

Hybrid Machine Learning Framework for Predictive Maintenance in Smart Manufacturing Using Sensors

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Abstract

Predictive maintenance has become an essential component of smart manufacturing systems for reducing unexpected equipment failures and improving operational efficiency. This study presents a hybrid machine learning framework for predictive maintenance using sensor-based machine operational data. The dataset consists of 5,000 machine operating records collected from sensor monitoring systems, including parameters such as operating hours, temperature, vibration, pressure, humidity, and machine load. A Random Forest model is first applied to analyze feature importance and identify the most influential parameters associated with machine failure. Subsequently, an Artificial Neural Network (ANN) model is employed to predict machine failure conditions based on the selected operational features. The dataset is divided into training and testing subsets using an 80–20 split to evaluate the predictive capability of the model. Experimental results indicate that load percentage and operating hours are the most influential factors affecting machine failure, followed by vibration and pressure. The proposed framework achieved an overall prediction accuracy of 84.5%. Although failure events represent a small portion of the dataset, the developed system demonstrates the capability to identify potential machine degradation patterns and support data-driven maintenance planning. The results highlight the potential of hybrid machine learning approaches for improving predictive maintenance decision-making in smart manufacturing environments.

Keywords

Predictive maintenance, Machine learning, Smart manufacturing, Sensor data, and Failure prediction.

1. Introduction

The rapid development of Industry 4.0 technologies has significantly transformed modern manufacturing systems by integrating advanced sensing, automation, and data analytics into production environments (Payel et al. 2023). Smart

manufacturing relies heavily on interconnected machines, sensors, and digital monitoring systems that continuously collect operational data from industrial equipment. This digital transformation enables manufacturing systems to operate more efficiently, improve product quality, and reduce operational costs. However, despite these advancements, unexpected machine failures remain a major challenge in industrial environments, often leading to production downtime, maintenance costs, and disruptions in supply chains.

Maintenance strategies play a crucial role in ensuring the reliability and efficiency of manufacturing systems (Yazdi 2024). Traditionally, industries have relied on reactive maintenance, where repairs are performed only after equipment failure occurs (Farhan et al. 2023). Although this approach requires minimal planning, it often results in unplanned downtime and high repair costs. Another commonly used strategy is preventive maintenance, where maintenance activities are scheduled at regular intervals regardless of the actual condition of the equipment. While preventive maintenance can reduce sudden failures, it may also lead to unnecessary maintenance operations and inefficient resource utilization.

In recent years, predictive maintenance has emerged as an effective solution for improving equipment reliability in smart manufacturing environments. Predictive maintenance utilizes real-time machine data, sensor signals, and historical operational records to predict potential failures before they occur. By identifying early signs of machine degradation, predictive maintenance enables maintenance teams to take proactive actions, thereby minimizing downtime and optimizing maintenance schedules. The availability of large volumes of industrial sensor data has made predictive maintenance increasingly feasible and valuable for modern manufacturing systems.

Machine learning (ML) techniques have become a powerful tool for analyzing complex industrial datasets and detecting hidden patterns associated with equipment failures. Various machine learning models, including support vector machines, decision trees, random forests, and neural networks, have been widely applied to predictive maintenance problems. These models can learn from historical machine behavior and identify relationships between operational parameters such as temperature, vibration, pressure, and machine load with the likelihood of equipment failure. Consequently, machine learning-based predictive maintenance systems can significantly enhance the ability of manufacturing organizations to monitor machine health and prevent unexpected breakdowns.

Despite the advantages of individual machine learning models, relying on a single model may limit prediction performance due to the complexity and variability of industrial operating conditions (Kapp et al. 2023). Different machine learning algorithms possess unique strengths in handling nonlinear relationships, feature interactions, and large datasets. Therefore, combining multiple models through a hybrid machine learning approach can improve prediction accuracy and robustness by leveraging the complementary strengths of different algorithms. Hybrid models have demonstrated promising results in various industrial applications where accurate failure prediction and decision support are critical.

In addition to failure prediction, manufacturing systems require practical decision-support mechanisms that translate model predictions into actionable maintenance strategies (Rosati et al. 2023). A predictive maintenance decision system can assist engineers and plant managers by identifying machines at risk, generating maintenance alerts, and prioritizing inspection activities. Such systems are particularly valuable in smart manufacturing environments where numerous machines operate simultaneously and manual monitoring becomes increasingly difficult.

Motivated by these challenges, this study proposes a hybrid machine learning-based predictive maintenance decision system for smart manufacturing environments. The proposed framework analyzes machine operational data obtained from multiple sensors and applies machine learning techniques to detect potential failure conditions. A hybrid modeling approach is employed to improve prediction reliability and support maintenance decision-making. The developed system aims to provide early warning signals for equipment degradation and assist maintenance teams in planning timely interventions.

The main contribution of this study is the development of a hybrid machine learning framework that integrates Random Forest-based feature analysis with neural network-based failure prediction for predictive maintenance decision support. The proposed approach demonstrates how sensor-based machine operational data can be effectively

utilized to identify potential failure conditions and support data-driven maintenance planning in smart manufacturing environments.

The remainder of this paper is organized as follows. Section 2 reviews existing literature. Section 3 describes the dataset and the proposed hybrid machine learning methodology. Section 4 presents the experimental results and performance evaluation. Section 5 discusses the implications of the proposed system for smart manufacturing environments, and Section 6 concludes the paper with recommendations for future research.

1.1 Objectives

The specific objectives of this study are:

- a. To analyze sensor-based machine operational data for identifying failure-related patterns.
- b. To develop a hybrid machine learning framework combining Random Forest-based feature analysis and neural network-based failure prediction.
- c. To support data-driven predictive maintenance decision-making in smart manufacturing environments.

2. Literature Review

Recent studies have emphasized the importance of data-driven maintenance in improving industrial reliability and operational performance. Yazdi (2024) discussed maintenance optimization techniques and highlighted the need for systematic maintenance planning in complex industrial systems. Farhan et al. (2023) applied a combined SWARA-FMEA approach for analyzing failure modes in engine-based power plants, showing the usefulness of structured failure analysis in maintenance decision-making.

With the growth of sensor-based monitoring, predictive maintenance has increasingly depended on effective data preprocessing and intelligent analysis. Bekar et al. (2020) demonstrated that proper data preprocessing is essential for improving predictive maintenance performance in industrial applications. Rosati et al. (2023) further showed that IoT and machine learning-based decision support systems can improve predictive maintenance by transforming operational data into useful maintenance insights.

Machine learning models have been widely used for prediction and classification tasks in engineering systems. Zhou et al. (2023) compared regression-based and machine learning approaches and showed the capability of advanced models to handle complex data patterns. Kapp et al. (2023) also demonstrated that machine learning models can improve prediction performance when supported by relevant physical system parameters.

However, rare failure detection remains a major challenge in predictive maintenance because failure cases are often much fewer than normal operating conditions. Dangut et al. (2023) addressed this issue using a deep hybrid learning approach for aircraft predictive maintenance. Belgacem and Chihi (2025) also emphasized the importance of reliable sensor systems for fault diagnosis and mitigation. These studies indicate that hybrid machine learning approaches can improve predictive maintenance systems by combining feature analysis, failure prediction, and decision-support capabilities.

3. Methods

3.1 Data Collection

The operational dataset was collected from sensor monitoring systems installed on rotating production equipment operating in a pharmaceutical manufacturing line. Machine operating conditions were recorded at regular monitoring intervals. Failure labels were assigned based on maintenance logs indicating abnormal operating behavior or maintenance intervention requirements.

The dataset includes several important machine condition variables, including operating hours, machine temperature, vibration level, internal system pressure, environmental humidity, and machine load percentage. These parameters are commonly monitored in smart manufacturing systems because they are directly associated with equipment performance and mechanical degradation. For example, abnormal vibration levels may indicate mechanical imbalance or bearing wear, while excessive temperature or pressure may signal potential system overload or malfunction.

Each record in the dataset corresponds to the operating condition of a specific machine at a particular time. In addition to the operational parameters, the dataset also includes a binary failure indicator representing the machine condition status. A value of 0 represents normal machine operation, while a value of 1 indicates a potential failure or maintenance

requirement. The dataset contains observations from multiple machines, allowing the model to learn patterns associated with different operating behaviors and failure conditions. A sample of the machine operational dataset used in this study is presented in Table 1. The dataset used in this study consists of 5,000 machine operational observations, where each record represents the operating condition of a machine at a specific time instance.

Table 1. Sample records from the operational dataset

Machine ID	Operating Hours	Temperature (°C)	Vibration (mm/s)	Pressure (bar)	Humidity (%)	Load (%)	Failure
M01	2150	72.4	2.9	31.2	44	68	0
M07	6180	91.5	4.7	42.3	47	93	1
M13	3895	79.2	3.6	34.1	42	76	0
M04	7050	94.8	5.1	43.6	49	96	1
M19	1450	68.7	2.5	29.7	40	61	0

3.2 Data Preprocessing

Before applying machine learning models, the dataset undergoes several preprocessing steps to improve model performance and ensure data consistency. Data preprocessing is an essential stage in predictive maintenance studies because industrial datasets often contain noise, scale differences among variables, and complex relationships between parameters (Bekar et al. 2020).

First, the dataset is inspected to identify missing values and abnormal entries. Any incomplete records are handled appropriately to ensure data quality. Next, numerical features such as temperature, vibration, pressure, humidity, and machine load are normalized to reduce scale differences among variables. Feature normalization helps machine learning models converge more efficiently and improves prediction accuracy.

Following normalization, the dataset is divided into two subsets: a training dataset and a testing dataset. The training dataset is used to build the predictive model, while the testing dataset is used to evaluate the model's performance on unseen data. Before model training, the dataset was randomly divided into training and testing subsets, where 80% of the data were used for training the machine-learning models and the remaining 20% were reserved for testing and performance evaluation. This separation helps ensure that the developed model can generalize effectively to new machine operating conditions.

3.3 Hybrid Machine Learning Model

To improve prediction accuracy and robustness, this study employs a hybrid machine learning framework combining Random Forest-based feature analysis and neural network prediction. Hybrid modeling is particularly useful in industrial applications because different algorithms can capture different patterns within complex operational datasets.

In the proposed framework, a Random Forest model is first applied to analyze feature importance and identify the most influential variables associated with machine failure. Random Forest is well suited for this task because it can handle nonlinear relationships and interactions among multiple variables while providing reliable feature ranking (Zhou et al. 2023).

After determining the most relevant features, a neural network-based classification model is used to predict the probability of machine failure. Neural networks are capable of capturing complex nonlinear relationships between machine operational parameters and failure conditions. By combining the strengths of Random Forest feature selection and neural network prediction, the hybrid approach improves model interpretability and predictive capability.

The Artificial Neural Network used in this study consists of one hidden layer with 32 neurons using ReLU activation, while the output layer employs a sigmoid activation function for binary classification, and the model was trained using the Adam optimizer with a learning rate of 0.001 for 50 epochs.

The hybrid model processes machine sensor data and produces a probability score representing the likelihood of machine failure. This probability score serves as the basis for the maintenance decision system.

In this study, the predictive maintenance task is formulated as a binary classification problem, where machine operational parameters are used to predict whether a machine is operating normally or approaching a potential failure condition.

Predictive maintenance formulation is as (1),

$$y = f(X) \quad (1)$$

Where, $X = [x_1, x_2, \dots, x_n]$ represents machine operational parameters, and y represents machine condition (failure or normal).

Feature vector representation is as (2),

$$X = [OH, T, V, P, H, L] \quad (2)$$

Where, OH = Operating hours, T = Temperature, V = Vibration, P = Pressure, H = Humidity, L = Machine load.

Hybrid prediction probability is as (3),

$$P(Failure) = g(f_{RF}(X)) \quad (3)$$

Where, $f_{RF}(X)$ represents feature selection using Random Forest, $g(.)$ represents prediction using the Neural Network model, $P(Failure)$ indicates the probability of machine failure.

3.4 Maintenance Decision System

The final stage of the methodology involves converting model predictions into actionable maintenance decisions. The predictive maintenance decision system categorizes machine conditions into three operational states based on the predicted failure probability.

Machines with low predicted failure probability are classified as operating under normal conditions. Machines with moderate risk levels are labeled as warning conditions, indicating that maintenance inspection may be required soon. Machines with high predicted failure probability are classified as requiring immediate maintenance intervention.

Decision rule equation is as (4),

$$D = \begin{cases} \text{Normal,} & P(Failure) < \theta_1 \\ \text{Warning,} & \theta_1 \leq P(Failure) < \theta_2 \\ \text{Maintenance Required,} & P(Failure) \geq \theta_2 \end{cases} \quad (4)$$

Where D represents the maintenance decision, $P(Failure)$ denotes the predicted probability of machine failure, and θ_1 and θ_2 are predefined decision thresholds used to classify machine operating conditions.

In this study, the threshold values were empirically set as $\theta_1 = 0.3$ and $\theta_2 = 0.6$ to categorize machine operating conditions into normal, warning, and maintenance-required states.

4. Results

4.1 Dataset Overview and Class Distribution

The dataset used in this study contains 5,000 machine operational observations with seven input variables describing machine operating conditions (see Table 2). Each record represents the operational state of a machine monitored through multiple sensors. The target variable indicates whether the machine is operating normally or experiencing a failure condition.

Table 2. Dataset overview

Metric	Value
Total Records	5000
Input Features	6
Normal Operation	4772
Failure Condition	228

The distribution of machine operating conditions shows that the majority of observations correspond to normal operating conditions, while a smaller portion represents failure states.

4.2 Descriptive Statistical Analysis

Descriptive statistics were computed to understand the operational ranges of machine parameters in the dataset. The analysis summarizes the central tendency and variability of the monitored variables, including operating hours, temperature, vibration, pressure, humidity, and machine load. These statistics provide an overview of machine operating conditions and help identify the general behavior of the monitored equipment (see Table 3).

Table 3. Descriptive statistics of operational parameters

Parameter	Mean	Std. Dev.	Min	Max
Operating Hours	4015.54	2279.87	51	7998
Temperature (°C)	71.92	11.15	29.8	110.82
Vibration (mm/s)	3.2	1.1	0.01	7.52
Pressure (bar)	31.04	5.46	12.1	52.73
Humidity (%)	45.89	8.89	11.29	78.5
Load (%)	67.33	18.73	35	99.99

The statistical results indicate that machine operating conditions vary considerably across observations, particularly in operating hours and load levels. Such variability provides sufficient information for machine learning models to identify patterns associated with machine degradation and potential failure conditions.

4.3 Correlation Analysis of Parameters

Correlation analysis was conducted using the Pearson correlation coefficient to examine the relationships between machine operational parameters and the failure condition. The analysis considered six operational variables: operating hours, temperature, vibration, pressure, humidity, and load.

Figure 1 presents the correlation matrix of the selected variables. The results show that operating hours and load percentage exhibit the strongest positive relationships with the failure variable, indicating that machines operating for longer durations and under higher loads are more likely to experience failure conditions. Vibration, temperature, and pressure also demonstrate moderate positive associations with failure, suggesting that abnormal mechanical conditions contribute to equipment degradation. In contrast, humidity shows a weak relationship with the failure variable, indicating limited influence on machine failure in the analyzed dataset.

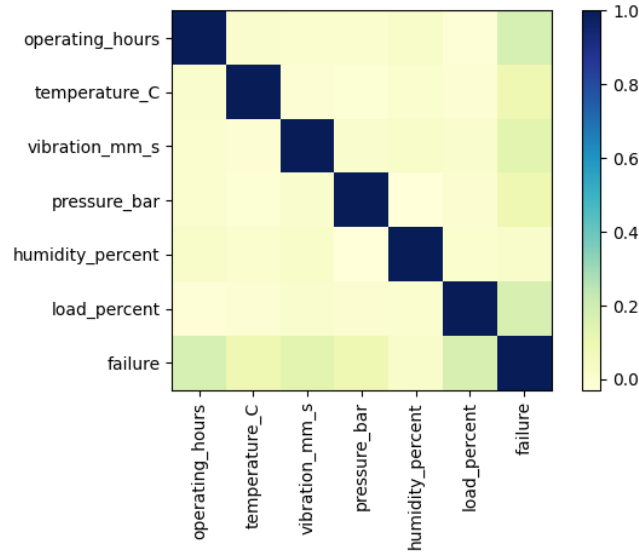


Figure 1. Correlation matrix of machine operational parameters

These relationships provide a preliminary indication of the operational parameters that are most relevant for predictive maintenance modeling and support the feature analysis performed in the subsequent subsection.

4.4 Feature Importance Analysis

Feature importance analysis was conducted using the Random Forest model to identify the machine parameters that most influence failure prediction. The model evaluates the contribution of each feature in reducing classification error across decision trees.

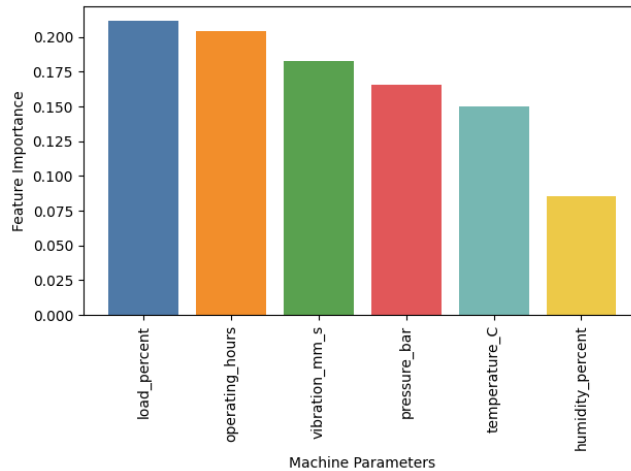


Figure 2. Feature importance of machine operational parameters obtained from the Random Forest model

The resulting importance scores are presented in Figure 2. The analysis indicates that load percent (0.2116) and operating hours (0.2044) are the most influential variables in predicting machine failure. These are followed by vibration level (0.1827) and pressure (0.1655), which also contribute significantly to the prediction process. Temperature shows moderate importance with a score of 0.1501, while humidity exhibits the lowest influence with an importance value of 0.0857 among the monitored parameters. These results indicate that machine operational stress factors, particularly high load conditions and extended operating durations, play the most significant role in predicting potential failure events.

4.5 Model Performance Evaluation

To evaluate the predictive capability of the proposed system, the dataset was divided into training (80%) and testing (20%) subsets. The Artificial Neural Network (ANN) model was trained using the training dataset and evaluated on the

unseen testing dataset. The performance of the model was assessed using standard classification metrics including accuracy, precision, recall, and F1-score (see Table 4).

Table 4. Performance evaluation of the predictive maintenance model

Metric	Value
Accuracy	0.845
Precision	0.0703
Recall	0.2
F1-score	0.104

The model achieved an overall accuracy of 84.5%. Considering the strong class imbalance in the dataset, the obtained accuracy indicates that the model can effectively distinguish general machine operating conditions while still identifying a portion of rare failure events. However, the relatively low precision and recall values indicate the inherent difficulty of predicting rare failure events in machine monitoring datasets.

4.6 Confusion Matrix and Prediction Performance

The classification performance of the predictive maintenance model was further analyzed using a confusion matrix. The confusion matrix presents the number of correctly and incorrectly classified instances for both normal operating conditions and machine failure cases.

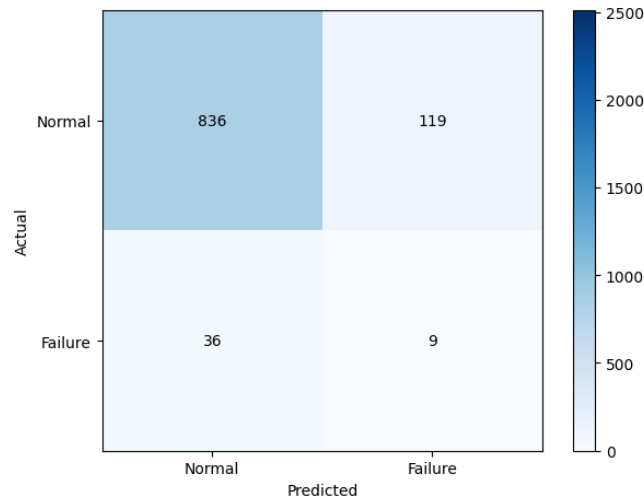


Figure 3. Confusion matrix of the predictive maintenance model

The model correctly classified 836 normal operating conditions, while 119 normal instances were incorrectly predicted as failure. For the failure class, the model correctly detected 9 failure cases, whereas 36 failure instances were misclassified as normal operation (see Figure 3).

These results indicate that the model is highly effective in identifying normal machine operating conditions but faces greater difficulty in detecting relatively rare failure events. This behavior is typical in predictive maintenance datasets where failure occurrences are significantly fewer than normal operational observations.

4.7 Maintenance Decision Interpretation

The predicted failure probabilities generated by the hybrid machine learning model were used to support maintenance decision-making through the predefined decision rule. Based on the predicted probability of failure, machine operating conditions were categorized into three states: normal operation, warning condition, and maintenance required.

Machines with low predicted failure probability are considered to be operating under normal conditions and do not require immediate intervention. When the predicted probability falls within the warning threshold range, the system indicates a potential risk of degradation and recommends inspection or preventive maintenance scheduling. Machines with high predicted failure probability are classified as requiring immediate maintenance action to prevent unexpected breakdowns.

This decision framework allows maintenance engineers to prioritize equipment inspection and allocate maintenance resources more effectively. By translating machine learning predictions into actionable maintenance categories, the proposed system supports data-driven maintenance planning in smart manufacturing environments.

5. Discussion

The results obtained from the predictive maintenance framework demonstrate the potential of machine learning techniques for supporting data-driven maintenance decisions in smart manufacturing environments. The analysis conducted in this study reveals several important insights regarding machine operational behavior, feature influence, and the effectiveness of predictive modeling for identifying potential equipment failure conditions.

The statistical and correlation analyses provide an initial understanding of the relationships between machine operational parameters and failure conditions. The correlation matrix indicates that operating hours and machine load exhibit the strongest relationships with machine failure, suggesting that prolonged machine operation and high workload conditions are key contributors to equipment degradation. This observation is consistent with typical industrial scenarios where mechanical components gradually deteriorate due to sustained operational stress and continuous usage. The correlation analysis also shows that vibration, temperature, and pressure exhibit moderate associations with failure conditions, reflecting the fact that abnormal mechanical behavior and thermal stress often precede equipment malfunction.

The feature importance analysis further confirms the influence of these parameters on predictive maintenance modeling. The Random Forest model identified load percent (0.2116) and operating hours (0.2044) as the most influential variables, indicating that operational stress factors play a major role in predicting machine failure events. These results highlight the significance of monitoring machine workload and usage duration in predictive maintenance systems. In addition, vibration (0.1827) and pressure (0.1655) also contribute significantly to the prediction process, suggesting that mechanical condition indicators are important signals for identifying early degradation patterns. Temperature (0.1501) demonstrates moderate importance, while humidity (0.0857) shows relatively limited influence in predicting machine failure in the analyzed dataset. These findings suggest that internal mechanical and operational conditions have a stronger impact on machine failure compared to environmental factors.

The predictive modeling results provide additional insights into the performance of the hybrid machine learning framework. The Artificial Neural Network model achieved an overall classification accuracy of 84.5%, indicating that the model can effectively distinguish between normal and abnormal machine operating conditions. However, a closer examination of the evaluation metrics and confusion matrix reveals that the model performs significantly better in identifying normal machine operation than in detecting failure events. This behavior is largely influenced by the imbalance in the dataset, where failure observations represent a relatively small portion of the total dataset. Such class imbalance is common in industrial monitoring systems because equipment typically operates normally for long periods before experiencing occasional failure events (Belgacem and Chihi 2025).

The confusion matrix results show that the model correctly classified 836 normal operating instances, while 119 normal observations were incorrectly predicted as failures. For the failure class, the model successfully identified 9 failure events, whereas 36 failure cases were misclassified as normal operation. These results indicate that although the model demonstrates strong performance in recognizing normal operating conditions, detecting rare failure events remains challenging in predictive maintenance datasets due to the limited availability of failure samples (Dangut et al. 2023). This limitation is commonly observed in predictive maintenance studies where failure occurrences are relatively infrequent compared to normal machine operation.

The relatively low recall value for failure prediction is primarily influenced by the imbalance in the dataset, where failure observations represent a small proportion of the total samples. Such imbalance is common in industrial monitoring datasets. Future studies may improve failure detection performance through techniques such as data resampling, Synthetic Minority Oversampling Technique (SMOTE), or cost-sensitive learning approaches.

Despite these challenges, the predictive maintenance decision framework proposed in this study provides a useful foundation for supporting maintenance planning in smart manufacturing environments. By integrating machine operational monitoring with machine learning-based prediction, the system enables maintenance teams to identify potential degradation patterns and prioritize equipment inspection activities. The decision rule framework further translates predicted failure probabilities into practical maintenance categories, allowing engineers to distinguish between normal operation, warning conditions, and situations requiring immediate maintenance intervention.

The results demonstrate that machine learning-based predictive maintenance systems can significantly enhance maintenance decision-making by utilizing operational data collected from manufacturing equipment. The analysis highlights the importance of monitoring key operational variables such as machine load, operating duration, and vibration levels to detect early signs of machine degradation. Although the current model demonstrates promising performance, further improvements can be achieved through advanced techniques such as data balancing strategies, ensemble learning models, and real-time sensor integration. The proposed framework therefore contributes to the development of intelligent maintenance systems that support proactive equipment management, reduced downtime, and improved operational reliability in smart manufacturing environments (Islam et al. 2025).

6. Conclusion

This study presented a hybrid machine learning-based predictive maintenance decision system for smart manufacturing environments. The framework utilized machine operational parameters, including operating hours, temperature, vibration, pressure, humidity, and machine load, to predict potential equipment failure conditions. The objective of the study was to develop a data-driven approach that can support maintenance planning by identifying operational factors associated with machine degradation and predicting failure risks.

The analysis results demonstrate that machine operational stress factors play a significant role in predictive maintenance modeling. Feature importance analysis revealed that load percent and operating hours were the most influential variables, followed by vibration and pressure, indicating that prolonged operation and high workload conditions contribute strongly to machine failure. The predictive modeling results further showed that the proposed approach achieved an overall classification accuracy of 84.5%, demonstrating the capability of the system to distinguish between normal operating conditions and potential failure states.

The confusion matrix analysis provided additional insight into the model's prediction performance, indicating that the model performs effectively in identifying normal machine conditions while detecting a portion of the failure cases. Although predicting rare failure events remains challenging, the proposed framework successfully demonstrates how machine learning models can support predictive maintenance by transforming machine monitoring data into actionable maintenance insights.

The proposed predictive maintenance decision system fulfills the study objective by integrating machine operational data analysis, hybrid machine learning modeling, and a decision rule framework for maintenance interpretation. The results highlight the potential of data-driven maintenance systems to improve equipment monitoring, reduce unexpected downtime, and support more efficient maintenance management in smart manufacturing environments. Such intelligent predictive maintenance systems can play an important role in advancing smart manufacturing by enabling proactive equipment management and improving the reliability and sustainability of industrial production systems.

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