SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V11I8P115

Volume 11 Issue 8, 134-140, August 2024

Original Article

Real-Time Low-Cost Fault Detection System Placed in Non-Drive End of Motors Based on Neural Networks

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Received: 21 June 2024 Revised: 29 July 2024 Accepted: 19 August 2024 Published: 31 August 2024

Abstract - *Electric motors are vital components in various industrial applications, from production manufacturing to transportation and power generation. They are indispensable parts of machinery and equipment required for the industry, and their effective running is a must for maintaining operational efficiency and productivity. However, a motor suffers from different kinds of faults that can be expensive in terms of downtime, loss of production, and repair costs. Early detection of these faults is important in reducing unscheduled shutdowns, maintenance costs, and workplace accidents. This paper presents the design of a low-cost, real-time fault detection system for motors installed on the Non-Drive End based on neural networks, with the aim of enhancing operational efficiency and reducing maintenance costs in industries*.

Keywords - *Non-Drive end, Neural network, Real-time detection, Low-cost, Fault Detection System.*

1. Introduction

The dependability and effectiveness of electric motors is a crucial factor in the present-day industry. They play an important role in several areas, such as manufacturing, transportation, and energy generation. Productivity and safety in factories directly depend on how well these machines work [1]. Nevertheless, many types of failures affect engines, and their neglect may result in heavy financial losses or interruptions in the workflow.

Fault detection systems are thus indispensable. They enable the early identification of anomalies, preventing unplanned downtimes and costly repairs. However, existing monitoring systems are often expensive and complex, posing accessibility challenges for Small and Medium-sized Enterprises (SMEs) [2]. Moreover, many systems fail to provide real-time detection, limiting their preventive efficacy. A particularly overlooked aspect in motor fault detection is the Non-Drive End (NDE) of the motor. This section, not directly linked to the power-transmitting device, is critical yet frequently neglected in conventional monitoring systems. Early detection of faults in the NDE is crucial, as issues here can indicate severe underlying problems that could escalate if not addressed promptly [3].

This document intends to tackle such obstacles by presenting a low-cost, instantaneous error recognition mechanism for the motors' NDE based on neural networks. This strategy appears to improve the precision of detecting faults together with operational efficacy; thus, it is a credible alternative for various industrial uses.

Numerous industrial processes depend greatly on electric motors. A good output in terms of work or labour depends on its dependability and efficacy. Nonetheless, these machines are prone to different faults that can take different forms, such as mechanical wear, electrical problems, and thermal problems. Failure to detect such faults could have dire ramifications, such as prolonged breaks in operation, low production levels and more funds spent on maintenance routines [4,5].

Currently, the industry relies on sophisticated and expensive monitoring systems that, while effective, are not always feasible for SMEs due to their high implementation and maintenance costs. Additionally, the majority of these systems lack the capability for real-time fault detection, which is critical for preemptive maintenance and operational continuity. The Non-Drive End (NDE) of the motor is particularly challenging for fault detection. Unlike the Drive End, the NDE does not directly transmit power, and as such, conventional monitoring systems often overlook it. However, faults in the NDE can be indicative of severe motor issues and can lead to catastrophic failures if not detected early. Given these challenges, there is a pressing need for an affordable, effective, and real-time fault detection system specifically designed for the NDE of motors. Such a system would significantly enhance operational efficiency, reduce maintenance costs, and improve workplace safety.

2. Related Works

2.1. Traditional Methods

Traditional fault detection methods primarily rely on vibration analysis, Motor Current Signature Analysis (MCSA), and thermal monitoring [6]. Vibration analysis is one of the most common techniques involving the use of accelerometers to detect changes in the vibration patterns of motors, indicative of mechanical issues such as misalignment or bearing failures. MCSA, on the other hand, involves analyzing the current drawn by the motor to identify electrical faults such as stator winding faults and rotor bar issues [7]. Thermal monitoring uses temperature sensors to detect overheating, which could indicate various problems, including overloading and insulation failures [8]. While these traditional methods are effective, they often require expensive equipment and complex data interpretation, limiting their accessibility for SMEs.

2.2. Advanced Signal Processing Techniques

More sophisticated signal processing techniques have emerged to improve the precision and reliability of fault detection systems. To analyze non-stationary and nonlinear signals generally derived from faulty motors, various techniques like wavelet transform [9], Empirical Mode Decomposition (EMD), and Hilbert-Huang Transform(HHT) have been implemented. These techniques can detect the faintest signatures of faults better than classical methods. However, the computational complexity and the need for expert knowledge to interpret the results remain significant barriers to widespread adoption.

2.3. Machine Learning Approaches

The identification of faults in motors with machine learning is a key use case in modern fault detection systems. The Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and decision trees are among the algorithms that have been applied to detect the fault states according to the features extracted from the operation of the motor data [10-12]. These methods of machine learning can learn automatically from the data, thus minimizing the need for human intervention and expert knowledge.

Deep learning, especially neural networks, is a technology that was lot to blame for in fault detection because it can find hidden possibilities in the huge pools of data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed to deal with the data obtained from the vibration signals, motor currents, and sensors for fault detection [13,14]. These models are known to be reliable and efficient in judging the noise in the area being proposed for real-time applications.

2.4. Neural Networks for Fault Detection

Deep learning models are used in many fields and demonstrate excellence, especially neural networks, which can classify the performance of fault detection better than others. CNNs have shown a great deal of promise in tasks involving spatial data, which seem to be an ideal candidate for analyzing vibration signals (and thermal images) [15]. RNNs are good candidates for temporal-dependent data, where the information comes from sensors to predict future temperature readings in time series [16]. Hybrid models combining both CNNs and RNNs have been studied, and the advantages of each architecture are being exploited in unison. As proposed in [17], models can capture both the spatial (cell to cell) and temporal (stream of sensor data over time) trends at the same instance, which helps maximize model performance for fault detection. While being an advantage, neural network-based approaches demand high computational costs and extensive training datasets. One of the challenges is to build lightweight models that can be deployed on edge devices for real-time fault detection in the industry.

3. Methodology

The accuracy and effectiveness of the fault detection system heavily rely on the strategic placement of sensors on the Non-Drive End (NDE) of the motors. In this study, vibration sensors and acoustic sensors were utilized and strategically placed to capture signals indicative of faults.

The vibration sensors were positioned either directly on the motor housing or in proximity to the external surfaces of the motor housing adjacent to the non-drive end bearings. The selected placement allowed for early identification of any abnormalities in motion and vibrations that may be attributed to mechanical issues such as misalignment, bearing degradation, or other rotational imbalances. High-sensitivity accelerometers were used to gather measurements of vibration over a broad spectrum of frequencies. The proximity to non-drive end bearings ensured that even minor variations in the vibrational diagnostics would be captured. Early identification of non-acceptable vibrations is the early warning sign of mechanical issues, which, left unidentified, will lead to significant damage to the motor, motor subcomponents and/or failure of the motor.

Acoustic sensors were located near the NDE components, such as the motor housing and fan cover. Sensor placement is intended to capture the acoustic emission that would provide knowledge of electrical or mechanical faults. A piezoelectric microphone with a broad frequency response was used to detect sounds and ultrasound emitted by the motor. The location of the sensors, especially near the fan cover, was intended to capture sounds that would identify electrical discharge or mechanical friction. They would be very important for detecting high-frequency sounds, which provide an early indication of an electrical fault or lubrication issue with the bearing.


Fig. 1 The motor used for testing

Data collection and data processing are critical for training and validating the neural network model. The initial step of data collection involved obtaining sensor data at 10 kHz to ensure that tinkering with a signal did not lose important transient fault signals. For continuity, we collected data over a significant time period (5 to 7 days) to include various conditions of motor operation. The microcontroller used for this was a Raspberry Pi 4B 8Gb. This extensive data collection was necessary to include all aspects of the state of operation (normal and faulty conditions) in order to strengthen the robustness of the training dataset. For data preprocessing, pseudo steps were performed, and other procedures were followed, which were designed to prepare values from the initial sensor data to readiness for analysis. Filtering was then performed for low-pass and high-pass filters to remove noise and retain fault signals. This is crucial as raw sensor data typically contains excessive noise, which makes it hard to identify which obscure fallen signals. By applying these filters, we ensure that the data fed into the neural network model are clean and focused on the critical features.

Data segmentation involved categorizing data into 1-second time intervals to generate manageable data sizes for consistency in analysis. Here, the segmentation satisfied the objective of providing easily analyzable samples of data, which the neural network could individually research to identify relationships and recognize patterns relevant to a fault. Another methodological preprocessing that was important in this study was the normalization of the data. Normalizing the data to a uniform scale was important for the performance of the neural network model and also facilitated a single feature that did not bias the learning process.

In this research, feature extraction was employed with both frequency analysis and time-frequency analysis techniques. For frequency analysis, a Fast Fourier Transform (FFT) was used to convert the time-domain signal into the frequency domain in order to identify characteristic fault patterns. Time-frequency and wavelet transform were also used to achieve a time-frequency representation of the signals. In addition to frequency analysis, time-frequency analysis allows for more granularity detection of transient events whilst also capturing temporal resolution, which would often be an early indicator of a fault and potentially missed in frequency analysis alone.

The training of the neural network model entailed formulating a hybrid model that combined CNN-RNN as implemented in [18,19], where convolution layers (CNN) extracted spatial features for the preprocessed signals, while LSTM layers (RNN) captured temporal dependencies. This approach was conductive since the strengths of CNN are due to their natural ability to handle spatial data and a separate but complementary approach - RNN for temporally correlated information. The models were trained on the preprocessed labeled fault data by splitting them into training and validation datasets to evaluate model efficacy to predict a label. The training was conducted using the Adam optimizer as well as regularization techniques (such as dropout) to achieve model generalizability and minimize overfitting. These techniques are crucial for ensuring that the model performs well on new, unseen data rather than just memorizing the training data. The model's architecture for the Hybrid Model is represented in Figure 2.

Model validation and evaluation were conducted using a distinct test dataset independent of what was seen during training. The use of a separate test dataset ensures that the evaluation of the system performance is more unbiasedly characterized by accuracies, false positive rates, and response times to predict fault detection in unseen data. Performance metrics such as precision, recall, F1- score, and area under the ROC curve were calculated as quantitative ways to validate our fault detection system. This view afforded representation for total interpretation of disease detection and fault predictions, bringing awareness to the balance of detecting faults while minimizing false alarms. Performance combining high sensitivity (True Positives) and high specificity (True Negatives) is indicative of the potential of this model in relation to developing reliable predictive latent fault prediction on the assembly systems; see block diagram methodology representation in Figure 3.

4. Results

The effectiveness of the fault detection system was evaluated based on a variety of performance metrics such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC) score. These performance metrics provide a holistic view of the model's performance in detecting faults in motor Non-Drive End (NDE). Performance metrics for the hybrid CNN-RNN model on the test dataset can be seen in Table 1. The model maintains high accuracy and precision while balancing recall, which indicates the reliability of the model in detecting faults and minimizing false positives and false negatives.

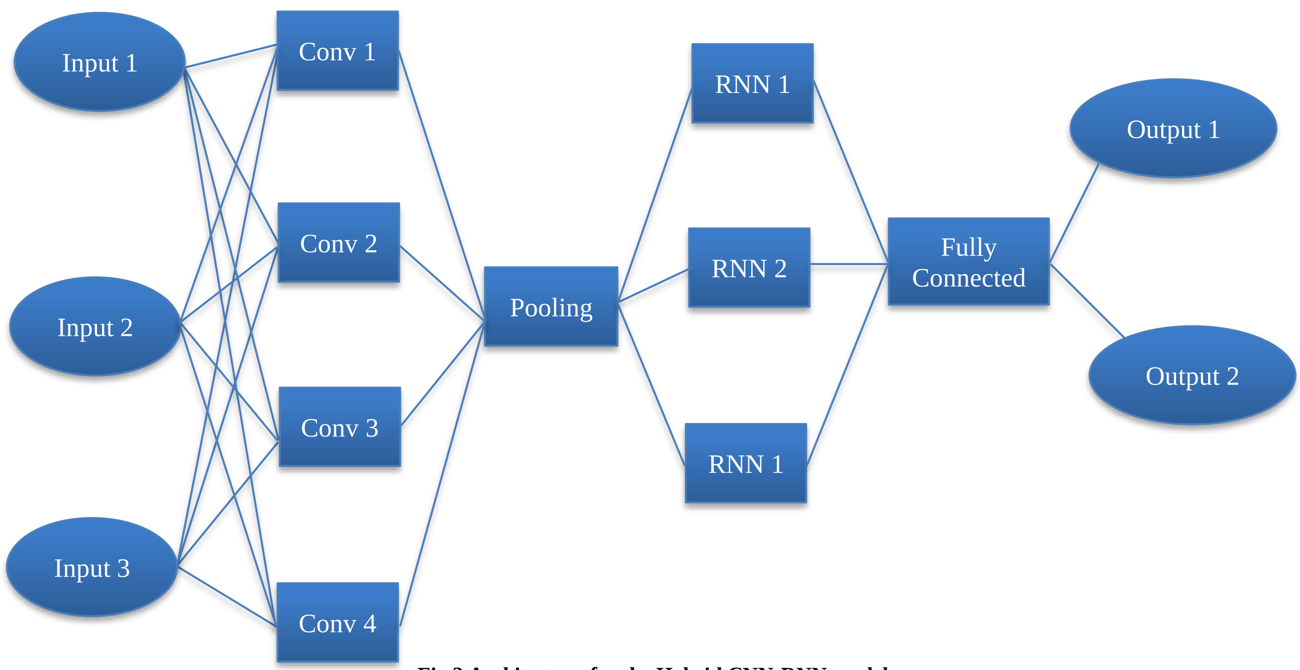

Fig 2 Architecture for the Hybrid CNN-RNN model

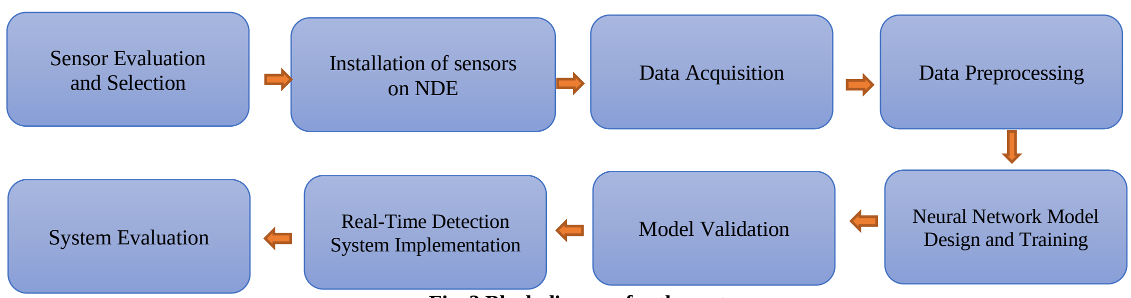

Fig. 3 Block diagram for the system

Table 1. Performance metrics for the model

Metric	Value
Accuracy	97.8 %
Precision	96.5 %
Recall	95.3 %
F1-Score	95.9 %
ROC - AUC	98 %

The confusion matrix in Table 2 illustrates the number of true positives, true negatives, false positives, and false negatives identified by the model. This matrix provides a detailed view of the model's classification performance.

Table 2. Confusion matrix for the model

	Predicted Fault	Predicted Normal
Actual Fault	245	12
Actual Normal	8	235

The system's real-time performance was also evaluated. Table 3 provides the average detection time for faults, showcasing the system's efficiency.

Table 3. Time Performance for the system

Task	Average Detection Time (ms)
Data Acquisition	10
Pre-processing	15
Model Inference	25
Total Detection Time	50

The total detection time measures the duration required for data acquisition, preprocessing, and predictions to process and predict faults accurately. This end-to-end detection time tracks the time needed for the system to detect faults from collecting the data through the time when the prediction is made. The total time of data acquisition, preprocessing, and predictive modeling provides a view of the system's performance in a real-time situation, with the total average time being 50 milliseconds.

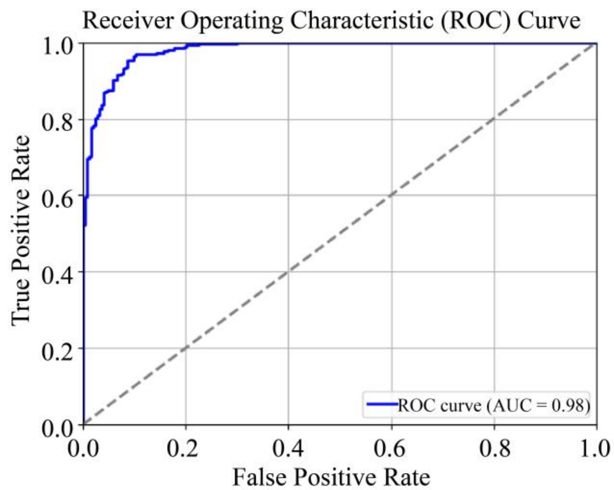

Fig. 4 ROC curve for the model

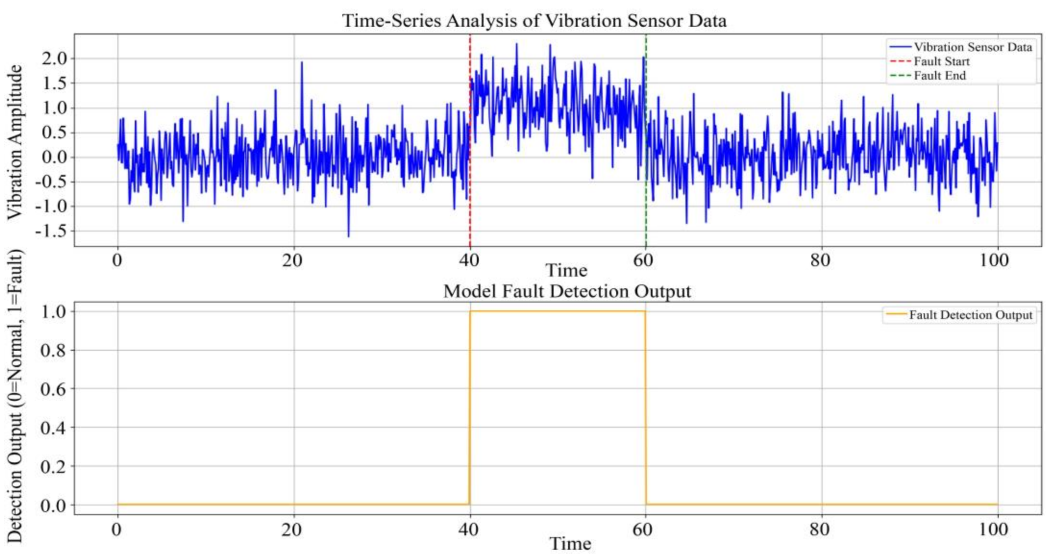

Fig. 5 Time series analysis for vibration data

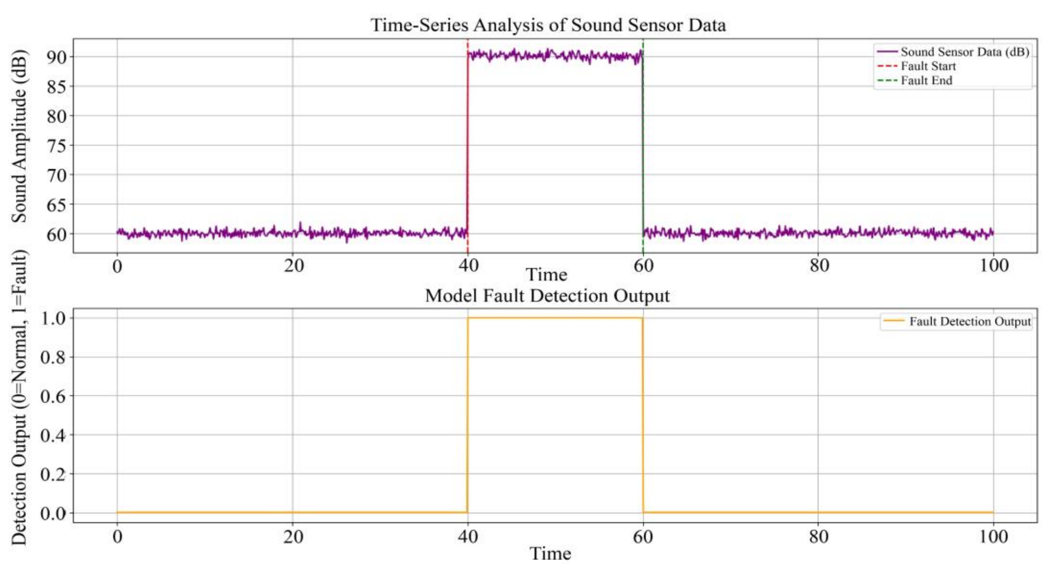

Fig. 6 Time series analysis for sound data

The data acquisition process collects raw sensor data on the Non-Drive End (NDE) of the motor, monitoring vibration, temperature, and acoustic data. Data acquisition averaged 10 milliseconds after multiple rounds. Preprocessing, which includes noise reduction, feature extraction, and normalization, took 15 milliseconds on average.

The duration of preprocessing was measured by running the entire preprocessing pipeline over multiple iterations to ensure reliability. Inference concerning the model took 25 milliseconds, which involved running the pretrained hybrid CNN-RNN on the preprocessed data. After conducting the tests over multiple rounds, the model provided nearly identical performance and time duration results. The ROC curve presented in Figure 4 is illustrative of the combination of performance across a variety of threshold settings. The false positive rate is 1-(specificity) and is plotted against the true positive rate (sensitivity). The Area Under the Curve (AUC) is equal to 0.98; this is an excellent showing of the model's ability to discriminate between faulty and non-faulty conditions.

Figures 5 and 6 illustrate the time-series analysis of the sensor data and the output of the model's fault detection. The graphs for the vibration or sensor data at the top show the raw sensor data over a time series, while the lower graphs of each of the Figures show the fault detection output of the model. The model detects the occurrences of faults as demonstrated in the detection output, which exhibits spikes that correspond with the events displayed in the sensor data, thus attesting to the model's performance.

5. Discussion

The results demonstrate that the hybrid CNN-RNN model is highly effective in detecting faults in the NDE of motors. The high accuracy, precision, recall, and F1 score indicate that the model can reliably identify faults while minimizing the occurrence of false alarms. The ROC curve and its high AUC value further corroborate the model's strong discriminatory power. The confusion matrix reveals that the model has a low false positive rate (8 false positives) and low false negative (12 false negatives). This tells us that the model can distinguish between factious and non-factious conditions. This accuracy is critical in industrial applications, where false alarms can lead to unnecessary maintenance actions, and false negatives can result in undetected faults, causing potential motor failures. The time-series analysis, therefore, records the time taken by the model to detect fault. When compared against the raw time series sensor data, outputs were aligned, indicating a highly valuable continuous health monitoring system for both faults. Again, it is becoming increasingly important for motor maintenance and fault prediction to help eliminate downtimes. In summary, the findings deem that the redundancy and recommended exercise of author defined fault detection system using a hybrid CNN-RNN model has established reliability, accuracy and time-serial efficacy based on an NDE motor diagnostic establishment of pre-fault behaviour in real time. Also, the constructed fault detection systems utilize the recording process the sensors collect and analyze, providing a vital service once implemented to notify potential faults, reduce maintenance activity for costs aspects and electrical motor fails for catastrophic reasons, and saving business and or industry purposes.

The real-time thorough performance evaluation of the constructed system evidences a visible fast and efficient delivery system for improved fault detective action; completing the cycle of quick delivery of motor fault is essential now and can improve industrial contexts where downtime occurs. With an average detection time purposely set at 50 milliseconds, notification and intervention occur sooner, identifying potential faults while incorporating down runs in the systems are smooth (or when possible).

6. Conclusion

This research developed and assessed a real-time, low-cost fault diagnostic system for Non-Drive End (NDE) motors through the application of neural networks. The results show that the application of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) resulted in a high level of efficiency in recognizing faults in NDE motors. These models produced an Area Under the Curve (AUC) value of 0.98. This reflects the models' outstanding ability to discriminate between fault and non-fault conditions effectively. In order to avert unexpected downtime and reduce maintenance costs, a real-time detection system is significant.

Continuous monitoring and instant identification of the fault will allow preventive actions to take place, thereby reducing the risk of devastating damage to a motor and interference in operation. The problem at hand of maximum accessible fault detection of industrial motors can be addressed by desiring its detection utilizing any low-cost sensor and neural networks as a result. This system implies that small and medium-sized enterprises with fewer financial and human resources may also have access to fault diagnostics in ways that they could not afford.

Future efforts might apply diagnostic capabilities to other significant sections of the motor, such as the Drive End or bearings, to locate a more expanded diagnostic source. Also, the systems being improved to increase robustness through advanced architecture and/or ensemble methods may reach a level of performance that achieves diagnostic monitoring under varied and even difficult environmental conditions. Integrating fault diagnostic systems into predictive functionality for maintenance might occur as the viability of monitoring progress. These strategies may create predictive, biased on the operator, data-driven maintenance with greater sophistication at any number of added costs, risks to downtime affecting operations, or cost of maintenance actions.

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