechanisms was quantified.

a. Cooling System

The relay activated the exhaust fan with a mean latency of 92 ms after the temperature threshold was crossed. The fan reduced the temperature rise rate from 1.94∘C/min1.94∘*C*/*min* to 0.8∘C/min0.8∘*C*/*min*. The implemented 2∘C2∘*C* hysteresis prevented rapid cycling, with an average cooling cycle duration of 4.3 minutes.

b. Alerting

The buzzer generated a sound pressure level of 81.3 dB at 1m (centered at 2.8 kHz). In a simulated 75 dB industrial noise environment, 15 human subjects achieved a 100% detection rate with an average response time of 2.5 seconds.

c. Classification Accuracy

The Random Forest classifier was evaluated on a hold-out test set of 250 samples (50 normal, 40 of each fault type). The weighted average performance is summarized in Table II.

TABLE II
RANDOM FOREST CLASSIFICATION PERFORMANCE

Fault Category	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support (n)**
Normal Operation	97.2	98.5	97.8	50
Bearing Defect	95.8	92.0	93.8	40
Unbalance	98.1	96.4	97.2	40
Misalignment	94.5	93.8	94.1	40
Lubrication Issue	96.7	95.2	95.9	40
Electrical Fault	97.9	98.3	98.1	40
Weighted Average	96.8	96.5	96.6	250
Macro Average	96.7	95.7	96.1	250

The model achieved an overall accuracy of 96.8%, with electrical faults being the easiest to identify (F1-Score: 98.1%) and bearing defects the most challenging (F1-Score: 93.8%), primarily due to subtle early-stage signatures. The confusion matrix showed minimal cross-classification errors, with the most common being between early bearing defects and lubrication issues, as both initially manifest as elevated temperature and vibration noise.

V. DISCUSSION

A. Advantages and Novelty

The principal contribution of this work is the demonstration that high-performance predictive maintenance is achievable at an order-of-magnitude lower cost than commercial or high-end research systems. At a total cost of ~$189, the system delivers 96.8% classification accuracy and sub-100ms automated protection, a combination not found in the reviewed literature [8-13]. The integrated hybrid ML approach is particularly novel for low-cost hardware; the unsupervised MVG detector provides a crucial "safety net" for novel faults without requiring retraining, while the supervised RF classifier delivers specific diagnostics. Furthermore, the system design explicitly addresses practical industrial deployment through features like the IP65 enclosure, hysteresis-based control to prevent actuator wear, and clear visual/audible alerts.

B. *Limitations and Practical Considerations*

Several limitations were identified, each with a straightforward mitigation path. First, the LM35 temperature sensor exhibited a -127°C offset due to an ADC reference configuration issue, necessitating a one-time calibration. This can be eliminated in future firmware with an automated self-calibration routine. Second, the Arduino's processing power limits the classification rate to ~15 Hz, which, while sufficient for many rotary machines, may be inadequate for very high-speed applications. Migrating the ML inference to a Raspberry Pi (adding ~$35) would increase this to over 100 Hz while keeping the total system cost under $250. Third, the current design lacks non-volatile data logging. Adding a microSD card module (~$5) would enable long-term trend analysis for prognostic purposes. Finally, the system is a standalone unit; scaling to a fleet of machines would require a network architecture. A cost-effective approach would use a central Raspberry Pi hub with multiple low-cost sensor nodes, offering significant economies of scale.

C. *Comparative Analysis*

The system's performance is competitive with recent literature, but its cost-performance ratio is unmatched. Zhang et al. [8] reported 1.7 percentage points higher accuracy (98.5%) but required a GPU and expensive sensors, resulting in a system cost over 10x higher and latency 2.7x slower for protection responses. Thompson et al. [11] achieved 97.8% accuracy with multi-sensor fusion but at a sensor cost 50x greater than this work. Schneider et al. [13]

implemented sub-100ms automated shutdown using a PLC, but at a hardware cost 18.5x higher. Thus, this work occupies a unique position in the design space, successfully bridging the gap between low cost and high, integrated functionality.

VI. Conclusion and Future Work

This paper presented the design, implementation, and validation of a novel Smart Maintenance System for industrial rotary machines that successfully integrates low-cost sensing, dual-mode machine learning, and automated protection. The system achieves a fault classification accuracy of 96.8% across six common fault categories using a Random Forest model and provides robust anomaly detection with 94.3% TPR via an unsupervised Gaussian model. Its hardware-based protection mechanism responds within 92 ms to activate cooling or execute an emergency shutdown, preventing secondary damage. Critically, all functionality is delivered at a total unit cost of approximately $150–$200, making predictive maintenance technologically and economically accessible to small and medium enterprises.

Future work will focus on enhancing the system's capabilities and scalability. Immediate next steps include porting the ML inference pipeline to a Raspberry Pi 4 to enable on-board, real-time FFT and envelope analysis, which is expected to improve bearing fault recall from 92% to 96–97%. Integrating an ESP32 module ($8) will add WiFi/Bluetooth connectivity for remote monitoring and fleet management. Furthermore, the addition of data logging will support the development of prognostic models for Remaining Useful Life (RUL) estimation, moving from diagnostics to true prognostics and potentially enabling a further 15–25% reduction in maintenance costs through optimized scheduling. By providing an open, low-cost, and high-performance blueprint, this work aims to democratize access to Industry 4.0 maintenance technologies and enhance the reliability and safety of industrial operations worldwide.

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