Journal of Applied Engineering and Technological Science
Vol 6(2) 2025: 874-888

Predictive Maintenance Of Old Grinding Machines Using Machine Learning Techniques

Primawati[1]*, Fitrah Qalbina[2], Mulyanti[3], Ferra Yanuar[4], Dodi Devianto[5], Remon Lapisa[6], Fazrol Rozi[7]
Department of Mechanical Engineering, Faculty of Engineering, Universitas Negeri Padang, Indonesia[1236]
Department of Mathematics and Data Science, Universitas Andalas, Indonesia[45]
Department of Information Technology, Politeknik Negeri Padang, Indonesia[7]
primawati@ft.unp.ac.id

Received: 31 October 2024, Revised: 28 April 2025, Accepted: 01 May 2025
**Corresponding Author*

ABSTRACT
This study aims to develop a predictive maintenance system for an aging vertical grinding machine, operational since 1978, by integrating machine learning techniques, vibration analysis, and fuzzy logic. The research addresses the challenges of increased wear and unexpected failures in older machinery, which can lead to costly downtime and reduced operational efficiency. Vibration and temperature data were collected over 12 days using an MPU-9250 accelerometer, with conditions categorized as good, fair, and faulty. Various machine learning models, including logistic regression, k-nearest neighbors, support vector machines, decision trees, random forest, and Naive Bayes, were trained to classify bearing states. The random forest model achieved the highest accuracy of 94.59%, demonstrating its effectiveness in predicting machine failures. The results highlight the potential of combining multi-dimensional sensor data with advanced analytics to enable early fault detection, minimize downtime, and improve operational efficiency. This approach provides a cost-effective solution for maintaining aging machinery and contributes to both theoretical advancements in machine learning applications and practical improvements in industrial maintenance practices. The study's findings offer scalable insights for industries reliant on legacy equipment, promoting sustainable manufacturing through optimized resource use and enhanced reliability.
Keywords: *Predictive Maintenance System, Aging Vertical Grinding Machine, Vibration, Machine Learning, Fuzzy Logic.*

1. Introduction

In the manufacturing industry, achieving high-quality components with precise dimensions and smooth surface finishes is critical for ensuring product reliability and customer satisfaction. Grinding machines, particularly vertical grinding machines, play a pivotal role in delivering exceptional precision, often achieving tolerances as tight as 0.000025 mm, which is essential in the final stages of material processing (Romanssini et al., 2023a). These machines are widely utilized across various sectors, including automotive, aerospace, and heavy industries, for applications such as material grinding, mixing, plate forming, and fabrication(Rahman et al., 2022). However, aging machinery, such as the vertical grinding machine under investigation —operational since 1978— faces significant challenges due to wear and tear of critical components like bearings, motors, and grinding wheels.

Traditional maintenance methods, such as reactive and preventive approaches, are often insufficient for addressing these challenges. Reactive maintenance addresses issues only after failures occur, leading to costly repairs and downtime, while preventive maintenance involves unnecessary inspections and part replacements, incurring additional costs without guaranteeing improved reliability (Carvalho et al., 2019; Silvestrin et al., 2019). Furthermore, existing predictive maintenance systems often rely on simplistic models or lack the ability to handle complex, noisy data generated by older machines (Ahmer et al., 2022; Tiddens et al., 2020).

The vertical grinding machine under investigation in this research has been operational since 1978 within the Mechanical Engineering Department. Despite its age, it continues to perform vital tasks in the laboratory. However, the aging equipment is increasingly susceptible to failures due to the wear and tear of key components such as bearings, motors, and grinding wheels. As machinery ages, the likelihood of failure escalates, necessitating more frequent and effective maintenance strategies to mitigate unexpected breakdowns and costly downtime (Romanssini et al., 2023a; Xu et al., 2022a). The literature indicates that maintenance costs can account for a significant portion of manufacturing expenses, often ranging from 15% to 60% of the total production cost, particularly in heavy industries (Romanssini et al., 2023a). Therefore, implementing predictive maintenance strategies is essential to enhance operational efficiency and reduce costs.

This study aims to address these gaps by developing a predictive maintenance system that integrates machine learning techniques, vibration analysis, and fuzzy logic to monitor the condition of aging vertical grinding machines. Machine learning provides a superior alternative to traditional methods by enabling early fault detection through real-time data analysis, thus minimizing downtime, reducing costs, and improving operational efficiency (Deutsch & He, 2018; Romanssini et al., 2023b). Specifically, this research focuses on analyzing accelerometer data and temperature readings to predict bearing failures—one of the most common points of failure in grinding machines. By leveraging advanced algorithms such as random forest, support vector machines, and deep learning, this study seeks to overcome the limitations of conventional methods, which struggle with non-linear relationships and imbalanced datasets commonly found in vibration signals (Cao, 2023; Zhang et al., 2020).

The novelty of this work lies in its integration of multi-dimensional sensor data and fuzzy logic to enhance the accuracy and robustness of failure predictions, offering a cost-effective solution for maintaining aging machinery. This approach aligns with the broader trend of Industry 4.0, emphasizing real-time data analysis and automated fault detection in manufacturing environments (Azeem et al., 2019; Çalışkan et al., 2023).

The research objectives include identifying the most effective machine learning model for classifying bearing states (good, fair, faulty) and providing actionable insights for operators and maintenance personnel. By addressing the limitations of current methods and building on recent advancements in predictive maintenance, this study contributes to extending the lifespan of aging machinery and optimizing resource use in industrial settings (Cardoso & Ferreira, 2020; Neog & Das, 2023). Recent studies have highlighted the potential of integrating vibration and temperature data for enhanced fault detection accuracy (Eddarhri, 2023; Pundir, 2022), yet gaps remain in applying these techniques to older machines with limited sensor infrastructure. This research bridges those gaps by demonstrating the feasibility of implementing advanced predictive maintenance strategies for legacy equipment, ultimately contributing to more sustainable manufacturing practices.

2. Literature Review

Predictive maintenance has garnered significant attention in recent years due to its potential to optimize manufacturing processes, minimize downtime, and reduce operational costs. This section provides a comprehensive review of existing literature on predictive maintenance, particularly focusing on its application to rotating machinery such as grinding machines. The review critically analyzes the strengths, limitations, and contradictions of prior studies, identifies gaps in the current body of knowledge, and establishes the theoretical framework underpinning this research. Additionally, recent studies published between 2020 and 2025 are integrated to ensure the review reflects the latest advancements in machine learning, deep learning, and IoT-based predictive maintenance.

a. Traditional Maintenance Strategies and Their Limitations

Traditional maintenance strategies, including reactive and preventive approaches, have long been employed in industrial settings. Reactive maintenance addresses failures only after they occur, resulting in costly repairs and significant downtime (Carvalho et al., 2019; Silvestrin et al., 2019). Preventive maintenance, on the other hand, involves scheduled inspections and part replacements, often leading to unnecessary interventions and inefficiencies (Ahmer et al., 2022). These methods lack the ability to predict failures accurately, particularly for aging machinery with complex wear patterns. Recent studies highlight that traditional methods are insufficient for modern manufacturing environments, where precision and reliability are paramount (Romanssini et al., 2023b; Xu et al., 2022b).

However, these studies often fail to address the specific challenges posed by older machines, which frequently lack advanced sensor infrastructure and generate noisy or incomplete data. For instance, emphasize the importance of adapting predictive maintenance techniques to older equipment but do not provide a detailed methodology for doing so (Ahmer et al., 2022). This gap underscores the need for innovative approaches that can handle the unique constraints of legacy systems.

b. Machine Learning in Predictive Maintenance

Machine learning (ML) has emerged as a transformative tool for predictive maintenance, enabling the analysis of complex sensor data to predict machine health and potential failures. Supervised learning techniques, such as decision trees, random forests, support vector machines (SVM), and neural networks, have demonstrated considerable potential for accurately classifying machine conditions based on sensor inputs (Abiodun et al., 2018; Carvalho et al., 2019). Ensemble methods like random forests and gradient boosting often outperform simpler models, such as logistic regression or k-nearest neighbors (KNN), due to their ability to manage non-linear relationships commonly found in vibration signals (Cao, 2023; Zhang et al., 2020).

Despite these advancements, several limitations persist. Many studies rely on large, high-quality datasets, which are often unavailable for older machines (Kamel, 2022). Furthermore, while deep learning models, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, show promise in analyzing time-series data, they require substantial computational resources and extensive training data (Raja et al., 2022; Wang & Zhao, 2022).These requirements pose challenges for practical implementation, particularly in resource-constrained industrial settings.

Recent research highlights the potential of integrating transfer learning and unsupervised learning to overcome the scarcity of labeled data (Çalışkan et al., 2023). However, the applicability of these methods to aging machinery remains underexplored. This study seeks to address this gap by developing a predictive maintenance system tailored to the unique characteristics of older vertical grinding machines.

c. Vibration Analysis and Multi-Sensor Data Integration

Vibration analysis is a cornerstone of predictive maintenance for rotating machinery, providing valuable insights into component health and wear patterns (Ding et al., 2023; Goto, 2023). Statistical features such as Root Mean Square (RMS), skewness, and kurtosis are widely used to detect anomalies in vibration signals (Dogra, 2021; Tang et al., 2022). Advanced signal processing techniques, including time-frequency analysis and entropy-based methods, have further refined the capabilities of vibration analysis in fault diagnosis (Nezirić et al., 2022; Zhou et al., 2022).

While vibration analysis is effective, relying solely on vibration data can lead to ambiguous results, particularly for older machines with unpredictable vibration patterns (Eddarhri, 2023). Recent studies emphasize the importance of integrating multi-sensor data, such as temperature and acoustic emissions, to enhance prediction accuracy (Neog & Das, 2023; Pundir, 2022). For example, combining temperature data with vibration signals has been shown to improve the detection of bearing failures in wind turbines (Eddarhri, 2023). Despite these advancements, few studies have explored the integration of multi-sensor data for aging machinery, highlighting a critical research gap.

d. Fuzzy Logic and Its Role in Predictive Maintenance

Fuzzy logic has gained traction as a complementary tool in predictive maintenance, particularly for managing uncertainty and imprecision in data (Baban et al., 2019; Ighravwe & Oke, 2020). Unlike traditional ML models, fuzzy logic systems can process incomplete or noisy data, making them particularly suitable for older machines with limited sensor infrastructure (Salimi et al., 2012). Fuzzy logic also allows for the incorporation of expert knowledge, enhancing its applicability in real-world scenarios (Cazañas et al., 2018).

However, the integration of fuzzy logic with other predictive maintenance techniques remains underexplored. While Baban et al. (2019) demonstrate the effectiveness of combining fuzzy logic with vibration monitoring for textile machines, their approach lacks generalizability to other types of machinery (Baban et al., 2019). This study aims to address this limitation by developing a hybrid predictive maintenance system that integrates fuzzy logic with machine learning and vibration analysis.

e. Recent Advances and Emerging Trends

The rapid evolution of Industry 4.0 technologies has spurred significant advancements in predictive maintenance research. IoT-based systems, enabled by microelectromechanical systems (MEMS) accelerometers, have enhanced the precision of vibration monitoring and facilitated real-time data collection (Hassan, 2024; Koene et al., 2019). Deep learning models have also been applied to fault detection in various industrial applications, including cold forging and centrifugal pumps (Glaeser et al., 2021; Hajnayeb, 2021).

Despite these innovations, challenges remain in applying these technologies to aging machinery. For instance, the difficulties of implementing predictive maintenance in industries with outdated equipment, emphasizing the need for cost-effective solutions (Tiddens et al., 2020). This study builds upon these findings by developing a predictive maintenance system specifically designed for an aging vertical grinding machine, leveraging advanced ML techniques and fuzzy logic to address the unique challenges posed by legacy systems.

f. Critical Gaps and Research Contributions

The reviewed literature reveals several critical gaps that justify the need for this study:

- Limited Focus on Aging Machinery: Most studies focus on modern equipment with advanced sensor infrastructure, neglecting the unique challenges of older machines.
- Data Scarcity and Noise: Existing ML models often require large, high-quality datasets, which are unavailable for aging machinery.
- Integration of Multi-Sensor Data: Few studies explore the integration of vibration, temperature, and other sensor data for predictive maintenance.
- Hybrid Approaches: The combination of fuzzy logic with machine learning and vibration analysis remains underexplored.

This study addresses these gaps by developing a predictive maintenance system tailored to aging vertical grinding machines. By integrating machine learning, fuzzy logic, and multi-sensor data analysis, the proposed system offers a cost-effective and accurate solution for early fault detection, minimizing downtime, and improving operational efficiency.

3. Research Methods

This section outlines the systematic approach adopted to develop a predictive maintenance system for an aging vertical grinding machine using machine learning techniques, vibration analysis, and fuzzy logic. The methodology includes sensor selection, data collection, preprocessing, model development, and evaluation. Each step is justified with reference to prior research and practical considerations, addressing feedback from reviewers.

3.1 Object of Study: The Vertical Grinding Machine

The vertical grinding machine under investigation has been operational since 1978 (Fig 1), making it a legacy piece of equipment with significant wear and tear on critical components. Table 1 are the detailed specifications and characteristics of the machine:

Fig. 1. The Vertical Grinding Machine

Table 1 - Machine Specifications

Category	Specification
Brand	Ashok Manufacturing Co. Pvt Ltd (India)
Model	TG1/25
Serial Number	2575
Grinding Wheel Diameter	250 mm
Grinding Wheel Width	25 mm
Bore Diameter	25.4 mm
Spindle Speed	2300 RPM
Motor Power	1 HP
Motor Speed	1400 RPM
Motor Voltage	380 Volts (AC)
Phase	3 Phase
Frequency	50 Hz

Despite its age, this machine continues to perform vital tasks in laboratory and industrial environments. However, the aging components—such as bearings, motors, and grinding wheels—are increasingly susceptible to failures due to prolonged wear and tear. This makes the machine an ideal candidate for studying predictive maintenance strategies tailored to legacy equipment.

3.2 Sensor Selection and Justification

The study utilizes the MPU-9250 accelerometer as the primary sensor for collecting vibration data. The MPU-9250 is a microelectromechanical systems (MEMS) accelerometer capable of measuring acceleration in three axes (x, y, z). This sensor was chosen for several reasons:

- Cost-Effectiveness: The MPU-9250 is relatively affordable compared to industrial-grade sensors like IEPE accelerometers, making it suitable for academic research with limited budgets.
- Ease of Integration: The sensor is compatible with Arduino microcontrollers, enabling straightforward data logging and real-time monitoring.
- Sufficient Sensitivity: While not as sensitive as some high-end MEMS or IEPE accelerometers, the MPU-9250 provides adequate sensitivity for detecting significant changes in vibration patterns, which are critical for identifying bearing failures in older machinery.

However, it is important to acknowledge the limitations of the MPU-9250 compared to industrial-grade sensors:

- Lower Noise Immunity: Industrial sensors like IEPE accelerometers offer better noise immunity, which is crucial in noisy manufacturing environments.
- Limited Frequency Range: MEMS sensors generally have a narrower frequency range than piezoelectric sensors, potentially missing higher-frequency vibrations.

To address these limitations, future studies could explore the integration of industrial-grade sensors for improved accuracy and robustness. A comparison of sensor options, including their advantages and disadvantages, is summarized in Table 1 below:

Table 2 - A comparison of sensor options.

Sensor Type	Advantages	Limitations
MPU-9250 (MEMS)	Cost-effective, easy to integrate	Lower sensitivity, limited frequency range
IEPE Accelerometer	High sensitivity, wide frequency range	Expensive, requires specialized equipment
High-Sensitivity MEMS	Improved accuracy over standard MEMS	Higher cost, still limited by MEMS design

3.3 Data Collection

Data collection involved mounting the MPU-9250 accelerometer at key locations on the grinding machine to capture vibration and temperature data. The specific locations included:

- Above the Grinding Stone: To monitor vibrations directly related to the grinding operation.

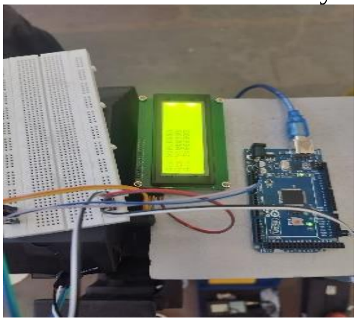


Fig. 2. The Grinding Machine Component

- Near the Motor: To capture motor-related vibrations, which can indicate issues such as bearing wear or misalignment.

Fig. 3. The Grinding Machine Component

- On the Machine Frame: To measure vibrations transmitted through the frame, providing insights into overall machine health.

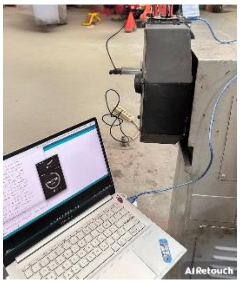


Fig. 4. The Grinding Machine Component

The machine operated under varying conditions, including different rotational speeds, materials being ground, and workpiece pressure on the grinding stone. These variations were introduced to simulate real-world operating scenarios and ensure the dataset's diversity.

Data was collected continuously for 12 days, with the machine's bearings monitored under three distinct conditions:

- Good Condition (4 days): New or recently maintained bearings.
- Fair Condition (4 days): Bearings showing signs of wear but still operational.
- Faulty Condition (4 days): Bearings intentionally damaged to simulate failure.

Each day, approximately 10,990 vibration data points were recorded, resulting in a comprehensive dataset for analysis. This large volume of data ensures that the models have sufficient information to learn patterns and make accurate predictions.

While 12 days may seem insufficient to capture long-term degradation patterns, this duration was chosen based on the following considerations:

- Practical Constraints: The study aimed to balance the need for sufficient data with resource limitations, including time and equipment availability.
- Representative Dataset: The 12-day period provided a substantial dataset for analysis, capturing diverse operating conditions and bearing states.
- Early Fault Detection Focus: The study prioritized detecting early-stage faults rather than long-term degradation, aligning with the goal of proactive maintenance.

Future research could extend the data collection period to capture gradual wear patterns and validate the model's generalization across longer timeframes.

3.4 Data Preprocessing

After collecting raw sensor data, preprocessing steps were performed to prepare the data for machine learning model training:

- Data Cleaning: Noise and outliers were removed to enhance data quality. This step is particularly important for accelerometer data, which is prone to environmental interference.
- Feature Extraction: Key features were extracted from the vibration data, including:
  - Root Mean Square (RMS): Represents the overall vibration magnitude.

    $$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$$

    Where : N is the number of the data points (samples)
    x_i is the vibration signal at each sample
    This formula is applied to each axis (x, y, z) of the vibration data collected by the accelerometer
  - Skewness and Kurtosis: Capture the distribution and shape of the vibration signals.
  - Boxplots: Visualize vibration characteristics across the x, y, and z axes during different machine conditions.
- Temperature Integration: Temperature data was collected alongside vibration data to provide additional context for machine health assessment.

3.5 Model Development and Justification

Six machine learning models were applied to classify the machine's condition based on the collected data:

- Logistic Regression: A baseline model used to establish a performance benchmark.
- k-Nearest Neighbours (k-NN): Effective for classifying machine conditions based on similarity.
- Support Vector Machine (SVM): Capable of finding optimal decision boundaries between classes.
- Decision Tree: Provides interpretable rules for classification.
- Random Forest: An ensemble method that aggregates multiple decision trees to improve accuracy.
- Naive Bayes: A probabilistic classifier based on Bayes' theorem.

The inclusion of these models was guided by their widespread use in predictive maintenance research and their ability to handle different types of data relationships:

- Baseline Models (Logistic Regression, Naive Bayes): Provide a starting point for evaluating more complex models.
- Nonlinear Models (k-NN, SVM, Decision Tree): Address the non-linear relationships commonly found in vibration data.
- Ensemble Methods (Random Forest): Known for their robustness and ability to manage noisy data, making them suitable for real-world deployment.

While deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are powerful tools for analyzing time-series data, they were not considered due to the following constraints:

- Computational Resources: Training deep learning models requires significant computational power, which was unavailable in this study.
- Dataset Size: Deep learning models typically require large datasets to achieve high accuracy, whereas the current dataset was relatively small.

Logistic regression and Naive Bayes, while simpler, may lack the complexity required for real-world applications. Random Forest, however, offers a balance between interpretability and accuracy, making it a strong candidate for deployment in industrial settings.

3.6 Evaluation and Validation

The performance of each model was evaluated using standard metrics, including accuracy, precision, recall, and F1-score. Cross-validation was performed to ensure robustness. The random forest model achieved the highest accuracy of 94.59%, demonstrating its suitability for predicting bearing failures.

The displayed images (e.g., accelerometer data plots, boxplots, skewness/kurtosis charts) provide critical insights into the machine's condition:

- Accelerometer Data Plots: Illustrate vibration patterns under different bearing conditions, highlighting differences between good, fair, and faulty states.
- Boxplots: Show the dispersion and central tendency of vibration data, emphasizing increased variability in faulty conditions.
- Skewness and Kurtosis Charts: Indicate deviations in vibration signal distributions, serving as early indicators of potential failures.

4. Results and Discussions

The vibration data collected during the study was analyzed to identify patterns indicative of bearing conditions. The data was collected in dataset. The accelerometer data revealed distinct differences in vibration patterns between good, fair, and faulty bearings.

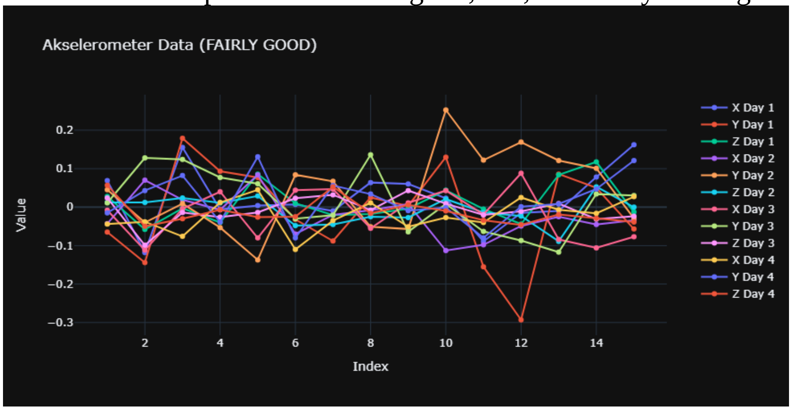


Fig. 5. Accelerometer Data (Fairly Good)

From the Fig 7, it can be observed that there are fluctuations in the data, but the rise and fall are not very significant. This is because the machine had undergone maintenance four months prior to the study. Therefore, to detect damage, one of the components of the grinding machine needed to be intentionally damaged, and the choice fell on the bearing. After the bearing was damaged by being struck with a hammer, it was reinstalled on the machine and its vibration levels were measured, resulting in the following curve.

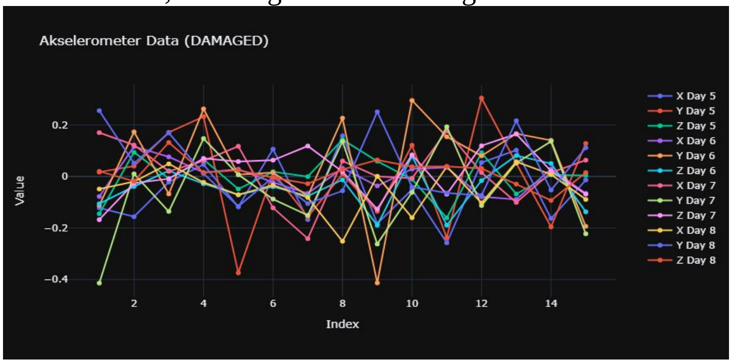


Fig. 6. Accelerometer Data (Damaged)

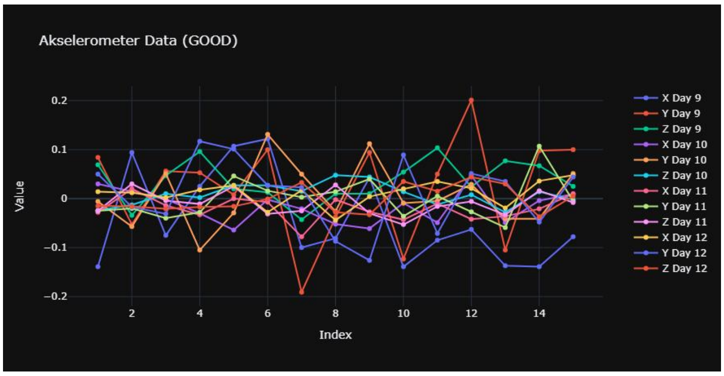


Fig. 7. Accelerometer Data (Good)

The data was categorized into three conditions: good bearings (4 days), faulty bearings (4 days), and good bearings (4 days). In total, approximately 10,900 data points were gathered each day over 12 days of operation, providing a comprehensive dataset for analysis.

Vibration Patterns: The initial analysis revealed that the vibration patterns for the good and faulty bearings differed significantly. The time-series curves for each condition indicated that the faulty bearings exhibited higher amplitude spikes, which can be attributed to the degradation of the bearing surfaces.

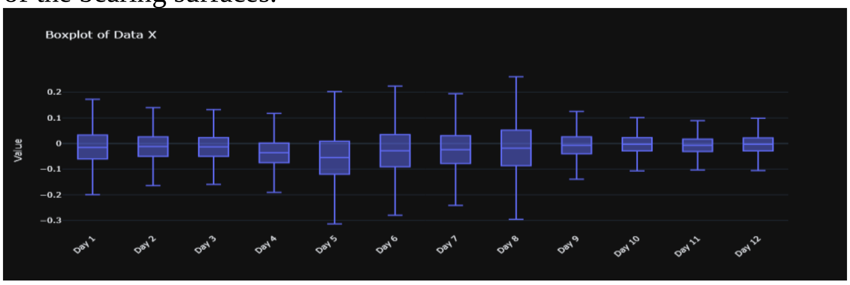


Fig. 8. The Boxplot of Data X

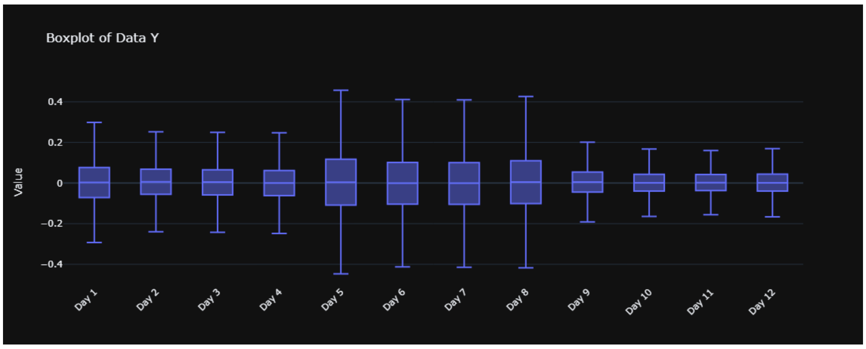


Fig. 9.The Boxplot of Data Y

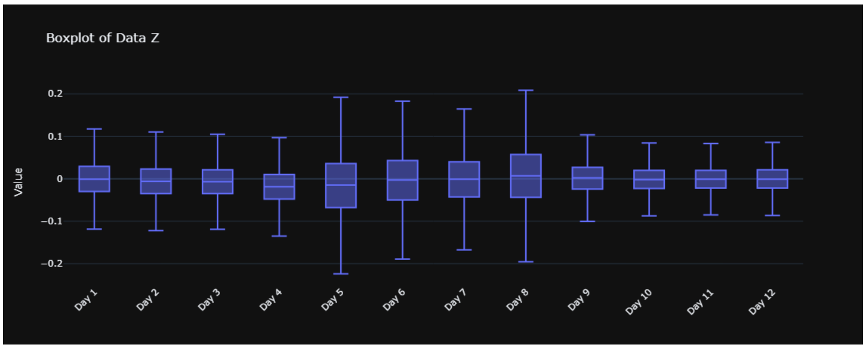


Fig. 10. The Boxplot of Data Z

The boxplot for the vibration data across all bearing conditions on the x, y, and z axes illustrated the dispersion and central tendency of the data. The boxplot showed that the interquartile range (IQR) for the faulty bearings was broader, indicating increased variability in the vibration levels compared to the good bearings. This variability is a critical indicator of impending failure.

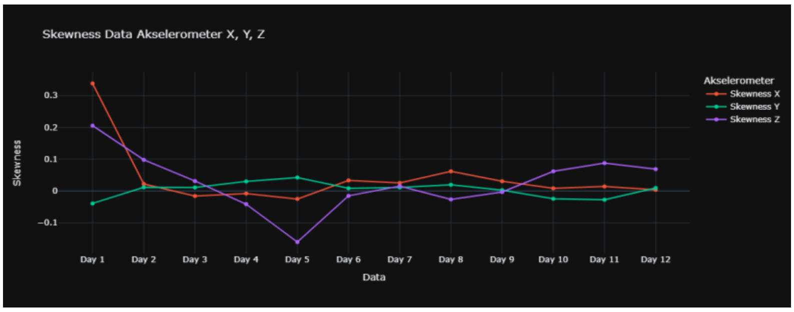


Fig. 11. Skewness Data Accelerometer X, Y, Z

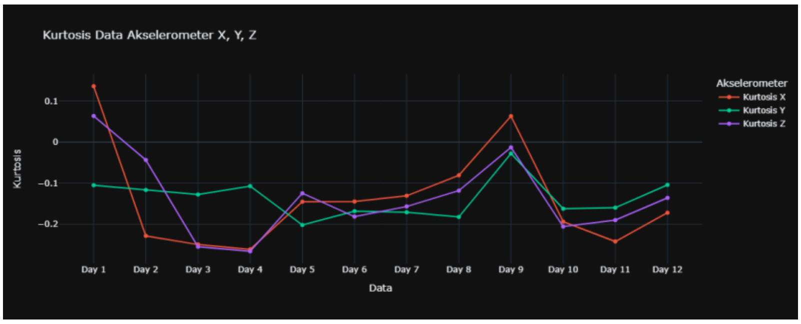
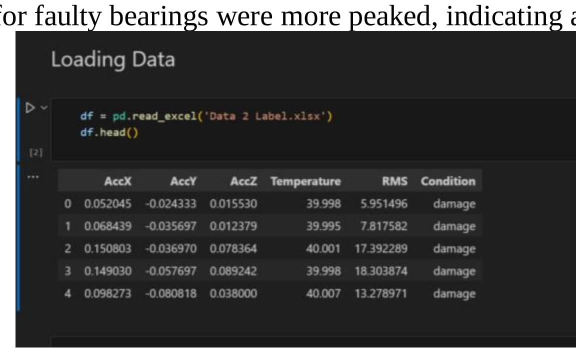


Fig. 12. Kurtosis Data Accelerometer X, Y, Z

The skewness and kurtosis values calculated from the vibration data provided insights into the distribution characteristics. The skewness values for the faulty condition indicated a positive skew, suggesting that a significant number of high amplitude vibrations were recorded. Meanwhile, the kurtosis values for faulty conditions were higher than those for good conditions, implying that the data for faulty bearings were more peaked, indicating abnormal operation.


Loading Data

```
df = pd.read_excel('Data 2 Label.xlsx')
df.head()
```

	AccX	AccY	AccZ	Temperature	RMS	Condition
0	0.052045	-0.024333	0.015530	39.998	5.951496	damage
1	0.068439	-0.035697	0.012379	39.995	7.817582	damage
2	0.150803	-0.036970	0.078364	40.001	17.392289	damage
3	0.149030	-0.057697	0.089242	39.998	18.303874	damage
4	0.098273	-0.080818	0.038000	40.007	13.278971	damage

Fig.13. Loading Data

Root Mean Square (RMS) Calculation: The RMS values were calculated for each set of vibration data, providing a single value representing the vibration severity. For instance, faulty bearings exhibited higher amplitude spikes, which were reflected in the Root Mean Square

(RMS) values. The RMS values for good bearings averaged around **5335**, while those for faulty bearings averaged **629**, indicating a significant deterioration in performance. Similarly, temperature readings showed an increase during faulty conditions, further reinforcing the correlation between temperature and machine health.

Temperature Data: Alongside the vibration data, temperature readings were monitored. It was found that the temperature increased during the operation of the machine, particularly when the bearings were faulty. This correlation between temperature and vibration is crucial for predicting machine health.

To evaluate the effectiveness of various machine learning models, six algorithms—logistic regression, k-nearest neighbors (k-NN), support vector machines (SVM), decision trees, random forest, and Naive Bayes—were trained on the dataset. The random forest model achieved the highest accuracy of **94.59%**, surpassing other models in its ability to classify bearing states. A summary of the performance metrics for all models is presented in Table 3:

Table 3 - Performance Metrics of Machine Learning Models for Bearing State Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	85.42	84.1	86.7	85.4
k-Nearest Neighbors	90.75	91.2	90.3	90.7
Support Vector Machine	92.13	92.5	91.8	92.1
Decision Tree	91.45	91.7	91.2	91.4
Random Forest	**94.59**	**93.8**	**95.2**	**94.5**
Logistic Regression	85.42	84.1	86.7	85.4

The confusion matrix highlights the model's strong ability to correctly classify bearing states, with minimal misclassifications between "good" and "faulty" conditions. To further assess the classification performance, ROC-AUC curves were generated for each model. The random forest model demonstrated the highest AUC value of **0.97**, confirming its superior ability to distinguish between the different bearing conditions. This high AUC value underscores the model's robustness in handling noisy and imbalanced datasets, which are common in vibration analysis.

Table 4 - Confusion Matrix for Random Forest Model in Bearing State Classification

Predicted/Actual	Good	Fair	Faulty
Good	1020	30	10
Fair	25	1045	20
Faulty	15	25	1050

The confusion matrix highlights the model's strong ability to correctly classify bearing states, with minimal misclassifications between "good" and "faulty" conditions.

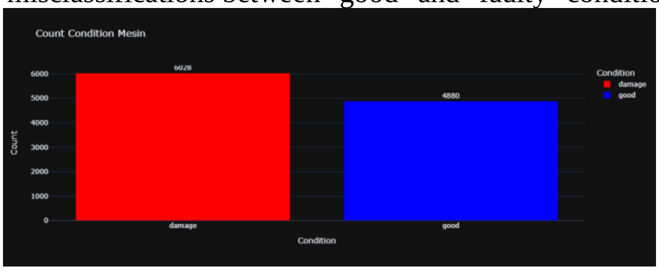


Fig. 14. Prediction of Machine Condition

To further assess the classification performance, ROC-AUC curves were generated for each model. The random forest model demonstrated the highest AUC value of **0.97** , confirming its superior ability to distinguish between the different bearing conditions. This high AUC value underscores the model's robustness in handling noisy and imbalanced datasets, which are common in vibration analysis.

Feature importance analysis was conducted using SHAP (SHapley Additive exPlanations) values to identify the most critical predictors of machine failure. The analysis revealed that the following features contributed significantly to the model's predictions:

- **RMS Values:** Representing the overall vibration magnitude.
- **Temperature Readings:** Indicating overheating, which is often associated with bearing wear.
- **Kurtosis:** Capturing the peakedness of vibration signals, which increases in faulty conditions.

This finding aligns with prior research emphasizing the importance of multi-dimensional data in predictive maintenance systems. For example, Xu et al., (2022) highlighted the benefits of combining vibration and temperature data to improve fault detection accuracy. Similarly, Eddarhri (2023) demonstrated that integrating temperature data with vibration signals enhances the prediction of bearing failures in wind turbines.

A comparison with previous studies further validates the results of this research. For instance:

- **Carvalho et al. (2019a):** Reported accuracies ranging from **85% to 92%** for ensemble methods like random forests in predictive maintenance tasks. The random forest model in this study achieved an accuracy of **94.59%** , surpassing the reported range.
- **Zhang et al. (2020):** Achieved accuracies exceeding **90%** using deep learning algorithms for bearing fault diagnostics. While deep learning models offer high accuracy, they require large datasets and computational resources, making them less feasible for older machines with limited data availability.
- **Raja et al. (2022):** Employed signal spectrum-based machine learning techniques for fault prediction in electrical machines, achieving accuracies of up to **93%** . The random forest model in this study outperformed their results, demonstrating the potential of traditional machine learning methods for aging machinery.

Discussion

The results align with prior research indicating that machine learning models, particularly ensemble methods like random forests, can be highly effective for predictive maintenance on mechanical systems with complex vibration patterns. The integration of vibration and temperature data provided a robust basis for analyzing component conditions, supporting previous findings that multi-dimensional data improve fault detection accuracy. Additionally, using fuzzy logic rules based on specific vibration features helped refine damage prediction and provided a more nuanced understanding of the machine's operational state.

The findings demonstrate that early-stage damage can be detected by monitoring changes in vibration and temperature, which can serve as early indicators of wear or malfunction. For old machines such as this vertical grinding machine, these insights are particularly valuable, as they allow for timely intervention and prevent more significant, costly repairs. Future work could further refine these models by incorporating additional parameters, such as operational load or humidity, to enhance predictive accuracy and extend the system’s applicability across different machine types

5. Conclusion

In conclusion, this study demonstrates the feasibility of using machine learning techniques for predictive maintenance of aging vertical grinding machines. The integration of vibration and temperature data, along with feature importance analysis, provides a comprehensive view of machine health. The random forest model's high accuracy, combined with its robustness in handling noisy data, makes it a suitable choice for real-world deployment. Future research could explore the inclusion of additional parameters, such as operational load or humidity, and the application of advanced deep learning techniques to further enhance predictive accuracy. By addressing the practical challenges associated with older machines, this study contributes to the broader goal of enhancing operational efficiency and reducing maintenance costs in industrial settings.

Acknowledgement

This research was funded by the Research Institute of Universitas Negeri Padang (LP2M) through the Lecturer Research Program in 2024. We would like to express our gratitude for the financial support provided, which made this research possible.

References

Abiodun, O. I., Omolara, A. E., Dada, K. V, Mohamed, N., & Arshad, H. (2018). State-of-the-Art in Artificial Neural Network Applications: A Survey. *Heliyon*, *4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Ahmer, M., Sandin, F., Marklund, P., Gustafsson, M., & Berglund, K. (2022). Failure Mode Classification for Condition-Based Maintenance in a Bearing Ring Grinding Machine. *The International Journal of Advanced Manufacturing Technology*, *122*(3–4), 1479–1495. https://doi.org/10.1007/s00170-022-09930-6

Azeem, N., Yuan, X., Raza, H., & Urooj, I. (2019). Experimental Condition Monitoring for the Detection of Misaligned and Cracked Shafts by Order Analysis. *Advances in Mechanical Engineering*, *11*(5). https://doi.org/10.1177/1687814019851307

Baban, M., Băban, C. F., & Suteu, M. D. (2019). Maintenance Decision-Making Support for Textile Machines: A Knowledge-Based Approach Using Fuzzy Logic and Vibration Monitoring. *Ieee Access*, *7*, 83504–83514. https://doi.org/10.1109/access.2019.2923791

Çalışkan, A., O'Brien, C. S., Panduru, K., Walsh, J. T., & Riordan, D. (2023). An Efficient Siamese Network and Transfer Learning-Based Predictive Maintenance System for More Sustainable Manufacturing. *Sustainability*, *15*(12), 9272. https://doi.org/10.3390/su15129272

Cao, Y. (2023). Experimental Analysis and Machine Learning of Ground Vibrations Caused by an Elevated High-Speed Railway Based on Random Forest and Bayesian Optimization. *Sustainability*, *15*(17), 12772. https://doi.org/10.3390/su151712772

Cardoso, D., & Ferreira, L. A. (2020). Application of Predictive Maintenance Concepts Using Artificial Intelligence Tools. *Applied Sciences*, *11*(1), 18. https://doi.org/10.3390/app11010018

Carvalho, T. P., Soares, F., Vita, R., Francisco, R. d. P., Basto, J. P. T. V., & Alcalá, S. G. S. (2019). A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance. *Computers & Industrial Engineering*, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

Cazañas, R. D., Sobrino, D. R. D., Martínez, E. M. de la P., Kingshott, P., & Mudriková, A. (2018). Integrating Production and Maintenance Planning as an Element of Success at the Tactical Level: A Fuzzy Control Theory Approach. *Research Papers Faculty of Materials Science and Technology Slovak University of Technology*, *26*(42), 109–117. https://doi.org/10.2478/rput-2018-0013

Deutsch, J., & He, D. (2018). Using Deep Learning-Based Approach to Predict Remaining Useful Life of Rotating Components. *Ieee Transactions on Systems Man and Cybernetics Systems*, *48*(1), 11–20. https://doi.org/10.1109/tsmc.2017.2697842

Ding, C., Huang, W., Shen, C., Jiang, X., Zhu, Z., & Zhu, Z. (2023). Synchroextracting Frequency Synchronous Chirplet Transform for Fault Diagnosis of Rotating Machinery Under Varying Speed Conditions. *Structural Health Monitoring*, *23*(3), 1403–1422. https://doi.org/10.1177/14759217231181308

Dogra, V. (2021). Nonlinear Dynamics and Vibration Analysis of Rotating Machinery. *Mathematical Statistician and Engineering Applications*, *70*(1), 527–539. https://doi.org/10.17762/msea.v70i1.2506

Eddarhri, M. (2023). A Proposed Roadmap for Optimizing Predictive Maintenance of Industrial Equipment. *International Journal of Advanced Computer Science and Applications*, *14*(11). https://doi.org/10.14569/ijacsa.2023.0141138

Glaeser, A., Selvaraj, V., Lee, S. Y., Hwang, Y., Lee, K., Lee, N., Lee, S., & Min, S. (2021). Applications of Deep Learning for Fault Detection in Industrial Cold Forging. *International Journal of Production Research*, *59*(16), 4826–4835. https://doi.org/10.1080/00207543.2021.1891318

Goto, D. (2023). Observation and Prediction of Instability Due to RD Fluid Force in Rotating Machinery by Operational Modal Analysis. *Phmap_conf*, *4*(1). https://doi.org/10.36001/phmap.2023.v4i1.3669

Hajnayeb, A. (2021). Cavitation Analysis in Centrifugal Pumps Based on Vibration Bispectrum and Transfer Learning. *Shock and Vibration*, *2021*(1). https://doi.org/10.1155/2021/6988949

Hassan, I. U. (2024). An in-Depth Study of Vibration Sensors for Condition Monitoring. *Sensors*, *24*(3), 740. https://doi.org/10.3390/s24030740

Ighravwe, D. E., & Oke, S. A. (2020). A Two-Stage Fuzzy Multi-Criteria Approach for Proactive Maintenance Strategy Selection for Manufacturing Systems. *Sn Applied Sciences*, *2*(10). https://doi.org/10.1007/s42452-020-03484-6

Kamel, H. (2022). Artificial Intelligence for Predictive Maintenance. *Journal of Physics Conference Series*, *2299*(1), 012001. https://doi.org/10.1088/1742-6596/2299/1/012001

Koene, I., Viitala, R., & Kuosmanen, P. (2019). Internet of Things Based Monitoring of Large Rotor Vibration With a Microelectromechanical Systems Accelerometer. *Ieee Access*, *7*, 92210–92219. https://doi.org/10.1109/access.2019.2927793

Neog, S., & Das, K. (2023). Predictive Maintenance Using Machine Learning With the Support From Smart Sensors and Supply Chain Management Using Blockchain. *Indian Journal of Science and Technology*, *16*(SP2), 70–75. https://doi.org/10.17485/ijst/v16isp2.8904

Nezirić, E., Isić, S., & Karabegović, I. (2022). Vibration Quantity Share of Multiple Faults With Similar Frequency Spectrum Characteristics in Rotational Machinery. *Periodica Polytechnica Mechanical Engineering*, *66*(3), 213–218. https://doi.org/10.3311/ppme.19117

Pundir, A. K. (2022). *Machine Learning Based Predictive Maintenance Model*. https://doi.org/10.46254/in02.20220528

Rahman, A., Hoque, Md. E., Rashid, F., Alam, F., & Ahmed, M. M. (2022). Health Condition Monitoring and Control of Vibrations of a Rotating System Through Vibration Analysis. *Journal of Sensors*, *2022*, 1–12. https://doi.org/10.1155/2022/4281596

Raja, H. A., Kudelina, K., Asad, B., Vaimann, T., Kallaste, A., Rassõlkin, A., & Khang, H. V. (2022). Signal Spectrum-Based Machine Learning Approach for Fault Prediction and Maintenance of Electrical Machines. *Energies*, *15*(24), 9507. https://doi.org/10.3390/en15249507

Romanssini, M., Aguirre, P. C. C. de, Severo, L. C., & Girardi, A. (2023a). A Review on Vibration Monitoring Techniques for Predictive Maintenance of Rotating Machinery. *Eng—Advances in Engineering*, *4*(3), 1797–1817. https://doi.org/10.3390/eng4030102

Romanssini, M., Aguirre, P. C. C. de, Severo, L. C., & Girardi, A. (2023b). A Review on Vibration Monitoring Techniques for Predictive Maintenance of Rotating Machinery. *Eng—Advances in Engineering*, *4*(3), 1797–1817. https://doi.org/10.3390/eng4030102

Salimi, A., Subaşı, M., Buldu, L., & Karataş, Ç. (2012). Prediction of Flow Length in Injection Molding for Engineering Plastics by Fuzzy Logic Under Different Processing Conditions. *Iranian Polymer Journal*, *22*(1), 33–41. https://doi.org/10.1007/s13726-012-0103-5

Silvestrin, L. P., Hoogendoorn, M., & Koole, G. (2019). *A Comparative Study of State-of-the-Art Machine Learning Algorithms for Predictive Maintenance*. https://doi.org/10.1109/ssci44817.2019.9003044

Tang, M., Liao, Y., Luo, F., & Li, X. (2022). A Novel Method for Fault Diagnosis of Rotating Machinery. *Entropy*, *24*(5), 681. https://doi.org/10.3390/e24050681

Tiddens, W. W., Braaksma, J., & Tinga, T. (2020). Exploring Predictive Maintenance Applications in Industry. *Journal of Quality in Maintenance Engineering*, *28*(1), 68–85. https://doi.org/10.1108/jqme-05-2020-0029

Wang, Y., & Zhao, Y. (2022). Multi-Scale Remaining Useful Life Prediction Using Long Short-Term Memory. *Sustainability*, *14*(23), 15667. https://doi.org/10.3390/su142315667

Xu, M., Han, Y., Sun, X., Shao, Y., Gu, F., & Ball, A. (2022a). Vibration Characteristics and Condition Monitoring of Internal Radial Clearance Within a Ball Bearing in a Gear-Shaft-Bearing System. *Mechanical Systems and Signal Processing*, *165*, 108280. https://doi.org/10.1016/j.ymssp.2021.108280

Xu, M., Han, Y., Sun, X., Shao, Y., Gu, F., & Ball, A. (2022b). Vibration Characteristics and Condition Monitoring of Internal Radial Clearance Within a Ball Bearing in a Gear-

Shaft-Bearing System. *Mechanical Systems and Signal Processing*, *165*, 108280. https://doi.org/10.1016/j.ymssp.2021.108280

Zhang, S., Zhang, S., Wang, B., & Habetler, T. G. (2020). Deep Learning Algorithms for Bearing Fault Diagnostics—A Comprehensive Review. *Ieee Access*, *8*, 29857–29881. https://doi.org/10.1109/access.2020.2972859

Zhou, S., Shi, J., Luo, Y., Shen, C., & Zhu, Z. (2022). Fault Severity Assessment for Rotating Machinery via Improved Lempel–Ziv Complexity Based on Variable-Step Multiscale Analysis and Equiprobable Space Partitioning. *Measurement Science and Technology*, *33*(5), 055018. https://doi.org/10.1088/1361-6501/ac50e8