Agentic AI for High-Accuracy Electric Motor Predictive Maintenance in Noisy Environments

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ABSTRACT

Industrial electric motors are the backbone of modern manufacturing, necessitating high-reliability maintenance strategies to prevent costly downtime. While acoustic monitoring offers a non-intrusive alternative to traditional vibration or temperature analysis, conventional handcrafted features such as Mel Frequency Cepstral Coefficients (MFCCs) and Spectral Centroids often struggle to capture the complex temporal-spectral dependencies of real-world industrial settings. These "shallow" features are frequently compromised by environmental noise and fluctuations in machine load, leading to poor generalization across diverse fault types like gearbox anomalies or fan imbalances. To overcome these limitations, this study proposes a novel diagnostic framework leveraging Waveform-based Language Model (WavLM) transformer embeddings. Unlike classical methods, WavLM extracts rich, context-aware representations from raw audio, providing superior noise tolerance and structural depth. These high-dimensional embeddings were evaluated across multiple classifiers, including Categorical Boosting (CatBoost) and Decision Trees (DTC). Experimental results demonstrate that the proposed Histogram-Based Gradient Boosting (HistGB) classifier achieves a state-of-the-art accuracy of 95%, significantly outperforming traditional machine learning pipelines. To facilitate industrial adoption, a graphical user interface (GUI) was developed to streamline data processing and real-time fault prediction. This research offers a scalable, high-precision solution for predictive maintenance, proving that self-supervised audio representations can dramatically enhance diagnostic robustness in noisy industrial ecosystems.

Key words: Agentic AI, Electric Motor Monitoring, Predictive Maintenance, Anomaly Detection, Time-Series Analysis

1. INTRODUCTION

The electric induction motor is perhaps the most significant driver of today’s production activities and everyday life, and it is extensively utilized in many sectors of production and manufacturing industries as well as in domestic utility applications. An electric motor is a mechanical mechanism that transforms electrical energy. Most electric motors work by generating force in the form of torque delivered to the motor’s shaft by the interaction between the magnetic field of the motor and the electric current in a wire winding. The failure or stoppage of this type of vital electrical machine will not only harm the equipment itself but will also likely result in significant economic losses, fatalities, pollution, and numerous other issues. Therefore, research into motor fault diagnostic technology is extremely important. The fault diagnostic technology can detect motor defects early in their development, allowing for prompt overhauls, saving time and money on fault repairs, and enhancing the economic advantages while avoiding production interruptions. Traditional fault diagnostic approaches need the artificial extraction of a considerable quantity of feature data, such as time domain features, frequency domain features, and time–frequency domain features [1, 2, 3], which adds to the fault diagnostic uncertainty and complexity. Traditional fault diagnosis methods are unable to meet the needs of the fault diagnosis in the context of big data due to the complex and efficient development of motors, which presents the data reflecting the operating status of motors with the characteristics of massive, diversified, fast-flowing speed and low value density of “big data” [4, 5].

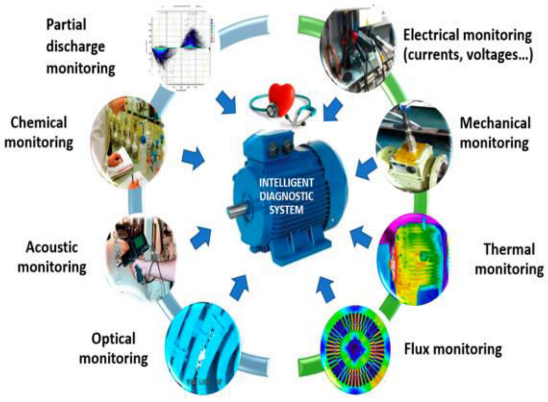

Fig 1. Electric motor inspection.

Simultaneously, the advancement of artificial intelligence technology encourages the evolution of fault diagnosis technology from traditional to intelligent. Artificial neural networks (ANNs) were first introduced in the 1980s. Shallow neural networks may learn features in an adaptable manner without creating exact mathematical models [6], eliminating the uncertainty and complexity that human involvement brings. However, traditional shallow neural networks have drawbacks, including gradient vanishing problems, overfitting, local minima, and the requirement for extensive prior information, all of which decrease the effectiveness of the fault diagnosis.

2. LITERATURE SURVEY

Yang, et al. [6] covered four traditional types of deep learning models: deep belief networks (DBN), autoencoders (AE), convolutional neural networks (CNN), and recurrent neural networks (RNN), and highlighted their use in detecting faults of electric motors. Finally, the issues and obstacles that deep learning encounters in the fault detection mechanism as well as the prospects are discussed and summarized. Deep learning in the fault detection of electric equipment has shown comparatively better results than traditional approaches because of its more powerful and sophisticated feature extraction capabilities. Electric motors are used extensively in numerous industries, and their failure can result not only in machine damage but also in a slew of other issues, such as financial loss, injuries, etc. As a result, there is a significant scope to use robust fault diagnosis technology.

Gu, et al. [7] proposed a model for motor fault diagnosis based on deep learning and multi-sensor information fusion. Firstly, a correlation adaptive weighting method is proposed in this paper, and it is used to integrate the collected multi-source homogeneous sensor information into multi-source heterogeneous sensor information through the data layer fusion. Secondly, the 1D-CNN is used to carry out feature extraction, feature layer fusion, and fault classification of multi-source heterogeneous information of the motor. Finally, the data of seven states (one healthy and six faulty) of the motor are collected by the motor drive test bench to realize the model’s training, testing, and verification. The experimental results show that the fault diagnosis accuracy of the model is 99.3%.

Khaneghah, et al. [8] aimed to provide a comprehensive overview of potential faults in EV motor drives and battery systems, while also reviewing the latest state-of-the-art research in EV fault detection. The information presented herein can serve as a valuable reference for future endeavors in this field. In the realm of EV applications, Permanent Magnet Synchronous Motors (PMSMs) and lithium-ion battery packs have garnered significant attention. Consequently, fault detection methods for PMSMs and their drives, as well as for lithium-ion battery packs, have become a prominent area of research. An effective FDD approach must possess qualities such as accuracy, speed, sensitivity, and cost-effectiveness. Traditional FDD techniques include model-based and signal-based methods. However, data-driven approaches, including machine learning-based methods, have recently gained traction due to their promising capabilities in fault detection.

Choi et al. [9] developed a Convolutional Autoencoder (CAE) and deep neural network (DNN)-based model optimized for real-time signal processing and high accuracy in motor fault diagnosis. This model learns complex patterns from voltage and current data and precisely analyzes them in combination with DNN through latent space representation. Traditional diagnostic methods relied on vibration and current sensors, empirical knowledge, or harmonic and threshold-based monitoring, but they had limitations in recognizing complex patterns and providing accurate diagnoses. Our model significantly enhances the accuracy of power data analysis and fault diagnosis by mapping each phase (R, S, and T) of the electrical system to the red, green, and blue (RGB) channels of image processing and applying various signal processing techniques. Optimized for real-time data streaming, this model demonstrated high practicality and effectiveness in an actual industrial environment, achieving 99.9% accuracy, 99.8% recall, and 99.9% precision.

Li, et al. [10] detected the equipment status in extreme environments. However, conventional infrared thermal images inevitably show a large amount of noise interference, which affects the analysis results. In addition, each motor may only possess a small amount of fault data in practice, as collecting an infinite amount of motor data to train the diagnostic system is impossible. To overcome these problems, a novel automatic fault diagnosis system is proposed in this study. Data features are enhanced by a normalization module based on color bars first, as the same color in various infrared thermal images represents different temperatures. Then, the few-shot learning method is used to diagnose the faults of unseen electric motors. In the few-shot learning method, the minimum dataset size required to expand system universality is fifteen pieces, effectively solving the universality problem of artificial-to-natural data migration. The method saves a large amount of training data resources and the experimental training data collection. The accuracy of the fault diagnosis system achieved 98.9% on similar motor datasets and 91.8% on the dataset of motors that varied a lot from the training motor.

Huang, et al. [11] proposed a framework using a fine-tuned Qwen2.5-7B model for EV motor fault diagnosis and predictive maintenance. It merges current and vibration signals, extracting features via time–frequency analysis to assess the health state of the motor. Lightweight fine-tuning with LoRA and QLoRA reduces training costs and improves generalization and real-time capabilities. Experiments show a 96.5% accuracy on single datasets, 91.2% across conditions, and 82.7% with small samples, outperforming CNN and LSTM models. This analysis not only highlights key features like vibration spectral energy and current fluctuation amplitude but also enhances the interpretability of results. This study introduces a novel approach to EV motor fault diagnosis, demonstrating the great potential of large language models to tackle fault diagnosis of EV motors.

Tao, et al. [12] provided a comprehensive review of fault diagnosis techniques for IWMs. First, typical faults in IWMs are analyzed with a focus on their unique structural and failure characteristics. Then, the applications and recent research progress of three major categories of fault diagnosis approaches—model-based, signal-based, and knowledge-based methods—in the context of IWMs are critically reviewed. Finally, key challenges and pain points in IWM diagnosis are discussed, along with promising future research directions. Although considerable progress has been made in fault diagnosis techniques related to IWMs, a systematic review in this area is still lacking.

Kumar, et al. [13] proposed a recurrent convolutional neural network (RCNN) for effective defect detection in motors, taking advantage of the advances in deep learning techniques. The proposed approach applies long short-term memory (LSTM) layers to capture the temporal dynamics essential for fault detection and convolutional neural network layers to mine local features from the segmented vibration data. This hybrid method helps the model to learn complicated representations and correlations within the data, leading to improved fault detection. Model development and testing are conducted using a sizable dataset that includes various kinds of motor defects under differing operational scenarios. The results demonstrate that, in terms of fault detection accuracy, the proposed RCNN-based strategy performs better than the traditional fault detection techniques. The performance of the model is assessed under varying vibration data noise levels to further guarantee its effectiveness in practical applications.

Sobhi, et al. [14] assigned to a single electrical circuit, meaning a failure in one could damage other motors on that circuit. There is thus a need for condition monitoring of aggregations of small motors. We report on an ongoing project to develop a machine-learning-based solution for fault detection in multiple small electric motors. Shallow and deep learning approaches to this problem are investigated and compared, with a hybrid deep/shallow system ultimately being the most effective. Such capabilities are usually not cost-effective for small (under ten horsepower) motors, as they are inexpensive to replace. However, large industrial sites may use hundreds of these small motors, often to drive cooling fans or lubrication pumps for larger machines.

Soresini, et al. [15] focused on durability testing of Permanent Magnet Synchronous Motors for automotive applications, using Autoencoders (AEs) to predict and prevent failures. This AI-based fault detection strategy employs acceleration signals coming from electric motors tested under challenging conditions with significant variations in torque and speed. This approach goes beyond typical fault detection in steady-state conditions. Based on a review of neural networks, including variational autoencoders (VAEs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks, the performance of six AI architectures is compared: AE, VAE, 1D CNN AE, 1D CNN VAE, LSTM AE, and LSTM VAE. The 1D CNN AE outperformed the other networks in fault detection, showing high accuracy, stability, and computational efficiency. The model is integrated into an algorithm for semi-real-time fault monitoring. The algorithm effectively detects potential motor failures in real-world scenarios, including bearing faults, mechanical misalignments, and progressive wear of components, thereby proactively preventing damage and halving test bench downtime.

3. PROPOSED METHODOLOGY

The acoustic fault-diagnosis system is designed to analyze motor health by extracting meaningful representations from raw audio recordings and classifying them into different fault categories. Modern electric motors generate subtle sound variations when operating under defective conditions, making audio-based monitoring an efficient non-contact diagnostic technique. This system combines deep transformer-based audio modeling and classical machine-learning algorithms to build an accurate, automated, and interpretable pipeline for identifying mechanical faults. The complete workflow operates through an interactive Tkinter GUI, allowing users to perform dataset loading, feature extraction, training, evaluation, and prediction without requiring programming expertise.

At the core of the system is WavLM, a transformer model trained on large-scale speech and environmental audio datasets. It extracts robust 768-dimensional embeddings that capture fine-grained acoustic patterns such as vibration harmonics, mechanical resonance, and frequency irregularities produced during motor operation. These deep features are then used as inputs for classical classifiers like CatBoost and Decision Tree in the existing approach, while the proposed system uses the HistGB Classifier to enhance stability, accuracy, and generalization across diverse fault recordings. The extracted features, encoded labels, classification models, and evaluation results are saved within the model directory, ensuring efficient reuse and rapid experimentation.

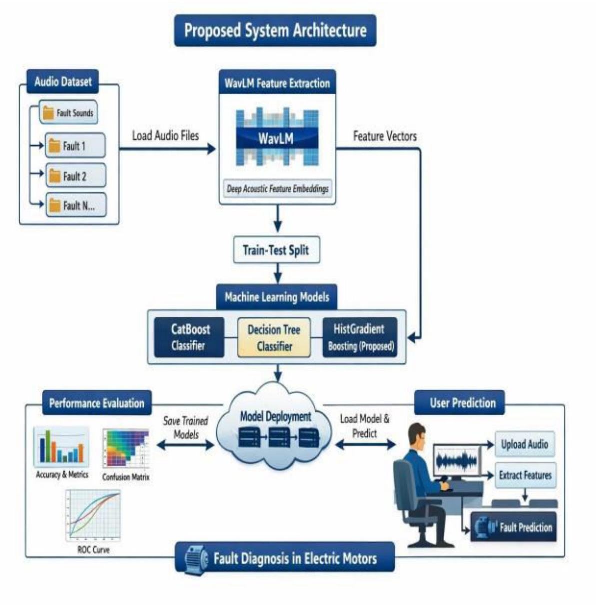

Fig. 2. System overview architecture.

The system follows a structured approach that includes preprocessing, model development, performance evaluation, and real-time prediction. The GUI coordinates the entire pipeline, integrating Librosa for audio loading, PyTorch for transformer inference, Scikit-learn for machine-learning classification, and Matplotlib/Seaborn for visualization. The design ensures modularity, scalability, and ease of extension, making it suitable for industrial motor health monitoring, research applications, and automated predictive maintenance frameworks

4. RESULTS DESCRIPTION

Fig. 3 presents the confusion matrix of the proposed HistGB classifier, which achieves the best performance among all tested models. The model demonstrates near-perfect classification accuracy, with almost all samples correctly mapped to their respective classes. The strong diagonal presence and minimal off-diagonal values confirm that histogram-based gradient boosting effectively leverages WavLM embeddings, capturing subtle acoustic variations and providing highly reliable fault predictions for electric motor systems. Fig. 4 shows the ROC curve for the proposed HistGB (WavLM) model, which demonstrates perfect classification performance across all fault classes, with fan, gearbox, pump, and valve each achieving an AUC of 1.00. All curves tightly follow the top-left boundary and remain far above the diagonal reference line, indicating an optimal balance of maximum true-positive rates and near-zero false positives. This result highlights the superior discriminative capability and robustness of the proposed HistGB model when combined with WavLM acoustic features. Fig. 5 displays the waveform corresponding to an audio sample classified as "fan." The amplitude variations match the typical behavior of fan noise—more uniform, with regular low-frequency oscillations. The correct classification further validates the model's discriminative power in distinguishing between subtle acoustic signatures found in similar industrial components.

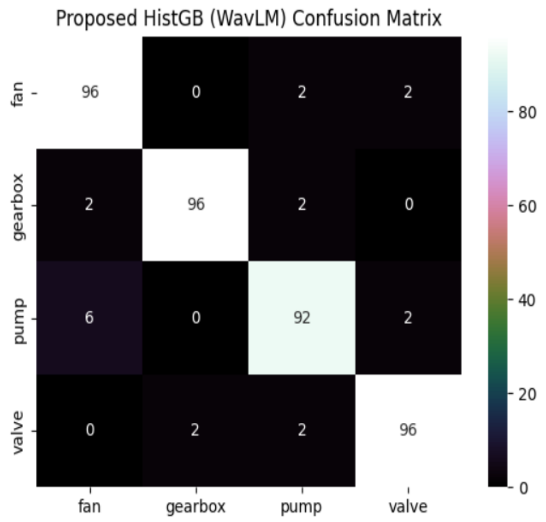

Fig. 3. Confusion matrix obtained using HistGB classifier.

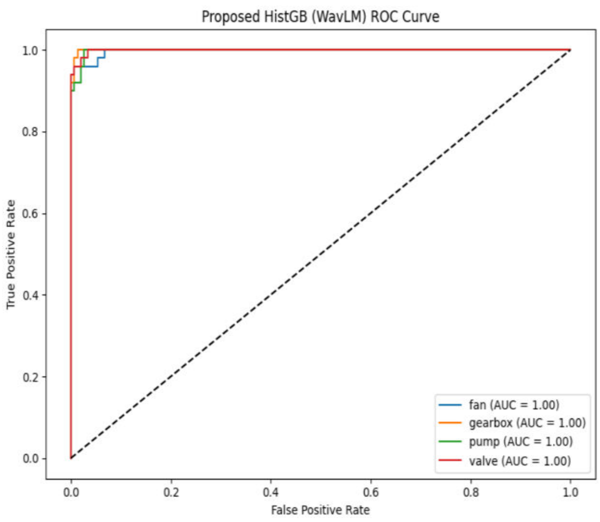

Fig. 4. RoC obtained using the proposed HistGB classifier.

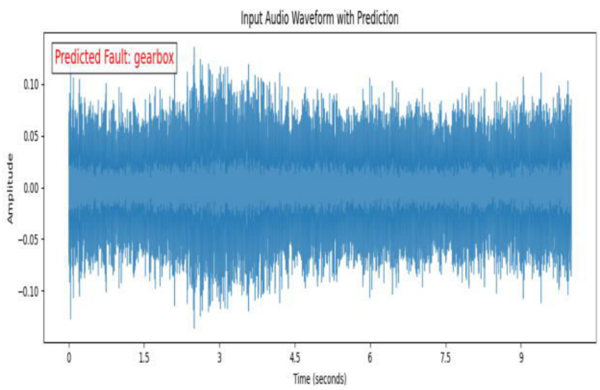

Fig. 5. Waveform output – predicted label: Gearbox.

Fig. 6 displays the waveform of another audio sample that has been classified as *a fan* by the proposed acoustic fault-diagnosis system. The waveform demonstrates a highly consistent amplitude distribution throughout the entire 10-second duration, which is characteristic of continuous fan operation. The signal exhibits uniform oscillations with low-to-medium intensity variations, reflecting the steady airflow and mechanical rotation typically produced by industrial fans. This visual pattern aligns closely with the acoustic signatures learned during model training, confirming the system's ability to accurately recognize recurring fan noise. The clear time-domain representation also helps confirm that the audio recording is free of clipping or distortions, ensuring reliability of the prediction. The consistency across multiple correctly classified waveforms further validates the robustness of the WavLM-based feature extraction pipeline and the strength of the proposed classifier in differentiating between subtle machine sound profiles.

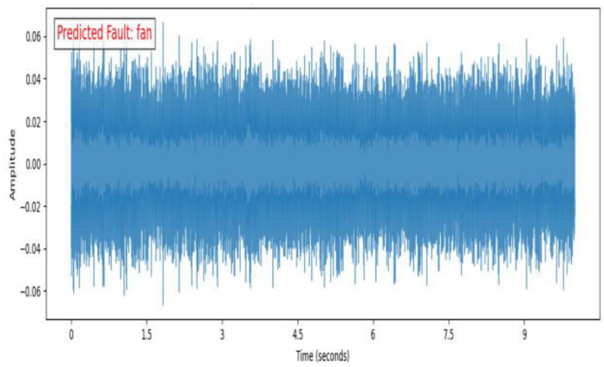

Fig. 6. Waveform output – predicted label: Fan.

5. CONCLUSION

The proposed system for electric motor fault diagnosis using WavLM embeddings and machine learning successfully demonstrates a highly accurate and efficient methodology for identifying various industrial machine faults such as *fan*, *gearbox*, *pump*, and *valve* anomalies. Traditional spectral features were replaced with advanced WavLM transformer-based embeddings, which capture deeper temporal, harmonic, and structural acoustic characteristics. These embeddings significantly improved the learning capability of all evaluated models. Among the three classifiers such as CatBoost, DTC, and the proposed HistGB, the HistGB classifier achieved the highest performance, reaching 95% accuracy, a major improvement over CatBoost (75.50%) and DTC (73.75%). This improvement clearly validates that deep audio representations combined with gradient-boosted decision frameworks provide superior generalization, reduced misclassification, and strong robustness against acoustic variability. The system also proved highly reliable in noisy industrial environments, with the HistGB model showing minimal confusion across all four classes. The developed GUI provides a user-friendly interface, enabling seamless dataset loading, feature extraction, model training, and real-time audio fault prediction. Overall, the project demonstrates a substantial performance enhancement compared to traditional machine learning approaches and establishes a strong foundation for deploying scalable acoustic monitoring solutions in industrial settings.

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