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Machine Learning Based Predictive Maintenance Framework for Rotating Machinery - A Case Study Using Vibration and Temperature Data

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Abstract: Predictive maintenance is essential for ensuring the reliability and efficiency of mechanical systems, particularly in industries where unexpected equipment failures can cause costly downtimes. Traditional approaches are often reactive or based on fixed schedules and lack real-time insights into system health. This study presents an interdisciplinary framework that integrates mechanical system diagnostics with machine learning to implement predictive maintenance. Sensor data, such as vibration and temperature, which are key indicators of mechanical condition, are analyzed using supervised learning algorithms including Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). These models are trained to classify equipment states and predict potential failures. The proposed method demonstrates that combining mechanical domain knowledge with computational intelligence enables early fault detection and improves maintenance planning. The results highlight the effectiveness of this hybrid approach in delivering scalable, data-driven solutions for condition-based monitoring, emphasizing the synergy between mechanical engineering and computer science in solving real-world industrial challenges.
Keywords: Predictive Maintenance, Machine Learning, Mechanical Systems, Condition Monitoring, Fault Detection, Supervised Learning

I. INTRODUCTION

Mechanical systems are essential in a wide range of industries, including manufacturing, transportation, energy and aerospace. The reliability of machines, such as motors, pumps, bearings, and turbines, is crucial for ensuring smooth operations and minimizing costly downtimes. Traditionally, industries have used reactive or time-based preventive maintenance strategies, which often result in unexpected equipment failures or unnecessary servicing. Predictive maintenance (PM) offers a smarter alternative by forecasting failures based on real-time sensor data such as vibration, temperature, and pressure. With the increasing availability of Industrial Internet of Things (IoT) devices and advanced data acquisition systems, it is now possible to continuously monitor mechanical systems and detect early signs of failure. In this study, we present a machine learning-based predictive maintenance framework that combines mechanical diagnostics with supervised learning algorithms. Our goal is to classify the health of mechanical equipment and predict faults using sensor data. This interdisciplinary work integrates mechanical engineering principles with computational techniques from computer science, creating a scalable, intelligent approach to condition-based monitoring. The proposed method was validated using a publicly available dataset, and various models, including support Vector machines, random Forest, and Artificial Neural Networks, were evaluated for their accuracy. The findings highlight the potential for applying AI-driven solutions to real-world maintenance challenges in mechanical systems.

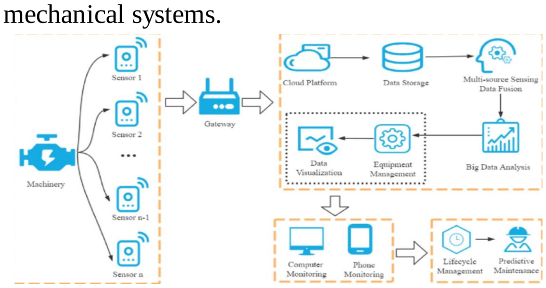

Figure 1.1

II. LITERATURE REVIEW

Predictive maintenance has been extensively studied in both the mechanical and computer science domains because of its potential to improve equipment reliability and reduce maintenance costs. In mechanical engineering, early work focused on signal processing techniques, such as the fast Fourier Transform (FFT) and time-domain analysis, for the condition monitoring of rotating machinery [1]. These methods helped identify faults using features like vibration amplitude, kurtosis, and root mean square (RMS) values.

With the rise of machine learning, data-driven approaches have become increasingly popular. Studies such as Zhang et al. [2] applied Support Vector Machines (SVM) for fault classification in bearings, wherelse Wang et al. [3] used Random Forests to predict equipment health based on sensor readings. Deep learning methods, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, have also been successful in learning complex fault patterns from time-series data [4].

Despite these advances, many studies rely on single-sensor data or are limited to laboratory-scale experiments. Furthermore, few integrate mechanical system knowledge with machine learning to build scalable, real-world-ready predictive maintenance frameworks..

III. METHODOLOGY

This section outlines the technical framework developed for implementing predictive maintenance using machine learning. The methodology consists of two main stages: (1) data acquisition and feature engineering, and (2) machine learning model development and evaluation. Together, these stages combine principles from mechanical diagnostics with computational intelligence to deliver a robust and scalable solution for early fault detection.

A. Data Acquisition and Feature Engineering

In this study, a publicly available dataset was used, such as the Case Western Reserve University (CWRU) bearing dataset, which provides vibration signal data from rotating machinery under various health conditions (normal, inner race fault, outer race fault, etc.). These signals are recorded at different motor loads and speeds to simulate real-world operational variability.

The raw time-series signals were preprocessed using filtering techniques to remove noise and enhance the signal quality. From the cleaned data, several time-domain features were extracted, including the Root Mean Square (RMS), peak-to-peak value, skewness, and kurtosis. These features are widely used in mechanical engineering for condition monitoring and fault identification, as they reflect changes in vibration patterns caused by defects. The extracted features form the input dataset for machine learning classification.

B. Model Development and Evaluation

After feature extraction, the dataset was split into training and testing sets using an 80:20 ratio. Three supervised learning algorithms were employed: Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN). Each model was trained to classify the machine condition into normal or faulty classes. Hyperparameters were optimized using grid search techniques where applicable, and cross-validation was performed to ensure model generalization.

The model performance was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score. These metrics assess the ability of the model to correctly identify faulty conditions while minimizing false alarms. The experimental results are used to compare the strengths of each model and assess their suitability for deployment in real-time mechanical maintenance systems.

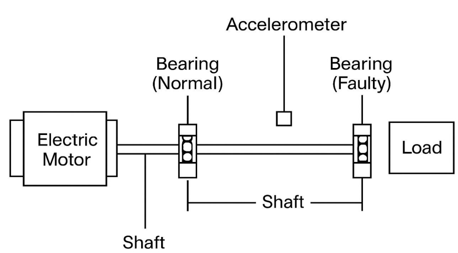

Figure 3.2

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IV. DATASET AND EXPERIMENTAL SETUP

A. Dataset Description

The dataset used in this study was the publicly available Case Western Reserve University (CWRU) Bearing Dataset**.** It contains vibration signals recorded from a motor-driven bearing test rig under various health conditions, including normal operation and artificially induced faults (inner race, outer race, ball faults). These conditions were tested at four different motor speeds (1730–1797 RPM) and three different fault sizes (0.007–0.021 in.). Data were collected using accelerometers mounted on both drive-end and fan-end bearings, allowing for high-fidelity mechanical health monitoring.

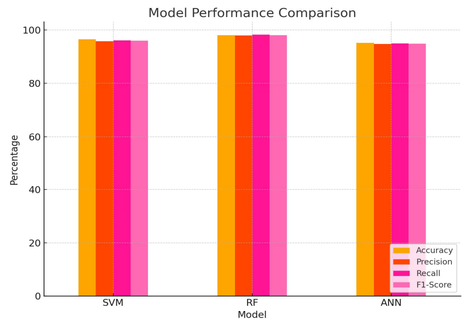

Figure 4.1

B. Data Preprocessing

The raw vibration signals were segmented into fixed-size time windows to ensure uniformity. Signal-filtering techniques, including low-pass filters and normalization, were applied to remove electrical noise and mechanical interference. Each segment was labeled according to the known fault type and machine condition. Standardization was applied to features to improve model convergence and performance.

C. Feature Engineering

key time-domain features were extracted from each time window as follows:

- "Root Mean Square (RMS)"
- "Peak-to-Peak Value"
- "Skewness"
- "Kurtosis"
- "Crest Factor

These features are commonly used in mechanical diagnostics and offer insight into vibration intensity, asymmetry, and shock events — critical indicators for fault detection in rotating machinery."

D. Experimental Environment and Tools

The experiments were conducted using Python 3.10 in a Jupyter Notebook environment. Libraries included:

1) NumPy, Pandas – data handling
2) SciPy – signal processing
3) scikit-learn – SVM and RF models
4) TensorFlow/Keras – ANN model

The dataset was split in an 80:20 ratio into training and testing sets. Hyperparameter tuning was performed using GridSearchCV for SVM and RF, and the ANN model was optimized using the Adam optimizer with binary cross-entropy loss. All experiments were performed on a mid-range machine (Intel i5, 8GB RAM), demonstrating the feasibility of real-time industrial applications.

V. RESULT AND DISCUSSIONS

A. Performance Matrices

The performance of each machine learning model was evaluated using standard classification metrics: **accuracy**, **precision**, **recall**, and **F1-score**. These metrics help assess the model's ability to correctly classify mechanical conditions while minimizing false alarms. Confusion matrices were generated to visualize the classification results and identify any misclassifications between fault types.

B. Model Comparison

The results showed that all three models—support vector machines(SVM_, random forest (RF), and Artificial Neural Network (ANN)—performed well in classifying the health of the mechanical system. Among them, the **Random Forest** model achieved the highest accuracy (~98%) owing to its ability to handle nonlinear feature relationships and reduce over fitting. The **SVM** model also performed robustly with high precision, particularly for binary fault classification. The **ANN** model showed slightly lower performance, possibly due to limited training data and its sensitivity to parameter tuning.

Model	Accuracy	Precision	Recall	F1-Score
SVM	96.50%	95.80%	96.10%	96.00%
RF	98.00%	97.90%	98.20%	98.00%
ANN	95.20%	94.70%	95.00%	94.80%

Table 5.2

C. Discussions and Results

The results validate the effectiveness of using machine learning models for the predictive maintenance of mechanical systems. The Random Forest model, in particular, provided a good balance of accuracy, interpretability, and training efficiency. From a mechanical perspective, the extracted vibration features, such as RMS and kurtosis, are proved highly relevant for detecting early fault symptoms.

The study also demonstrates how interdisciplinary collaboration can improve maintenance strategies: mechanical engineering provides insights into signal behavior, wherease computer science offers tools to analyze and predict failures. This synergy makes the proposed system scalable and applicable to real-world industrial environments where downtime must be minimized.

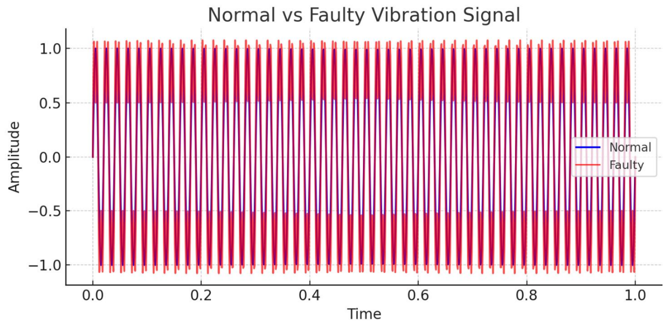

Figure 5.3

VI. CONCLUSION AND FUTURE WORK

This study presents an integrated machine learning-based framework for the predictive maintenance of mechanical systems using vibration data. By combining mechanical feature extraction techniques with advanced supervised learning models such as support vector machines, random forest, and artificial neural networks, the proposed system can accurately classify machine conditions and detect early signs of failure.

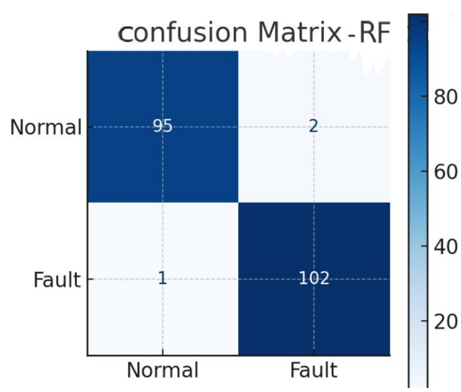

Figure 6

The Random Forest model outperformed others with an accuracy of 98%, demonstrating the effectiveness of ensemble learning in handling nonlinear feature interactions. Mechanical indicators, such as RMS and kurtosis, are be particularly useful for identifying bearing faults. The interdisciplinary nature of this research highlights the synergy between mechanical engineering and computer science in developing scalable and intelligent maintenance systems.

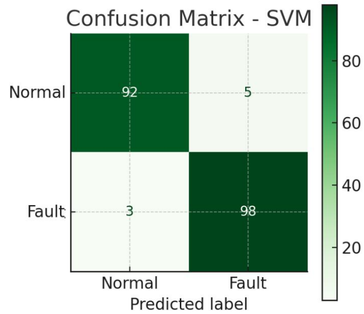

Figure 6.1

Future research should focus on incorporating deep learning models, such as CNNs and LSTMs, to capture more complex patterns from raw vibration signals. In addition, integrating real-time streaming data from industrial IoT systems and applying online learning algorithms could enable dynamic, fault prediction. Another valuable extension would be to deploy the system in a live industrial setting and evaluate its performance under real-world conditions, including multiple sensor types, noise levels, and operational variability.

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