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Predictive Maintenance Systems Using Data-Driven Diagnostics for Industrial Rotating Machinery

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Abstract

The recent development in the digitalization of industries has brought about the creation of large volumes of sensor data from engineering systems, hence the rapid use of machine learning (ML) in making intelligent decisions regarding maintenance in such industries. This research centers on industrial rotary equipment, especially electric motors and bearings that experience extensive damage and sudden breakdowns during production. Traditional maintenance procedures have been ineffective in detecting and analyzing faults within such industrial equipment. To overcome this challenge, a diagnostic approach based on past historical sensor data including vibrations, acoustic sensors, and temperatures is proposed. Z-Score normalization technique has been suggested as a means of normalizing sensor data by eliminating any variation in scale. Extraction of features is done through the use of Discrete Wavelet Transform (DWT) to detect time-frequency features of non-stationary signals of vibration, acoustic, and temperature sensors for proper fault detection and classification. MBO-kernel-SVM is recommended as a technique for finding optimal SVM hyperparameters for fault detection. The MBO algorithm is a nature-inspired metaheuristic approach that mimics the migratory behavior of butterflies to search for optimum solutions. This was achieved through the use of balance in exploration and exploitation to attain efficiency in solving complex optimization problems. Test results obtained from simulations done using Python software showed that the accuracy of the algorithm is 98% while the precision, recall, and F1 score values are all 0.98. The proposed approach uses a combination of diagnostics and prognostics for early detection of faults.

Keywords: Predictive Maintenance, Machine Lear ning, Fault Detection, Condition Monitoring, Industrial Rotating Machinery.

1. Introduction

By integrating the Internet of Thing (IoT), Cyber-Physical Systems, cloud computing, and digital twin into intelligent connected and data-enabled industrial facilities, the current era, known as Industry 4.0, transforms the manufacturing industry and its processes [1]. All of these developments make it easier to apply the predictive maintenance (PdM) strategy, which is based on the use of smart sensors for ongoing machine operation monitoring to detect malfunctions and schedule maintenance [2]. At present, predictive maintenance (PdM) is actively used in various sectors including manufacturing industry, energy sector, renewable energy systems, healthcare industry and process industries for improving reliability, reducing downtimes, improving energy efficiency and optimizing system performance. The transformation from conventional to intelligent and condition-based approaches emphasizes the necessity of monitoring and intelligent decision making within industrial ecosystems [3]. Artificial intelligence (AI), machine learning (ML), and deep learning (DL) technologies are used extensively in the implementation of intelligent decision support systems and predictive maintenance. They are used in the creation of statistical learning models, supervised and unsupervised learning algorithms, and deep learning (DL) models. To improve model performance, sophisticated methods also use cloud computing, IoT enabled data collection, and automated data labeling [4, 5]. Moreover, reinforcement learning and explainable AI techniques are under development for the purpose of improving maintenance decision making and fault diagnosis in intelligent manufacturing [6]. However, there are some difficulties associated with the application of predictive maintenance systems in industrial applications. The lack of high-quality labeled data is one of the main issues, which restricts the efficacy and efficiency of AI/ML-based systems [7]. Furthermore, many of the current methods overemphasize their predictive power while ignoring the integration of the system's mission cycle, decision-making strategy, and other operational restrictions. Data heterogeneity, model interpretability, scalability, and the complexity of combining physics-based and data-driven models are other factors [8].

1.1 Aim of the research: The purpose of this research endeavor is to create a method for predictive maintenance of industrial systems utilizing artificial intelligence, data mining, and machine learning approaches that allow for accurate defect diagnosis, condition monitoring, and predictions for lifespan.

1.2 Organization of the research: Section 1 provides background information and motivation about predictive maintenance systems in industry 4.0 environments. The same section discusses the role of machine learning, artificial intelligence, and the internet of things in the digital transformation of industries. Section 2 explores related work on predictive maintenance utilizing data analytics, the digital twin approach, and SVM, kernel-SVM, and DL. Section 3 looks at the MBO-Kernel-SVM algorithm. The experimental findings, performance comparison of the suggested model with alternative models, and metrics for assessing model efficacy are all included in Section 4. The research's conclusion is displayed in section 5.

2. Related work

Recent research on predictive maintenance, SHM, and digital twin technology in industry systems have been included in Table 1 below. The research have been discussed in terms of research objectives, methods employed, results of the experiments conducted, and limitations faced in the process. In general, the table represents how data-based and AI technologies have evolved to meet their objectives.

Table 1: Previous research on Predictive Maintenance Systems

Ref	Research Aim	Technique used	Experimental Results	Limitation
[9]	To review and classify data-driven systems for structural condition monitoring and prediction.	Systematic review with taxonomy of sensing, communication, and ML/statistical models.	Developed a structured taxonomy and comparative analysis of methods.	Poor real-world scalability and high computational cost for real-time use.
[10]	To predict and optimize maintenance of hospital Heating, Ventilation, and Air Conditioning systems.	ML models and forecasting like Seasonal Auto-Regressive Integrated Moving Average and Prophet.	Improved maintenance efficiency and reduced operational costs.	Sensitive to data quality and weak real-time adaptability.

[11]	To improve predictive maintenance in maritime machinery for safer and more efficient vessel operation.	Convolutional Neural Network-based fault detection using raw vibration signals from motor ball bearings.	Achieved effective classification of bearing health conditions and fault types.	Limited generalization due to laboratory-based data and noisy real-world maritime conditions.
[12]	To optimize maintenance scheduling in power systems.	Pareto analysis and optimization-based deterioration prediction.	Reduced maintenance cost and improved system stability.	Difficult under dynamic and uncertain fault conditions.
[13]	To predict RUL in cyber-physical systems using DL models.	Temporal Convolutional Network and optimized Long Short Term Memory-based hybrid models.	High prediction accuracy and strong model performance.	Limited generalization across operating conditions.
[14]	To develop a drift detection framework for Industry 4.0 systems.	Ensemble ML and DL models	Good performance in drift detection and classification metrics.	Data heterogeneity and scalability issues.
[15]	To develop a hybrid and cognitive digital twin for predictive maintenance.	Digital Twin pipeline integrating AI/ML models.	Reduced downtime and improved energy efficiency.	Complexity in integration and scalability limitations.
[16]	To build an explainable AI-based predictive maintenance system.	Multi-sensor ML models such as K-nearest neighbor, SVM, Random Forest.	Improved fault detection with better interpretability.	Remaining black-box limitations and scalability constraints.

Research gap: Predictive maintenance methods like SVM, Random Forest, KNN, and DL models have a number of shortcomings, including the need for human parameter adjustment, sensitivity to feature scaling, generalizability, and incapacity to handle non-linear fault classification problems.The methodology proposed here brings about a novel framework using Kernel SVM for non-linear fault classification, DWT for efficient time-frequency feature extraction, and Z-score normalization for proper data normalization. The use of MBO makes the system more accurate, robust, and generalizable due to its automatic parameter optimization of SVM.

3. Materials and methods

The approach outlined above is based on an industrial data-driven predictive maintenance framework wherein the sensor signals are first captured and preprocessed through the normalization of signal data. The feature extraction technique utilized in the approach involves employing DWT to determine the time-frequency attributes associated with the faults of the machine. An SVM-based classification model receives the feature set produced by the aforementioned procedure and uses it to categorize the machine's failure circumstances. As demonstrated in Figure 1, MBO is used to increase the classification algorithm's accuracy by fine-tuning the SVM-based classifier's parameters.

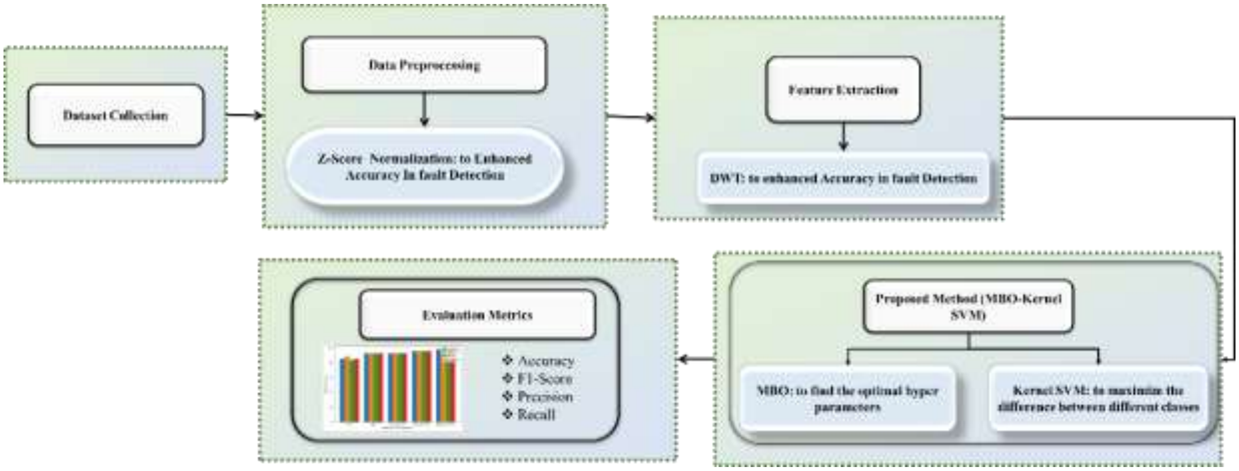

Figure 1: Methodology of the proposed flow

3.1 Dataset description: An open-source database (https://www.kaggle.com/datasets/colabsss/rotating-machinery-fault-monitoring-data) that is intended to be useful for the condition monitoring and fault analysis of industrial rotating machinery provided the data used to develop the predictive maintenance approach. Vibration signals, temperature readings, acoustic data, electrical parameters, lubrication, operating data, maintenance, and machine failure modes are among the operational parameters and sensor readings included in the dataset. The dataset, which consists of 8,900 records representing various machine settings, is split into 20% for testing and 80% for training. Several Predictive Maintenance tasks, including fault identification, machine state assessment, anomaly detection, and useful life forecast, are made possible by the gathered data.

3.2 Data preprocessing using Z-score normalization: It is a statistical preprocessing method that converts raw measurements into a common scale with zero mean and unit variance so to normalize sensor data. The primary goals of employing Z-score normalization in this research is to increase feature comparability, remove data bias brought on by different sensor magnitudes, and boost the stability and effectiveness of machine learning models in fault identification and remaining usable life prediction.

$$Z_{score} = \frac{rss(m)-\mu}{\sigma} \qquad (1)$$

$$rss_{j,i} = [rss(1), rss(2), \ldots rss(M)] \qquad for\ 1 \leq m \leq M \qquad (2)$$

Equations (1) and (2) Z_{-score} define the nth observation, where $rss(m)$ is the residual sum of squares for that point. Here, μ represents the mean of all RSS values, and σ is their standard deviation. The vector notation $rss_{j,i}$ = $[rss(1), rss(2), \ldots rss(M)]$ lists all RSS values for indices j and i, where M is the total number of observations, allowing for the standardization of errors.

3.3 DWT for Feature Extraction in Machine Condition Monitoring: DWT is a signal processing technique that decomposes a non-stationary signal into multiple frequency sub-bands at different resolution levels, enabling simultaneous time–frequency analysis and its objective is to extract meaningful features from vibration, acoustic, and temperature sensor signals by capturing localized variations in machine behavior, thereby improving fault detection accuracy and supporting effective condition monitoring in predictive maintenance systems.

$$DWT\ (m,n) = \frac{1}{\sqrt{2^m}} \sum_k f(k)\, \psi \left[\frac{n-k2^m}{2^m}\right] \qquad (3)$$

Here, $f(k)$in Equation. (3) is the discrete input signal sampled from sensor data and $\sum_k$ corresponds to the time/sampling index. In addition, function ψ refers to the mother wavelet. Here, m is the decomposition level which determines the resolution in frequency domain and n is the translation factor which moves the wavelet in time on signal $f(k)$. Variable k refers to the sampling index, while 2^m is responsible for the dilation of the wavelet to analyze both high and low frequencies in $\frac{1}{\sqrt{2^m}}$.

3.4 Predictive maintenance system using MBO-Kernel-SVM

MBO-Kernel SVM method is a hybrid intelligent model whereby the MBO optimization technique is used in order to automatically find the optimal values of the hyperparameters associated with SVM, such as the cost function and kernel parameters. This approach's main goal is to improve SVM models' generalization and prediction accuracy for defect detection and condition monitoring. By successfully learning non-linear data patterns from the sensors, this would result in more reliable and effective predictive maintenance.

3.4.1 Kernel SVM for Fault Detection and Predictive Maintenance: Kernel SVM is a supervised learning technique that involves use of hyperplanes in multidimensional spaces to classify data. This is done through application of kernel functions for handling non-linear data patterns. The aim of Kernel SVM is to maximize the distance between the hyperplanes while reducing classification errors.

$$f(x) = w^T \phi(x) + b \quad (4)$$

$$K(x, y) = \phi(x)^T \phi(y) \quad (5)$$

$$K(x, y) = exp(-\gamma \parallel x - y \parallel^2) \quad (6)$$

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \; ; \; \xi_i \geq 0 \quad (7)$$

The model's classification output is represented by $f(x)$ in Equation (4), where x is the input feature vector derived from sensor signals, w^T is the weight vector defining the separating hyperplane, $\phi(x)$ is the nonlinear mapping function that converts input data into a higher-dimensional space, and b is the bias term used to modify the decision boundary. The similarity measure between two input samples, x and y, is represented by $K(x, y)$ in Equation (5), whereas $\phi(x)^T \phi(y)$ indicates the inner product in transformed feature space without explicitly computing the mapping. The exponential function is denoted by exp apply in Equation (6), the squared Euclidean distance between two feature vectors is represented by $\parallel x - y \parallel^2$, and the kernel parameter governing the influence of data points is denoted by γ.In Equation (7), y_i represents the class label of the i^{th} sample, x_i denotes the input training sample, and ξ_i is the slack variable that allows certain classification errors to improve model flexibility and generalization.

3.4.2 MBO for SVM Hyperparameter Tuning: MBO is a nature-inspired metaheuristic algorithm mimicking monarch butterfly migration to efficiently explore and exploit complex optimization problems. It is used to automatically tune hyperparameters of the Kernel SVM, including the penalty and kernel parameters, which affect model performance. The main goal is to find the optimal parameter combination to maximize classification accuracy and minimize prediction errors in fault detection. Through the continuous updating of the population and fitness evaluation process, the performance of SVM can be improved significantly through MBO algorithm due to its increased ability to learn.

$$Fitness = max(Accuracy) \quad (8)$$

$$M_i^{t+1} = \begin{cases} M_{best}, if\ rand \leq p \\ M_r, otherwise \end{cases} \quad (9)$$

$$c = \frac{W_{max}}{t^2} \quad (10)$$

$$M_i^{t+1} = \begin{cases} M_i^{t+1}, if\ f(M_i^{t+1}) > f(M_i^t) \\ M_i^{t+1}, otherwise \end{cases} \quad (11)$$

From the above equations (8-11), $Fitness$ represents the objective function used in MBO, max indicates that the optimization process aims to maximize this accuracy value across all possible solutions explored during the search process, and $Accuracy$ represents the classification performance of the SVM model for a given set of parameters. M_i^{t+1} is the updated position of the i^{th} butterfly at iteration $t + 1$, while M_{best} represents the best solution found for p. The term $rand$ is a randomly generated number between 0 and 1, and M_r is the migration probability that decides whether a butterfly updates its position toward the global best solution. The parameter c represents a scaling or adjustment factor controlling step size, while w_{max} and t^2 are used to regulate the convergence behavior over iterations. The condition $f(M_i^{t+1}) > f(M_i^t)$ ensures that the new solution replaces the old one only if it improves the fitness value; otherwise, the previous solution is retained (Algorithm 1).

Algorithm 1: MBO–Kernel SVM-Based Predictive Maintenance Framework

$\boldsymbol{Input}$:

$D \rightarrow Rotating\ machinery\ dataset;\ MaxIter \rightarrow Maximum\ number\ of\ MBO\ iterations;\ C, \gamma \rightarrow Search\ space\ for\ SVM\ hyperparameters;\ N \rightarrow Number\ of\ samples$

$\boldsymbol{Output}$:

$O \rightarrow Fault\ classification/machine\ health\ prediction$

$Begin$

1. $Load\ Dataset\ D$

$Import\ sensor - based\ condition\ monitoring\ data\ from\ industrial\ machinery.$

2. $Data\ Preprocessing\ (Z - score\ Normalization)$

$For\ each\ feature\ x\ in\ D\ do:$

$Z = (x - \mu) / \sigma$

$End\ For$

$\rightarrow\ Standardize\ data\ to\ remove\ scale\ variations\ and\ improve\ stability.$

3. $Feature\ Extraction\ using\ DWT$

$For\ each\ signal\ segment, do:$

$$DWT(m,n) = \frac{1}{\sqrt{2^m}} \sum_k f(k)\psi\left[\frac{n - k2^m}{2^m}\right]$$

$End\ For$

4. $Initialize\ Kernel\ SVM\ Model$

$f(x) = w^T\phi(x) + b$

$Initialize\ C\ and\ \gamma\ randomly\ within\ the\ search\ space.$

5. $MBO - Based\ Hyperparameter\ Optimization$

$For\ iter\ =\ 1\ to\ MaxIter\ do:$

$Evaluate\ fitness\ and\ update\ the\ solution:$

$M_i^{t+1} = M_{best}, if\ rand \le p$

$Otherwise, apply\ local\ adjustment$

$Retain\ the\ best\ solution:$

$keep\ a\ new\ solution$

$Else$

$retain\ old\ solution$

$End\ For$

6. $Fault\ Detection\ /\ Prediction$

$Apply\ a\ trained\ model\ to\ classify\ the\ machine\ condition$

End

The method for predictive maintenance of rotating machinery is demonstrated by the suggested method 1, which is based on feature extraction, data preprocessing, and machine learning classifier optimization. Z-score normalization is used to first standardize the data. The DWT approach is then used to transform the data into a time-frequency representation. Lastly, the Kernel SVM is learnt, and MBO is used to tune the model's hyperparameters for high fault classification accuracy.

4. Results and discussion

In contrast to other ML algorithms such as SVM, K-Nearest Neighbor (KNN), Decision Tree (DT), and Random Forest (RF), this section examines the experimental examination of the suggested method for predictive maintenance of rotating machinery [16]. The models' performance is compared using a number of metrics, including F1-Score, Accuracy, Precision, and Recall. Python is used to implement this algorithm.

4.1 Operational Condition and Feature Behavior Analysis: Figure 2 illustrates multidimensional condition monitoring and operational behavior analysis through vibration, load, temperature, and health indicators. These include: Figure 2(a): Condition indicator with values ranging from 0-25,000 operational hours, whereby values lie between 50-80 units while reference thresholds fall between 55 units. Consistency of performance is depicted by values. Figure 2(b): Correlation of load percentages ranging from 35%-100% against vibration characteristics ranging from 55-90 units. Different states are evident in high vibrations above 75 units. Figure 2(c): Density plot of vibration Root Mean Square (RMS) values ranging from 0-6.0 and condition values ranging from 55-92 units. Consistent performance can be seen with RMS values lying between 2-5 and conditions ranging from 65-85.

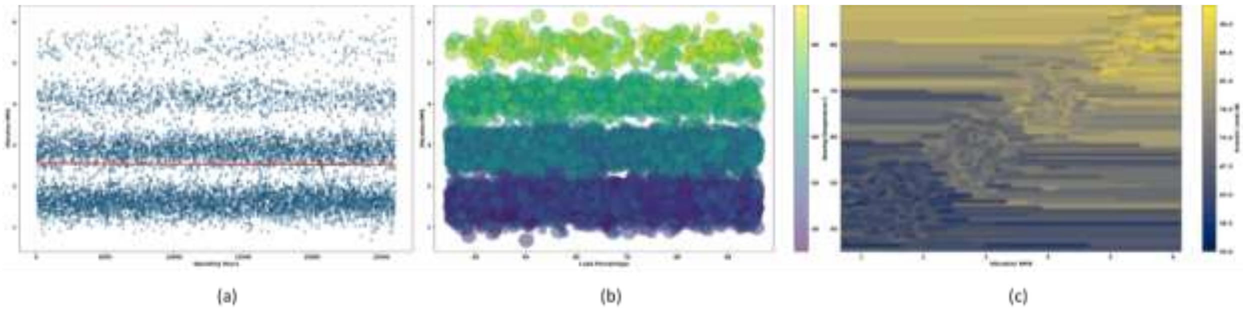

Figure 2: Analysis of (a) Long-term operational condition monitoring analysis (b)Load-dependent vibration behavior analysis (c)Vibration and condition-state density analysis.

Analysis of feature interaction and statistics for predictive condition assessment is presented in Figure 3. Figure 3(a) illustrates five normalized features vibration RMS, vibration peak, bearing temperature, motor temperature, and acoustic level. Features like vibration RMS and peak remain less than 15 units, whereas temperature features significantly rise up from 40–85°C. The acoustic feature values lie between 55 and 85 units, depicting highly separable features. Distribution of bearing temperature from 40–90°C is displayed in Figure 3(b), with maximum peaks at 50°C, 60°C, 70°C, and 80°C, showing different thermal behaviors. In addition, Figure 3(c) presents a smooth graph over a span of −5 to 3 with magnitude from 500 to 1300 units.

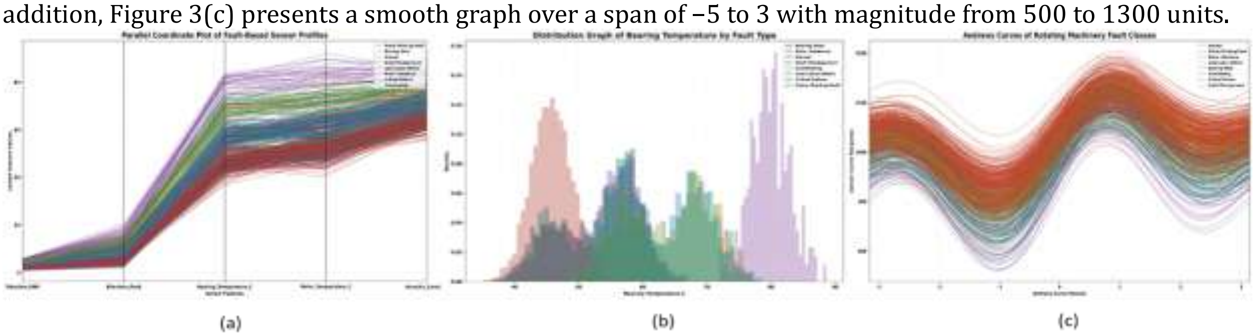

Figure 3: Analysis of (a) Multi-feature operational pattern analysis (b)Temperature distribution analysis across operating states, (c) Condition-response variation analysis.

4.2 Metrics Evaluation

Accuracy: By dividing the percentage of right classifications by the total number of samples, accuracy may be calculated to determine how accurate a model is overall. It offers a useful summary of the model's performance, but in situations when classes are unbalanced, it may produce inaccurate results. **Precision:** The precision shows what percentage of the predictions that were marked as positive turned out to be correct. This metric allows estimating the model's performance in terms of false positive errors, which are vital in the context of fault detection systems. **Recall:** The percentage of all actual positive cases that the model predicted is known as recall. Because it indicates if the system detects all possible issues and prevents false negatives, it is a crucial indicator for predictive maintenance. **F1-score:** The F1-Score is a measure that displays the precision and recall harmonic mean.

4.3 Performance evaluation: The proposed MBO–Kernel SVM was trained on the existing industrial rotating machinery dataset. Performance comparisons with baseline machine learning models (SVM, KNN, DT, RF) [16]. As presented in Table 2, the proposed model was able to provide an accuracy of 97%, precision of 0.97, recall of 0.97, and F1 score of 0.97. These findings reflect higher fault detection rates and balance in the classifier's output, proving its superiority compared to other existing approaches.

Table 2: Performance evaluation of the proposed model trained on the existing dataset

Metrics	Accuracy	Precision	Recall	F1 score
SVM [16]	85%	0.89	0.85	0.84
KNN [16]	93%	0.93	0.93	0.93

Decision Tree [16]	93%	0.93	0.93	0.93
Random Forest [16]	96%	0.96	0.96	0.96
MBO-Kernel SVM [proposed]	97%	0.97	0.97	0.97

A rotating machinery failure monitoring dataset was used to train both the suggested MBO–Kernel SVM and the current (SVM, KNN, DT, and RF [16]) approaches. As shown in Table 3, the recommended method may achieve 98% Accuracy, Precision, Recall, and F1-Score, all of which are valued at 0.98. It is effective in detecting complicated fault conditions, thus leading to improved predictive maintenance efficiency among industrial rotating machinery systems such as those indicated in Figure 4.

Table 3: Comparison of existing and proposed models trained on the rotating machinery fault monitoring dataset

Metrics	Accuracy	Precision	Recall	F1 score
SVM	89%	0.91	0.87	0.88
KNN	95%	0.95	0.95	0.95
Decision Tree	95%	0.95	0.95	0.95
Random Forest	97%	0.97	0.97	0.97
MBO-Kernel SVM [proposed]	98%	0.98	0.98	0.98

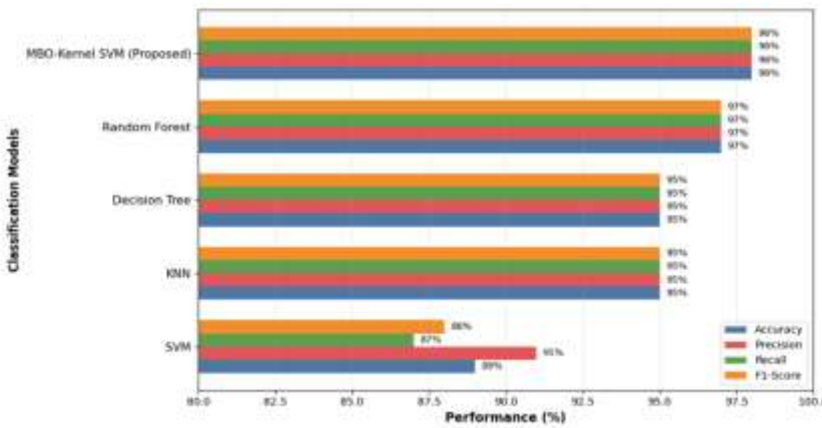

Figure 4: Representation of existing trained in the proposed model

The suggested MBO-Kernel SVM model compensates for the shortcomings of conventional predictive maintenance techniques such as SVM, KNN, DT, and RF [16] by being incapable of coping with nonlinear fault signatures, scaling features, and optimizing hyperparameters manually. The conventional models have difficulty dealing with nonstationary sensor data due to different industrial environments. Thanks to the incorporation of Z-score normalization, DWT for extracting time-frequency features, and MBO for self-tuning optimization, the proposed model greatly improves fault detection capability.

5. Conclusion

Research introduces a data-based predictive maintenance scheme for rotating machines in industries, which makes use of Z-score normalization as a preprocessing technique, DWT for time–frequency analysis, and Kernel SVM optimized using MBO to enable precise fault classification and monitoring of machinery conditions. The proposed method ensures robustness and reliability of prediction in circumstances of nonlinear sensing data by providing increased performance in terms of fault detection accuracy and improved model generalization. According to experiments, the framework, which is implemented in the Python programming language, produces an accuracy rate of 98%, a precision value of 0.98, a recall value of 0.98, and an F1 measure of 0.98. Nonetheless, the proposed solution suffers from limitations concerning reliance on labeled data sets, additional costs associated with optimization, and lack of adaptation to highly dynamic industrial settings which has been addressed in future.

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