Wear Fault Diagnosis in Journal Bearings Using Vibration Analysis and AI

Nazik A. Jebur
Mechanical Engineering Department
University of Technology
Iraq

Wafa A. Soud
Mechanical Engineering Department
University of Technology
Iraq

In this study, machine learning models for identifying wear defects in journal bearings under various operating circumstances are compared. Healthy, low, and high wear states were simulated using an experimental test rig. Information Gain, Gain Ratio, Gini Index, and other feature selection techniques were used to analyze vibration signals from precision sensors. Relevance was used to rank features like Root Mean Square, Peak-to-Peak, and Peak. Using accuracy, precision, recall, F1-score, specificity, and log loss, models from Gradient Boosting, AdaBoost, Random Forest, k-nearest Neighbours, Support Vector Machine, and Decision Tree were assessed. Gradient Boosting performed best overall and had the highest accuracy (99.5%). Random Forest and AdaBoost also showed high classification accuracy. More features were beneficial for simpler models like k-Nearest Neighbours and Decision Tree. Random Forest and Gradient Boosting successfully decreased misclassification between related fault classes. The findings highlight the importance of selecting the appropriate models and features. Advanced feature engineering and parameter optimization could lead to further enhancements.

Keywords: *Journal Bearings, Machine Learning, Fault Diagnosis, Vibration Analysis, Feature Selection.*

1. INTRODUCTION

In industrial and automotive rotating gear, journal bea–rings minimize friction and support shafts. High loads, fluctuating speeds, and contamination cause wear, misalignment, and other faults in these bearings. Jour–nal-bearing failure may disrupt operations, jeopardize safety, and cost money.

Recent vibration analysis and machine learning advances have altered journal-bearing fault diagnostics. Simple statistical defect identification and catego–rization and hand inspection have been superseded by complex algorithms and AI. Vibration signal kurtosis, skewness, and RMS predict bearing failures. Journal-bearing failure diagnostics study uses advanced com–putational algorithms, feature selection methods, and machine learning models to increase accuracy and reliability.

Nikolakopoulos and Papadopoulos (2009) [1] pro–posed a new wear model for misaligned journal bea–rings to examine how wear and misalignment affect bearing performance. Oil layer thickness inversely impacts aligned bearing wear throughout the bearing length, according to the study. The two-dimensional model relates misalignment angles to film thickness better than Dufrene's wear model. Misalignment influences friction coefficients and minimum film thickness for different Sommerfeld values, the study revealed. The results show that journal-bearing designs must integrate wear and misalignment effects to imp–rove dependability in severe working situations. For fault diagnosis in internal combustion (IC) engine main bearings, Moosavian et al. (2013) [2] compared K-Nearest Neighbour (KNN) and Artificial Neural Net–work (ANN) classification systems. The study applied vibration signals under normal, oil-starved, and high-wear conditions. From vibration signals, power spectral density (PSD) analysis recovered thirty frequency-do–main traits. Trained and tested on 180 samples both classifiers Ann had 90.5% PSD feature test accuracy; KNN had 85.7%.ANN classified better, but KNN was faster. The study showed that PSD feature extraction works and that classifier selection is crucial for journal-bearing problem identification. These insights help build reliable IC engine condition monitoring systems. Machado and Cavalca (2016) [3] verified the rotor-bearing system cylindrical hydrodynamic bearing wear model experimentally. Experimental directional frequ–ency responses (DFR) and simulations using the aut–hors' numerical model were compared to assess how wear impacts dynamic behavior. The rotor was mo–deled using finite elements at various wear depths and angles. DFR sensitivity to wear factors increased dra–matically with wear depth in backward precession components. The wear model accurately anticipated wear anisotropic effects across the validated frequency band. This study indicates that numerical modeling and experimental validation can detect hydrodynamic bea–ring wear. Pule et al. (2022) [4] used PCA and SVM to diagnose ball-bearing problems at various speeds. Using

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Correspondence to: Nazik A. Jebur
Mechanical Engineering Department
University of Technology, Iraq
E-mail: nazikabdulwakid@uomustansiriyah.edu.iq
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vibration data, the study assessed healthy bearings, ball damage, inner and outer race faults, and combined difficulties. PCA reduced dimensionality and compu–tational complexity for the SVM classifier. Despite fault detection speed adjustments, the model classified 97.4% accurately. In difficult operational conditions, PCA-SVM minimized manual feature engineering and effec–tively categorized faults. According to the study, pre–dictive maintenance systems for industrial applications with less data may apply this approach.

Dubaish and Jaber (2023) [5] developed a gearbox failure simulator for diagnosis. A controlled vibration signal analysis-based two-stage helical gearbox testing framework was devised. LabVIEW with NI DAQ detected gear tooth defects from vibration data. Experimental results demonstrated significant vibration signals between healthy and dysfunctional states at varied speeds and loads. Gearbox condition monitoring systems simulate and diagnose test equipment faults using advanced machine-learning algorithms, Baqer et al. (2023) [6]. Artificial neural networks and vibration signal processing identify belt-driven rotating system pollution. The study found that contamination decre–ases belt performance and safety in demanding situ–ations. Kurtosis, skewness, RMS, and mean time-domain vibration were discussed for clean, moist, and powder-contaminated belts. Backpropagation ANN model pollutant status accuracy was 100% in different operating scenarios. This shows that machine learning and vibration analysis improve predictive maintenance and belt-driven system condition monitoring.

Yilin et al. (2023) [7] SVM and hybrid feature selection diagnosed journal-bearing failures in realistic operational scenarios. The study used long-term vibration data from vertical and horizontal rotor sys–tems with muddy water-induced wear and peeling. The hybrid feature selection approach optimized SVM mo–del features utilizing Fisher score (FS) and Sequential Forward Selection. In experiments, SVM model accu–racy was 97.14% for vertical and 100% for horizontal rotor systems. The mean RMS value was best for hori–zontal rotor system problem detection, whereas vertical systems needed an RMS average coefficient of vari–ation. Diagnostic accuracy and computational effi–ciency improve when rotating equipment condition monitoring insights are selected.Goto et al. (2023) [8] created a mathematical model to evaluate journal bearing wear beyond machine learning model training data limits using experimental and simulation data. Journal bearing clearance was increased utilizing a horizontal rotating shaft system model to simulate wear.Time-domain properties including RMS, kurtosis, skewness, and DWT were extracted from experimental and simulated data. For wear diagnosis, Fisher Score and Wrapper emphasized features, and the CV of kurtosis in the x-displacement was most essential. Experimental wear categorization was accurate with simulation-trained SVM. This study found that si–mulation-based data augmentation and feature selec–tion improve rotating machinery wear diagnostics machine learning models. Jebur and Soud (2024) [9] outlined journal-bearing fault diagnosis and condition monitoring advancements. Machine learning and vibration analysis showed that ensemble models like CNNEPDNN improved diagnosis accuracy and convergence speed by 15–20% over single models. Convolutional autoencoders predicted wear with 91% accuracy. Unstandardized evaluation criteria and insu–fficient diagnostic procedure generalization across operational environments were major issues the study revealed. Creating real-world diagnostic models requ–ires teamwork, the scientists said.Bhat et al. (2024) [10] investigated machine learning hydrodynamic co–nical journal-bearing defect detection. SVM, KNN, and RF classifiers were examined for HCJB interior surface scratches and wear flaws. A particular test setup recorded vibration signals under varying speed and load conditions. The mean, root mean square, kurtosis, skewness, and standard deviation were obtained. RF has the highest accuracy at 93.93%, followed by SVM and KNN at 87.88%. The study found that signal pro–cessing and AI-enhanced rotating machinery problem diagnosis. The findings enable comprehensive indus–trial condition monitoring systems. Dubaish and Jaber (2024) [11] A comparison between SVM and ANN for gearbox problem diagnosis. Wavelet Packet Transform (WPT) and time-domain statistical analysis identified vibration signal characteristics. The Gain Ratio method selected suitable features for SVM and ANN classi–fication. ANN outperformed SVM in noisy environ–ments with 98% classification accuracy versus 96% for SVM. These data suggest that ANN performs better in complex fault conditions. The study also proposed ANN-based gearbox failure detection and machine dependability methods for industry and underlined the importance of feature extraction and selection in diag–nostic accuracy. Ogaili et al. (2024) [12] used vibration analysis and machine learning to compare wind turbine gearbox automated condition monitoring. A study used SVM, KNN, and Naive Bayes to diagnose gearbox bearing and gear failures. Kurtosis, skewness, and root mean square (RMS) were extracted from 750-kW turbine testbed vibration data under varied failure con–ditions to improve problem detection. Naive Bayes outscored SVM and KNN with 95.7% accuracy. Using complex feature-fault correlations, Naive Bayes clas–sifies flaws. This study revealed that machine learning improves wind turbine condition monitoring system reliability and efficiency.Ogaili et al. (2024) [13] analyzed ball-bearing defect detection and categori–zation using vibration data and statistics. The resear–chers collected mean, median, standard deviation, skewness, kurtosis, and dominant frequency from wa–velet-transformed vibration signals. A Random Forest model trained and assessed with these features classi–fied defects 90.42% accurately. Seven problems were employed to test the model's ball-bearing defect diag–nosis accuracy. The authors stressed feature selection and correlation analysis, which showed mean, median, skewness, and kurtosis crucial to model correctness. Even in noisy environments, the Random Forest model diagnosed defects well. Jaber and Shakir (2024) [14] evaluated ANNs for spinning shaft crack detection and localization. The study emphasized industrial crack diagnostics for safety, reliability, and cost optimi–zation. Vibration signal analysis prioritized filtered signal features using the Reliefalgorithm to optimize ANN model input. In trials, the ANN model recognized crack depths and locations with 94.4% accuracy across rotating speeds. Authors say signal pre-processing and feature selection increase fault detection system reliability and precision. This research prepares spinning machinery for preventive maintenance. Jaber (2024) [15] tested bearing problem diagnostics using temporal vibration signals, machine learning models, and feature selection. Time-domain statistical feature extraction methods including RMS, kurtosis, and skewness improved fault detection, especially for early-stage damage. Prioritizing essential qualities with Information Gain (IG) and FCBF. We examined three machine learning classifiers: KNN, Support Vector Machines (SVM), and Naïve Bayes. The best model was KNN-FCBF with 99.1% AUC, 97% AC, and 96% F1-score. Combining temporal characteristics with improved machine learning for bearing defect diagnosis produced a computationally efficient and accurate commercial technique.

Although several recent studies have demonstrated the use of machine learning for fault diagnosis in rotating machinery, many have relied on limited model comparisons or have not fully explored the influence of feature selection on classification performance. Additionally, some works have focused on fault detection without considering multiple levels of wear. This study distinguishes itself by evaluating several AI models under controlled experimental settings and by analyzing how varying the number of input features affects model accuracy across different wear conditions.

Recent work published in FME Transactions on artificial intelligence application in rotating equipment diagnostics and vibration-based defect identification has addressed for example, whereas Jawad and Jaber [16] used CUSUM control charts combined with statistical vibration indicators for early fault diagnosis, Jamadar et al. [17] suggested a deep learning-based approach for diagnosing rolling element bearing failures using vibration features. Al-Khafaji and Jaber [18] compared artificial intelligence classifiers for fault categorization in rotating machines. Moreover, Abd Soud and Baqer [19] investigated, using FFT and statistical approaches, the vibration behavior of several bearing types. These contributions together support the significance of intelligent vibration analysis approaches, which fit the scope and approach of the present work. This study builds on previous research on bearing diagnostics and condition monitoring, focusing on evaluating a wider spectrum of classification models across various wear levels and input factors to enhance model interpretability and diagnosis reliability. [20,21]

The remaining study is organized as follows: Section 2 summarizes the experimental technique, including the test rig design, components, and data collection for journal-bearing scenarios at different wear levels. Machine learning model implementation, training, and evaluation are covered in Section 3. Section 4 examines machine learning models, feature selection, and confusion matrices. Section 5 summarizes the study's findings, highlights Gradient Boosting and other models' diagnostic efficacy, and suggests future research.

2. EXPERIMENTAL WORK

An integrated test platform was utilized to study journal-bearing vibrations and detect faults caused by wear under varying levels, categorized as low and high wear. The main components of the test rig are summarized in Table 1, which provides a detailed description of each element used in the experimental setup. Additionally, the design and structure of the test platform are illustrated in Figure 1, showcasing the actual test rig and its components. To ensure reliable and accurate fault analysis, vibrations were measured using precision sensors. These measurements provided essential data for evaluating the performance and condition of the journal bearings under different levels of wear. Detailed specifications and configurations of the sensors used in this study will be discussed in subsequent sections.

The test rig was carefully designed to replicate operational conditions effectively, enabling a compre–hensive analysis of wear-induced faults in journal bearings.

Table 1. Main Components of the Test Rig

Component	Description
Shaft	Made of C-45 steel, 20 mm diameter, 500 mm length.
Motor	A 1 HP GAMAK three-phase induction motor 2860 RPM. Variable Frequency Drives controlled speed.
Journal Bearings	Made of copper with a 20-mm inner diameter, 0.05-mm clearance, and 28-mm length. Bearings had oil supply holes to decrease vibrations.
Rotating Disk	Weighing 8 kg with a 5-gram balance weight to mimic wear during operation.

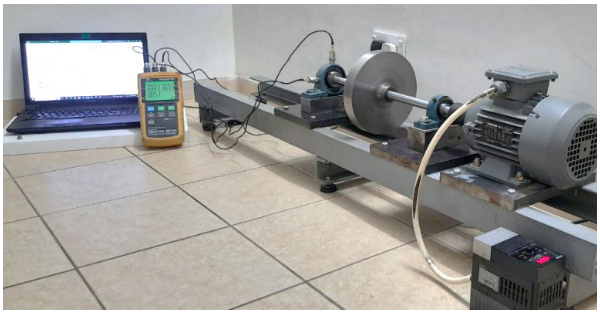


Figure 1. Test Rig Used in the Study

The table and picture give a complete overview of the test rig, explaining the experimental approach and system components.

2.1 Tools and Instruments Employed

This study used high-precision sensors to log vibration data on SD cards in real time for Excel analysis. The BVB-8207SD vibration meter measured acceleration, velocity, and displacement. The vibration measurement apparatus is depicted in Figure 2 and described in Table 2.

Figure 2. Vibration Measurement Device

Table 2. Specifications of the BVB-8207SD Vibration Meter

Feature	Description
Measurement Types	Acceleration, Vibration Velocity, Displacement
Frequency Range	10 Hz - 1 kHz
Display Units	Metric and Imperial
Data Logging	Real-time (1 to 3600 seconds), Manual
Data Storage	SD Card (1 GB to 16 GB)
Data Transfer	Direct to Excel via SD card

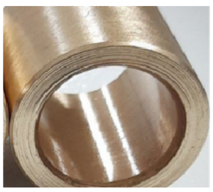
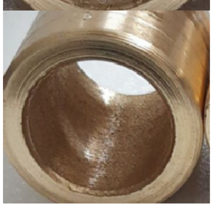
2.2 Journal Bearing Characteristics and Specifications

In the investigation, bushing copper alloy UNS C37000 journal bearings were used. These bearings support the system's shaft and ensure stability in varied operating conditions. These bearings featured a 20-mm shaft di–ameter, 0.05-mm clearance, and 28-mm length. They had 7476.255 MPa Young's modulus, a 5 mm oil hole for lubrication, and a 30 mm outside diameter. These criteria optimized study performance and reliability.

2.3 Assessment of Bearing Condition

Journal bearings were assessed at three operational integrity levels. Table 3 summarizes these levels, and illustrations illustrate each circumstance.

Table 3. Bearing Condition Levels and Descriptions

Condition Level	Description	Visual Representation
Healthy	The bearing is in a normal operational state, free from wear or damage.	
Low Wear	Noticeable wear is present, but the bearing remains operational with minor performance degradation.	
High Wear	Significant wear is evident, posing a risk of bearing failure if corrective actions are not implemented.	

Three major levels of journal-bearing condition were assessed, each indicating a different operational state. In decent condition, the bearing works. Low wear indicates severe wear, yet the bearing is still usable with moderate performance loss. Heavy wear reduces bearing performance and threatens failure without repair. This classification method helps maintainers make judgments and control system performance by measuring fault severity and bearing condition.

2.4 Data collection and feature extraction

Piezoelectric sensors accurately extracted statistical information, allowing extensive vibration data analysis to identify faults and monitor bearing mechanical condition. The main statistical features were Root Mean Square (RMS), Peak, and Peak-to-Peak values. These properties were necessary for pattern recog–nition, bearing defect detection, and system perfor–mance evaluation. The vibration data-derived values of these features are shown in Table 4, [14,15].

Table 4. Feature Formulas

Feature Name	Formula
Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Peak-to-Peak	$xpp = \max\left(X_i\right) - \min\left(X_i\right)$
Peak	$xp = \max\left(X_i\right)$

2.5 Machine Learning Models

Many machine learning algorithms classify and regress, each with benefits. Decision trees separate data hierarchically and interpretably. Data is classified using closest neighbor majority in non-parametric KNN. Random Forest reduces overfitting and improves accuracy with several decision trees. Gradient Boos–ting reduces errors for weak learners, while AdaBoost weights misclassified samples to enhance predictions. Finally, SVMs determine the optimum hyperplane to separate classes with the largest margin in high-di–mensional spaces. Machine learning relies on these algorithms for picture identification, medical diagnosis, and financial predictions [16,17].

3. RESULTS AND DISCUSSION

Figure 3 shows system amplitude values (in mm) under three operating conditions: Healthy (blue line), Low wear (orange line), and High wear (gray line). Health is good at 0.01 mm amplitude. Under low wear, amp–litude values above 0.02 mm indicate wear. High wear causes sharp and unpredictable variations over 0.02 mm, indicating performance instability. These elem–ents are essential for system diagnosis and repair. Fig. 4 depicts the organized machine learning model eva–luation process. Import the dataset (File) and select important columns to focus on the most informative aspects. Rank and Distributions were utilized to un–derstand the dataset and prioritize features by target variable relevance.

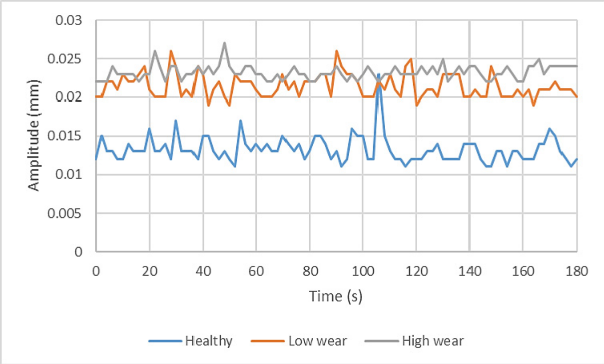


Figure 3. Time Domain Vibration Signals for Different Bearing Statesat 1800 RPM

The "Test and Score" widget trained and assessed Gradient Boosting, AdaBoost, Random Forest, Tree, SVM, and KNN machine learning models. This stage as–sessed accuracy, precision, recall, and F1-score. To ana–lyze and compare model performance, confusion mat–rices, ROC analysis, and scatter plots were constructed.

The performance of machine learning models, as shown in Table 5, was assessed using CA, F1 Score, Precision, Recall, MCC, Specificity, and Log Loss. The input features used for these evaluations include P-P: Peak-to-Peak, P: Peak, and RMS: Root Mean Square, which were ranked based on feature importance using metrics such as Information Gain, Gain Ratio, Gini Index, ANOVA, Chi-squared (χ^2), Relief F, and FCBF. The ranking analysis revealed that P-P: Peak-to-Peak holds the highest importance across most metrics, followed by RMS: Root Mean Square and P: Peak. Gradient Boosting performed best overall, with the highest Classification Accuracy (99.5%) and the highest scores in F1 (0.995), Precision (0.995), Recall (0.995), MCC (0.993), and Specificity (0.998) as shown in Table 5. Its Log Loss of 0.011 shows that it can make confident and accurate probabilistic predictions, making it the most dependable model for the dataset. AdaBoost and Random Forest could replace Gradient Boosting with excellent Classification Accuracy (99.4% and 99.3%, respectively) and strong performance across other measures.

Table 5. Evaluation Metrics for Machine Learning Models

Model	CA	F1	Prec.	Recall	MCC	Spec.	Log Loss
Tree	0.987	0.987	0.987	0.987	0.981	0.994	0.196
KNN	0.992	0.992	0.992	0.992	0.988	0.996	0.071
Random Forest	0.993	0.993	0.993	0.993	0.989	0.996	0.017
Boosting	0.995	0.995	0.995	0.995	0.993	0.998	0.011
AdaBoost	0.994	0.994	0.994	0.994	0.990	0.997	0.032
SVM	0.438	0.432	0.527	0.438	0.166	0.719	1.059

As shown in Table 6, the KNN model has 99.2% Classification Accuracy, but its Log Loss of 0.071 suggests lesser prediction confidence. Figure 5 shows the Support Vector Machine (SVM) scored poorest, with 43.8% Classification Accuracy and low scores across all parameters. Insufficient hyperparameter twe–aking or dataset misalignment may explain this result's low-class separation efficiency.

According to Table 5 and Figure 5, Gradient Boosting beats all assessment measures and is the best model for this dataset. When computational efficiency matters, AdaBoost and Random Forest work. Hyper–parameter adjustment, feature engineering, and kernel type investigation may increase SVM performance.

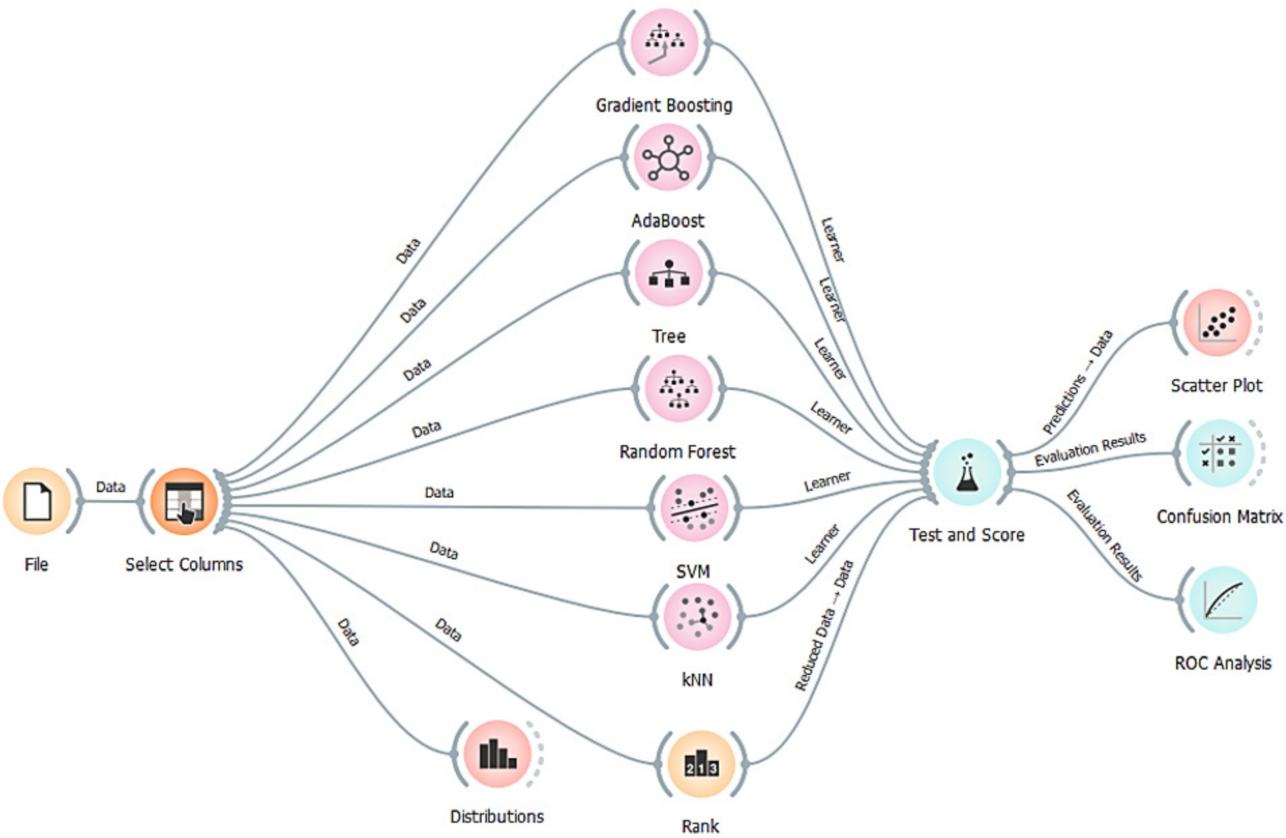


Figure 4. Machine Learning Workflow

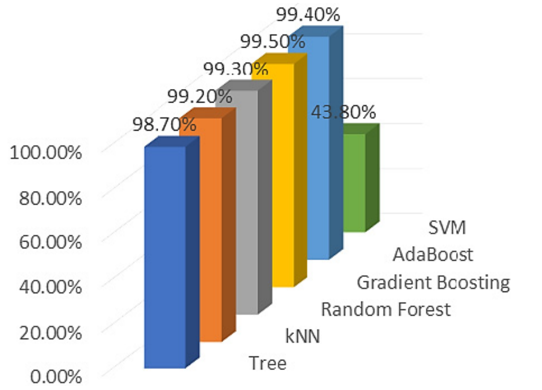


Figure 5. Comparison of Classification Accuracy Across Different Models.

Confusion Matrix Analysis

The confusion matrices reveal the tested models' cate–gorization performance for Healthy, High wear, and Low wear. Table 6 shows how model accuracy and misclassification rates differ.

Table 6. True Positive Rates (TPR) and Key Errors for Each Model

Model	Healthy (TPR)	High wear (TPR)	Low wear (TPR)	Key Observations
Gradient Boosting	100.0%	99.7%	98.9%	Minimal errors between High wear and Low wear.
Random Forest	100.0%	98.9%	99.2%	Strong performance, slightly weaker than Gradient Boosting.
Tree	100.0%	98.4%	97.8%	Higher errors in distinguishing Low wear and High wear.
KNN	100.0%	98.9%	98.6%	Consistent performance with low misclassification rates.
AdaBoost	99.7%	99.7%	98.6%	Comparable to Gradient Boosting, with slight errors.
SVM	49.2%	26.9%	55.2%	Significant misclassifications in all categories.

In Table 6, Gradient Boosting accurately identified "Healthy", "High wear" and "Low wear" with 99.7% and 98.9% accuracy. Overlapping "High wear" and "Low wear" is handled properly. Random Forest pre–dicted "Healthy" cases with 100% accuracy and slig–htly lower accuracy for other categories than Gradient Boosting. Random Forest uses ensemble-based majo–rity voting, while Gradient Boosting iteratively opti–mizes predictions. PoorSVM classification. 49.2% of "Healthy" cases were misclassified as "Low wear." As in other categories, the model failed to distinguish between groups, resulting in 26.9% accuracy for "High wear" and 55.2% for "Low wear." Lack of kernel mo–difications or dataset complexity prohibited the SVM model from classifying. Confusion matrices show Gra–dient Boosting and Random Forest perform well on this dataset. Both models performed well with few misclassifications, although SVM was inaccurate. Fi–gures 6 and 7 demonstrate model training and testing time variation. Tree model training and testing took 0.1 seconds, and Gradient Boosting 10 seconds.AdaBoost had the longest testing time (0.5 seconds), however SVM and Random Forest balanced training and testing, showing that application requirements and perfor–mance should determine model selection.

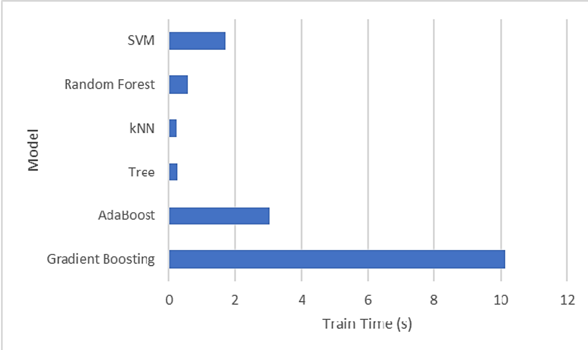


Figure 6. Training Time Comparison for Classification Models

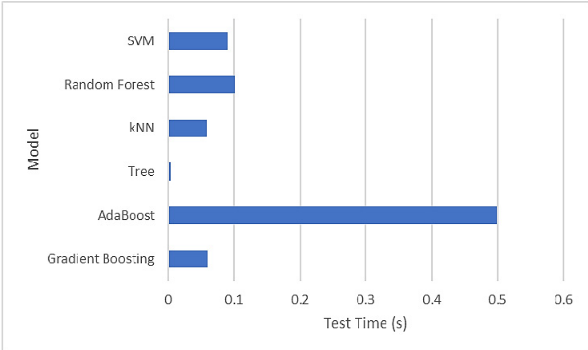


Figure 7.Testing Time Comparison for Classification Models

Impact of Feature Selection on Classification Accuracy

Figure 8 shows the classification accuracy (AC) of Random Forest, Tree, KNN, Gradient Boosting, Ada–Boost, and SVM under three scenarios: Series 1 represents the accuracy with a single feature, Series 2 with two features, and Series 3 with three features. The image indicates that feature count increases classi–fication accuracy, emphasizing feature selection's role in model performance. With one feature, Gradient Boosting, AdaBoost, and Random Forest models exc–eeded 95% accuracy. With more features, KNN and Tree models get better at categorization. The SVM model had the lowest accuracy across all scenarios, with less than 50% accuracy with one feature, although it improved with more features. This comparison shows that feature selection and model choice are crucial to classification performance, with advanced models like Gradient Boosting and AdaBoost yielding stable and dependable results across feature counts.

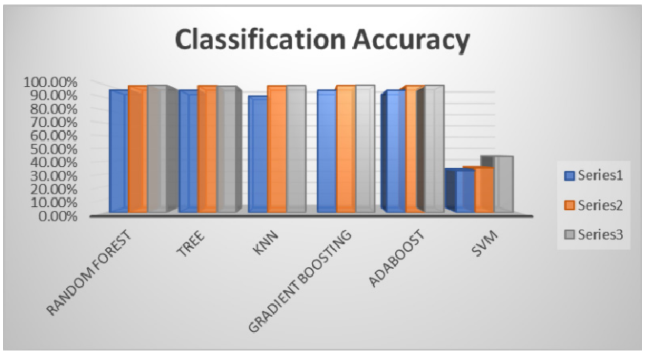


Figure 8. Classification Accuracy for Different Models with Varying Feature Counts

4. CONCLUSIONS

This study assessed machine learning categorization models by accuracy, precision, recall, and computing economy. Gradient Boosting performed best with 99.5% classification accuracy and high F1-score, MCC, and Specificity. Log Loss is low, boosting pro–babilistic prediction accuracy. AdaBoost and Random Forest had high accuracy and computing efficiency. Changing model feature counts influenced classifi–cation accuracy under feature selection. Gradient Boosting, AdaBoost, and Random Forest achieved above 95% accuracy with one feature, whereas KNN and Tree improved with more features. SVM per–formed poorly across all measures, making it un–suitable for this dataset without optimization or feature engineering. Confusion matrices showed that Gradient Boosting and Random Forest reduce misclassifications, especially for overlapping classes like "High wear" and "Low wear." In contrast, SVM has high misc–lassification rates, emphasizing model selection and hyperparameter adjustment. Due to its iterative opti–mization method, Gradient Boosting took the longest to train, while Tree and KNN models were compu–tationally efficient but less accurate. Gradient Boosting is the best model for the dataset because of its cons–istent classification accuracy and reliability. AdaBoost and Random Forest are good computationally efficient options. The study emphasizes feature selection, model choice, and optimization methodologies for classi–fication task performance. Future research could imp–rove performance and applicability to difficult datasets by using advanced feature engineering, hyperparameter optimization, and alternative methods. This study has important implications for the predictive maintenance of rotating machinery, especially journal bearings. Vibration analysis combined with AI-based classifi–cation approaches like KNN and Gradient Boosting can reduce unplanned downtime and improve fault diagnosis. This improves engineering intelligent con–dition monitoring systems by providing more depen–dable and automatic diagnostic tools.

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ДИЈАГНОЗА ХАБАЊА КЛИЗНИХ ЛЕЖАЈЕВА КОРИШЋЕЊЕМ АНАЛИЗЕ ВИБРАЦИЈА И ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ

Н.А. Јебур, В.А. Соуд

У овој студији, упоређују се модели машинског учења за идентификацију хабања клизних лежајева под различитим радним околностима. Симулирана су здрава, ниска и висока стања хабања помоћу експерименталне испитне платформе. Информа–циони добитак, однос добитка, Џинијев индекс и друге технике избора карактеристика коришћене су за анализу вибрационих сигнала са прецизних сензора. Релевантност је коришћена за рангирање карактеристика као што су средња квадратна вредност, однос од врха до врха и врх. Користећи тачност, прецизност, присетљивост, F1-скор, спе–цифичност и губитак логаритама, процењени су модели из Gradient Boosting-a, AdaBoost-a, Random Forest-a, k-најближих суседа, Support Vector Mac–hine-a и Decision Tree-a. Gradient Boosting је пока–зао најбоље резултате укупно и имао је највећу тачност (99,5%). Random Forest и AdaBoost су такође показали високу тачност класификације. Више карактеристика је било корисно за једнос–тавније моделе попут k-најближих суседа и Decision Tree-a. Random Forest и Gradient Boosting су успешно смањили погрешну класификацију између повезаних класа кварова. Резултати истичу важност избора одговарајућих модела и карак–теристика. Напредно инжењерство карактеристика и оптимизација параметара могли би довести до даљих побољшања.