



Machine Learning-Based Fault Diagnosis of Rotating Mechanical Equipment

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Peer Review Information	Abstract
<i>Submission: 28 Jan 2020</i> <i>Revision: 13 Feb 2020</i> <i>Acceptance: 28 March 2020</i> Keywords <i>Rotating machinery, fault diagnosis, vibration analysis, machine learning, predictive maintenance</i>	Rotating mechanical equipment such as motors, pumps, gearboxes and bearing-supported shafts can develop faults that generate subtle changes in vibration signals before functional failure. This paper presents a step-by-step machine-learning methodology for vibration-based fault diagnosis, combining signal conditioning, engineered time- and frequency-domain features, feature scaling, supervised classification and cross-validated performance assessment. The literature foundation is restricted to studies published up to 2020. To demonstrate the methodology without presenting fabricated field measurements, a reproducible simulation-based case study is used with four operating states: healthy, imbalance, misalignment and bearing fault. One-second vibration segments are generated under speed, amplitude and noise variability; twelve diagnostic features are extracted and three conventional classifiers are compared using stratified five-fold cross-validation. In the illustrative experiment, the radial-basis-function support vector machine achieved 96.25% accuracy, followed by random forest at 94.38% and k-nearest neighbours at 91.67%. The strongest residual confusion occurred between healthy and imbalance conditions, while misalignment was separated consistently. The results show how a transparent feature-based workflow can support fault diagnosis when datasets are limited, while also providing a baseline for later deep-learning or transfer-learning extensions. The proposed framework is suitable as a methodology template for laboratory validation and subsequent industrial deployment.

Introduction

Unexpected faults in rotating equipment can cause production interruptions, secondary mechanical damage and increased maintenance cost. Common conditions include rotor imbalance, shaft misalignment, rolling-element bearing defects and gear damage. Because these faults modify periodic forces, impacts and structural resonances, vibration measurements remain a practical source of condition information. Earlier intelligent diagnosis studies demonstrated that support vector machines (SVMs) and artificial neural networks (ANNs) can separate fault classes when informative features

are available [1], while broader work established SVMs as a useful tool for machine condition monitoring because of their generalisation ability on small and medium datasets [2].

The central challenge is not merely to train a classifier, but to construct a complete diagnostic pipeline that is robust to speed variation, sensor noise and operating-load changes. Signal decomposition and ANN-based bearing diagnosis showed that adaptive signal processing can improve feature quality [3]. Subsequently, deep neural networks [4], convolutional neural networks (CNNs) [5], and one-dimensional CNN

architectures intended for real-time motor monitoring [6] reduced dependence on manual feature design. Reviews of artificial intelligence for rotating machinery nevertheless emphasized that data quality, representative operating conditions and model validation remain decisive regardless of the learning algorithm [7].

Accordingly, this paper develops a methodology that is intentionally transparent and reproducible. The objective is to diagnose four representative conditions using vibration segments, engineered statistical and spectral features, and three supervised learning models. The paper also defines an evaluation procedure that prevents data leakage and reports class-level errors rather than accuracy alone. A simulation-based demonstration is included only to illustrate the proposed procedure; industrial conclusions would require validation with measurements collected from actual machines under controlled fault conditions.

Literature Review

Machine-learning fault diagnosis has evolved from feature-based statistical learning toward representation learning. Jack and Nandi [1] compared SVM and ANN fault detectors and augmented classification with genetic-algorithm feature selection, illustrating the importance of selecting discriminative descriptors. Widodo and Yang [2] reviewed SVM-based condition monitoring and highlighted its suitability for nonlinear classification. For bearing diagnostics, Ben Ali et al. [3] coupled empirical mode decomposition with ANN classification, showing the value of isolating fault-sensitive signal components before learning.

From 2016 onward, deep architectures increasingly learned features directly from measured signals. Jia et al. [4] used deep neural networks to mine fault characteristics from frequency-domain data of rotating machinery. Janssens et al. [5] demonstrated CNN-based fault detection for rotating machinery, and Ince et al. [6] proposed a one-dimensional CNN intended

for fast motor fault detection. Liu et al. [7] later synthesized k-nearest neighbours, naive Bayes, SVM, ANN and deep-learning approaches in a broad review of rotating machinery diagnosis. Cerrada et al. [8] focused specifically on data-driven fault severity assessment of rolling bearings and underlined the difference between simple fault classification and quantitative severity estimation.

Temporal modelling has also been explored: Yang et al. [9] applied long short-term memory recurrent networks to rotating machinery signals. Zhao et al. [10] reviewed deep learning for machine health monitoring and identified autoencoders, deep belief networks, CNNs and recurrent networks as major architectures. Finally, Lei et al. [11] provided a 2020 roadmap of intelligent fault diagnosis and discussed the transition from conventional machine learning to deep and transfer-learning methods. These studies collectively motivate a baseline methodology in which signal quality, feature design, validation and interpretability are controlled before more complex models are introduced.

Additional studies reinforced the shift toward automated representation learning. Li et al. [12] proposed deep statistical feature learning from vibration measurements for rotating machinery. Wen et al. [13] presented a CNN-based data-driven diagnosis method that converted machine measurements into learned image-like representations, while Zhang et al. [14] explicitly investigated bearing diagnosis under noisy environments and changing loads. In the renewable-energy sector, Stetco et al. [15] reviewed machine-learning methods for wind-turbine condition monitoring, emphasizing that operating variability, feature construction and validation design can strongly affect reported performance. These contributions strengthen the need for a methodology that first establishes a leakage-free, interpretable baseline before introducing more complex deep models.

Table 1. Representative literature used to define the methodology (all published up to 2020).

Study	Method	Application	Methodological contribution
Jack & Nandi [1]	SVM, ANN, GA	Machine faults	Feature selection and supervised fault/no-fault classification.
Ben Ali et al. [3]	EMD + ANN	Rolling bearing	Adaptive decomposition before feature-based neural classification.
Jia et al. [4]	Deep neural network	Bearings/gears	Automatic mining of fault characteristics from spectral inputs.
Janssens et al. [5]	CNN	Rotating machinery	Learned representations for fault detection from vibration data.

Lei et al. [11]	Review/road map	Machine diagnosis	Framework linking conventional ML, deep learning and future IFD challenges.
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Methodology

The proposed workflow is organized as seven sequential steps. The implementation is deliberately feature-based so that each stage can be inspected, replaced or validated independently. Deep models discussed in [4]-[6] and [9]-[11] can later be substituted at the classification stage when substantially larger labelled datasets are available.

Step 1: Vibration data acquisition and case definition

For an experimental implementation, an accelerometer should be mounted close to the bearing housing in the radial direction, with a sampling rate high enough to capture shaft harmonics and bearing-impact resonances. Each record should be assigned a verified condition label based on controlled faults or maintenance inspection. In the present methodological demonstration, four classes are generated synthetically: healthy, imbalance, misalignment and bearing fault. A total of 480 one-second segments are used (120 per class) at 4096 Hz. Shaft frequency varies from 26 to 34 Hz and both amplitude and additive noise are randomized. Healthy records contain a dominant rotational component; imbalance increases the 1× component; misalignment increases 2× and 3× harmonics; and the bearing-fault class adds repeated damped high-frequency impacts. This variability is introduced to avoid unrealistically identical class signatures.

Step 2: Signal pre-processing and segmentation

Each vibration segment is mean-centered to remove DC offset. For physical measurements, detrending and a machine-appropriate band-pass filter should be applied after verifying that diagnostic frequency bands are not attenuated. Signals are divided into fixed-length windows with no overlap between validation folds from the same parent record, thereby preventing leakage. Amplitude normalization is applied only when it does not remove physically meaningful fault intensity information. The segmentation strategy follows the general data-quality emphasis identified in reviews of rotating-machinery AI diagnosis [7,11].

Step 3: Diagnostic feature extraction

Twelve features are calculated for each segment. Time-domain descriptors are root-mean-square

value, standard deviation, peak-to-peak amplitude, skewness, kurtosis, crest factor and shape factor. Frequency-domain descriptors are spectral centroid and normalized spectral-energy ratios in 20-45 Hz, 45-75 Hz, 75-110 Hz and 400-1200 Hz bands. The first three bands capture rotational harmonics across the simulated speed range, while the high-frequency band captures impulsive bearing resonance. The key formulas are $RMS = \sqrt{(1/N)\sum x_i^2}$, crest factor = $\max|x_i|/RMS$, and kurtosis = $E[(x-\mu)^4]/\sigma^4$. Such engineered features provide a compact baseline when data volume is insufficient for end-to-end deep learning [2,3,7].

Step 4: Feature scaling and optional selection

Features with different units and numerical ranges are standardized to zero mean and unit variance inside each training fold. This operation is performed within the cross-validation pipeline so information from validation samples cannot influence the training transformation. For high-dimensional applications, mutual information, recursive feature elimination or principal component analysis may be added, but all twelve descriptors are retained in the present demonstration to preserve interpretability.

Step 5: Machine-learning model training

Three classifiers are compared. The first is an RBF-SVM with $C = 5$ and the default scale-dependent kernel width. The second is a random forest with 250 trees and a minimum leaf size of two samples. The third is distance-weighted k-nearest neighbours with $k = 7$. These models represent margin-based, ensemble-tree and instance-based learning families. SVM is included because it has a long history in machinery monitoring [1,2], while the random forest and k-NN provide useful nonlinear baselines with different assumptions.

Step 6: Cross-validation and performance metrics

Performance is estimated using stratified five-fold cross-validation with shuffling and a fixed random seed. The same folds are used for all models. Accuracy is supplemented by macro-averaged precision, recall and F1-score so that every class contributes equally. A confusion matrix is inspected to identify physically plausible confusions. For class c , precision = $TP/(TP+FP)$, recall = $TP/(TP+FN)$, and $F1 = 2 \cdot \text{precision} \cdot \text{recall} / (\text{precision} + \text{recall})$. In an industrial study, repeated cross-validation or a

held-out machine-level test set should be added when multiple machines or operating campaigns are available.

Step 7: Diagnostic decision and deployment

The selected classifier can be embedded in an online monitoring pipeline that processes consecutive vibration windows and outputs the most probable fault state. A practical system should smooth isolated predictions over several

windows, log feature values and model confidence, and trigger inspection only after a persistence rule is satisfied. Model retraining should be initiated when operating conditions, sensors or machine configuration change materially. This lifecycle view is consistent with the broader intelligent-diagnosis roadmap described by Lei et al. [11].

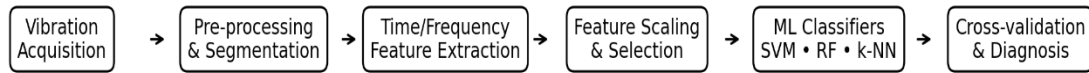


Figure 1. Step-by-step machine-learning workflow for rotating-equipment fault diagnosis.

Results

The following values are results of the simulation-based demonstration described in Step 1, not measurements from an industrial test rig. They are included to verify that the proposed

preprocessing, feature extraction and evaluation sequence produces a complete and auditable diagnosis workflow. Each classifier receives exactly the same 480 feature vectors and five cross-validation folds.

Table 2. Five-fold cross-validated performance on the illustrative four-class vibration dataset.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM (RBF)	96.25	96.28	96.25	96.26
Random Forest	94.38	94.49	94.38	94.41
k-NN	91.67	92.00	91.67	91.75

The RBF-SVM produced the highest overall accuracy (96.25%) and macro F1-score (96.26%). The random forest was close at 94.38% accuracy, while k-NN showed greater sensitivity to overlap in the local feature space. For the SVM, the confusion matrix contained 112/120 correct healthy predictions, 113/120 correct imbalance predictions, 120/120 correct misalignment predictions and 117/120 correct bearing-fault predictions. Most errors were healthy-versus-imbalance confusions, which is reasonable because both classes are dominated by the 1× rotational component and differ mainly in amplitude statistics. The misalignment signature was easiest to separate because its 2× and 3× energy components were deliberately stronger.

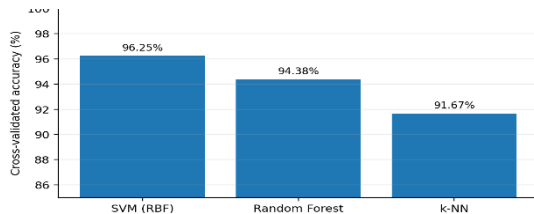


Figure 2. Cross-validated accuracy of the three illustrative machine-learning classifiers.

These results support the use of a feature-based SVM as a strong baseline for limited-data studies, consistent with the earlier SVM literature [1,2]. However, the literature also shows why deeper architectures become attractive when raw signals, operating variability and dataset size increase [4-6,9,10]. Therefore, classifier ranking should not be generalized beyond the present demonstration. The more important result is the evaluation structure: identical folds, fold-wise scaling, multiple metrics and explicit examination of the confusion matrix. That structure can be transferred directly to real bearing, gearbox, pump or motor datasets.

Conclusion and Discussion

This paper presented a complete methodology for machine-learning-based fault diagnosis of rotating mechanical equipment using vibration signals. The procedure begins with condition-labelled data acquisition and controlled segmentation, continues through statistical and spectral feature extraction, performs fold-wise scaling and supervised learning, and ends with cross-validated diagnosis and deployment rules. The literature up to 2020 shows a clear progression from SVM/ANN approaches [1-3] to deep neural, convolutional and recurrent models

[4-6,9,10], while review studies emphasize the importance of representative data and validation practice [7,11]. In the simulation-based demonstration, SVM achieved the highest accuracy among the three conventional classifiers, followed by random forest and k-NN. This result illustrates the effectiveness of physically meaningful feature design under limited data, not superiority over deep learning in general. Deep models can automatically learn richer representations, but they also increase data and tuning requirements and may be more difficult to interpret. Fault-severity estimation, which is distinct from simple categorical diagnosis, should additionally consider approaches such as those reviewed by Cerrada et al. [8].

The main limitation is that the quantitative results are based on synthetic signals rather than measurements from a specific industrial asset. Future work should repeat the exact pipeline on experimental bearing and gearbox datasets, include variable loads and speeds, test sensor placement sensitivity, evaluate class imbalance, and perform machine-level holdout validation. Transfer learning or domain adaptation can then be added to address distribution differences between laboratory and field data. With these extensions, the proposed methodology can serve as a rigorous baseline for predictive-maintenance fault diagnosis. From a practical maintenance perspective, the diagnosis model should be treated as one component of a decision-support system rather than as an isolated accuracy score. Sensor mounting, sampling frequency, operating load and rotational speed must be recorded together with the vibration signal so that model errors can be traced to physical conditions. Studies using learned vibration representations [12,13] and noise-robust CNN training [14] show that changing operating domains can alter feature distributions substantially. Therefore, thresholds for alarms should be validated against maintenance consequences: false alarms increase inspection cost, whereas missed faults can permit damage progression. The recommended development sequence is to begin with the feature-based baseline described here, establish a machine-level test set, and only then compare deep architectures on the same splits. For fleets such as wind turbines, where machines operate under broad environmental variability, the condition-monitoring literature similarly stresses the importance of representative data and model generalisation [15]. This staged comparison preserves interpretability, makes performance gains attributable to the learning method rather than to different data partitions,

and provides a defensible path from laboratory diagnosis to predictive-maintenance deployment.

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