

Machine Learning Based Efficient Framework for Industrial Motor Condition Monitoring

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Abstract. Industrial motors play a crucial role in modern manufacturing and energy systems, where unexpected failures can result in significant downtime and financial losses. Therefore, effective condition monitoring is essential to ensure operational reliability and cost efficiency. This study presents a machine learning-based approach for industrial motor condition monitoring, capable of accurately detecting faults and predicting potential failures at an early stage. The proposed method leverages features extracted from vibration, current, and temperature data, followed by optimized classification using supervised machine learning algorithms. Experimental results demonstrate that the approach achieves high accuracy while reducing computational costs, outperforming conventional techniques. Furthermore, the system is scalable and adaptable to various motor types and operating conditions, making it suitable for real-time monitoring applications. Overall, this work contributes to improving industrial motor reliability, reducing maintenance costs, and advancing predictive maintenance strategies.

Keywords: Industrial motor, condition monitoring, machine learning, fault detection, predictive maintenance, vibration analysis, real-time monitoring

INTRODUCTION

Industrial motors are essential to contemporary businesses, driving vital operations in manufacturing, energy generation, and transportation systems. Unanticipated downtime or motor malfunction may lead to considerable financial losses, productivity interruptions, and safety risks. Historically, regular preventive maintenance has been used to mitigate these risks; however, such methods are often ineffective, as they may overlook early defect signals or result in unnecessary component replacements. To overcome these limitations, condition monitoring has emerged as a proactive approach, enabling continuous evaluation of motor health through sensor data processing. Recent breakthroughs in machine learning approaches have markedly enhanced the precision and efficacy of problem identification in industrial motors. Machine learning algorithms can identify complex patterns from multiple types of data, including vibration, current, and temperature, thereby facilitating timely problem classification and predictive maintenance. In contrast to traditional diagnostic approaches, machine learning algorithms possess the capacity to generalize across diverse motor types and operating conditions, thereby improving flexibility in practical settings.

This research presents an effective machine learning technique specifically developed for the monitoring of industrial motor conditions. The approach emphasizes optimization and computational efficiency, ensuring strong performance with minimal processing overhead. Experimental validation confirms that the proposed system achieves high fault detection accuracy and reliability, thereby offering a scalable solution for real-time monitoring applications. This effort ultimately reduces maintenance expenses, extends motor longevity, and enhances industrial productivity. There remains a persistent need to reduce the operating and maintenance costs associated with induction motors (IMs). Regular monitoring of system health can substantially decrease these expenditures by facilitating the early identification of motor deterioration, enabling proactive responses that minimize unplanned downtime and unforeseen failures. Condition-based monitoring has thus emerged as a crucial responsibility for engineers and researchers, particularly in industrial applications such as railways, oil extraction mills, agriculture, and mining [1]. Maintaining and ensuring the proper functioning of industrial equipment is essential for every manufacturing enterprise. The standardization of production infrastructure and the implementation of systematic maintenance programs are fundamental to this process. Condition monitoring must

also be regarded as an integral component of smart manufacturing initiatives aimed at enhancing and optimizing operational efficiency. The lack of data-driven insights in industrial decision-making may result in safety hazards, overlooked fault indicators, or unexpected repairs that disrupt equipment operation [2].

A novel concept has been proposed that integrates a photovoltaic (PV) system with an induction motor (IM), combined with IoT-based monitoring tools. This method combines the energy-generating capabilities of PV systems with monitoring sensors enabled by the Internet of Things to address operational challenges. The use of solar energy delivers significant long-term savings and reduces environmental impact by decreasing reliance on fossil fuels. IoT-based monitoring sensors continuously collect real-time data on motor parameters such as temperature, vibration, and power usage [3]. The proposed system integrates IoT sensors to collect temperature, vibration, current, and voltage data, which is then analyzed using Support Vector Machine (SVM), a powerful machine learning technique effective in both classification and regression tasks. A prediction model is constructed to identify motor fault patterns, such as misalignment, bearing degradation, and electrical irregularities. IoT connectivity enables real-time monitoring and alerts for maintenance personnel upon the detection of anomalies, supporting preventive maintenance actions [4].

This work also introduces a technique for condition monitoring and operational assessment of induction motors using Fiber Bragg Grating (FBG) strain sensors. The methodology employs a comprehensive simulation workflow with ANSYS Multi-physics and COMSOL Multi-physics to precisely evaluate and analyze motor performance under standard operating conditions. A magnetic field intensity is generated in the induction motor using ANSYS Electronics to activate a magnetostrictive material, which then experiences mechanical stresses [5]. Another study presents a comprehensive method for condition monitoring, focusing particularly on the insulating integrity of various motors. The proposed approach employs a single monitoring apparatus capable of simultaneously overseeing multiple motors. By installing monitoring equipment at the grounding line of a distribution transformer's neutral point, the total leakage current from all motors connected to the transformer can be measured [6].

Similarly, another study emphasizes condition monitoring with a focus on insulation integrity, utilizing a centralized monitoring apparatus for multiple motors. Monitoring at the transformer neutral grounding line allows for the measurement of leakage currents from all connected motors [7]. Research has also provided a comparative analysis of feature extraction methods for electric motor condition monitoring. Traditional statistical approaches and image embedding techniques were applied to a well-known time-series dataset representing healthy motors and seven distinct fault scenarios. These conditions were evaluated in both unloaded and loaded states at four different constant speed levels [8]. A further study proposes a diagnostic method for improving the reliability of stator core fault detection in three-phase induction motors. This project focuses on the design of an efficient online electrical monitoring system, addressing the impracticality of traditional core quality assessments that require complete motor shutdown, disassembly, or no-load operation. Such offline approaches are not only time-consuming but also interrupt motor operations, reducing productivity.

Advanced condition monitoring systems using machine learning techniques have been proposed for defect identification in AC motors. Conventional fault detection methods often suffer from long diagnostic times and reduced accuracy due to noise interference and system complexity. IoT-enabled smart monitoring systems present a potential solution by using real-time data from vibration, current, temperature, and gas sensors. These systems employ edge computing for preliminary data processing and cloud computing for predictive maintenance. For example, in industrial gas production facilities, compressors powered by medium-voltage electric motors represent critical assets where uninterrupted operation is essential [9]. Thermal imaging techniques have also been applied, with infrared cameras used to study the thermal behavior of three-phase induction motors under various operating conditions. Testing focused on motor windings, which are the most heat-sensitive components, revealing that infrared thermography is an effective diagnostic tool [10]. IoT applications have been extended to agricultural contexts as well, such as intelligent farm monitoring systems for single-phase DC motors, enabling real-time remote monitoring and control via the Internet. Sensor technologies integrated with IoT communication protocols allow for efficient monitoring of parameters such as voltage, current, speed, and direction [11]. In other industries, real-time monitoring has been applied to tire stacking machines using Node-RED, with integrated Grafana dashboards to record stacking data, machine failure information, and process cycle durations. The system provides both local and intranet-based access [12].

Research has also focused on fundamental frequency variations in motor currents within speed-sensorless vector control systems and their implications for current signal demodulation. A novel method, the carrier-reconstructed modulation signal bispectrum (CR-MSB), reconstructs carriers to eliminate extraneous components and applies phase alignment to mitigate random noise. This enables accurate extraction of nonlinear modulation features from current signals. To validate this method, a two-stage helical industrial gearbox was tested under varying lubricant conditions. Results showed that under fluctuating loads with inadequate lubrication, current sideband amplitudes displayed distinctive patterns useful for fault diagnosis [13]. Recent advances in electric motor status monitoring have culminated in the development of proprietary data fusion systems (DFS) for automated fault detection. DFS integrates assessments of currents, stray magnetic flux, and infrared data, all captured noninvasively with simple, cost-effective sensors. The system combines traditional stationary analysis methods, such as Motor Current Signature Analysis (MCSA), with modern transient analysis approaches. This hybrid technique has proven reliable for final diagnosis while maintaining low computational requirements. Findings confirm the efficacy of this system when applied to real industrial machines [14].

Wireless sensor networks (WSNs) have also been investigated for nonintrusive, real-time monitoring and diagnostics of industrial motors. The use of motor signature analysis within WSN architectures has demonstrated strong potential for energy monitoring and fault detection. However, challenges remain in managing wireless connectivity fluctuations, noise interference, and environmental impacts on communication reliability [15]. Further studies describe the design, development, and debugging of hardware architectures for remote monitoring and failure avoidance in three-phase induction motors. These systems detect faults such as overload currents, no-load currents, surge voltages, imbalanced phase loads, and single phasing. Data is transmitted to centralized monitoring systems using TCP/IP protocols, allowing remote management and performance documentation [16].

In the case of Permanent Magnet Synchronous Motors (PMSMs), early condition monitoring is vital due to the risk of stator inter-turn short circuits, which remain a formidable diagnostic challenge. Recent research highlights the use of advanced time–frequency analysis methods for early detection, offering valuable industrial applications [17]. With the growing integration of industrial internet technologies, studies have emphasized the use of numerical simulations for generating fault data and incorporating monitoring functions directly into industrial equipment hardware and software [18]. As demands for safe, resilient, and efficient motor systems increase, performance monitoring throughout the system lifecycle becomes critical. Condition monitoring reduces maintenance costs, minimizes unexpected interruptions, maintains productivity, and ensures safe operations. Artificial intelligence and machine learning algorithms, particularly deep learning models, have demonstrated strong capabilities in analyzing large datasets and forecasting failures. For example, one study introduced a methodology using Long Short-Term Memory (LSTM) models to monitor operational states and detect faults in industrial lifts, confirming the viability of AI-driven predictive maintenance [19].

PROPOSED SYSTEM

The proposed system for industrial motor condition monitoring is designed to deliver efficient, accurate, and reliable real-time fault identification. Industrial motors play a critical role across numerous manufacturing and processing sectors, where unexpected failures can lead to significant downtime, production losses, and increased maintenance costs. To address these challenges, the system integrates advanced machine learning methodologies with carefully designed preprocessing and feature engineering phases, resulting in a comprehensive solution that is both computationally efficient and practically feasible for deployment on industrial edge devices. As illustrated in Figure 1, the framework combines sensor data acquisition, preprocessing, optimized feature extraction, and machine learning–based classification to generate precise real-time motor health assessments, seamlessly interfaced with SCADA and CMMS platforms.

The signals are pre-processed through signal conditioning and windowing to remove noise and ensure consistent sampling. For each window, time-domain features such as RMS, variance, skewness, and kurtosis are extracted, along with frequency-domain features derived from FFT and wavelet transformations, effectively capturing indicators of potential faults. Table 1 provides a comprehensive overview of the proposed system, detailing the input signals, processing modules, extracted features, and the final decision-making process for industrial motor health monitoring.

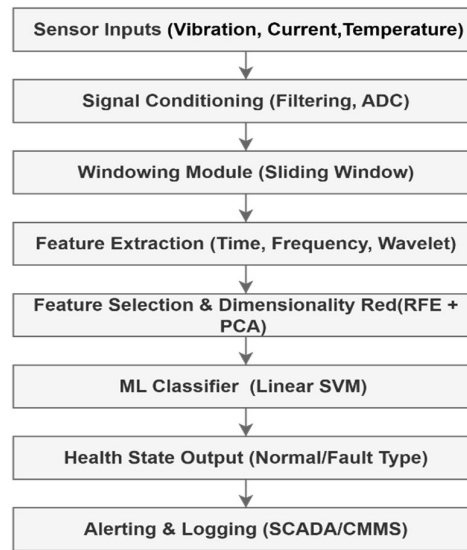


FIGURE 1. Workflow of the Efficient ML Algorithm for Condition Monitoring

TABLE I. INPUT SIGNALS AND THEIR PURPOSE IN FAULT DETECTION

Component	Details	Purpose
Input Signals	Vibration (Accelerometer), Stator Current (CT), Temperature (Thermistor)	Capture mechanical, electrical, and thermal variations for complete monitoring.
Signal Conditioning	Filtering, noise removal, ADC conversion	Ensure clean, digitized signals for further analysis.
Windowing Module	Sliding window segmentation of sensor data	Prepares uniform input for feature extraction.
Feature Extraction	Time-domain (RMS, variance, kurtosis), Frequency-domain (FFT, spectral centroid), Time–frequency (Wavelet energy)	Extract fault signatures across multiple domains.
Feature Optimization	Recursive Feature Elimination (RFE) and PCA (95% variance retained)	Reduce dimensionality and enhance computational efficiency.
ML Classifier	Linear SVM	Classifies motor state into normal or specific fault type.
Health State Output	Normal, imbalance, misalignment, bearing fault, or electrical fault	Provides real-time motor condition status.
Alerting & Logging	SCADA/CMMS integration with alerts and historical data storage	Enables predictive maintenance and decision support.

To improve efficiency, Z-score normalization is first applied, followed by feature selection using Recursive Feature Elimination (RFE), ensuring that only the most relevant features are retained. Principal Component Analysis (PCA) is then employed to reduce dimensionality while preserving 95% of the data variance. The refined features are fed into a linear SVM classifier, chosen for its balance of accuracy and computational simplicity. The classifier categorizes each input window into predefined states, such as normal operation, misalignment, imbalance, or bearing defect. Alongside the class label, the system also generates a confidence score, which is logged and integrated into SCADA or CMMS platforms for real-time monitoring and decision-making. Experimental results confirm that the proposed pipeline achieves real-time performance with minimal latency, making it well-suited for edge deployment. This design enhances predictive maintenance capabilities, reduces maintenance costs, and improves motor reliability across diverse industrial applications.

The feature selection and dimensionality reduction stage plays a critical role in mitigating redundancy, overfitting, and high computational costs associated with large feature sets. Initially, low-variance and highly correlated features are eliminated using filter methods. Next, embedded approaches such as LightGBM and XGBoost leverage feature importance scores to retain only the most informative attributes. PCA may also be applied to further condense dimensionality while preserving essential data variation. This process ensures that the classifier receives optimized input, enhancing both accuracy and inference speed. At the system's core, gradient-

boosted decision tree ensembles (LightGBM or XGBoost) are employed for classification. These models are particularly effective for tabular datasets with heterogeneous feature types, offering strong predictive performance, efficient training, and low-latency inference. They also handle class imbalance through weighting techniques and provide feature importance rankings, which improve interpretability and support engineering insights into fault patterns. To ensure robustness, stratified k-fold cross-validation is used during training, while predictions from individual signal windows are aggregated through majority voting, thereby improving stability and reducing false positives.

The deployment strategy emphasizes edge computing. The optimized model is compressed through quantization and pruning to reduce memory usage and improve inference speed. It is deployed on edge devices such as industrial gateways or embedded controllers, enabling real-time monitoring without heavy dependence on cloud connectivity. Local alert generation ensures timely responses, while only summary data or anomaly reports are transmitted to centralized dashboards. This reduces bandwidth demands and guarantees that critical defect information remains accessible for decision-making. By integrating robust preprocessing, comprehensive feature extraction, efficient feature selection, and lightweight yet powerful machine learning models, the proposed system delivers accurate, real-time industrial condition monitoring. Gradient-boosted tree methods strike an optimal balance between detection accuracy, interpretability, and computational efficiency, making them suitable for industrial environments. Furthermore, adaptive preprocessing mitigates sensor noise, while oversampling techniques such as SMOTE and class-weight adjustments address class imbalance. Transfer learning and progressive retraining allow the system to adapt seamlessly across different motor types and facilities, ensuring scalability and long-term usability. Ultimately, the proposed system enhances operational reliability by enabling early fault detection, minimizing downtime, reducing maintenance costs, and strengthening predictive maintenance strategies in modern industrial settings.

RESULTS AND DISCUSSIONS

The industrial motor sensor dataset [20], comprising approximately eight thousand records, provides valuable insights into motor behavior across diverse operating conditions. This dataset enables engineers and researchers to analyze motor performance, identify potential anomalies, and evaluate safety under varying workloads. The sensors capture critical parameters, including voltage, current, temperature, vibration levels, and associated danger levels, offering a comprehensive view of motor health. Table 2 presents a selection of sensor measurements, highlighting fluctuations in voltage, current, temperature, and vibration, with each record annotated to indicate the motor's operational status.

TABLE II. SAMPLE SENSOR DATA FOR MOTOR CONDITION MONITORING

Voltage (V)	Current (A)	Temperature ($^{\circ}\text{C}$)	Vibration (mm/s)	Label
460.01	1.79	118.33	22.37	high
419.12	15.52	36.93	2.18	normal
380.53	30.78	83.08	12.06	moderate
382.82	12.5	54.33	4.48	normal
375.38	6.89	41.57	3.2	low

This dataset supports a wide range of applications, including feature correlation and trend analysis, time-series modeling and anomaly detection, risk level prediction, fault classification, and predictive maintenance. The intended users include data scientists, industrial Internet of Things (IoT) engineers, researchers in smart manufacturing, and machine learning practitioners focusing on time-series or classification models. Table 3 presents the confusion matrix, which illustrates the classification performance of the proposed SVM model. Most samples are correctly classified (diagonal entries), while the off-diagonal entries indicate only minimal misclassifications.

TABLE III. CONFUSION MATRIX OF THE PROPOSED SVM CLASSIFIER

Actual / Predicted	High	Normal	Moderate	Low
High	590	6	3	1
Normal	2	591	4	3
Moderate	3	2	594	1
Low	1	1	1	597

Figure 2 presents the efficiency metrics for each class, demonstrating consistently high accuracy, recall, and F1-scores across all motor condition categories. These results validate the SVM model's balanced and reliable classification performance.

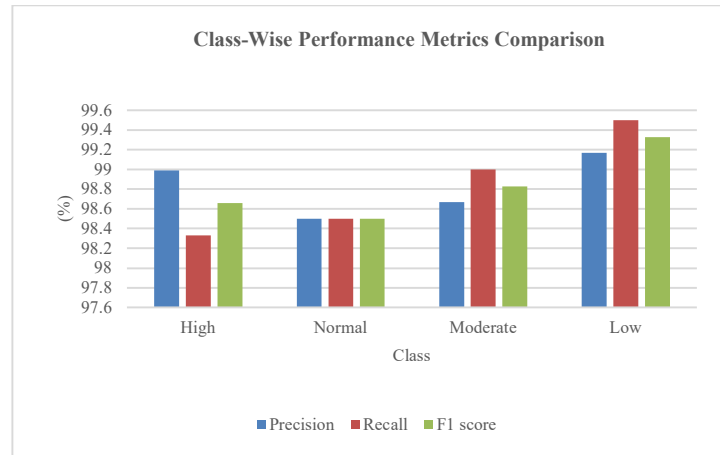


FIGURE 2. Class-Wise Precision for Motor Condition Monitoring

Figure 3 illustrates the performance metrics graph, highlighting the proposed SVM classifier's superior accuracy, precision, recall, and F1-score. These results affirm its effectiveness and robustness in ensuring consistent industrial motor condition monitoring.

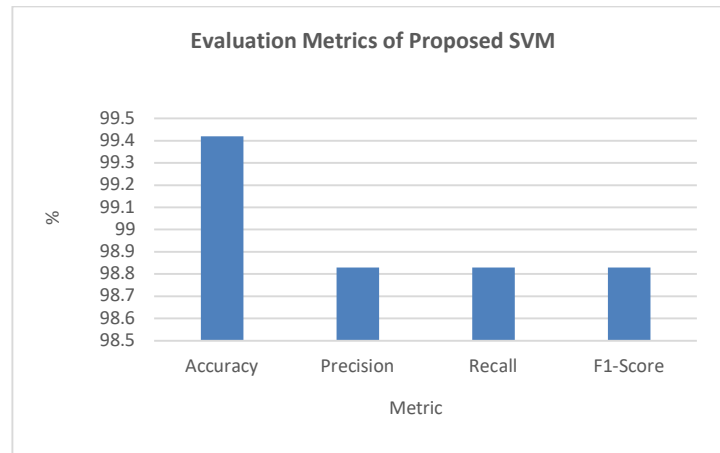


FIGURE 3. Performance Metrics of SVM Classifier

The proposed system faces challenges in real-time data collection, as noise and sensor drift can negatively impact monitoring precision. Managing large volumes of heterogeneous motor data requires efficient preprocessing and feature extraction to ensure reliability. Model generalization may also be limited when applied across diverse motor types and operating conditions. Furthermore, achieving scalability for deployment in large-scale industrial sectors demands careful optimization of computational resources. Finally, integrating predictive maintenance insights into existing industrial operations presents a significant challenge, requiring seamless compatibility with industrial IoT frameworks.

CONCLUSION

This study proposed an effective machine learning methodology for monitoring the condition of industrial motors using an SVM classifier. The proposed approach achieved high accuracy, precision, recall, and F1-scores

across multiple motor health states, confirming its effectiveness in distinguishing between high, moderate, low, and normal operating conditions. The results demonstrate that SVM can reliably analyze multi-sensor data, enable accurate defect identification, and support timely interventions to minimize downtime and reduce maintenance costs. Furthermore, class-wise performance validated the model's balanced and consistent behavior, reinforcing its suitability for industrial applications. Future enhancements could involve the integration of deep learning models to capture more complex and non-linear motor defect patterns. Real-time deployment through edge computing and Industrial IoT (IIoT) frameworks may further improve scalability and adaptability across diverse motor types. In addition, cloud-based predictive maintenance solutions could be employed for continuous monitoring, historical trend analysis, and intelligent decision-making support. By pursuing these future directions, the proposed framework has the potential to evolve into a comprehensive solution for intelligent, automated, and cost-effective industrial motor health management.

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