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AI-BASED PREDICTIVE MAINTENANCE AND CUTTING FORCE MONITORING SYSTEM USING MACHINE LEARNING

L Rambabu[1], G Mohan[1], CH Bhanu Prakash[1] and Dr. Vijaybabu[2]

[1]B.Tech Students, Department of Mechanical Engineering
[2]Associate Professor, Department of Mechanical Engineering
GMRIT Deemed to be University (Autonomous), GMR Nagar, Rajam – 532 127, Andhra Pradesh, India

ABSTRACT:

Unexpected failures of rotating machinery cause damage, lost production time and higher maintenance cost. This paper presents an AI-based predictive maintenance and cutting force monitoring system built on a laboratory-scale cutting rig with a 12 V DC motor, a rotating shaft, two pillow-block bearings and a cutting blade. Motor current, sensed by a current sensor, serves as an indirect indicator of cutting load, while a tri-axial accelerometer and K-type thermocouples on each bearing record vibration and temperature. An ESP32 microcontroller acquires all signals and passes them to a computer, where the data are stored in CSV format and analysed in Python. A balanced data set of 60,000 samples was collected for four bearing-health combinations (good/bad) at five load levels (0–100 %). Logistic Regression, Support Vector Machine (SVM), Decision Tree and Random Forest models were compared using RMSE and R^2. The Decision Tree and Random Forest models predicted bearing condition with testing R^2 of 0.93–0.99 for individual bearings and about 0.95 for the combined condition, clearly outperforming SVM and Logistic Regression. Vibration and temperature proved to be the informative signals; the motor current showed no measurable change with load or bearing condition in the collected data.

Keywords*: Predictive maintenance, cutting force monitoring, machine learning, condition monitoring, current sensing, ESP32, Random Forest, bearing fault, IoT.*

1. INTRODUCTION

Modern manufacturing systems are expected to deliver high productivity and consistent quality with minimum unplanned downtime. Reactive maintenance repairs equipment only after it fails, and scheduled preventive maintenance services it at fixed intervals whether or not service is needed. Predictive maintenance is a condition-based strategy in which operating data are analysed to anticipate failures before they occur, so that maintenance action is linked to the actual state of the machine [1, 8].

In machining, the cutting load changes with tool condition, workpiece interaction and set-up rigidity, which makes it a useful process signal. A dedicated force dynamometer is expensive, so this work infers the cutting load from the current drawn by the DC motor: a higher load raises motor torque and therefore current. Vibration and temperature are added as complementary indicators of the health of the rotating elements. The signals are acquired by a low-cost ESP32 development board and analysed with machine-learning (ML) algorithms.

The objectives of the work are (i) to build an experimental cutting-load monitoring rig, (ii) to acquire current, vibration and temperature data through the ESP32, (iii) to prepare a structured, labelled data set, and (iv) to train and compare ML models that identify the condition of the bearings and support a maintenance decision. The main contribution is an integrated, low-cost architecture that links motor-current-based load sensing with ML-based predictive maintenance on a machining-oriented demonstrator, together with a quantitative comparison of four ML models on a 60,000-sample data set.

2. LITERATURE REVIEW

Earlier studies show that the performance of AI-based maintenance depends strongly on data availability, sensor infrastructure and integration with existing systems [2]. Neural-network-based anomaly detection on temperature and pressure data can reveal deviations from normal operation [3], and continuous real-time analysis allows early fault detection and safer operation [4]. Preprocessing steps such as noise filtering, normalisation and missing-value treatment, together with IoT connectivity, improve the quality of the information supplied to AI models [5], while feature engineering converts raw measurements such as vibration spectra, temperature gradients and power consumption into informative condition indicators [6].

Combining vibration, temperature, acoustic and electrical measurements gives a more complete picture of machine health, although poor-quality data reduce reliability [7]. Vibration analysis has been used to identify early failure signs in automotive engines and assembly equipment [8], and the integration of legacy machinery with IoT sensors remains a practical difficulty [9]. A recent review of machine-learning, deep-learning, sensor-fusion and IoT approaches in industrial automation identifies data quality, legacy systems, cybersecurity and workforce skills as the main challenges [10].

The literature therefore gives a broad framework for AI-enabled predictive maintenance but little detail on a compact machining-oriented rig that connects a motor-current cutting-load signal with vibration and temperature measurements in one traceable pipeline. The present work addresses this application-level gap.

3. METHODOLOGY

3.1 System Architecture and Components

The experimental rig (Fig. 1) consists of a steel frame carrying a rotating shaft supported by two pillow-block bearings, a cutting blade at one end of the shaft, and a 12 V DC motor that drives the shaft through a chain and sprocket. The information path is: sensors → ESP32 acquisition → data logging → preprocessing → feature extraction → ML model → condition/maintenance indication. The mechanical load path is kept separate from the electronic processing path, so the load signal can be calibrated independently and the analysis can be repeated from stored data. The components are listed in Table 1.

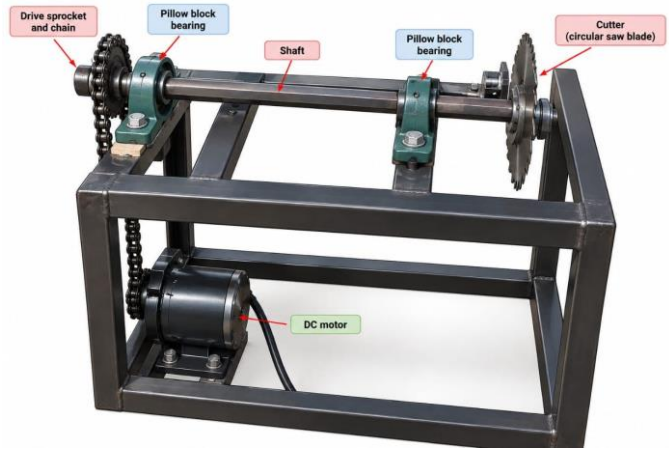


Fig. 1: Experimental cutting-force monitoring rig

Table 1: Components and their functions

S.No.	Component	Specification	Function
1	DC motor	12 V DC	Drives the rotating shaft
2	Pillow-block bearings (2)	Shaft-support bearings	Support and align the shaft
3	Cutting blade	Circular saw blade	Performs the cutting operation
4	Current sensor	Current sensor module	Measures motor current (load indicator)
5	Accelerometer (one per bearing)	3-axis digital, ±2 g	Measures vibration
6	K-type thermocouple (one per bearing)	Temperature sensor	Measures bearing temperature
7	ESP32	Wi-Fi/Bluetooth microcontroller	Data acquisition and communication
8	SMPS	12 V DC output	Powers the system

3.2 Data Acquisition and Experimental Matrix

The current sensor is connected in series with the motor supply so that the full motor current passes through it. The accelerometers are rigidly mounted on the bearing housings and the thermocouples are fixed at the bearings. The ESP32 reads the nine sensor channels (two temperatures, three acceleration components for each bearing, and the motor current) and sends them to a computer through USB or Wi-Fi, where they are logged in CSV format with a test ID and condition labels.

The health of each bearing was set to good or bad, giving four bearing combinations, and each combination was run at five load levels (0, 25, 50, 75 and 100 %). This gives 20 test conditions with 3,000 samples each, i.e. 60,000 samples in total (Table 2). The data set is balanced, with 15,000 samples for each bearing combination, which avoids bias towards any class during training.

Table 2: Experimental test matrix

Factor	Levels	Measured outputs
Bearing-1 condition	Good / Bad	Vibration (x, y, z), temperature
Bearing-2 condition	Good / Bad	Vibration (x, y, z), temperature
Motor load	0, 25, 50, 75, 100 %	Motor current
Combined conditions	4 bearing combinations × 5 loads = 20	3,000 samples each; 60,000 in total

3.3 Preprocessing and Machine-Learning Models

The data contain no missing values; acceleration readings are limited to ±19.61 m/s² by the sensor range, and 485 of the 60,000 rows (0.8 %) are exact duplicates. Candidate features include the mean, maximum, minimum, RMS, standard deviation and peak-to-peak value of the current, RMS, peak and crest factor of the vibration, and the mean, maximum and gradient of the temperature. The data were divided into training and testing subsets.

Four models were trained and compared: Logistic Regression, Support Vector Machine (SVM), Decision Tree and Random Forest. Three data sets with the same readings but different label coding were used: Set 1 (numeric good/bad labels) and Set 2 (text labels), in which a separate model was built for each bearing, and Set 3, in which a single combined code represents the condition of both bearings. Each model was evaluated on training data and on test data not used for fitting, using the root-mean-square error (RMSE) and the coefficient of determination (R^2) between predicted and actual condition labels.

4. RESULTS AND DISCUSSION

4.1 Sensor Behaviour

Over the whole data set the mean motor current was 14.50 A with a standard deviation of 0.87 A (range 12.79–16.20 A). The mean current stayed between 14.48 A and 14.53 A at every load level and for every bearing combination, so the curves in Fig. 2 are almost flat and overlap. The sample-to-sample variation (about 0.87 A) is far larger than the differences between conditions, so in these experiments the motor current alone did not reveal the applied load or the health of the bearings. A more sensitive current measurement or a wider range of loads would be needed to use it as a cutting-load indicator.

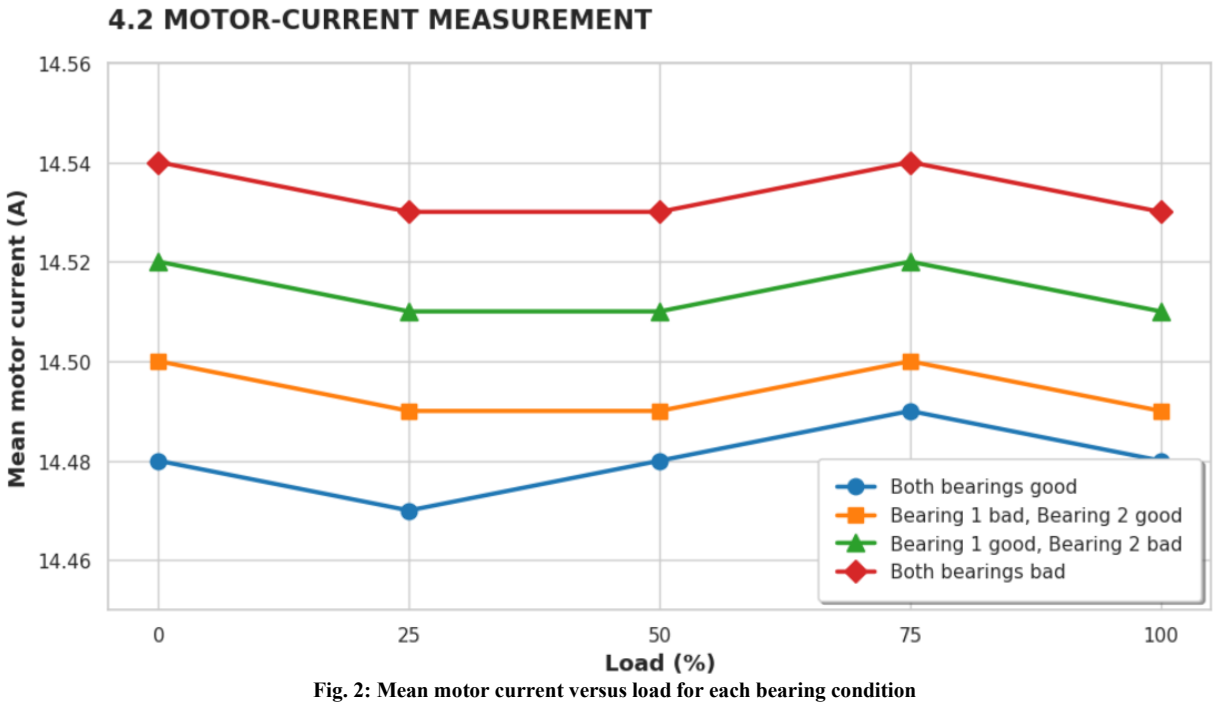


Fig. 2: Mean motor current versus load for each bearing condition

Vibration and temperature, in contrast, separate good and bad bearings clearly (Table 3). A bad bearing ran hotter, with a mean temperature of about

29.45 °C against 27.1–28.0 °C for a good bearing, and its maximum was 33.33 °C against about 29.8 °C. The mean vibration magnitude at Bearing 1 was about 17.6 m/s² when bad and 13.0 m/s² when good. Temperature also rose with load, from 27.65 °C at 0 % load to 29.51 °C at 75 % load for Bearing 1. About 15 % of the Bearing-2 z-axis and 7 % of the y-axis readings reach the ±2 g sensor limit, so the largest vibration peaks are clipped; a wider-range accelerometer should be used in future tests.

Table 3: Mean sensor readings for each bearing condition

Bearing condition	Temp. B1 (°C)	Temp. B2 (°C)	Vib. B1 (m/s²)	Vib. B2 (m/s²)	Current (A)
Both bearings good	28.01	27.11	12.97	14.37	14.50
B1 bad, B2 good	29.45	27.11	17.62	14.38	14.49
B1 good, B2 bad	27.98	29.45	13.02	18.92	14.49
Both bearings bad	29.45	29.45	17.18	18.52	14.50

4.2 Model Performance

Table 4 and Fig. 3 compare the four models on the test data. Set 2 holds the same data as Set 1 with text labels and gave identical results, so it is not repeated. For the individual bearings the Random Forest and Decision Tree models were far more accurate than the other two: for Bearing 1 the testing R² was 0.9391 (Random Forest) and 0.9320 (Decision Tree) against 0.6782 for SVM and 0.4204 for Logistic Regression; for Bearing 2 it was 0.9864 (Decision Tree), 0.9855 (Random Forest), 0.8759 (SVM) and 0.7578 (Logistic Regression). Every model predicted Bearing 2 better than Bearing 1, as the heat map in Fig. 4 shows.

Table 4: Testing results of the four models (best R² in bold)

Model	B1 RMSE	B1 R²	B2 RMSE	B2 R²	Set 3 RMSE	Set 3 R²
Logistic Regression	0.3807	0.4204	0.2460	0.7578	0.2745	0.5981
SVM	0.2836	0.6782	0.1761	0.8759	0.2223	0.7364
Decision Tree	0.1304	0.9320	0.0584	**0.9864**	0.0941	**0.9528**
Random Forest	0.1233	**0.9391**	0.0602	0.9855	0.0999	0.9467

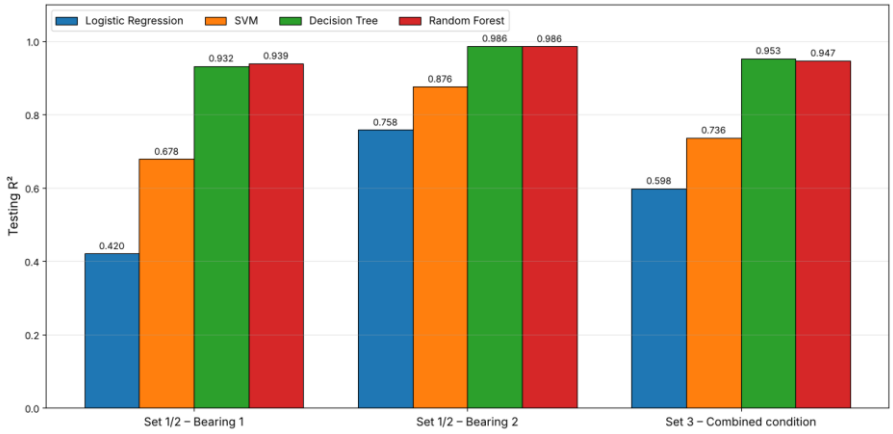


Fig. 3: Testing R² of the four models for each data set

For the combined condition (Set 3) the Decision Tree gave the best testing result (RMSE 0.0941, R² 0.9528), slightly ahead of Random Forest (R² 0.9467), followed by SVM (R² 0.7364) and Logistic Regression (R² 0.5981). Random Forest fitted the training data most closely but lost more accuracy on the test data (Bearing 1: training R² 0.9909 against testing R² 0.9391), whereas the Decision Tree showed a much smaller gap (0.9466 against 0.9320). Logistic Regression and SVM scored similarly on training and test data but at a low level, which suggests that the relation between the sensor readings and the bearing condition is nonlinear. Because the Decision Tree is accurate, stable and easy to interpret, it is also the more suitable choice for later implementation on a small controller such as the ESP32.

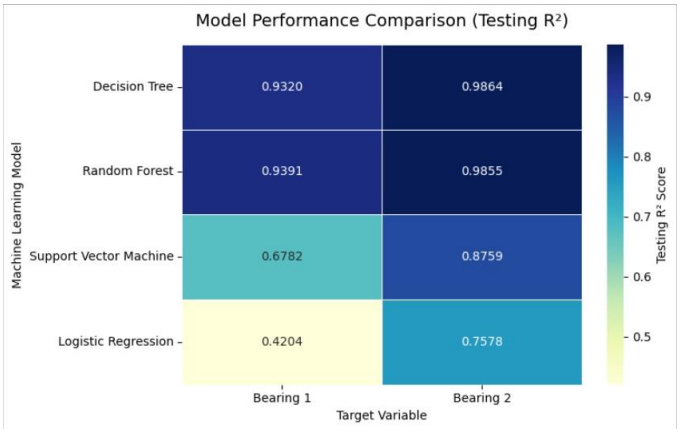


Fig. 4: Heat map of testing R² for each model and bearing

Fig. 5 plots predicted against actual values for the Decision Tree model. The test points cluster closely around the line of perfect prediction over the whole range, with no systematic offset, which is consistent with the high R² values in Table 4.

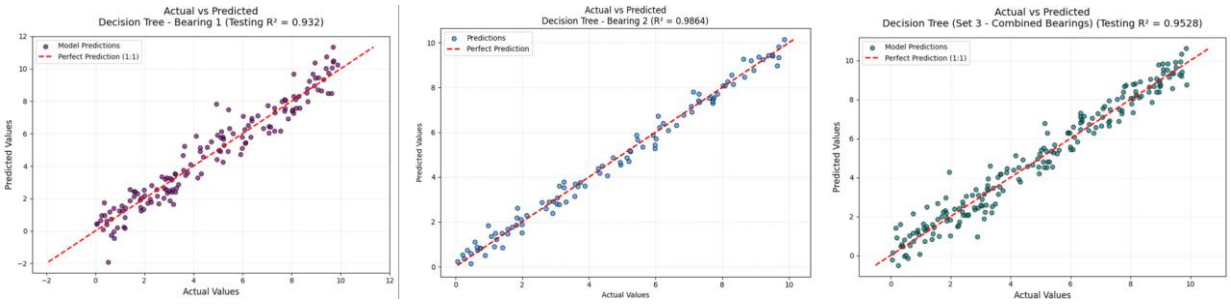


Fig. 5: Actual versus predicted values for the Decision Tree model: (a) Bearing 1, (b) Bearing 2 and (c) combined bearings

4.3 Maintenance Decision and Limitations

The model output is converted into an operational indication: a normal condition means continue operation, a warning means inspect the machine or tool, and an abnormal condition means stop or schedule maintenance, subject to the safe operating procedure. Because each bearing is labelled only good or bad, the trained models currently support a two-state output; an intermediate warning level would need data from partly worn bearings or thresholds set from the model output.

Three limitations should be noted. First, the labels are categories, so accuracy, precision, recall, F1-score and a confusion matrix would describe fault detection more clearly than RMSE and R². Second, the 3,000 samples of each condition were recorded consecutively, so a random train/test split may place near-identical samples in both subsets and make the test scores higher than they would be on separately recorded runs. Third, no sensor-calibration data were collected, so the current values are the raw sensor outputs in amperes.

5. CONCLUSION

An AI-based predictive maintenance and cutting force monitoring system was developed using a motor-driven shaft, cutting blade, current sensor, vibration and temperature sensors, and an ESP32 controller. Data for four bearing-health combinations at five loads (60,000 samples) were collected and used to train four ML models. Decision Tree and Random Forest models predicted bearing condition with testing R² of 0.93–0.99 for the individual bearings and about 0.95 for the combined condition, clearly better than SVM and Logistic Regression. Vibration and temperature were the most informative signals, while the motor current showed no measurable change with load.

Future work should add accuracy and confusion-matrix evaluation, test on separately recorded runs, use a wider-range accelerometer, include sensor-calibration data, add an intermediate warning level, and implement the Decision Tree on the ESP32 for edge inference with an IoT dashboard.

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