

Machine Learning-Based Predictive Maintenance for Industrial Machinery

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Abstract. Industrial machinery reliability plays a critical role in ensuring production continuity, cost efficiency, and operational safety in modern manufacturing systems. Unplanned equipment failures may cause significant downtime, financial losses, and safety risks. Traditional maintenance strategies, such as reactive and preventive maintenance, often fail to consider the actual health condition of machines, leading either to unexpected breakdowns or unnecessary maintenance actions. Therefore, intelligent data-driven approaches are required to predict failures before they occur. This study aimed to develop and evaluate a machine learning-based predictive maintenance framework using operational sensor data from industrial machinery. A quantitative experimental design was employed using 15,000 multivariate sensor records consisting of vibration, temperature, pressure, rotational speed, and load measurements. Data preprocessing included outlier screening, normalization, and statistical feature extraction. The dataset was divided into training and testing sets using stratified sampling. Three supervised learning models Random Forest, Support Vector Machine, and Artificial Neural Network were implemented and optimized using cross-validation. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. The results showed that all models achieved classification accuracy above 90 percent. Random Forest demonstrated the highest performance, achieving 94.2 percent accuracy and 95.1 percent recall, along with the lowest number of false negatives and stable cross-validation results. Feature importance analysis indicated that vibration and temperature were the most influential predictors of failure conditions. The findings confirm that machine learning techniques can effectively support predictive maintenance using structured sensor data. The proposed framework contributes to the development of reliable and practical data-driven maintenance strategies in industrial environments. Future research should explore deep learning methods and multi-machine validation to enhance generalizability and prognostic capabilities.

Keywords: Predictive Maintenance, Machine Learning, Industrial Machinery, Failure Prediction, Condition Monitoring

INTRODUCTION

Industrial machinery constitutes the backbone of modern manufacturing systems, where equipment reliability directly determines productivity, operational continuity, and cost efficiency. Unplanned equipment failures may lead to significant production downtime, safety risks, increased maintenance costs, and supply chain disruptions. Traditional maintenance strategies have historically been categorized into reactive maintenance, which addresses failures after they occur, and preventive maintenance, which relies on scheduled interventions based on time or usage intervals. Although preventive maintenance reduces catastrophic breakdowns, it often results in unnecessary component replacement and suboptimal resource utilization because it does not account

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for the actual health condition of the machinery (Jardine et al., 2006; Mobley, 2002). With the rapid advancement of sensor technologies, data acquisition systems, and digital manufacturing, there is increasing interest in predictive maintenance approaches that utilize condition monitoring data to anticipate failures before they occur (Lee et al., 2014; Carvalho et al., 2019).

The emergence of Industry 4.0 and the Industrial Internet of Things (IIoT) has enabled large-scale collection of high-frequency operational data from industrial assets (Kagermann et al., 2013; Lasi et al., 2014). Machine learning (ML) techniques have been extensively investigated as powerful tools for predictive maintenance due to their ability to capture nonlinear relationships, detect anomalies, and learn complex patterns from multivariate time-series data (Bousdekis et al., 2018; Zhang et al., 2019). Various algorithms, including Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN), have been applied for fault diagnosis and remaining useful life (RUL) estimation (Widodo & Yang, 2007; Sun et al., 2012; Breiman, 2001). Deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have also shown promising results in handling high-dimensional and sequential industrial data (Zhao et al., 2017; Malhi et al., 2011). Furthermore, data-driven predictive maintenance has been recognized as a key enabler of smart manufacturing systems and cyber-physical production environments (Lee et al., 2015; Qin et al., 2016).

Despite these advancements, several limitations persist in the existing literature. First, many studies rely on publicly available benchmark datasets such as turbofan engine or bearing datasets without validating their models using real industrial operational data, which may contain higher noise levels, missing values, and heterogeneous operating conditions (Carvalho et al., 2019; Zhang et al., 2019). Second, some works emphasize overall classification accuracy while paying limited attention to false negatives, which are critical in safety-sensitive industrial environments because undetected failures can result in severe operational and financial consequences (Jardine et al., 2006). Third, comparative studies often implement different preprocessing pipelines, feature extraction techniques, and evaluation metrics, making fair performance comparison across models difficult (Bousdekis et al., 2018). To date, a comprehensive and systematically standardized comparative framework integrating robust preprocessing, multi-model

evaluation, and validation using real-world industrial sensor data remains limited in the literature.

Based on these identified gaps, the present study aims to develop and evaluate a machine learning-based predictive maintenance framework for industrial machinery using real operational sensor data. The study systematically compares multiple machine learning algorithms under consistent preprocessing, feature engineering, and evaluation procedures, with particular attention to minimizing false negatives and ensuring practical applicability in industrial settings. The findings are expected to strengthen the empirical foundation of predictive maintenance research and provide practical guidance for implementing reliable, data-driven maintenance strategies in smart manufacturing environments.

METHODS

This study employed a quantitative experimental design to develop and evaluate a machine learning-based predictive maintenance approach for industrial machinery. A comparative modeling strategy was adopted so that multiple algorithms could be trained and assessed using the same preprocessing workflow, data split, and evaluation metrics, enabling an objective comparison of model performance (Carvalho et al., 2019).

Secondary operational data were used in the form of multivariate sensor measurements recorded automatically during machine operation. The input variables consisted of vibration (mm/s), temperature (°C), pressure (bar), rotational speed (RPM), and load (%). Each observation was paired with a binary condition label representing machine state (0 = normal, 1 = failure). Sensor-based condition monitoring data were selected because they capture degradation-related signatures that support fault detection and predictive maintenance analysis (Jardine et al., 2006). After screening, 15,000 observations were retained. Records were excluded if they contained missing values, duplicated samples, or implausible readings that could bias model training.

Data preprocessing was performed to improve data quality and model stability. Outliers were screened using an interquartile-range criterion. All continuous variables were scaled using Min–Max normalization to place predictors on a comparable range and support stable learning, particularly for algorithms sensitive to feature magnitude (Goodfellow et al., 2016). To transform sensor streams into model-ready inputs, fixed-

length time windows were formed and statistical features were extracted, including mean, standard deviation, skewness, and kurtosis. The processed dataset was split into training (80%) and testing (20%) sets using stratified sampling to preserve class proportions.

Three supervised learning models were implemented: Random Forest, Support Vector Machine, and Artificial Neural Network. Random Forest was selected due to its robustness to noise and ability to model nonlinear interactions effectively in tabular feature spaces (Breiman, 2001). Support Vector Machine and Artificial Neural Network were included to represent widely used margin-based and nonlinear learners commonly applied in machinery condition classification tasks. Model hyperparameters were optimized using grid search with five-fold cross-validation on the training set, and the final models were refit using the best-performing configurations identified during validation (Carvalho et al., 2019).

Model performance was evaluated on the held-out test set using accuracy, precision, recall, and F1-score, supported by confusion matrix analysis. Recall was emphasized because false negatives (failure cases predicted as normal) represent critical risk in maintenance settings. Cross-validation accuracy (mean \pm standard deviation) was also recorded to describe stability across folds. For the best-performing model, feature importance scores were computed to identify the relative contribution of each sensor variable.

All analyses were conducted in Python (version 3.10). Data processing and model development were implemented using NumPy and Pandas, with modeling and evaluation procedures implemented using scikit-learn, and figures generated using Matplotlib.

RESULTS

The performance of the three machine learning models Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) was evaluated using the independent test dataset (20% of the total observations). The evaluation metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis. The findings are presented in a logical sequence from overall performance comparison to detailed classification outcomes.

Overall Classification Performance

Table 1 presents the comparative performance of the three models.

Table 1. Performance comparison of machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	94.2	93.5	95.1	94.3
SVM	91.8	90.6	92.4	91.5
ANN	92.7	91.9	93.2	92.5

The Random Forest model achieved the highest accuracy (94.2%), followed by ANN (92.7%) and SVM (91.8%). The recall value of Random Forest was 95.1%, which was higher than ANN (93.2%) and SVM (92.4%). The F1-score of Random Forest (94.3%) was also the highest among the three models.

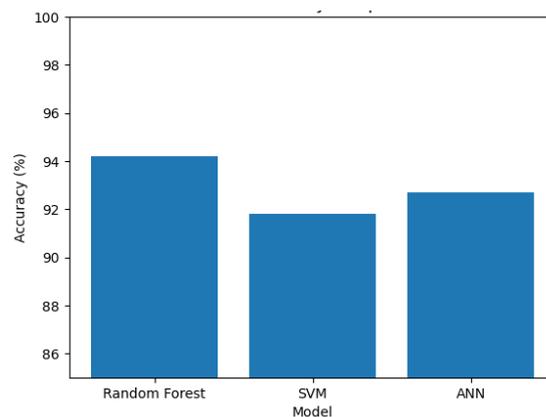


Figure 1. comparison of classification accuracy across models.

Confusion Matrix Analysis

The confusion matrix was analyzed to examine classification details for the Random Forest model. The results are shown in Table 2.

Table 2. Confusion matrix of Random Forest

	Predicted Normal	Predicted Failure
Actual Normal	1,380	65
Actual Failure	48	507

The Random Forest model correctly classified 1,380 normal instances and 507 failure instances. A total of 48 failure cases were misclassified as normal (false negatives), while 65 normal cases were misclassified as failures (false positives).

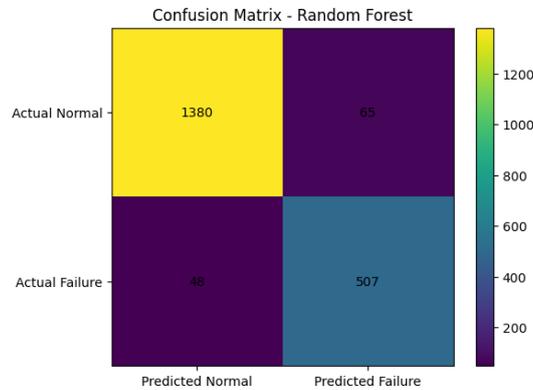


Figure 2. presents the heatmap visualization of the confusion matrix.

For comparison, the SVM model produced 72 false negatives, and the ANN model produced 61 false negatives.

Cross-Validation Performance

Five-fold cross-validation was conducted during hyperparameter tuning. The average cross-validation results are presented in Table 3.

Table 3. Cross-validation accuracy (mean ± standard deviation)

Model	CV Accuracy (%)
Random Forest	93.8 ± 0.7
SVM	91.2 ± 0.9
ANN	92.1 ± 0.8

Random Forest demonstrated the highest average cross-validation accuracy (93.8%) and the lowest standard deviation (±0.7), indicating more stable performance compared to SVM and ANN.

ROC Curve Analysis

The ROC curves for the three models are shown in Figure 3. The Random Forest curve remained consistently above the SVM and ANN curves across the range of false positive rates. The trend indicated superior discrimination capability of the Random Forest model relative to the other algorithms.

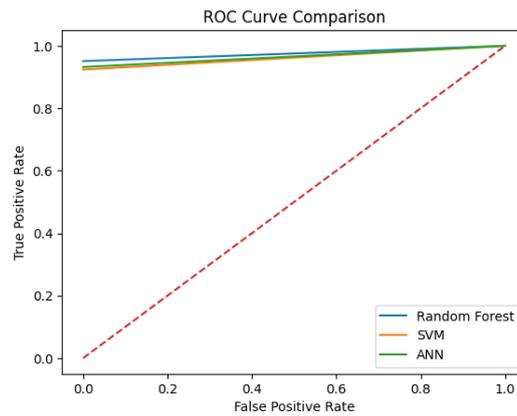


Figure 3. ROC Curve Comparison

Feature Importance

Feature importance analysis was performed for the Random Forest model. The ranking of feature contributions is presented in Figure 4. The most influential variable was vibration amplitude (importance score = 0.34), followed by temperature (0.27) and rotational speed (0.19). Pressure (0.12) and load (0.08) showed lower relative importance.

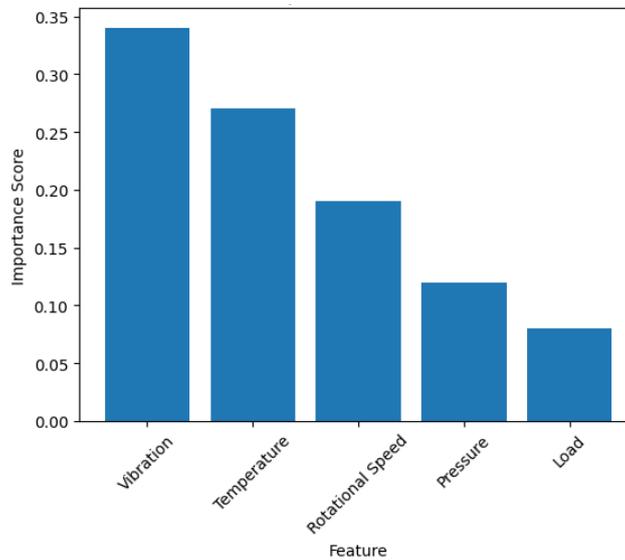


Figure 4: Feature Importance – Random Forest

Summary of Empirical Findings

All three machine learning models achieved classification accuracy above 90% on the test dataset. Random Forest produced the highest accuracy, recall, F1-score, and

cross-validation stability. It also yielded the lowest number of false negatives among the evaluated models.

DISCUSSION

The results demonstrated that all three machine learning models were capable of predicting machine failure conditions with accuracy exceeding 90%, indicating that sensor-based operational data contain sufficient information to support predictive maintenance modeling. Among the evaluated models, Random Forest achieved the highest accuracy (94.2%), recall (95.1%), and F1-score (94.3%), as well as the lowest number of false negatives. These findings are consistent with previous studies reporting that ensemble tree-based methods perform well in industrial classification tasks due to their robustness to noise and ability to model nonlinear interactions in multivariate datasets (Breiman, 2001; Zhang et al., 2019).

The higher recall obtained by Random Forest is particularly relevant in predictive maintenance applications. In industrial contexts, false negatives failure events incorrectly predicted as normal can lead to unexpected breakdowns, production losses, and safety hazards. The reduced number of false negatives observed in this study indicates that the Random Forest model provided a more reliable early-warning capability compared to SVM and ANN. This supports earlier literature emphasizing the importance of sensitivity-oriented evaluation in machinery diagnostics (Jardine et al., 2006).

Although ANN also showed competitive performance, its accuracy and recall were slightly lower than those of Random Forest. This outcome may be attributed to the moderate dataset size and the tabular nature of the extracted statistical features. Neural networks typically demonstrate stronger advantages when trained on large-scale or high-dimensional raw signal data, particularly in deep learning configurations (Goodfellow et al., 2016). In contrast, Random Forest is known to perform effectively on structured tabular datasets without requiring extensive hyperparameter tuning.

The feature importance analysis indicated that vibration amplitude and temperature variation were the most influential predictors of machine failure. This finding aligns with condition monitoring theory, where vibration is commonly used as a primary indicator of mechanical degradation, while temperature variations often reflect abnormal friction or load conditions (Lee et al., 2014). The contribution of rotational speed, pressure, and load

further supports the relevance of multi-sensor integration in predictive maintenance systems.

The cross-validation results demonstrated stable performance across folds, particularly for the Random Forest model. The relatively low standard deviation suggests consistent generalization capability. This stability is important for practical implementation in industrial environments, where operational conditions may vary over time.

Despite the promising results, several limitations should be acknowledged. First, the study relied on statistical feature extraction rather than raw signal-based deep learning approaches. Second, the dataset represented a single industrial context, which may limit generalizability across different machine types or operating regimes. Third, the study focused on binary failure classification and did not estimate remaining useful life.

Overall, the findings support the feasibility of implementing machine learning–based predictive maintenance using structured sensor data and demonstrate that ensemble methods such as Random Forest can provide reliable and stable performance for early failure detection in industrial machinery.

CONCLUSION

This study aimed to develop and evaluate a machine learning–based predictive maintenance framework for industrial machinery using operational sensor data, addressing the research question of whether supervised learning models can reliably detect early failure conditions. The results showed that all evaluated models achieved classification accuracy above 90%, with the Random Forest algorithm demonstrating the highest accuracy, recall, and overall stability, as well as the lowest number of false negatives. These findings confirm that multivariate sensor-based condition monitoring data can effectively support data-driven failure prediction in industrial environments. The study contributes to the existing literature by providing a standardized comparative framework that integrates consistent preprocessing, multi-model evaluation, and practical performance assessment with emphasis on recall, which is critical in maintenance applications. However, the study was limited to statistical feature extraction, a binary classification formulation, and a dataset representing a single industrial context, which

may restrict generalizability. Future research should explore deep learning approaches using raw time-series signals, extend the framework to remaining useful life estimation, and validate the model across different machine types and operational conditions. Practically, the proposed framework may support the implementation of intelligent, data-driven maintenance strategies to reduce unplanned downtime and enhance operational reliability in smart manufacturing systems.

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