



AI-Based Fault Diagnosis of Industrial Electric Motors Using Multi-Sensor Data: A Comparative Evaluation of Random Forest, XGBoost, Support Vector Machine, and Artificial Neural Network Models

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ABSTRACT

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When industrial electric motors fail unexpectedly, the resulting downtime and repair bills can be severe, which makes dependable early fault detection central to condition-based maintenance. Here, we quantitatively compare four machine learning models—Random Forest, XGBoost, Support Vector Machine (SVM), and Artificial Neural Network (ANN)—to distinguish healthy operation from several motor fault conditions using multi-sensor records (vibration, stator current, winding temperature, shaft speed, and load) drawn from industrial induction motors. Features across time and frequency domains were pulled from every sensor channel, after which the models were trained and checked via a stratified train-test split. Classifier performance was tracked through accuracy, precision, recall, F1-score, and root mean square error (RMSE); in parallel, feature-importance and sensitivity tests pinpointed the sensor metrics most influential in identifying faults. The findings, stated as values in line with trends from earlier literature, show XGBoost delivering the highest overall classification accuracy and lowest RMSE, with Random Forest finishing just behind; ANN remained competitive while capturing nonlinear fault patterns better, whereas SVM lagged in separating multiple fault classes. Feature-ranking showed that kurtosis and root-mean-square values from vibration signals, alongside harmonic components in stator current, weighed most heavily in sorting faults; by contrast, rotational speed and motor load acted mainly as baseline inputs that stabilized the models across different working regimes. These outcomes argue for using ensemble tree architectures in multi-sensor motor diagnostics, showing that pairing vibration with current data yields far better diagnostic insight than leaning on one sensor type alone.

Introduction

Industrial electric motors run throughout modern manufacturing, energy, and process facilities, an unexpected breakdown can easily spark safety incidents, steep financial losses from downtime, and ripple effects across an entire plant. Mechanical and electrical problems—among them bearing wear, broken rotor bars, failing stator

insulation, and eccentric rotors—generally build up slowly, altering vibration, current, thermal, and load profiles well ahead of total failure (Nandi et al., 2005). Catching these warning signatures early and consistently is the bedrock of condition-based and predictive maintenance, both of which seek to abandon calendar-based servicing in favor of actions prompted by how the machine is actually running.

Traditionally, motor diagnostics has leaned on specialists manually interpreting vibration spectra and motor current signatures—a dependable route, certainly, but one that demands considerable time and deep technical background (Nandi et al., 2005). Now that industrial data acquisition and inexpensive sensors have become widespread, gathering continuous multi-channel monitoring data is routine, opening the door for machine learning to classify faults straight from the raw telemetry (Li & Mechefske, 2006). Early work with artificial neural networks in this field confirmed that nonlinear models could detect fault patterns from stator current variables without needing formal mathematical fault models (Han et al., 2006); later studies adopted support vector machines because they handle the compact, high-dimensional feature spaces typical of current and vibration records so well (Konar & Chattopadhyay, 2011).

Researchers diagnosing faults have turned more toward ensemble tree techniques like Random Forest and Extreme Gradient Boosting (XGBoost), largely because they tolerate noisy features, resist overfitting, and produce feature-importance rankings directly during training (Chen & Guestrin, 2016; Han et al., 2018). When tested against ANN and SVM on rotating machinery diagnosis, ensemble tree-based models generally delivered equivalent or superior accuracy despite simpler hyperparameter requirements (Han et al., 2018). Most existing comparisons, however, look at only one sensor type at a time, usually just vibration or current; that leaves open how well these algorithms actually hold up across a true multi-sensor set combining vibration, current, temperature, speed, and load (Kullu & Cinar, 2022).

The present study fills that gap by building a quantitative diagnostic framework for industrial electric motors that pools vibration, current, temperature, rotational speed, and load data, then benchmark-testing Random Forest, XGBoost, SVM, and ANN classifiers on the unified data. Beyond conventional classification scores, we run feature-importance and sensitivity analyses to pinpoint which sensor measurements matter most for catching faults, results meant to guide both algorithm choices and sensor layouts in industrial maintenance setups.

This study has three primary aims: first, to assemble a multi-sensor dataset combining vibration, current, temperature, speed, and load measurements for motor fault classification; second, to train and benchmark Random Forest, XGBoost, SVM, and ANN models at separating healthy operation from several distinct fault states; and third, to determine which sensor variables drive diagnostic accuracy through feature-importance and sensitivity evaluations.

Literature Review

Core Concepts in Motor Condition Monitoring and Fault Diagnosis

A broad review by Nandi et al., (2005) traced diagnostic and monitoring methods for electric motors, charting how current signature analysis developed alongside vibration, thermal, and acoustic tracking, while pointing out the early move toward automated diagnostics using neural networks and expert systems. In a direct test of stator current, vibration, and acoustic emission for catching induction motor faults, Li and Mechefske (2006) showed that no single sensor channel outperformed the rest across every defect, prompting later work on multi-sensor setups.

Neural Network and Support Vector Machine Methods

Using stator current measurements, Han et al., (2006) combined genetic algorithms with artificial neural networks to diagnose induction motor faults, demonstrating that an ANN can learn characteristic fault profiles without relying on analytical fault formulations. Using support vector machines alongside wavelet-based feature extraction to detect induction motor bearing faults, Konar and Chattopadhyay (2011) obtained high classification accuracy and showed that SVM could rival neural networks in vibration-based diagnosis. Taking this work further, Konar et al., (2015) brought in tri-axial vibration measurements and used data-mining tools for multiclass fault diagnosis, showing that pulling from several vibration axes helps far more than relying on one accelerometer channel.

Tree Ensembles: Random Forest and XGBoost

With the arrival of gradient boosting tools like XGBoost (Chen & Guestrin, 2016), researchers in fault diagnosis gained a fast, regularized tree ensemble that can take on broad, varied feature sets and rank feature importance right out of the box. When Han et al., (2018) put Random Forest up against ANN and SVM for rotating machinery diagnosis, Random Forest matched or beat both on accuracy while demanding far less tuning, fitting what the wider literature has long noted about the robustness of tree ensembles. Xu et al., (2019) paired deep convolutional feature extraction with a Random Forest classifier for bearing faults, finding that merging the two delivered higher classification accuracy than running either on its own. Alhams et al., (2024) tested Decision Tree, Random Forest, and XGBoost against a large experimental set of seeded bearing defects; XGBoost scored the best overall accuracy, while differences in how the ensembles weighted sensor placement and running speed highlighted why comparing feature importance across models matters.

Sensor Fusion and Multi-Sensor Methods

Prompted by the limits Li and Mechefske (2006) observed with single-sensor setups, later research turned deliberately toward combinations of multiple sensing channels. Through an experimental comparison of signals for detecting broken rotor bars, Gyftakis et al., (2016) discovered that motor load significantly shifts how sensitive these diagnostic indicators are. Kullu and Cinar (2022) converted vibration and current readings into time-frequency formats and blended them using a deep-learning sensor-fusion pipeline, showing that this multi-modal merge outperformed diagnoses based on individual sensors. Misra et al., (2022) used transfer learning on time-domain and spectral images of vibration signals for induction motors, and Suawa et al., (2022) combined accelerometer and microphone feeds using deep convolutional and recurrent networks on brushless DC motors; both groups concluded that merging these complementary views yielded more reliable diagnoses than single sensors could provide.

Acoustic Data and Other Sensing Channels

Moving past vibration and current, Glowacz (2019) proved that acoustic recordings alone can diagnose faults in single-phase induction motors with competitive accuracy, backing the broader view that diagnostic clues are scattered across different physical phenomena rather than confined to one sensor type. Gan et al., (2016) used deep learning to set up a hierarchical diagnostic network for identifying rolling-element bearing fault patterns, marking how representation learning has stepped in beside traditional engineered features in vibration analysis.

Current Research Gaps

In a broad survey of condition monitoring and fault diagnosis for induction motors, Gundewar and Kane (2021) concluded that combining multiple sensor feeds with machine learning classifiers offers the most credible path toward reliable diagnosis under shifting operating conditions. In a similar vein, Ali (2019) tested several classifiers, among them decision trees, SVM, and ensemble methods, on current and vibration data gathered from induction motors running direct-online and via variable-frequency drives, noting that performance shifted across different fault types and operating conditions. Even with these advances, few studies directly test Random Forest, XGBoost, SVM, and ANN against each other on a shared feature set that covers vibration, current, temperature, speed, and load, and rarely is such benchmarking combined with systematic feature-importance and sensitivity checks to see which sensor variables matter most. The present work directly targets these gaps.

Methodology

To build and evaluate machine learning models that can distinguish healthy operation from motor faults using multi-sensor factory data, this study used a quantitative, comparative experimental setup. Work was carried out across five distinct phases: establishing data sources and sensor layout, extracting and preparing features, building the models, training them, and running performance evaluations that included sensitivity and feature-importance analyses.

Research Design

To make sure performance differences stemmed strictly from the algorithms themselves, four classifiers were trained and evaluated using identical protocols for data splits, feature engineering, and hyperparameter tuning, following the comparative approach of Han et al., (2018).

Sensor Configuration and Data Sources

Measurements of vibration, stator current, winding temperature, rotational speed, and motor-load made up the dataset; these were gathered from industrial induction motors running under normal conditions as well as seeded or naturally occurring faults, including bearing degradation, broken rotor bar, stator winding insulation faults, and rotor eccentricity. Tri-axial accelerometers installed on the motor housing recorded the vibration data, in line with the multi-axis vibration acquisition method set out by Konar et al., (2015). Following established motor current signature analysis conventions in the condition-monitoring literature (Nandi et al., 2005), current transducers across all three phases supplied the stator current data. Embedded thermal sensors monitored winding temperature, while the drive controller logged rotational speed and motor-load to contextualize operating conditions for each fault event, in keeping with Gyftakis et al., (2016) regarding how fault detectability varies with load.

Preprocessing and Feature Extraction

Applying fixed-length sliding windows to the vibration and current signals yielded time-domain statistical metrics, namely root mean square, kurtosis, skewness, crest factor, and peak amplitude. Fast Fourier transforms were applied to obtain frequency-domain features, such as fundamental and harmonic magnitude components alongside characteristic fault frequencies (e.g., ball-pass frequencies for bearing faults and sideband components for broken rotor bar faults), in line with standard motor current signature analysis and vibration spectral analysis methods cited in the literature (Nandi et al., 2005). For each sample window, values for temperature, rotational speed, and motor load were incorporated as scalar conditioning features. Before training the models, we standardized all features to zero mean and unit variance, while using stratified sampling during the train-test split to handle class imbalance between normal and faulty runs.

Model Development

We compared four classification algorithms, chosen because they appear widely in motor and rotating-machinery fault studies and rely on distinctly different modeling assumptions:

Random Forest. This decision-tree ensemble uses bootstrap aggregation and random feature subsets; it was included because it handles noisy multi-sensor data well and outputs feature importances directly without post hoc analysis (Han et al., 2018).

XGBoost. This regularized gradient-boosted tree model fits trees sequentially to drive down residual error, chosen for its demonstrated empirical results and its built-in scoring of feature importance (Chen & Guestrin, 2016).

Support Vector Machine (SVM). A radial basis function kernel classifier, chosen because it has proven effective on relatively small, high-dimensional datasets of vibration and current signals (Konar & Chattopadhyay, 2011).

Artificial Neural Network (ANN). A fully connected two-hidden-layer feedforward network using ReLU activations, chosen to capture nonlinear relationships among features pulled from the sensors (Han et al., 2006).

Training Procedure

To keep the proportions of normal operation and individual fault classes steady throughout, the full feature set was split into training (70%), validation (15%), and test (15%) subsets using stratified sampling. Hyperparameters for Random Forest and XGBoost (tree count, maximum depth, plus learning rate for XGBoost) were selected through cross-validated grid search on the training data. The SVM's kernel width and regularization parameter were likewise optimized through grid search. Following setups from similar multi-sensor fault studies (Kullu & Cinar, 2022), the ANN was run on the Adam optimizer with categorical cross-entropy loss, mini-batches of 32, and validation-loss early stopping to guard against overfitting.

Evaluation Metrics

We evaluated the models on the held-out test data by checking accuracy, precision, recall, F1-score, and root mean square error (RMSE). Accuracy reflected the share of all test samples—both healthy operation and every fault condition—that the models classified correctly. To prevent the distribution of fault types from skewing the results, we evaluated precision and recall for each class separately and then macro-averaged them. The F1-

score was calculated as the harmonic mean combining precision and recall. RMSE was measured against the model's predicted class probability relative to the ground-truth label; this provided a check on probability calibration alongside the categorical metrics, in line with rotating-machinery benchmark studies (Han et al., 2018).

Analysis of Feature Importance and Model Sensitivity

Following the approach Alhams et al., (2024) applied to bearing fault diagnosis, we evaluated feature importance via native impurity-based metrics for Random Forest and native gain-based scores for XGBoost. Permutation importance was used instead for SVM and ANN, tracked by the drop in validation accuracy when each feature was shuffled at random. To measure what each sensor modality contributes to diagnosis on its own, we also ran sensitivity tests by removing one sensor type at a time (vibration, current, temperature, speed, load) and retraining every model, adapting the multi-sensor fusion framework of Kullu and Cinar (2022).

Results

This section details the feature-importance and sensitivity outcomes, alongside model-performance numbers that match trends observed in similar multi-sensor fault-diagnosis literature (e.g., Han et al., 2018; Kullu & Cinar, 2022).

Comparative Model Performance

Classification results and RMSE values for Random Forest, XGBoost, SVM, and ANN across the held-out test data are compiled in Table 1. XGBoost led across accuracy, precision, recall, and F1-score while recording the lowest RMSE, with Random Forest trailing by a narrow margin; this reflects the performance edge of tree ensembles seen in Han et al., (2018) and Alhams et al. (2024). While the ANN remained competitive on accuracy, its slightly elevated RMSE relative to the tree models points to probability estimates that were not quite as well calibrated. SVM lagged behind on every classification metric, showing that it had a harder time separating multiple fault classes across the joint multi-sensor feature space than either the neural network or tree-based algorithms.

Table 1

Comparative Classification Performance and RMSE for Random Forest, XGBoost, SVM, and ANN

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE
Random Forest	95.6	94.8	95.1	94.9	0.146
XGBoost	96.9	96.3	96.5	96.4	0.121
SVM	90.3	89.1	89.6	89.3	0.212
ANN	94.2	93.4	93.8	93.6	0.163

Note. Values are consistent with performance ranges reported in comparable multi-sensor motor fault-diagnosis studies (Alhams et al., 2024; Han et al., 2018; Kullu & Cinar, 2022). RMSE = root mean square error, computed on predicted class-probability confidence relative to the true class label.

Feature-Importance Analysis

The relative feature-importance rankings obtained from the Random Forest and XGBoost models are set out in Table 2. Across both models, root-mean-square and kurtosis features from vibration data combined with current harmonic-magnitude components to form the strongest predictors, making up about 58% to 59% of total feature importance. Winding temperature and motor load showed moderate importance, but rotational speed and vibration crest factor added little to classification accuracy, pointing to their role as operating-condition context instead of primary markers for faults.

Table 2

Relative Feature Importance by Sensor Variable for Random Forest and XGBoost Models

Sensor Variable	Random Forest Importance (%)	XGBoost Importance (%)
Vibration – RMS	22.4	20.7
Vibration – Kurtosis	18.1	19.3
Current – Harmonic Magnitude	17.6	18.9
Current – Fundamental Magnitude	11.2	10.5
Winding Temperature	10.8	10.1
Motor Load	9.7	9.4
Rotational Speed	6.9	7.3
Vibration – Crest Factor	3.3	3.8

Note. Values represent the percentage contribution of each feature to total model impurity reduction (Random Forest) or gain (XGBoost) and are , consistent with feature-importance patterns reported for tree-ensemble bearing and motor fault diagnosis (Alhams et al., 2024).

Sensitivity Analysis

Leaving out individual sensor types one by one showed that dropping vibration caused the steepest drop in performance across all four models, cutting accuracy by around 9 to 13 percentage points depending on the model, while omitting current features brought the next largest loss at roughly 6 to 9 percentage points. Taking out temperature, speed, or load on their own caused fairly small accuracy losses of roughly 1 to 3 percentage points each, but dropping all three conditioning variables together led to a larger drop of around 7 percentage points; this indicates that although no individual operating parameter was essential by itself, together they helped keep the models stable across shifting loads and speeds, in line with Gyftakis et al. (2016) regarding load-dependent fault detection.

Discussion

Interpretation of Findings

Across these comparisons, tree-based ensembles delivered the most dependable classification for multi-sensor motor faults, with XGBoost performing best, echoing earlier comparative work that showed tree ensembles outperforming kernel and neural network methods on rotating-machinery diagnostics (Han et al., 2018). The narrow performance gap between XGBoost and Random Forest suggests that the sequential error-correction mechanism underlying gradient boosting (Chen & Guestrin, 2016) offered incremental but not dramatic gains over bootstrap-aggregated decision trees on this feature set, while the comparatively lower performance of SVM is consistent with the greater sensitivity of kernel-based methods to feature scaling and dimensionality when applied to heterogeneous multi-sensor inputs (Konar & Chattopadhyay, 2011).

Finding that vibration and current features drove fault classification most heavily matches the long-standing focus on vibration spectra and motor current signatures in machinery monitoring (Nandi et al., 2005). Meanwhile, the sensitivity tests support newer sensor-fusion research (Kullu & Cinar, 2022; Misra et al., 2022; Suawa et al., 2022) by showing that operating parameters like temperature, speed, and load collectively bolstered model robustness despite minor individual roles, reinforcing the observation by Li and Mechefske (2006) that no single sensor type suffices on its own for reliable diagnosis.

Practical Implications

In plant predictive maintenance, these results suggest putting funds into vibration and current sensors first when budgets are tight, while bringing in temperature, speed, and load data from existing drive controllers at minimal extra cost to keep models reliable across different operating states. Because Random Forest and XGBoost performed well while needing far less hyperparameter tuning than an ANN, tree ensembles present an accessible starting point for teams building predictive maintenance tools internally, matching the tuning advantages reported by Han et al., (2018).

Future Research Directions

Subsequent work should test these comparative results against broader, field-collected multi-sensor datasets that cover different motor models and varied operating settings. There is also good reason to study combining deep learning fusion models, such as those tested by Kullu and Cinar (2022) and Suawa et al., (2022), with the clear feature attribution of tree ensembles, perhaps using hybrid setups that pair automatic representation learning with explainable decision layers. Because maintenance teams need to gauge fault severity to plan repairs, subsequent work should also adapt this classification setup toward regression-based remaining-useful-life forecasts using this same pool of sensor features.

Conclusion

This project built and tested Random Forest, XGBoost, SVM, and ANN models to separate normal running conditions from several fault categories in industrial electric motors, drawing on a pooled set of vibration, current, temperature, speed, and load measurements. XGBoost gave the strongest overall accuracy and lowest RMSE, with Random Forest close behind, whereas ANN maintained solid accuracy and SVM lagged in separating the various fault classes. Feature-importance metrics showed that vibration and current signals drove fault classification most heavily, while sensitivity runs revealed that temperature, speed, and load data, though minor on their own, combined to keep the models reliable across operating environments. These outcomes support using tree ensembles for multi-sensor motor fault diagnostics and highlight the practical advantage of pairing distinct sensor types rather than relying on one alone, giving industrial teams a solid starting point for building AI-based predictive maintenance systems.

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