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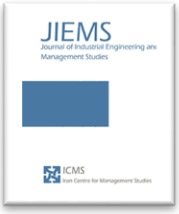

Data-Driven Prognostics of Industrial Pumps: Condition Assessment and Time-to-Change Estimation Using Ensemble Methods

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Abstract

Unplanned pump failures inflict high operational costs, rendering traditional maintenance strategies inefficient. While Machine Learning (ML) has advanced fault diagnosis, a critical gap remains in simultaneously classifying operational states and predicting the "Time Remaining until a State Change" (TRSC) using real-world, imbalanced data. This study addresses this necessity by developing an integrated predictive maintenance framework for industrial centrifugal pumps. Leveraging a four-year vibration dataset (2020–2024), we employ Random Forest (RF), XGBoost, and Multi-Layer Perceptron (MLP), utilizing SMOTE and jittering augmentation to mitigate data scarcity and imbalance. The study makes two primary contributions: (1) accurate classification of four operational states (Normal to Failure), and (2) precise regression of TRSC to optimize spare parts logistics. Results indicate that ensemble models (RF/XGBoost) achieve classification accuracies exceeding 92% and TRSC prediction with an RMSE below 25 days, significantly outperforming MLP. Furthermore, SHAP analysis reveals that horizontal and axial vibrations are the dominant precursors to failure. These findings offer a robust, interpretable tool for shifting towards condition-based maintenance, ensuring reliability and cost efficiency.

Keywords: Pump, Random Forest, Extreme Gradient Boosting, Multilayer Perceptron, vibration analysis

Paper Type: Original Research

1. Introduction

Pumps are essential components in fluid transportation systems in multiple industrial fields, where their reliable operation directly affects process efficiency, safety, and productivity (Zhang et al., 2016; Peng et al., 2024; Dutta et al., 2022; Riedemann et al., 2024; Patil & Jadhav, 2025). Pump failures can lead to unscheduled downtime, decreased production, and potential safety risks, highlighting the importance of early fault identification and predictive upkeep (Dutta et al., 2022; Saxena, 2025). Industry 4.0 technologies, including IoT-enabled sensors and AI-driven monitoring systems, are increasingly deployed to enhance pump reliability, enable real-time diagnostics, and extend equipment lifespan (Ney & Wehn, 2025; Saxena, 2025). Traditional maintenance strategies, such as fixed-schedule preventive maintenance or reactive interventions following failures, often suffer from delayed fault detection, higher unplanned downtime, and increased operational costs (Vithi & Chibaya, 2024; Prabu et al., 2025; Thakkar & Kumar, 2024). On the other hand, predictive maintenance (PdM) driven by AI employs real-time sensor data and advanced analytics to quickly detect problems, enhance maintenance timelines, and reduce unexpected downtimes (Wada et al., 2024). Evidence from multiple sectors demonstrates the effectiveness of AI-PdM: in power systems, false alarms are reduced by up to 50% and unplanned outages by approximately 35% (Rana, 2025); in manufacturing, maintenance costs decrease by 25–35% while unplanned downtime drops by 40% (Thakkar & Kumar, 2024; Prabu et al., 2025; Wada et al., 2024); and across oil & gas, mining, and maritime operations, predictive maintenance improves equipment uptime, extends asset lifespan, and enhances operational safety (Simion et al., 2024; Rojas et al., 2025; Maguluri et al., 2024). Collectively, these findings highlight the economic and operational advantages of AI-driven PdM. Abnormal vibrations and noise are among the earliest indicators of mechanical faults in pumps, including misalignment, bearing wear, and rotor imbalance (Chao et al., 2020; Karakulov, 2022; Yu et al., 2023). Correctly diagnosing these conditions is difficult because of the intricate characteristics of vibration signals, which are often masked by industrial noise (Zhu et al., 2018; Konieczny & Stojek, 2021). Moreover, fault data are limited, whereas most measurements reflect normal operation, resulting in highly imbalanced datasets (Hu et al., 2020; Konieczny & Stojek, 2021; Kazemi et al., 2023). Laboratory experiments further differ from the

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variable and noisy conditions of real industrial environments (Cabrera et al., 2023). Addressing these challenges, this study focuses on the following objectives:

- classify the operational condition of pumps by analyzing their vibration signals.
- Predicting the remaining time until the pumps' operational status changes

This research's main innovation entails applying and comparing three algorithms XGBoost, Random Forest, and MLP to identify the operational status class and the remaining days until a class change occurs. Additionally, we utilized these algorithms for a case study employing actual data. The remainder of this document is organized as follows: Section 2 reviews key literature regarding predictive maintenance. Section 3 outlines the problem statement, dataset, and methodology, detailing data preprocessing, balancing, augmentation, hyperparameter tuning, and the machine learning models used. Section 4 offers the findings and analysis, covering both operational status classification and Prediction of time remaining until the operational state change, along with feature importance analysis. Section 5 offers managerial insights, practical implications, limitations of the study, and directions for future research. Overall, this research advances predictive maintenance toward an intelligent, proactive framework for managing industrial pumps.

2. Literature Review

2.1. Maintenance Strategies

The management of physical assets has evolved through distinct stages, reflecting increasing sophistication and data utilization (Fabić, 2025):

Reactive Maintenance (RM): The most fundamental approach, often called "run-to-failure," entails conducting maintenance solely after a total equipment malfunction (Henderson & Sanders, 2025). While this method eliminates monitoring costs, it is highly inefficient and risky due to unexpected downtimes, emergency repairs, and the potential propagation of failures to interconnected systems (Fabić, 2025).

Preventive Maintenance (PM): Preventive strategies rely on scheduled inspections, periodic servicing, and the replacement of consumable components. Major overhauls are performed based on predefined time intervals or operational thresholds. Although PM improves reliability compared to reactive approaches, frequent inspections and premature replacements of functional components can increase overall maintenance costs (Fabić, 2025).

Predictive Maintenance (PdM): Commonly referred to as condition-based maintenance (CBM), PdM represents a substantial advancement in maintenance practices (Rojek et al., 2023). In this approach, maintenance interventions are triggered by real-time data and predictive models, often leveraging artificial intelligence to forecast likely failure times. PdM enables optimized scheduling of repairs, effective resource allocation, and mitigation of unplanned downtime, shifting maintenance from a reactive expense center to a strategic value creator (Fabić, 2025; Diaby et al., 2023). This evolutionary trajectory underscores a critical shift: maintenance is no longer merely an unavoidable expense but a key contributor to operational continuity, revenue generation, and workplace safety. Effective implementation of AI-driven PdM systems requires an understanding of this transformation and the incorporation of live monitoring, data analysis, and forecasting algorithms.

2.2. Concepts and Technologies Required for PdM Implementation

The effective implementation of an AI-powered predictive maintenance (PdM) system depends on the combination of advanced technologies and well-defined conceptual frameworks. Key components and enablers are summarized as follows:

- System Architecture: A typical PdM framework operates in three sequential stages. First, real-time operational data are collected via IoT sensors. Next, these data undergo preprocessing and pattern recognition through advanced artificial intelligence algorithms. Finally, predictive insights are communicated to decision-making modules, delivering actionable recommendations to managers and stakeholders through intuitive interfaces (Ucar, Karakose, & Kırımça, 2024).
- Industry 4.0 Enablers: The rise of PdM is closely linked to Industry 4.0 technologies. Affordable IoT sensors enable continuous monitoring of equipment health, , as big data analytics enables the handling of extensive sensor data. Moreover, digital twin technology offers a lively virtual representation of physical assets, allows organizations to simulate operational scenarios and evaluate the effects of varying conditions on equipment performance (Rojek et al., 2023).
- Standardized Maintenance Definition: The European Standard (EN 13306:2017) describes maintenance as "the combination of all technical, administrative and managerial actions during the life cycle of an item

intended to retain it in, or restore it to, a state in which it can perform the required function." This comprehensive definition serves as a foundational framework for modern maintenance practices (EN 13306:2017, 2017).

- IA and ML: AI and ML are crucial to PdM systems. Algorithms in machine learning examine sensor data to reveal intricate patterns, detect anomalies, perform fault diagnostics, and estimate remaining useful life (RUL). These capabilities underpin PdM's principal advantage: accurate and timely prediction of failures, enabling proactive interventions and optimized asset management (Ucar, Karakose, & Kırımça, 2024).

This integration of IoT, AI/ML, digital twins, and standardized maintenance concepts constitutes a robust framework for predictive maintenance, providing both operational efficiency and strategic value in industrial settings.

2.3. Failure Prediction in Rotating Machinery

This section reviews recent advances in predictive maintenance (PdM) for pumps and other rotating machinery, highlighting machine learning applications, signal-processing innovations, and remaining useful life (RUL) prediction methods. Menanno and Salsano (2023) proposed a machine learning (ML) approach for centrifugal pumps, employing a Support Vector Machine (SVM) combined with a sliding-window preprocessing technique. Their methodology extracted numerical features from acoustic and vibration signals to classify five discrete pump states: healthy, impeller fracture, impeller blockage, inner bearing defect, and outer bearing defect. The model achieved 99.7% accuracy and demonstrated practical advantages due to its simplicity, lower computational demands, and rapid training time. This study underscores the potential of ML techniques, particularly SVM with advanced preprocessing, to enhance maintenance strategies in manufacturing environments. AI-based PdM framework that includes explainable AI (XAI) techniques like LIME, Partial Dependence Plots (PDP), SHAP, and Individual Conditional Expectation (ICE) was introduced by Gawde et al. (2024). Their multi-stage approach involved multi-sensor data collection, frequency-domain feature extraction, AI algorithm comparison, and XAI-based interpretability. The results demonstrated that XAI effectively identifies influential features driving maintenance recommendations, increasing stakeholder trust and enabling informed decision-making. Gao, Ahmad, and Kim (2024) developed an innovative framework for RUL prediction and fault diagnosis, featuring a novel signal-denoising method (OACYCBD), a hybrid health indicator, and a hybrid invertible neural network (HINN) integrating INN and LSTM layers. Their approach outperformed SVM, CNN, and LSTM models in terms of RMSE, achieving robust accuracy across varying fault frequencies. However, the computational complexity of the method remains a limitation. Das et al. (2023) offered an extensive overview of ML-based fault diagnosis, analyzing vibration, image, and audio data sources, feature extraction methods, data-fusion techniques, and algorithms such as SVM and CNN. Their study identified key research gaps, including the management of compound faults and generalization of models to real-world operational variability. Khan et al. (2021) investigated predictive maintenance for aircraft hydraulic and engine systems, employing sliding-window analysis and ML algorithms including neural networks, logistic regression, and LSTM networks. Their findings highlighted the superior accuracy of LSTM for early fault detection and anomaly prediction in safety-critical systems. Albuflaseh (2025) applied ensemble ML models to detect motor unit imbalances in pumps using vibration data. Among multiple classifiers, Random Forest achieved the highest accuracy (99.3%), demonstrating the efficacy of ensemble methods in structured feature extraction. Recent studies on centrifugal pumps employed Multilayer Perceptron (MLP) classifiers and vibration-based frequency-domain assessment through Fast Fourier Transform (FFT) to detect mechanical and flow-induced faults, including impeller defects and cavitation (Garousi et al., 2024). Bhattarai et al. (2023) compared CNN and ANN models, showing CNN's superior performance (99.89% validation accuracy) in time-series feature extraction using sliding-window techniques. Zhi et al. (2025) further advanced fault diagnosis by integrating CNN with BiLSTM networks, achieving 100% detection accuracy for vertical centrifugal pumps and demonstrating faster convergence compared to single-architecture models. Table 1 summarizes previous research on predictive maintenance for pumps and rotating equipment using machine learning techniques, highlighting methodologies, innovations, and key outcomes.

Table 1. Overview of Recent Studies on Predictive Maintenance for Rotating Machinery Using Machine Learning

Study (Year)	Algorithm / Method	Innovation	Main Findings	Data Type	Application	Performance / Accuracy
Menanno & Salsano, 2023	SVM + sliding-window pre-processing	Application of SVM for pump state prediction	Classified 5 pump states accurately; simple, fast training	Acoustic & vibration signals	Centrifugal pumps	Accuracy: 99.7 %
Gawde et al. 2024	AI algorithms with XAI (LIME, SHAP, PDP, ICE)	Integration of XAI for interpretability	Identified influential features; increased stakeholder trust	Multi-sensor	Industrial rotating machinery	N/A
Gao, Ahmad & Kim, 2024	OACYCBD denoising; HINN	Novel denoising + health indicator; hybrid neural network	Lower RMSE than SVM, CNN, LSTM; accurate RUL prediction	Vibration signals	Industrial bearings	RMSE: 0.485 / 0.233 / 0.043
Das et al. 2023	SVM, CNN (review)	Structured framework; identified research gaps	Highlighted prevalence of vibration data; supervised learning; generalization challenges	Vibration, image, audio	Rotating machinery	N/A
Khan et al. 2021	Neural networks, Logistic Regression, LSTM	Sliding-window pattern detection	Early fault detection; superior LSTM performance	Time-series from hydraulic & engine systems	Fighter aircraft systems	High accuracy
Albuflaseh, 2025	Random Forest, LR, LSVM, NN, DT	Ensemble methods for pump motor units	RF achieved highest accuracy; effective for structured vibration features	Vibration signals	Pump motor units	RF Accuracy: 99.3 %
Garousi et al., 2024	MLP	Vibration-based fault classification	Accurate detection of impeller defects and cavitation; reduced reliance on expert knowledge	Vibration signals	Centrifugal pumps	High
Bhattarai et al. 2023	CNN vs ANN	Sliding-window time-series processing	CNN outperformed ANN; automated feature extraction	Vibration signals	Centrifugal pumps	CNN Accuracy: 99.89 %
Zhi et al. 2025	CNN + BiLSTM	Multichannel spatial-temporal feature extraction	100 % accuracy; faster convergence than single CNN	Vibration signals	Vertical centrifugal pumps	Accuracy: 100 %
This Study, 2025	RF, MLP, XGBoost + Data enhancement using jittering method	Comparison of 3 algorithms RF, XGBOOT AND MLP + validation with a real-world case study	Operational status classification + estimated time to operational status change	Vibration signals	Motor & Pump	Classification Accuracy: XGBoost 0.93, RF 0.92, MLP 0.70; RUL (RF) RMSE: 23.10, MAE: 11.34, R^2: 0.554

3. Methodology

3.1. Materials and Data Collection

The present study utilizes vibration data collected from four distinct measurement points on industrial pumps (Pump Model EA-200-50, Pump Iran Company). Data acquisition was performed over a four-year period, from March 2020 to March 2024, by the Condition Monitoring Unit of Pump Iran, located in Tehran, Iran. During each inspection, conducted approximately every 60 days, vibration signals were recorded along three primary directions: axial, horizontal, and vertical. The signals were captured using sensors mounted directly on the pump bodies. Each sample consists of three numerical values representing vibration intensity in the respective directions. To evaluate the operational state of the pumps, each data sample was assigned a functional label corresponding to one of four predefined conditions: Normal Operation, Warning, Maintenance Required, and Verge of Failure. Additionally, each record includes a numerical variable representing the number of days the pump remained in the assigned state. This variable serves as the target for modeling the time remaining until the operational state changes, defined as the minimum duration the pump is expected to continue operating under the same condition (Figure 1).

3.2. Data Preprocessing

A robust preprocessing workflow was established to guarantee data quality and improve the reliability of subsequent modeling. Outliers were detected and removed using the adjusted z-score technique (Iglewicz & Hoaglin, 1993), while missing values were imputed to maintain dataset integrity. Subsequently, all features underwent scaling through Min-Max normalization to the [0,1] range standardizing vibration magnitudes and enabling quicker convergence during model training (Singh & Singh, 2020). The preprocessed dataset was randomized and divided into training (80%) and testing (20%) subsets through stratified sampling to maintain class distributions, minimizing potential sampling bias and ensuring reproducibility. The input feature matrix consisted of vibration signals measured along axial, horizontal, and vertical directions. The modeling framework targeted two objectives:

1. Operational State Classification: Categorization of pump status into four predefined classes Normal (0), Warning (1), Maintenance Required (2), and Verge of Failure (3).
2. time remaining until the operational state changes (TRSC): Regression of the minimum number of days a pump is expected to continue operating under the current condition.

This preprocessing pipeline ensures high-quality, standardized inputs for machine learning models, enhancing predictive accuracy and reliability in both classification and time remaining until the operational state changes tasks (Figure1).

3.3. Data Balancing Using SMOTE

In classification tasks, one of the major challenges is class imbalance, that can lead to degraded effectiveness of machine learning models and bias towards majority classes (Johnson and Khoshgoftaar 2019). In the current dataset, the number of samples across the four classes normal, warning, repair needed, and verge of failure varies significantly, increasing the risk of model misclassification. To tackle this problem, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to create synthetic samples for classes that are underrepresented (Chawla et al. 2002). This technique creates new synthetic examples by blending existing minority class samples with their k-nearest neighbors, enhancing diversity and minimizing the likelihood of overfitting (Fig. 1) The generation process is governed by the following relation:

$$x_{new} = x_i + \delta \times (x_{zi} - x_i) \quad (1)$$

where x_i represents an instance from the minority class, x_{zi} denotes one of its closest neighbors, and $\delta \in [0,1]$ is a randomly selected coefficient. SMOTE was applied exclusively to the training data to prevent data leakage. The balancing process resulted in equal representation of all four classes in the training set, thus improving model robustness and its ability to correctly identify minority class instances during inference. The updated class distribution before and after applying SMOTE is presented in Table 2. The balanced dataset was then used for downstream predictive modeling tasks, including multiclass classification based on the three vibration axes (axial, horizontal, vertical) and regression-based prediction of remaining operational days for each classified state.

Table 2. Sample distribution before and after applying SMOTE.

Class	Sample Count	
	Before SMOTE	After SMOTE
0 – Normal	48	140
1 – Warning	140	140
2 – Repair Needed	42	140
3 – Verge of failure	24	140

3.4. Data Augmentation

The data augmentation is achieved through a jittering technique, which aims to boost the size and variety of the training datasets artificially. This technique is particularly crucial in machine learning applications encountering limited or imbalanced data. This approach enables models to learn more generalizable and robust patterns, thereby enhancing accuracy and improving generalization performance (Shorten and Khoshgoftaar 2019). In vibration signal analysis, a common augmentation method involves adding controlled random noise to features, increasing data variability without altering the intrinsic characteristics of the signals (Um et al. 2017). In this study, to expand the volume and diversity of vibration data collected from four pump measurement points, we applied data augmentation by injecting uniformly distributed random noise with a range of ±0.05 to the three primary vibration features: Axial, Horizontal, and Vertical (Fig. 1). This augmentation process is mathematically expressed as:

$$x_i' = x_i + \epsilon_i,\ \ \epsilon_i \sim U(-0.05, 0.05) \tag{2}$$

where x_i represents the original feature value and ϵ_i denotes the uniformly distributed random noise within the specified range. The noise amplitude was carefully chosen to ensure that the augmented samples remain within their original classes, avoiding any class boundary crossing or mislabeling. This constraint preserves the integrity and consistency of class labels, preventing the augmented data from being mistakenly assigned to different categories, which is critical for maintaining model reliability (Um et al. 2017). Additionally, target variables including Situation (classification label) and Day (remaining duration in the class) were retained unchanged in the augmented samples, enabling simultaneous application of the augmented dataset for both classification and regression tasks.

3.5. Hyperparameter Optimization

As shown in Figure. 1, this research utilized three well-known and efficient machine learning algorithms: RF, MLP, and XGBoost, to develop predictive models. A Randomized Search strategy was employed to determine the best hyperparameter settings and improve the predictive performance of each model. Unlike exhaustive grid search methods, this approach performs an intelligent, stochastic sampling within the high-dimensional hyperparameter space $\Theta \subseteq \mathrm{R}^{\mathrm{d}}$, significantly reducing computational cost while still exploring a diverse set of parameter combinations (Bergstra and Bengio 2012; Sathiya, Chinnadurai, and Ramabalan 2022). Formally, the goal is to determine the hyperparameter vector $\theta^* \in \Theta$ that maximizes the model evaluation function $f(\theta)$, commonly defined as a performance metric such as classification accuracy or mean squared error obtained via cross-validation:

$$\theta^* = \arg\max_{\theta \in \theta} f(\theta) \tag{3}$$

Here, $f(\theta)$ represents the average validation score across $k-fold$ cross validation, where the dataset divided into $k = 5$ groups. For every fold i, the model undergoes training on $k-1$ groups and is evaluated on the leftover group, producing a validation score $score_i(\theta)$. The aggregate performance is computed as:

$$f(\theta) = \frac{1}{k} \sum_{i=1}^{k} score_i(\theta) \tag{4}$$

In this study, the randomized search was executed over $N = 100$ iterations. At each iteration j, a random hyperparameter set $\theta_j \in \Theta$ was sampled, evaluated via cross-validation, and recorded. The optimal hyperparameters were selected as:

$$\theta^* = \arg \max_{j=1,\dots,N} f(\theta_j) \tag{5}$$

This methodology offers a more efficient exploration of the hyperparameter space compared to exhaustive grid searches, particularly in scenarios involving numerous hyperparameters with wide value ranges. The integration of randomized search with 5-fold cross validation further ensures robust model evaluation and mitigates overfitting risks (Rimal et al. 2024). The optimized hyperparameter sets for each algorithm, including key structural and learning parameters, are summarized in Table 3.

Table 3. Optimized hyperparameters for (RF), (MLP), and XGBoost models in classification and regression tasks.

Model	Parameter	Classification	Regression
RF	N estimators	300	200
	Min samples leaf	1	1
	solver	adam	sgd
	Max depth	40	20
	Min samples split	10	2
MLP	Max iter	1000	500
	Learning rate	adaptive	adaptive
	Hidden layer sizes	256,128	256,128
	Early stopping	FALSE	FALSE
	activation	tanh	relu
XGBoost	ubsample	0.8	0.8
	N estimators	100	100
	Max depth	10	7
	Learning rate	0.2	0.1
	Colsample bytree	1	1

3.6. Machine Learning Algorithms

3.6.1. Random Forest

The RF algorithm is an ensemble learning technique that builds a set of decision trees in a way that is both independent and random, aggregating their outputs to generate a final prediction (Breiman 2001). RF enhances accuracy and generalizability by bagging and randomly sampling feature subsets at each node to boost tree diversity. Key advantages of RF include high accuracy, robustness against overfitting, capability to handle outliers and missing data, and efficacy in both classification and regression assignments with intricate, nonlinear datasets (Sarwar et al. 2023). In classification tasks, the ultimate prediction is based on majority voting from all trees:

$$y\hat{} = mode\{h_1(x), h_2(x), \ldots, h_M(x) \tag{6}$$

Where $h_i(x)$ represents the prediction from i^{th} tree for input x, and M indicates the overall count of trees. In regression tasks, the forecasted value is the mean of all tree results:

$$y\hat{} = \frac{1}{M}\sum_{i=1}^{M}\sum = h_i(x) \tag{7}$$

Where $y\hat{}$ is the predicted output and $h_i(x)$ is the output of the i^{th} tree.

3.6.2. Multilayer Perceptron

The MLP is a kind of feedforward artificial neural network made up of several layers, including an input layer, one or more hidden layers, and an output layer. It models complex nonlinear relationships by computing weighted sums of inputs followed by nonlinear activation functions, which enable it to capture intricate patterns within data (Nugroho et al. 2022; Kim et al. 2022). The output of each neuron can be mathematically expressed as:

$$y = \phi(\sum_{i=1}^{n} w_i x_i + b) \tag{8}$$

Where w_i are the synaptic weights, x_i the input features, b the bias term, and ϕ the nonlinear activation function. In classification tasks, MLP typically employs a softmax activation function in the output layer to estimate class probabilities:

$$y\hat{}_j = \frac{e^{z_j}}{\sum_k e^{z_k}} \tag{9}$$

Where z_j is the input to the output neuron for class j. For regression problems, a linear output neuron is generally used, optimized by minimizing mean squared error (Nugroho et al. 2022). MLP networks are highly versatile, capable of handling nonlinear and high-dimensional data without requiring explicit feature extraction or prior assumptions about data distribution. However, their performance depends heavily on hyperparameter tuning, including the number of hidden layers, neurons per layer, learning rate, and regularization techniques to prevent overfitting (Kim et al. 2022). Training is usually performed via backpropagation and gradient descent optimization (Vijayan et al. 2021).

3.6.3. Extreme Gradient Boosting (XGBoost)

XGBoost is a powerful and scalable gradient boosting framework that builds an ensemble of decision trees one after another, where each tree seeks to correct the mistakes of its predecessors by enhancing a differentiable loss function using gradient-based methods (Chen and Guestrin 2016). (Chen and Guestrin 2016). The model seeks to minimize this objective function:

$$L(\phi) = \sum_{i=1}^{n} l\left(y_i, y^{\wedge(t)}_{i}\right) + \sum_{k=1}^{t} + \Omega(f_k) \tag{10}$$

Where l is the loss function (logistic loss for classification or squared error for regression), $y^{\wedge(t)}_{i}$ denotes the prediction at iteration t, and Ω is a regularization component that discourages model complexity to avoid overfitting. The additive update rule is:

$$y^{\wedge(t)}_{i} = y^{\wedge(t-1)}_{i} + f_t(x_i) \tag{11}$$

Where f_t is the newly added tree model.

XGBoost incorporates several innovations such as second-order Taylor expansion for loss approximation, shrinkage, column subsampling, and a novel regularization framework to improve accuracy and reduce overfitting. It supports both classification and regression tasks effectively and is known for its high predictive performance on complex and large-scale datasets (Xia et al. 2024).

3.7. Model Evaluation Metrics

In the end, the efficacy of the models was methodically assessed employing a range of recognized metrics, as defined in the subsequent equations. For classification tasks, the assessment criteria included accuracy, precision, recall, and F1-score, mathematically defined as follows(Powers 2020).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$Precision = \frac{TP}{TP + FP} \tag{13}$$

$$Recall = \frac{TP}{TP + FN} \tag{14}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{15}$$

Where TP, TN, FP, and FN represent the counts of true positives, true negatives, false positives, and false negatives, respectively.For regression problems, model performance was measured using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics provided a comprehensive assessment of predictive accuracy and the model's ability to generalize to unseen data, and are mathematically defined as follows

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y^{\wedge}_{i}\right)^2} \tag{16}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y^{\wedge}_{i}\right| \tag{17}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y^{\wedge}_{i}\right)^2}{\sum_{i=1}^{n}\left(y_i - y^{-}_{i}\right)^2} \tag{18}$$

Where y_i represents the observed values, $y^{\wedge}_{i}$ the predicted values, y^{-} the mean of the observed values, and n the total number of samples. Together, these indicators form a thorough framework for evaluating a model's predictive precision and its ability to generalize. Recent studies have consistently adopted and validated them as the benchmark metrics for both classification and regression tasks.

3.8. Feature Importance Analysis

Feature importance was quantified using the SHapley Additive exPlanations (SHAP) framework (Lundberg and Lee, 2017). was used to quantify feature importance. SHAP values, rooted in cooperative game theory, attribute a contribution score to each feature in relation to the model's output. The Shapley value for feature i is mathematically expressed as:

$$[f(S) - (\{i\} \cup f(S] \quad \frac{!|S|!(|N|-|S|-1)|}{!|N|} \quad \sum_{S \subseteq N \setminus \{i\}} = i\phi \tag{19}$$

where N denotes the collection of all input features, S signifies any subset of features excluding iii, $f(S)$denotes the model output when solely the features in S are considered, and $i\phi$ is the Shapley value quantifying the marginal contribution of feature i.

SHAP values were calculated for every predictive model, covering both classification and regression tasks. For tree-based models (Random Forest and XGBoost), the TreeExplainer method was employed, while for the neural network model (MLP), the KernelExplainer was used due to its non-tree structure.

For every model, the mean absolute SHAP value was determined for the three vibration components (axial, horizontal, and vertical), representing their average contribution across the dataset. In classification tasks, SHAP values were further computed for each class to determine the features most influential for each operational state.

3.9. Software and Implementation

All computational analyses, including data preprocessing, augmentation, model development, and performance evaluation, were conducted using Python (Rossum 2009). Data manipulation and numerical operations were performed using the pandas and numpy libraries (McKinney 2010). To address class imbalance, SMOTE was applied using the imbalanced-learn package. Machine learning models, including random forests, and multilayer perceptrons, were implemented and optimized using the scikit-learn library (Pedregosa et al. 2011).

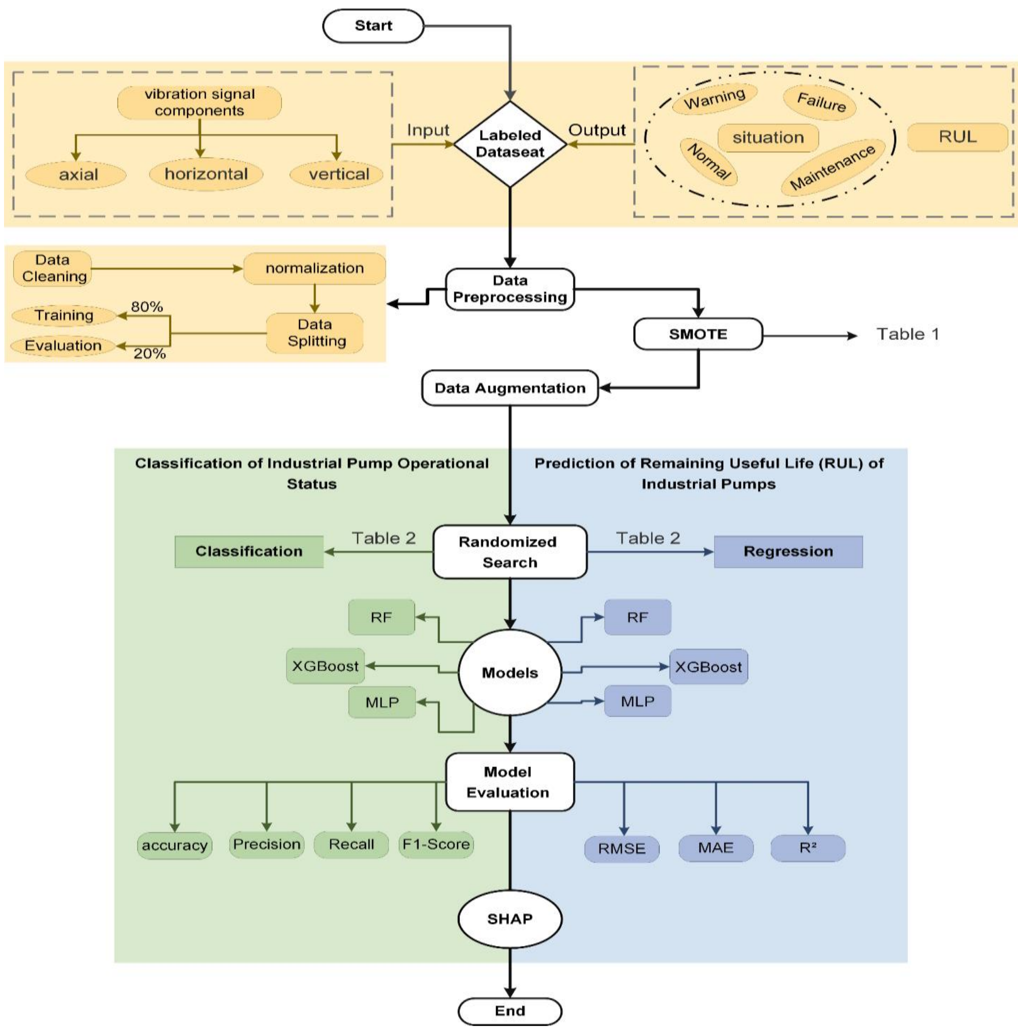

Figure 1. Framework of the machine learning approach used for situation and RUL prediction

4. Results and Discussion

4.1. Classification of Industrial Pump Operational Status

The primary aim of this study was to classify the operational status of industrial pumps into four categories, Normal, Warning, Maintenance Required, and Verge of Failure. Three machine learning algorithms, RF, MLP, and XGBoost, were employed for this purpose, with hyperparameters optimized using a Randomized Search strategy (Bergstra & Bengio, 2012). The optimized hyperparameters for each model are summarized in Table 3, enabling effective utilization of each algorithm. The evaluation of model performance utilized conventional classification metrics such as Accuracy, Precision, Recall, and F1-Score, which are detailed in Table 4. The XGBoost model achieved the highest accuracy of 0.93, corroborating previous studies that highlight XGBoost's exceptional capacity to manage high-dimensional and noisy datasets, making it highly effective for industrial classification tasks (Chen & Guestrin, 2016). Random Forest achieved a comparable accuracy of 0.92, benefiting from its ensemble of decision trees that robustly capture nonlinear and complex feature interactions (Breiman, 2001). The MLP model yielded a lower accuracy of 0.70, likely reflecting its sensitivity to hyperparameter tuning and the need for larger datasets to achieve optimal learning (Goodfellow et al., 2016; Figure. 2). Hyperparameter optimization via randomized search was a key factor in model performance, as it reduced computational overhead while allowing extensive exploration of the parameter space and mitigating overfitting (Rimal et al., 2024). This approach ensured high generalizability on unseen test data. These findings align with previous research in industrial machinery condition monitoring, which confirms the benefits of machine learning methods for fault detection and operational condition categorization. Saeed et al. (2025) showcased the efficacy of deep learning techniques for identifying faults in industrial settings with limited resources.

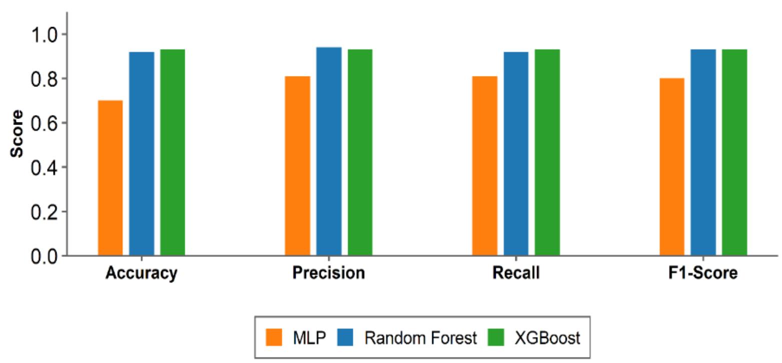

Figure 2. Comparison of classification performance metrics for Random Forest (RF), Multilayer Perceptron (MLP), and Extreme Gradient Boosting (XGBoost) models in predicting the operational status of an industrial pump

4.2. Prediction of time remaining until the operational state change (TRSC):

The second objective of this study was to predict the time remaining until the operational state change (TRSC) of industrial pumps, Defined as the minimum number of days until a change in the current operating state of the pump. Accurate TRSC prediction is essential for enhancing PdM strategies, minimizing unplanned downtime, and improving overall system reliability. Three ML algorithms; RF, MLP, and XGBoost, were employed. Hyperparameters of each model were independently optimized using a Randomized Search strategy (Bergstra and Bengio, 2012), with the finalized settings summarized in Table 3. Model performance was assessed using RMSE, MAE, and R^2, as reported in Table 4. RF demonstrated superior predictive performance (RMSE = 23.099, MAE = 11.342, R^2 = 0.554), explaining ~55.4% of the variance in TRSC. XGBoost showed comparable performance (RMSE = 23.837, MAE = 10.672, R^2 = 0.525), while MLP exhibited lower accuracy (RMSE = 27.44, MAE = 19.546, R^2 = 0.37; Figure. 3). The robust performance of RF is attributed to its ensemble-based decision tree architecture, which effectively captures nonlinear relationships, handles noisy inputs, and mitigates overfitting (Mohammed, 2023). XGBoost benefits from gradient boosting, enabling effective error reduction, though further hyperparameter tuning could improve results (Chen and Guestrin, 2016). The lower performance of MLP is likely due to its sensitivity to hyperparameter settings and the need for larger datasets for optimal generalization (Goodfellow et al., 2016). Overall, ensemble-based models, particularly RF, provide a reliable approach for TRSC prediction, thereby supporting effective PdM and operational efficiency (Kumar et al., 2024; Mohammed, 2023).

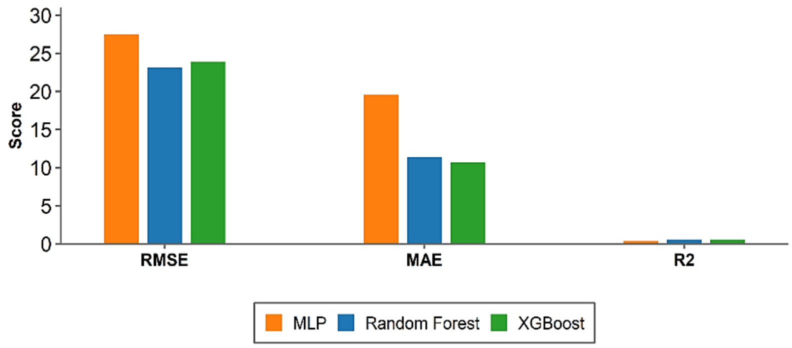

Figure 3. Comparison of regression performance metrics for Random Forest (RF), Multilayer Perceptron (MLP), and Extreme Gradient Boosting (XGBoost) models in predicting the time remaining until the operational state change (TRSC) of industrial pump.

Table 4. Comparison of performance metrics for RF, MLP, and XGBoost models in classification and regression tasks

Models	Metric	RF	MLP	XGBoost
Classification	F1-Score	0.93	0.8	0.93
	Precision	0.94	0.81	0.93
	accuracy	0.92	0.7	0.93
	Recall	0.92	0.81	0.93
Regression	RMSE	23.099	27.44	23.837
	MAE	11.342	19.546	10.672
	R2 Score	0.554	0.37	0.525

4.3. Feature Importance Analysis Using SHAP

4.3.1. Classification Task

SHAP analysis for the classification models revealed that the most influential vibration components varied across classes and algorithms (Figure. 4). For XGBoost, horizontal vibrations dominated in Classes 1 and 2 (≈2.53 and ≈2.06, respectively), axial vibrations were most important for Class 0 (≈2.40), and vertical vibrations contributed notably to Class 2 (≈2.06) (Figure. 4A). In the Random Forest model, horizontal and axial vibrations consistently contributed more than vertical vibrations across all classes, with SHAP values ranging approximately 0.10–0.25 (Figure. 4B). The MLP model exhibited smaller SHAP values overall, with horizontal (≈0.13–0.14) and axial (≈0.066–0.067) vibrations remaining the main contributors (Figure. 4C). These results indicate that the relevance of vibration directions depends on the operational state of the pump.

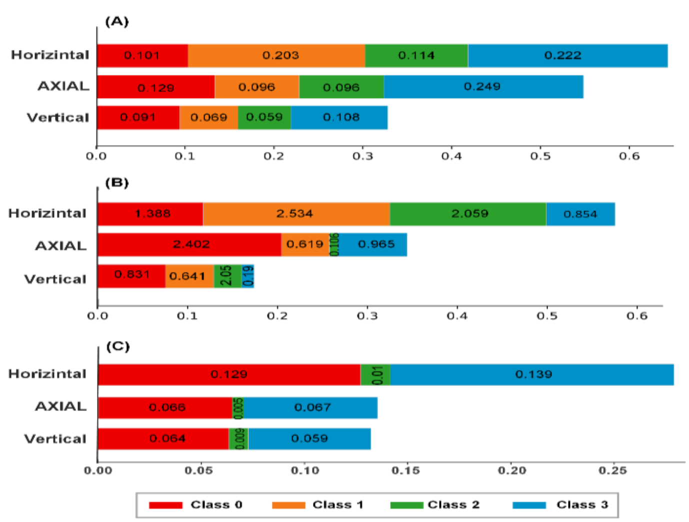

Figure. 4. Feature Importance of Vibration Components in Pump Operational Status Classification. Mean absolute SHAP values of axial, horizontal, and vertical vibration signals for each class (0–3) across three classification models: (A) XGBoost, (B) Random Forest, and (C) Multi-Layer Perceptron (MLP).

4.3.1. Regression Task

For TRSC prediction, horizontal vibrations consistently showed the highest mean absolute SHAP values across all models (RF: ≈16.75, XGBoost: ≈10.55, MLP: ≈9.37), highlighting their dominant role in estimating Prediction of time remaining until the operational state change (Figure. 5). Axial vibrations were also significant, especially in XGBoost (≈11.86) and Random Forest (≈11.24), whereas vertical vibrations had comparatively lower contributions (RF: ≈7.04, XGBoost: ≈5.54, MLP: ≈8.21) (Figure. 5). In general, the most significant factors for TRSC estimation were the horizontal and axial vibration components, emphasizing the importance of monitoring these directions for effective predictive maintenance.

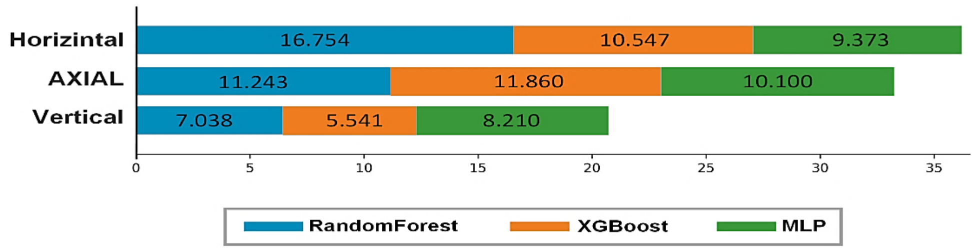

Figure. 5. Feature Importance of Vibration Components in Prediction of time remaining until the operational state change. Mean absolute SHAP values of axial, horizontal, and vertical vibration signals across three regression models: Random Forest (RF), XGBoost, and Multi-Layer Perceptron (MLP), highlighting the dominant contribution of horizontal and axial vibrations in estimating TRSC.

5. Managerial Insights

The deployment of ensemble machine learning models, particularly Random Forest and XGBoost, offers a transformative opportunity for industrial maintenance management. Real time vibration monitoring combined with predictive analytics enables early fault detection with classification accuracies exceeding 92 %, significantly reducing the frequency and cost of emergency repairs. Organizations are encouraged to integrate these models into IoT platforms to automate alerts and interventions, moving away from traditional calendar-based maintenance schedules. Accurate Prediction of time remaining until the operational state change, achieving RMSE values below 25 days, allow firms to transition from reactive to condition-based spare parts management. Aligning procurement cycles with model predictions optimizes working capital, minimizes excess stock, and prevents production interruptions, highlighting the need for close collaboration between procurement and finance teams to adjust safety stock dynamically. The relative simplicity and interpretability of Random Forest models also empower maintenance personnel. Unlike complex neural networks, Random Forest provides transparent decision rules and feature-importance insights, reducing training overhead and encouraging organizational adoption. Successful implementation further requires ensuring high-quality sensor data through calibration, involving frontline teams to overcome cultural resistance, and maintaining data integrity with robust cybersecurity protocols. By integrating technical rigor with change management, organizations can enhance reliability, reduce costs, and support strategic decision-making.

5.1. Conclusion

This study developed a machine-learning framework for two critical tasks in industrial pump monitoring: operational state classification and Prediction of time remaining until the operational state change. Three algorithms Random Forest, Multilayer Perceptron (MLP), and XGBoost were trained on triaxial vibration data collected between 2020 and 2024, using randomized hyperparameter search. Ensemble methods, particularly XGBoost (accuracy = 0.93) and Random Forest (accuracy = 0.92), achieved the highest classification performance, while MLP attained an accuracy of 0.70. For RUL estimation, Random Forest outperformed the other models with an RMSE of 23.10 days, MAE of 11.34 days, and R^2 of 0.554. These results highlight the superior ability of ensemble models to identify complex patterns, handle noisy data, and mitigate overfitting, providing reliable early fault detection and accurate life-span estimation for industrial pumps.

5.2. Contribution to Knowledge

By empirically comparing Random Forest, XGBoost, and MLP within the Prognostics and Health Management (PHM) domain, the research offers practical insights into algorithm selection for industrial applications, demonstrating the advantages of ensemble learning over simpler neural network architectures in real world conditions.Finally, to validate the efficiency and accuracy of the proposed algorithms, this study introduces and utilizes a real world dataset collected from pump vibration recordings.

Practical Implications

Implementing the Random Forest model in manufacturing settings can provide high-accuracy Prediction of time remaining until the operational state change with minimal configuration complexity. Organizations adopting this framework can expect to reduce emergency maintenance costs by enabling timely fault detection and preventive actions, optimize spare-parts inventory through precise estimations of component replacement needs, and increase production uptime by minimizing unplanned downtime and its associated opportunity costs.

Study Limitations

Despite its contributions, this study also has limitations. The dataset was limited to a single type of industrial pump operating under specific environmental and loading conditions, which may restrict generalizability to other equipment or industries. The MLP model required extensive data and fine tuning, posing challenges for deployment in settings with limited computational resources or smaller datasets. Finally, the absence of field-scale trials within live production lines constrains the assessment of real-world performance and integration challenges.

Future Research Directions

Future studies should explore multi-sensor fusion, incorporating temperature, pressure, and other modalities alongside digital twin technologies to enhance prognostic accuracy. Developing hybrid, explainable AI (XAI) architectures could also foster greater stakeholder trust and facilitate wider adoption across diverse sectors, including petrochemicals, power generation, and mining.

Data Availability

The dataset created and examined throughout this research is publicly accessible in the Figshare repository and can be retrieved using the following DOI: 10.6084/m9.figshare.29553872 (Ehsan Heydari, 2025).

References

Albuflaseh, Abdulrahman. 2025. “Machinery Imbalance Failure Prediction Based on Pump – Motor Vibration Readings.” Rochester Institute of Technology. Accessed From. https://repository.rit.edu/theses/12056/.

Bergstra, James, and Yoshua Bengio. 2012. “Random Search for Hyper-Parameter Optimization.” The Journal of Machine Learning Research 13 (1): 281–305.

Bhattarai, Aasma, Amit Gupta, Abishek Kafle, Prajwal Sapkota, Sailesh Chitrakar, Ole Gunnar Dahlhaug, and Suman Pradhan. 2023. “Application of Machine Learning Algorithm for Fault Detection in Pump.” In International Conference on the Efficiency and Performance Engineering Network, 235–47. Springer.

Breiman, Leo. 2001. “Random Forests.” Machine Learning 45: 5–32.

Cabrera, D., Villacís, M., Cerrada, M., Sánchez, R., Li, C., Sancho, F., Long, J., & Estupiñan, E. (2023). Adversarial Fault Detector Guided by One-Class Learning for a Multistage Centrifugal Pump. IEEE/ASME Transactions on Mechatronics, 28, 1395-1403. https://doi.org/10.1109/TMECH.2022.3226347.

Chao, Q., Tao, J., Wei, X., & Liu, C. (2020). Identification of cavitation intensity for high-speed aviation hydraulic pumps using 2D convolutional neural networks with an input of RGB-based vibration data. Measurement Science and Technology, 31. https://doi.org/10.1088/1361-6501/ab8d5a.

Chawla, Nitesh V, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. 2002. “SMOTE: Synthetic Minority over-Sampling Technique.” Journal of Artificial Intelligence Research 16: 321–57.

Chen, Tianqi, and Carlos Guestrin. 2016. “Xgboost: A Scalable Tree Boosting System.” In Proceedings of the 22nd Acm Sigkdd International Conference on Knowledge Discovery and Data Mining, 785–94.

Diaby, Hadi, Derek D. Snaidauf, Don Williams, Edward Bowen, and Ephraim Schoenbrun. 2023. “Using AI-Enabled Predictive Maintenance to Help Maximize Asset Value.” www.deloitte.com/us/AIInstitute.

Dutta, N., Kaliannan, P., & Paramasivam, S. (2022). A comprehensive review on fault detection and analysis in the pumping system. International Journal of Ambient Energy, 43, 6878 - 6898. https://doi.org/10.1080/01430750.2022.2056917.

Ehsan Heydari. 2025. “Pump Vibration Data at 4 Points and Three Different Directions.” figshare. https://doi.org/https://doi.org/10.6084/m9.figshare.29553872.v1.

EN 13306:2017. 2017. "BSI Standards Publication Maintenance Maintenance. Maintenance Terminology. BS EN 13306:2017." British Standard Institution, London, UK.

Fabić, Marko. 2025. "Application of AI-Based Predictive Maintenance for Industrial Processes." Tehnicki Glasnik 19: 154–58. https://doi.org/10.31803/tg-20250404124706.

Gao, Yangde, Zahoor Ahmad, and Jong Myon Kim. 2024. "Fault Diagnosis of Rotating Machinery Using an Optimal Blind Deconvolution Method and Hybrid Invertible Neural Network." Sensors 24 (1). https://doi.org/10.3390/s24010256.

Garousi, Masoud Hatami, Mahdi Karimi, Paolo Casoli, Massimo Rundo, and Rasoul Fallahzadeh. 2024. "Vibration Analysis of a Centrifugal Pump with Healthy and Defective Impellers and Fault Detection Using Multi-Layer Perceptron." Eng 5 (4): 2511–30. https://doi.org/10.3390/eng5040131.

Gawde, Shreyas, Shruti Patil, Satish Kumar, Pooja Kamat, Ketan Kotecha, and Sultan Alfarhood. 2024. "Explainable Predictive Maintenance of Rotating Machines Using LIME, SHAP, PDP, ICE." IEEE Access 12 (March): 29345–61. https://doi.org/10.1109/ACCESS.2024.3367110.

Goodfellow, Ian, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. 2016. Deep Learning. Vol. 1. MIT press Cambridge.

Henderson, James, and Mark Sanders. 2025. "AI Driven Predictive Maintenance: Reducing Downtime and Enhancing Productivity in Manufacturing Environments," 0–15. https://doi.org/10.20944/preprints202504.0602.v1.

Hu, Q., Ohata, E., Silva, F., Ramalho, G., Han, T., & Filho, P. (2020). A new online approach for classification of pumps vibration patterns based on intelligent IoT system. Measurement, 151, 107138. https://doi.org/10.1016/j.measurement.2019.107138.

Iglewicz, Boris, and David Hoaglin. 1993. "The ASQC Basic References in Quality Control: Statistical Techniques." How to Detect and Handle Outliers 16: 1–87.

Johnson, Justin M, and Taghi M Khoshgoftaar. 2019. "Survey on Deep Learning with Class Imbalance." Journal of Big Data 6 (1): 1–54.

Karakulov, I. (2022). CLASSIFICATION OF THE TECHNICAL CONDITION OF WATER PUMPING EQUIPMENT USING CONVOLUTIONAL NEURAL NETWORKS. Applied Mathematics and Control Sciences. https://doi.org/10.15593/2499-9873/2022.2.02.

Kazemi, Z., Andersen, P., Lemming, J., & Larsen, P. (2023). Artificial Intelligence-Based Diagnosis of Hydraulic Centrifugal Pumps Using Vibration Sensor: Feature Extraction and Failure Classification. 2023 IEEE 32nd International Symposium on Industrial Electronics (ISIE), 1-6. https://doi.org/10.1109/ISIE51358.2023.10227930.

Khan, Khalid, Muhammad Sohaib, Azaz Rashid, Saddam Ali, Hammad Akbar, Abdul Basit, and Tanvir Ahmad. 2021. "Recent Trends and Challenges in Predictive Maintenance of Aircraft's Engine and Hydraulic System." Journal of the Brazilian Society of Mechanical Sciences and Engineering 43 (8): 1–17. https://doi.org/10.1007/s40430-021-03121-2.

Kim, Heonho, Taewoong Ryu, Chanhee Lee, Hyeonmo Kim, Eunchul Yoon, Bay Vo, Jerry Chun-Wei Lin, and Unil Yun. 2022. "EHMIN: Efficient Approach of List Based High-Utility Pattern Mining with Negative Unit Profits." Expert Systems with Applications 209: 118214.

Konieczny, J., & Stojek, J. (2021). Use of the K-Nearest Neighbour Classifier in Wear Condition Classification of a Positive Displacement Pump. Sensors (Basel, Switzerland), 21. https://doi.org/10.3390/s21186247.

Kumar, Shahil, Krish Kumar Raj, Maurizio Cirrincione, Giansalvo Cirrincione, Vincenzo Franzitta, and Rahul Ranjeev Kumar. 2024. "A Comprehensive Review of Remaining Useful Life Estimation Approaches for Rotating Machinery." Energies 17 (22): 5538.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.

https://doi.org/10.48550/arXiv.1705.07874

Maguluri, L., Suganthi, D., Dhote, G., Kapila, D., Jadhav, M., & Neelima, S. (2024). AI-enhanced predictive maintenance in hybrid roll-to-roll manufacturing integrating multi-sensor data and self-supervised learning. The International Journal of Advanced Manufacturing Technology. https://doi.org/10.1007/s00170-024-14263-7.

McKinney, Wes. 2010. "Data Structures for Statistical Computing in Python." Scipy 445 (1): 51–56.

Menanno, Marialuisa, and Anita Salsano. 2023. "Centrifugal Pump Fault Diagnosis Using a Predictive Maintenance Model," no. July 2023. https://doi.org/10.46254/eu6.20230422.

Mohammed, Awsan. 2023. "Data Driven-Based Model for Predicting Pump Failures in the Oil and Gas Industry." Engineering Failure Analysis 145: 107019.

Ney, J., & Wehn, N. (2025). ECNN: A Low-complex, Adjustable CNN for Industrial Pump Monitoring Using Vibration Data. 2025 IEEE Symposium on Computational Intelligence on Engineering/Cyber Physical Systems Companion (CIES Companion), 1-5. https://doi.org/10.1109/CIESCompanion65073.2025.11010817.

Nugroho, Waego Hadi, Samingun Handoyo, Hsing-Chuan Hsieh, Yusnita Julyarni Akri, and Donna DwinitaAdelia. 2022. "Modeling Multioutput Response Uses Ridge Regression and MLP Neural Network with Tuning Hyperparameter through Cross Validation." International Journal of Advanced Computer Science and Applications 13 (9).

Oguzhan das, et al. 2023. "Machine Learning for Fault Analysis in Rotating Machinery: A Comprehensive Review." Heliyon 9 (6): e17584. https://doi.org/10.1016/j.heliyon.2023.e17584.

Patil, S., & Jadhav, M. (2025). An Overview on Industrial Waste Water Submersible Pump. International Journal on Science and Technology. https://doi.org/10.71097/ijsat.v16.i1.1793.

Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, and Vincent Dubourg. 2011. "Scikit-Learn: Machine Learning in Python." The Journal of Machine Learning Research 12: 2825–30.

Peng, G., Huang, X., Zhou, L., Zhou, G., & Zhou, H. (2020). Solid-liquid two-phase flow and wear analysis in a large-scale centrifugal slurry pump. Engineering Failure Analysis, 114, 104602. https://doi.org/10.1016/j.engfailanal.2020.104602.

Powers, David M W. 2020. "Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation." ArXiv Preprint ArXiv:2010.16061.

Prabu, S., Senthilraja, R., Ali, A., Jayapoorani, S., & Arun, M. (2025). AI-Driven Predictive Maintenance for Smart Manufacturing Systems Using Digital Twin Technology. International Journal of Computational and Experimental Science and Engineering. https://doi.org/10.22399/ijcesen.1099.

Rana, S. (2025). AI-DRIVEN FAULT DETECTION AND PREDICTIVE MAINTENANCE IN ELECTRICAL POWER SYSTEMS: A SYSTEMATIC REVIEW OF DATA-DRIVEN APPROACHES, DIGITAL TWINS, AND SELF-HEALING GRIDS. American Journal of Advanced Technology and Engineering Solutions. https://doi.org/10.63125/4p25x993.

Riedemann, J., Reyes, E., Sarasiri, N., Pena, R., & Andrade, I. (2024). Renewable Source-Based Water Pumping Electrification in Mines: Current technologies and future trends. IEEE Electrification Magazine, 12, 38-44. https://doi.org/10.1109/MELE.2023.3348349.

Rimal, Yagyanath, Navneet Sharma, and Abeer Alsadoon. 2024. "The Accuracy of Machine Learning Models Relies on Hyperparameter Tuning: Student Result Classification Using Random Forest, Randomized Search, Grid Search, Bayesian, Genetic, and Optuna Algorithms." Multimedia Tools and Applications 83 (30): 74349–64.

Rojas, L., Peña, Á., & García, J. (2025). AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management. Applied Sciences. https://doi.org/10.3390/app15063337.

Rojek, Izabela, Małgorzata Jasiulewicz-Kaczmarek, Mariusz Piechowski, and Dariusz Mikołajewski. 2023. "An Artificial Intelligence Approach for Improving Maintenance to Supervise Machine Failures and Support Their Repair." Applied Sciences (Switzerland) 13 (8). https://doi.org/10.3390/app13084971.

Rossum, Van. 2009. "Python 3 Reference Manual." (No Title).

Saeed, Ali, Muazzam A. Khan, Usman Akram, Waeal J. Obidallah, Soyiba Jawed, and Awais Ahmad. 2025. "Deep Learning Based Approaches for Intelligent Industrial Machinery Health Management and Fault Diagnosis in Resource-Constrained Environments." Scientific Reports 15 (1): 1114.

Sarwar, Ayesha, Muhammad Faheem Mushtaq, Urooj Akram, Furqan Rustam, Ameer Hamza, Vaibhav Rupapara, and Saleem Ullah. 2023. "IoT Networks Attacks Detection Using Multi-Novel Features and Extra Tree Random-Voting Ensemble Classifier (ER-VEC)." Journal of Ambient Intelligence and Humanized Computing 14 (12): 16637–51.

Sathiya, V, M Chinnadurai, and S Ramabalan. 2022. "Mobile Robot Path Planning Using Fuzzy Enhanced Improved Multi-Objective Particle Swarm Optimization (FIMOPSO)." Expert Systems with Applications 198: 116875.

Shorten, Connor, and Taghi M Khoshgoftaar. 2019. "A Survey on Image Data Augmentation for Deep Learning." Journal of Big Data. https://doi.org/10.1186/s40537-019-0197-0.

Saxena, A. (2025). Application of Data Science in Pump Maintenance. International Journal For Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2025.v07i01.37055.

Simion, D., Postolache, F., Fleacă, B., & Fleacă, E. (2024). AI-Driven Predictive Maintenance in Modern Maritime Transport—Enhancing Operational Efficiency and Reliability. Applied Sciences. https://doi.org/10.3390/app14209439.

Singh, Dalwinder, and Birmohan Singh. 2020. "Investigating the Impact of Data Normalization on Classification Performance." Applied Soft Computing 97: 105524.

Thakkar, D., & Kumar, R. (2024). AI-Driven Predictive Maintenance for Industrial Assets using Edge Computing and Machine Learning. Journal for Research in Applied Sciences and Biotechnology. https://doi.org/10.55544/jrasb.3.1.55.

Ucar, Aysegul, Mehmet Karakose, and Necim Kırımça. 2024. "Applied Sciences Artificial Intelligence for Predictive Maintenance Applications :"

Um, Terry T, Franz M J Pfister, Daniel Pichler, Satoshi Endo, Muriel Lang, Sandra Hirche, Urban Fietzek, and Dana Kulić. 2017. "Data Augmentation of Wearable Sensor Data for Parkinson's Disease Monitoring Using Convolutional Neural Networks." In Proceedings of the 19th ACM International Conference on Multimodal Interaction, 216–20.

Vijayan, Midhula, Preeth Raguraman, and R Mohan. 2021. "A Fully Residual Convolutional Neural Network for Background Subtraction." Pattern Recognition Letters 146: 63–69.

Vithi, Nontuthuzelo Lindokuhle, and Colin Chibaya. 2024. "Advancements in Predictive Maintenance: A Bibliometric Review of Diagnostic Models Using Machine Learning Techniques." Analytics 3 (4): 493–507. https://doi.org/10.3390/analytics3040028.

Wada, I., Bello, S., Ige, O., Chianumba, E., & Adebayo, S. (2024). AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. International Journal of Science and Research Archive. https://doi.org/10.30574/ijsra.2024.13.1.1992.

Xia, Yuxuan, Shanshan Jiang, Lingyi Meng, and Xin Ju. 2024. "XGBoost-B-GHM: An Ensemble Model with Feature Selection and GHM Loss Function Optimization for Credit Scoring." Systems 12 (7).

Yu, B., Lee, J., Kim, Y., Lee, T., Kim, Y., Jang, H., Park, J., & Park, J. (2023). A Study on Fault Classification for Condition-Based Maintenance of Auxiliary Pump in Ship's Engine Systems Using HHT and CNN. Journal of Applied Reliability. https://doi.org/10.33162/jar.2023.12.23.4.366.

Zhang, J., Zhang, H., He, Y., & Tao, W. (2016). A comprehensive review on advances and applications of industrial heat pumps based on the practices in China. Applied Energy, 178, 800-825. https://doi.org/10.1016/J.APENERGY.2016.06.049.

Zhi, Yifan, Qian Huang, Fudong Tao, Huairui Li, Da Hao, Haoyang Qin, and Qiang Fu. 2025. "Research on Fault Diagnosis of Vertical Centrifugal Pump Based on Multi-Channel Information Fusion." Processes 13 (4). https://doi.org/10.3390/pr13041152.

Zhu, R., Li, Y., Huang, Q., Li, S., Zhang, X., Li, H., & Fu, Q. (2023). Research on Vertical SEC Centrifugal Pump Multi-Fault Diagnosis Based on WPT–SVM. E