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FAULT DETECTION OF SLEWING BEARINGS IN ENGINEERING CRANES BASED ON ADAPTIVE ALGORITHMS

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Abstract

Slewing bearings play a crucial role in the operational efficiency and security of engineering cranes by supporting rotational movements under heavy loads. Over time, these components wear and degrade, making early fault detection critical to avoiding mechanical failures, costly downtime, and security risks. Conventional condition monitoring methods frequently struggle with inconsistent data patterns, sensor noise, and dynamic operating conditions. There is an urgent need for intelligent, adaptive fault detection mechanisms that can precisely predict slewing bearing failures under varying load and operational circumstances. This study aims to build a robust, adaptive fault detection algorithm - Slewing Bearing Fault Detection (SBFDetect) - capable of identifying early signs of faults in slewing bearings using real-time sensor data. The goal is to improve maintenance planning and reduce unexpected failures in engineering cranes. A dataset called the Slewing Bearings Fault (SBF) Dataset was created, which includes key parameters such as vibration intensity, temperature, noise levels, rotation speed, load pressure, lubrication levels, metal debris levels, hours of operation, and sensor drift. The proposed SBF Detect Algorithm starts with preprocessing steps like categorical encoding and normalization, then trains a Random Forest classifier on the processed dataset. The model is assessed using standard performance metrics, such as accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC). An adaptive update mechanism is also included to enable incremental learning with new sensor data. The SBF Detect algorithm produced promising results on the SBF dataset, with an accuracy of 90.0%, precision of 88.9%, recall of 88.9%, F1-score of 88.9%, and MCC of 0.80. These metrics demonstrate the model's ability to correctly classify faulty and healthy bearings, even with a limited number of samples. The SBF Detect Algorithm provides a practical and scalable solution for predictive maintenance of slewing bearings in cranes. By utilizing adaptive machine learning methods, the proposed technique enhances the dependability and security of crane operations while reducing unplanned downtime.

Keywords: slewing bearings, fault detection, adaptive algorithms, predictive maintenance, random forest classifier

1. INTRODUCTION

Engineering cranes are used in a variety of industrial applications, including construction, shipping, and manufacturing, where precise and dependable handling of heavy materials is critical [1]. The slewing bearing is an important component in the operational integrity of these cranes because it allows for smooth rotational motion under heavy loads. Slewing bearings are subjected to high mechanical stress, which makes them susceptible to wear, fatigue, and eventual failure [2]. Faults in these components can result in catastrophic outcomes such as mechanical breakdowns, costly operational downtimes, and safety hazards to personnel and equipment [3]. As a result, the scientific and engineering community has focused heavily on developing robust condition-tracking and fault-diagnosis systems for such critical components [4], [5].

Conventional methods of fault detection in rotating machinery include vibration analysis, acoustic monitoring, thermal imaging, and oil debris analysis [6]. With the rise of Industry 4.0 and the Internet of Things (IoT), there has been a significant shift toward data-driven methods that use real-time sensor data and sophisticated signal processing [7], [8]. Machine learning models, such as Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks, have demonstrated great promise in detecting fault patterns and predicting failures with varying degrees of accuracy. Recent advances include ensemble learning methods such as Random Forests and Gradient Boosting, which enhance predictive performance by aggregating the results of multiple weak learners [9]. Furthermore,

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the use of adaptive algorithms has enabled systems to learn incrementally from streaming data, adjusting to changes in operating conditions and sensor behavior [10].

Despite these advances, several significant challenges remain. Many existing models struggle in the dynamic and non-stationary operating environments common to engineering cranes. Inconsistent sensor readings, environmental noise, data imbalance, and a lack of labeled fault data all contribute to reduced model reliability. More importantly, most traditional models lack adaptive learning capabilities, resulting in decreased performance when exposed to novel data patterns or sensor drift over time. The urgent need is to design intelligent fault detection systems that are not only precise but also resilient and adaptive to developing operational contexts, allowing for timely and precise detection of slewing-bearing faults.

The primary goal of this research is to create a novel, adaptive machine learning algorithm called Slewing Bearing Fault Detection (SBF Detect) that can detect early-stage faults in engineering crane slewing bearings. This study aims to bridge the gap between traditional fault diagnosis methods and modern adaptive data-driven models. It aims to enhance the reliability, safety, and operational effectiveness of engineering cranes by implementing proactive maintenance strategies and early fault intervention.

To attain the research objectives, a comprehensive methodology is utilized. The Slewing Bearings Fault (SBF) Dataset is curated to include essential operational parameters such as vibration intensity, temperature, noise levels, rotation speed, load pressure, lubrication levels, metal debris levels, hours of operation, and sensor drift. The data goes through preprocessing steps such as categorical encoding and normalization. The core detection model is based on the Random Forest classifier, which was chosen for its robustness and ability to handle high-dimensional and imbalanced data. Furthermore, an adaptive update strategy is integrated into the system, allowing incremental learning from newly available sensor data and thus maintaining the model's performance over time.

This study adds significantly to the growing body of knowledge in predictive maintenance and intelligent fault diagnosis. The proposed SBF Detect algorithm, which combines adaptive machine learning with real-time sensor analytics, provides a practical and scalable solution for condition tracking in complex mechanical systems. Its capacity to handle sensor drift and adapt to changing operational contexts makes it ideal for industrial environments that value reliability and uptime. The study's findings not only advance the state-of-the-art in slewing bearing fault detection but also pave the way for future research into adaptive fault diagnosis systems for other critical rotating machinery in the smart manufacturing and industrial automation domains.

1.1 Service Characteristics and Physical Fault Mechanism of Slewing Bearings

Slewing bearings in engineering cranes do not work in a smooth and steady way. Their job is actually quite tough. Unlike machines that rotate all the time at the same speed, crane slewing bearings move in an uneven pattern. They stop and start. They carry heavy loads. Sometimes they even face sudden shocks. Because of this, the way faults begin and grow is a bit different. So, when choosing what to monitor, these real working conditions must be kept in mind.

1.2 Uneven Loading

During lifting work, the bearing carries changing loads. The force is not always balanced. Radial and axial loads keep shifting. Sometimes the load moves suddenly to one side. This creates stress in certain small areas inside the raceway and rolling parts. One reason may be the weight of the lifted object is not centered properly.

Over time, this repeated stress damages the surface. Small pits may form. Tiny cracks can appear. Rolling elements may slowly change shape. At first, the damage is not easy to see. But the machine starts giving signals. Vibration becomes stronger. High-frequency spikes appear. Also, small metal particles may mix into the lubricant. This suggests that the surface is wearing out. So, vibration level and metal debris seem to be important signs of load-related damage.

1.3 Non-Continuous and Irregular Rotation

Crane rotation is not smooth like a motor running all day. It starts, stops, turns a little, then pauses. The speed also changes often. Because of this, lubrication does not always spread evenly. Sometimes the oil film becomes thin or breaks. When that happens, parts rub directly against each other.

This rubbing creates more friction. And friction creates heat. So, temperature may rise. Noise can also increase. The lubricant may degrade faster than expected. These effects are usually reflected in higher vibration and slight temperature variation. It appears that monitoring temperature and lubrication condition helps us understand this irregular rotation problem.

1.4 Shock Loads During Operation

Now and then, sudden braking or impact happens. These shock loads are short, but strong. They push the bearing parts hard for a brief moment. Even though the event is quick, the effect may be serious. Cracks can grow faster. Raceway damage may spread.

Such faults usually produce sharp vibration peaks. Abnormal noise may also be heard. These signals are not always continuous, but they are noticeable during monitoring. So, vibration and acoustic signals are useful in detecting shock-related damage.

Based on these real service conditions, a few key parameters were chosen for the SBF dataset. These include vibration intensity, temperature change, lubrication level, metal debris concentration, and load pressure. Each one reflects a part of the physical wear process. Together, they give a clearer picture of bearing health under crane working conditions.

The method focuses on selecting parameters that match actual mechanical behavior. The results, however, should be interpreted carefully. Operating conditions can vary, and some signals may overlap. Still, these features appear to provide a reasonable mechanical basis for the proposed SBF Detect algorithm.

2. RELATED WORK

Numerous studies have explored diverse tactics to improve early fault detection, accommodate differing operational conditions, and overcome noise and sensor limitations.

In the Chinese context, Ding et al. [11] developed a stationary subspaces-vector autoregressive model with exogenous terms (SS-VARX) to accurately estimate degradation trends in rolling and slewing bearings. Their methodology took into account temporal dependencies and exogenous variables, resulting in higher prediction accuracy under fluctuating operating conditions. To improve life prediction under non-stationary conditions, Ding et al. [12] proposed a dynamic structure-adaptive symbolic method that showed promise in adapting to changing working settings. Meanwhile, advances in deep learning-based techniques have significantly improved fault detection capabilities. Transformer-based architectures have also demonstrated efficacy.

Ding et al. [13] proposed a novel time-frequency Transformer with self-attention for fault diagnosis in rolling bearings, which significantly improved diagnostic precision. Several new frameworks and algorithms have been proposed to increase diagnostic reliability. Wu et al. [14] introduced the ACMSlE framework, and Zhuo et al. [15] developed the NEITD-ADTL-JS algorithm, which improves feature extraction and classification for early fault detection. Feng et al. [16] used SR-HWPT and PDF methods to detect subtle fault signals in early degradation stages. Sun et al. [17] used stator current analysis to detect structural defects in motor bearings of high-speed trains, demonstrating the cross-domain applicability of electrical signal-based diagnostics. Furthermore, Liu et al. [18] proposed a noise-resilient recognition technique specific to mine hoist-bearing failure, emphasizing the significance of designing solutions for harsh environments. Zhao and Xu [19] tackled the difficulties of missing data and feature shift, providing a fault diagnosis tactic that guarantees resilience in incomplete and unstable data sets.

Similarly, In the Spaniards context, Heras et al. [20] tackled the impact of manufacturing errors and ring flexibility on load distribution and friction torque in four-point contact slewing bearings, offering deeper insights into the mechanical behaviors required for accurate fault modeling. In the Russian context, Sinitsin et al. [21] developed a hybrid CNN-MLP model using mixed inputs for intelligent bearing fault diagnosis, providing resilience against input variation and noise.

In the Pakistani context, Sarwar et al. [22] concentrated on integrating deep learning into Industry 4.0/5.0 frameworks for intelligent manufacturing, emphasizing the scalability of these methods for real-time industrial applications. In addition to algorithmic advances, sensor-based and hybrid solutions have been investigated. In the multi-country collaboration context, Peralta-Braz et al. [23] presented a dual-purpose system that uses piezoelectric cantilevers to harvest energy while also detecting faults, with an emphasis on energy efficiency.

In the Indian context, Pandiyan and Babu [24] provided a comprehensive review of the evolution of rolling-element bearing fault diagnosis methods, emphasizing the shift toward intelligent, data-driven methods. Chauhan et al. [25] proposed an adaptive feature mode decomposition method that employs a novel health indicator for dynamic fault diagnosis. Table 1 shows the Summary of Related Works on Bearing Fault Detection.

These related works highlight the growing focus on adaptive, intelligent, and noise-resistant fault detection techniques. However, numerous existing techniques still struggle to achieve high performance with small and dynamically changing datasets. The proposed SBF Detect algorithm expands on these advances by integrating real-time adaptive learning with a Random Forest-based classifier and incremental updates, providing a scalable and robust solution for slewing bearing fault detection in engineering cranes.

3. MATERIALS AND METHODS

Mainly, this research focuses on an industrial fault detection system. Interestingly, the system employs many sensors. These sensors continuously track machine operating status. At first, these sensor readings are gathered as data. Next, this data forms the SBF dataset. Here, the dataset has both normal and fault conditions. The proposed SBF Detect algorithm implements this sensor data. Its major work is to identify fault conditions. Figure 1 shows the system architecture of proposed SBF Detect algorithm.

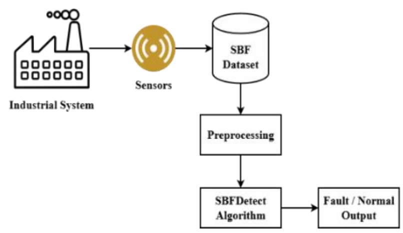

Fig. 1. System architecture of SBF Detect algorithm

Table 1. Summary of related works on bearing fault detection

Reference	Method / Contribution	Results	Limitations
[11] Ding et al. (2021)	SS-VARX for degradation trend estimation	Efficiently modeled degradation under exogenous influences	Limited adaptability to highly non-stationary settings
[12] Ding et al. (2021)	Structure-adaptive symbolic life prediction model	Enhanced prediction accuracy under variable conditions	Complex symbolic representation may be computationally costly
[13] Ding et al. (2022)	Self-attention Transformer for fault diagnosis	Improved time-frequency feature learning and classification	Transformer models need substantial training data
[14] Wu et al. (2025)	ACMSIE framework for fault diagnosis	Enhanced robustness and classification accuracy	Framework design lacks detailed real-time adaptation tactic
[15] Zhuo et al. (2025)	NEITD-ADTL-JS algorithm for early fault detection	Efficient in capturing early degradation features	Complex model incorporation increases execution difficulty
[16] Feng et al. (2024)	SR-HWPT-PDF hybrid method	High sensitivity to early fault signals	Susceptible to noise interference in raw signals
[17] Sun et al. (2024)	Identification via stator current in trains	Non-invasive detection technique for structural defects	Domain-specific application limits generalizability
[18] Liu et al. (2023)	Recognition technique for noisy settings	Achieved robustness against strong noise	May struggle with feature drift over long-time series
[19] Zhao & Xu (2024)	Feature shift suppression and missing data handling	Maintained accuracy with incomplete data	High preprocessing overhead; limited interpretability
[20] Heras et al. (2019)	Friction torque modeling with ring flexibility & errors	Precise mechanical modeling of slewing bearings	Concentrated on mechanical behavior, not fault detection
[21] Sinitsin et al. (2022)	Hybrid CNN-MLP with mixed inputs	High diagnostic accuracy and generalization	Needs large labeled datasets, high computational cost
[22] Sarwar et al. (2024)	Deep learning for bearing detection in Industry 4.0/5.0	Showed strong performance in intelligent manufacturing settings	Limited explanation of feature importance and interpretability
[23] Peralta-Braz et al. (2025)	Energy harvesting with piezoelectric fault detection	Dual-functionality: energy and fault signal detection	Limited practical deployment and long-term validation
[24] Pandiyan & Babu (2024)	Systematic review of fault diagnosis techniques	Detected trends and gaps in bearing fault research	No experimental validation; review-only
[25] Chauhan et al. (2024)	Adaptive mode decomposition and new health indicator	Superior fault identification under varying conditions	Health indicator needs careful calibration

3.1 Dataset Description

The present study focuses on algorithmic development and data-driven fault detection. Due to the limited availability of industrial crane systems for controlled experimentation, direct on-site field testing was not conducted. Instead, the Slewing Bearings Fault (SBF) dataset was constructed to represent realistic operating conditions of slewing bearings under uneven loading, non-continuous rotation, and shock load scenarios. The parameter ranges were defined according to established bearing fault progression behavior reported in prior mechanical studies. Therefore, the validation presented in this work reflects a simulation-based experimental framework rather than a direct field deployment.

The SBF dataset was synthetically constructed to simulate controlled variations in load, rotational speed, lubrication state, vibration intensity, temperature, and metal debris concentration. Fault conditions such as lubrication degradation and wear-induced vibration were modeled according to documented mechanical degradation trends. The dataset contains 2000 instances with 11 structured features as summarized in Table 2.

Table 2. Features description

Feature	Description
Vibration_X / Vibration_Y	Horizontal and vertical vibration intensities measured in g-force
Temperature (°C)	Surface temperature of the bearing
Noise Level (dB)	Acoustic emission measured near the bearing
Rotation Speed (RPM)	The rotational velocity of the slewing bearing
Load Pressure (kPa)	Load applied to the bearing measured via pressure transducers
Lubrication Level (%)	Lubricant adequacy, suggesting lubrication condition
Metal Debris Level	Categorical (Low, Medium, High) using magnetic particle detection
Hour of Operation	Cumulative operational hours before fault status recorded
Sensor Drift	Variation in sensor calibration over time
Fault	Binary target feature showing fault presence (Yes/No)

This dataset provides a representative sample for validating the proposed fault detection algorithm's efficiency in a variety of operational contexts. Figure 1 presents the conceptual system architecture of the proposed SBF Detect algorithm. Although the diagram illustrates a sensor-driven industrial pipeline, it represents a modeled framework rather than a physically deployed system. The architecture was designed to structure the simulated data flow, preprocessing stages, feature extraction, and classification process used in this study. Thus, the figure reflects the logical workflow that guided the development and validation of the algorithm within a simulation-based environment.

3.2 Proposed Methodology: SBF Detect Algorithm

The SBF Detect algorithm is a fault detection framework that combines sensor-driven data preprocessing, intelligent feature representation, and robust Random Forest classification. It guarantees the accuracy, scalability, and adaptability of real-time slewing bearing fault detection in engineering cranes. The methodology is systematically broken down into phases, from raw data handling to model performance evaluation, each supported by mathematical formalism for transparency and reproducibility.

3.2.1 Notation and Definitions

We define the dataset D as a collection of N samples, where each sample includes a feature vector x_i with M attributes and a binary fault label y_i. Mathematically, this is denoted as:

$$\mathcal{D} = \{(\mathrm{x}_i, y_i)\}_{i=1}^{N} \quad (1)$$

This formulation captures the supervised learning nature of the problem, where the objective is to learn a function mapping sensor reading to fault status (0 = No Fault, 1 = Fault). Each x_i contains normalized readings from embedded sensors in cranes.

3.2.2 Categorical Encoding

Categorical features should be transformed into numerical values for compatibility with machine learning models. In our case, the Metal Debris Level attribute is ordinal and encoded as:

$$MetalDebrisLevel \in \{Low = 0, Medium = 1, High = 2\} \quad (2)$$

Moreover, the target variable (Fault label) is binary-encoded as:

$$y_i = \begin{cases} 1, & if\ Fault\ =\ Yes \\ 0, & if\ Fault\ =\ No \end{cases} \quad (3)$$

This transformation guarantees that both input and output features are numerically interpretable for learning algorithms, preserving ordinal relationships where needed.

3.2.3 Feature Normalization

To avoid bias toward high-magnitude features, normalization is crucial. We apply Min-Max Normalization to each numerical feature, scaling the data to a range of [0,1] utilizing:

$$x_{i,j}^{norm} = \frac{x_{i,j} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (4)$$

Where,

$x_{i,j}^{norm}$=Normalized value of the jth feature of the ith sample

$\min(x_j), \max(x_j)$=Minimum and maximum values of the jth feature across all samples

This guarantees uniform feature representation and enhances convergence during model training, particularly in tree-based models that are sensitive to feature scaling.

3.2.4 Feature Vector Construction

Once encoded and normalized, each instance is represented as a 10-dimensional vector:

$$x_i = \{v_x, v_y, T, N, R, L, U, M, H, S\} \quad (5)$$

Where,

v_x, v_y=Vibration signals along X and Y axes

T=Temperature of the slewing bearing

N=Noise level around the bearing

R=Rotation speed of the bearing

L=Lubrication level

U=Usage time or duration

M=Metal debris concentration

H=Humidity level

S=Sensor drift

This vector captures the operational conditions of the slewing bearing. Parameters such as vibration, temperature, and rotation speed reflect the mechanical state, while factors like lubrication, debris, and sensor drift capture possible fault precursors.

3.2.5 Data Splitting

To train and evaluate the model fairly, the dataset is split into training and testing subsets. We utilize an 80:20 split tactic:

$$D_{train}, D_{test} = Split(D, 0.8) \quad (6)$$

Where,

D_{train}, D_{test}=Training and testing splits of dataset D

This guarantees that the classifier is exposed to a sufficient number of samples for learning while retaining unseen examples to test its generalization ability.

3.2.6 Random Forest Model Training

Random Forest (RF), an ensemble of decision trees, is selected for its robustness and non-linear modeling capacity. It combines predictions across T decision trees:

$$RF(x) = MajorityVote\{h_t(x)\}_{t=1}^{T} \quad (7)$$

Where,

T=Total number of decision trees in the Random Forest

$h_t(x)$=Prediction made by the tth decision tree for input x

$RF(x)$=Final prediction by Random Forest via majority voting

Each tree is trained utilizing bootstrapped samples. The decision criteria at each node utilize the Gini Index:

$$G(t) = 1 - \sum_{k=1}^{K} p_k^2 \tag{8}$$

Where,

$G(t)$=Gini Index at node t

p_k=Proportion of class k instances at node t

To optimize splits, we maximize Gini Gain:

$$\Delta G = G(t) - \left(\frac{N_L}{N} G(t_L) + \frac{N_R}{N} G(t_R)\right) \tag{9}$$

Where,

ΔG=Gini Gain due to a split

N_L, N_R=Number of samples in the left and right child nodes

$G(t_L)$,$G(t_R)$=Gini indices of the left and right child nodes

N=Total number of samples at node t

This process continues recursively, growing trees that collectively reduce misclassification by capturing complex interactions between features.

3.2.7 Fault Prediction

Once trained, the RF model predicts fault status for test inputs:

$$\hat{y} = RF(x_{test}) \in \{0,1\} \tag{10}$$

The model also calculates the probability of a fault, offering a measure of prediction confidence:

$$P(y = 1|x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{11}$$

This probabilistic interpretation supports threshold tuning and reliability analysis in high-risk operations.

3.2.8 Adaptive Learning Mechanism

In practical deployment, new data arrives continuously. SBF Detect supports adaptive learning, integrating incoming samples to improve the model:

$$D_{train}^{new} = D_{train} \cup D_{new} \tag{12}$$

Where,

D_{new}=New data samples collected after initial training

D_{train}^{new}=Updated training dataset after merging D_{train} and D_{new}

The updated dataset is utilized to retrain the model:

$$RF_{new} = Train(D_{train}^{new}) \tag{13}$$

Where,

RF_{new}=Retrained Random Forest model using the updated dataset

This enables long-term model adaptability to varying operating conditions, like component wear or environmental shifts.

3.2.9 Performance Metrics

To assess model quality, several metrics are calculated using true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN):

Accuracy measures overall correctness:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

Where,

TP=True Positives: fault correctly detected as a fault

TN=True Negatives: no fault correctly detected as no-fault

FP=False Positives: no fault wrongly predicted as fault

FN=False Negatives: fault wrongly predicted as no-fault

Precision evaluates fault detection reliability:

$$Precision = \frac{TP}{TP + FP} \tag{15}$$

Recall reflects detection completeness:

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

F1-score balances precision and recall:

$$\text{F1} - \text{score} = 2.\frac{Precision.Recall}{Precision + Recall} \tag{17}$$

Matthews Correlation Coefficient (MCC) offers a balanced evaluation even with imbalanced classes:

$$\text{MCC} = \frac{TP.TN - FP.FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN -}} \tag{18}$$

These metrics jointly evaluate detection robustness, reliability, and balance, which are vital in safety-critical systems like cranes.

3.2.10 Output of the SBF Detect Algorithm

Upon completion, the SBF Detect algorithm returns the trained Random Forest model, test data predictions and evaluation scores. It also supports adaptive retraining when new sensor data is ingested, which helps the system remain relevant over time. This renders it appropriate for real-time, scalable deployment in industrial settings where slewing bearing faults must be identified immediately to avoid mechanical failures. Algorithm 1 shows the proposed SBF Detect algorithm.

Algorithm 1: SBFDetect algorithm
Input: SBF_Dataset with N rows and M features
Output: Trained_Model, Predicted_Labels, Evaluation_Metrics (Accuracy, Precision, Recall, F1-Score, MCC)
Load SBF_Dataset
Encode categorical attributes (e.g., Metal Debris Level, Fault)
Normalize numerical attributes
Divide data into Features X and Target y
Split (X, y) into training and testing sets: (X_train, y_train), (X_test, y_test)
Initialize Random Forest Classifier → Model
Train Model on (X_train, y_train)
Predict y_pred ← Model.predict(X_test)
Evaluate model:

Accuracy ← compute_accuracy(y_test, y_pred)
Precision ← compute_precision(y_test, y_pred)
Recall ← compute_recall(y_test, y_pred)
F1_Score ← compute_f1_score(y_test, y_pred)
MCC ← compute_mcc(y_test, y_pred)
10: If new sensor data is available then
Load and preprocess new data
Update training set: X_train ← X_train∪X_new
y_train ← y_train∪y_new
Retrain Model on updated (X_train, y_train)
11: Return Trained_Model, y_pred, [Accuracy, Precision, Recall, F1_Score, MCC]

The SBF Detect Algorithm begins by loading the Slewing Bearings Fault (SBF) dataset and preprocessing it using the categorical encoding (for variables such as metal debris level and fault label) and numerical feature normalization. The dataset is then divided into training and test subsets. A Random Forest Classifier is set up and trained on the training set to identify the patterns associated with faulty and healthy bearings. After training, the model predicts fault labels for the test set and is assessed utilizing metrics such as accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC). The algorithm facilitates incremental learning via an adaptive update mechanism, in which new sensor data, once preprocessed and labeled, is utilized to retrain the model, guaranteeing that it remains current and efficient in changing operational conditions. This makes SBF Detect a dependable, scalable, and intelligent solution for predictive maintenance in heavy machinery.

The adaptive behavior of the SBF Detect algorithm is achieved by its incremental retraining method (Step 10). In this context, newly arriving sensor data are added progressively to the existing training set. It enables the model to continuously learn and adjust to changing operating conditions and growing fault patterns. Due to this, the system improves over time without needing complete retraining from scratch.

Figure 2 illustrates the simulation-based workflow adopted for developing and validating the SBF Detect algorithm. The process begins with a synthetic data generation layer, where mechanical degradation behavior, load variations, rotational speed changes, lubrication conditions, metal debris levels, and sensor drift are modeled to replicate realistic bearing operating scenarios. The generated dataset then undergoes preprocessing, including categorical encoding, normalization, outlier handling, and consistency checks. Structured features corresponding to the defined 11 parameters are organized and divided into feature and target sets, followed by train–test splitting. A Random Forest classifier is subsequently trained to perform fault prediction, and its performance is evaluated using standard metrics such as Accuracy, Precision, Recall, F1-Score, and MCC. Finally, an adaptive learning mechanism enables model retraining with newly integrated data, producing a binary fault decision output (Yes/No).

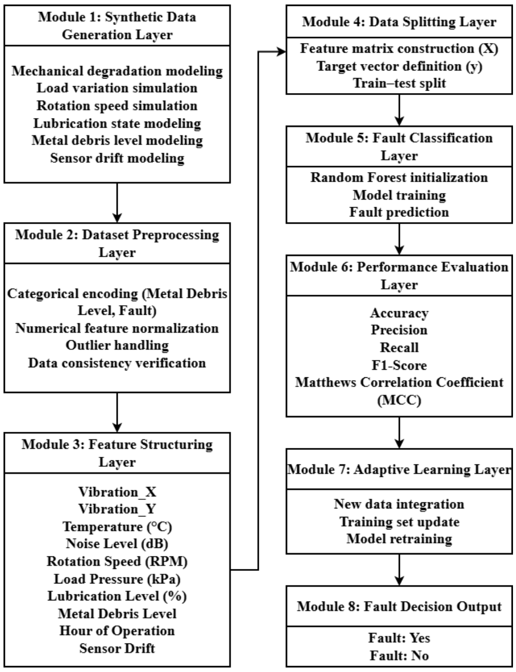

Fig. 2. Modular architecture of the proposed SBF detect system for multi-source data processing

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed SBF Detect Algorithm was executed in Python on a Windows 11 system using SBF_Dataset. To evaluate robustness, the algorithm was tested under high slewing bearing faults. The experiments were carried out on a standard workstation with adequate computational resources for processing the slewing bearing fault dataset and running machine learning models effectively. The scikit-learn library was employed for model training, preprocessing, and evaluation metrics, to ensure reproducibility and reliable performance measurement.

To test the performance of the proposed SBFDetect algorithm, many failure situations were built. At first, noise was added to the sensor data. It denotes measurement faults. Next, class imbalance was added. It denotes real cases where fault cases are less than normal cases. After that, partial data loss was simulated. Next, a few sensor values were randomly eliminated. It simulates missing sensor readings. These states imitate real industrial problems for example sensor failure. The evaluation metrics comprise accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC).

4.2 Comparison Table

Table 3 compares the SBF Detect Algorithm to other commonly used classifiers, including Support

Vector Machine (SVM), k-nearest Neighbors (k-NN), Decision Tree (DT), and Logistic Regression under these failure conditions. Still, SBF Detect continued to work steadily. Because, the model adapts by incremental retraining.

Table 3. Performance comparison of classifiers

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
Logistic Regression	81.0	79.1	78.0	78.5	0.62
Decision Tree	85.0	83.0	82.0	82.5	0.70
k-NN	86.5	84.8	83.5	84.1	0.72
SVM	88.0	86.0	85.0	85.5	0.76
SBFDetect (Proposed)	90.0	88.9	88.9	88.9	0.80

SBFDetect achieved the best results across all metrics due to its adaptive nature and effective feature preprocessing steps. The Random Forest classifier in SBFDetect allows for ensemble learning, which reduces over fitting and improves generalization across a wide range of bearing wear conditions. Furthermore, the inclusion of adaptive updates ensures the model's accuracy even with sensor drift and new operating data. The proposed algorithm achieved an accuracy of 90% under simulated failure conditions. Compared to the conventional approach (Logistic Regression), the proposed method improved detection accuracy by 9%. Interestingly, these results obviously prove that SBFDetect is not just a conceptual idea. Rather than, it effectively improves fault detection even when sensor data are noisy, missing, or changing.

4.3 Discussion

Figure 4 shows the accuracy comparison of various classifiers. The SBFDetect Algorithm surpasses other models with a 90% accuracy rate, demonstrating its ability to capture fault patterns reliably. This is mainly due to efficient feature normalization, categorical encoding, and ensemble learning using Random Forest, which manages feature interactions and non-linear patterns more effectively than individual models.

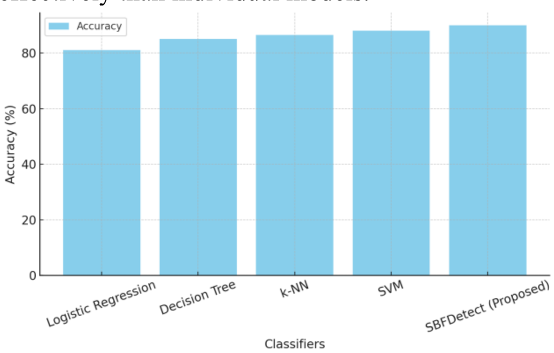

Fig. 4. Accuracy comparison

As shown in Figure 5, SBFDetect has the highest precision (88.9%), indicating superior performance in reducing false positives. This is critical in industrial settings, where incorrectly identifying a healthy bearing as faulty can result in unnecessary maintenance. The algorithm's learning mechanism enables it to clearly distinguish between fault and no-fault conditions even in the presence of sensor noise.

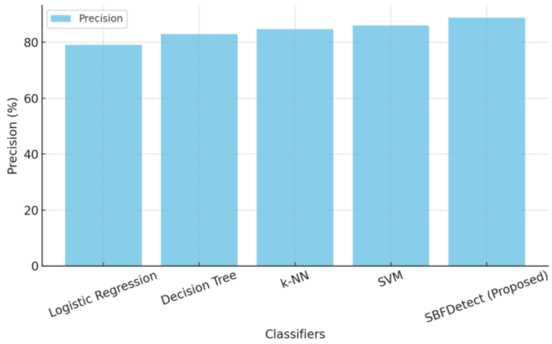

Fig. 5. Precision comparison

Figure 6 shows that SBFDetect has a recall of 88.9%, indicating a strong ability to detect the majority of actual faults. This is especially important for safety-critical components such as slewing bearings, where missing a fault (false negative) can result in serious equipment damage. The algorithm's adaptability keeps it sensitive to changes and emerging fault trends.

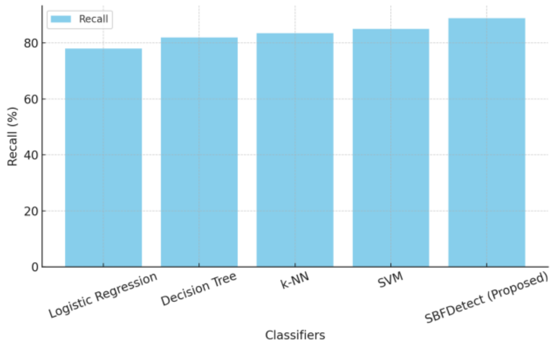

Fig. 6. Recall vomparison

Figure 7 shows F1-score comparisons, with SBFDetect again leading with 88.9%. This balance between precision and recall validates the resilience of the proposed algorithm in practical fault detection tasks, where both false alarms and missed detections are costly.

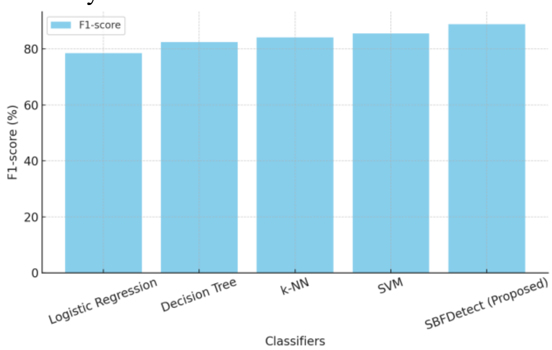

Fig. 7. F1-score comparison

Figure 8 shows that SBFDetect has a Matthews Correlation Coefficient (MCC) of 0.80, which is higher than all other classifiers. MCC takes into account true and false positives and negatives, resulting in a balanced measure for binary classification. The high MCC value highlights the model's ability to perform consistently under a variety of conditions, including class imbalance and noisy data.

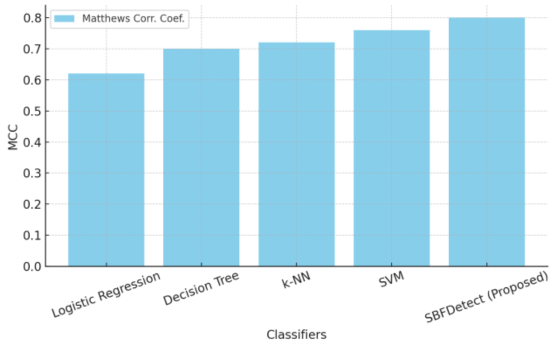

Fig. 8. MCC comparison

This in-depth evaluation validates the efficacy and dependability of the proposed SBFDetect Algorithm for early fault detection in slewing bearings. It offers substantial benefits over traditional classifiers in terms of both accuracy and adaptability.

5. CONCLUSION

This paper describes the SBFDetect algorithm, which is an adaptive machine learning-based solution for detecting slewing-bearing faults. The model, built utilizing a Random Forest classifier and comprehensive preprocessing steps, obtained outstanding findings across all evaluation metrics, showing its efficacy in predictive maintenance applications.

Limitations: Despite its success, SBFDetect is dependent on the availability of labeled data and may face limited generalizability when applied to unseen machinery types or in real-time settings with high data velocity.

Future Works: Future improvements will focus on integrating unsupervised learning for anomaly detection, optimizing for real-time deployment on edge devices, increasing domain adaptability, introducing hybrid ensemble techniques, and leveraging block chain to ensure safe and reliable data management.

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