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***Abstract*— This paper presents an innovative approach for detecting inter-turn short circuit (ISF) faults in Permanent Magnet Synchronous Machines (PMSMs). By using zero-sequence voltage signals, identified as the most effective for ISF detection, Fast Fourier Transform (FFT) analysis is applied to extract relevant signal characteristics. Additionally, the integration of Artificial Intelligence (AI) techniques, such as SVM, KNN, and decision trees, allows for the automation of fault detection and classification, enhancing the accuracy and reliability of machine monitoring. The results show that the SVM and KNN models are particularly effective in fault detection, achieving perfect precision and recall. The combined use of these techniques not only optimizes fault detection efficiency but also enhances overall PMSM performance by reducing failure risks and enabling predictive maintenance. This work represents a significant advancement toward smarter and more responsive maintenance solutions for electrical machines.**

Keywords—Inter-turn short circuit (ISF); Permanent Magnet Synchronous Machines (PMSM); zero-sequence voltage; Fast Fourier Transform (FFT); Artificial Intelligence.

I. Introduction

Electric motors, particularly Permanent Magnet Synchronous Machines (PMSMs) [1], play a crucial role in many modern applications, especially in electric vehicles (EVs), due to their high efficiency, power density, and compact design. These motors are essential for systems where performance, reliability, and durability are critical. However, real-time monitoring of their operating status and the implementation of preventive maintenance strategies remain significant challenges, especially when these motors are installed in hard-to-reach environments. A substantial portion of operational costs in the electric vehicle industry are dedicated to maintenance, highlighting the need for advanced fault detection solutions to optimize performance and extend the lifespan of these machines.

Faults in PMSMs, especially inter-turn short circuits (ISF), can lead to catastrophic failures if not detected early. Therefore, early and accurate fault detection is essential to prevent unexpected downtime and irreversible damage. Numerous studies have proposed methods for diagnosing these faults and improving maintenance in electric machines. For example, [8] presents a method combining parameter estimation and machine learning to diagnose faults in electric motors, enabling precise classification of healthy and faulty states. The study in [7] focuses on diagnostic algorithms for an automotive power generation system, aiming to detect faults in critical components such as the alternator and voltage regulator.

Several studies have also focused specifically on fault detection in PMSMs. For instance, [11] uses rotor speed signature analysis and Vold-Kalman filtering to monitor insulation degradation in PMSMs, providing a fault-tolerant method for detecting anomalies. Further, studies like [6] and [13] have proposed fault-tolerant control strategies for PMSM motors in critical applications, demonstrating how these strategies can improve motor reliability in the event of faults while maintaining optimal performance.

In this context, [9] explores a fault diagnosis approach based on an artificial neural network (ANN) to detect and classify three types of faults in the stator of a Permanent Magnet Synchronous Machine (PMSM) using simulation data. This approach enables faster and more accurate identification of stator faults, a key component for the proper functioning of the motor. Moreover, [10] examines the use of transfer learning with a convolutional neural network (CNN) to diagnose

PMSM faults, comparing various diagnostic techniques based on model data. These AI-driven approaches pave the way for more efficient and adaptive diagnostic systems capable of learning and improving with new data.

This paper presents an innovative method for detecting inter-turn short circuit (ISF) faults in Permanent Magnet Synchronous Machines (PMSMs). The main steps of this approach are as follows:

- Utilizing zero-sequence voltage signals, identified as the most effective for ISF detection.
- Applying Fast Fourier Transform (FFT) analysis to extract relevant signal characteristics.
- Integrating Artificial Intelligence (AI) techniques such as SVM, KNN, and decision trees to automate fault detection and classification.
- Evaluating the performance of AI models, where the results show that SVM and KNN are particularly effective, achieving perfect precision and recall.
- Optimizing fault detection efficiency, improving PMSM performance, and reducing failure risks through predictive maintenance. This approach represents a significant advancement toward smarter and more responsive maintenance solutions for electrical machines.

This article is structured as follows: Section II presents the electrical model, while Section III describes the fault detection method. Section IV is dedicated to simulation validation. Finally, the article concludes with Section V.

II. Electrical Model

A. Mathematical Model in Healthy State

In the healthy state, the stator voltages in the abc coordinate system can be expressed in matrix form as follows:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L & M & M \\ M & L & M \\ M & M & L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} \varepsilon_a \\ \varepsilon_b \\ \varepsilon_c \end{bmatrix} \quad (1)$$

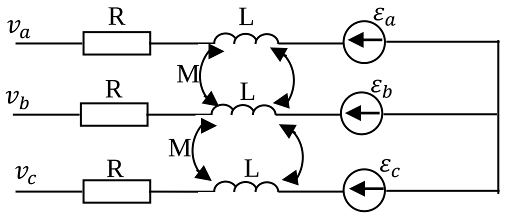


Fig.1. Electrical schematic of the healthy motor model

The stator voltages in the phases a, b, c are denoted as v_a, v_b, v_c respectively. The phase currents in these phases are i_a, i_b, i_c . R represents the phase resistance, L is the self-inductance, and M is the mutual inductance between the phases. The back electromotive forces (EMFs) of phases a, b, and c are denoted as ε_a, ε_b, ε_c, et which depend on the magnetic flux and the electrical angle θ_e.

The back EMFs in the phases are given by:

$$\begin{cases} \varepsilon_a = \frac{d}{dt}(\phi_f \cos\theta_e) \\ \varepsilon_b = \frac{d}{dt}\left(\phi_f (\cos\theta_e - \frac{2\pi}{3})\right) \\ \varepsilon_c = \frac{d}{dt}\left(\phi_f \cos(\theta_e + \frac{2\pi}{3})\right) \end{cases} \quad (2)$$

Figure 1 shows the electrical diagram of the healthy motor model, where the induced voltages ε_a, ε_b and ε_c in each phase are associated with the stator resistances and inductances, along with the phase currents i_a, i_b, and i_c under normal operating conditions.

B. Mathematical Model in Faulty State (ISF)

In Figure 2, when an ISF (Inter-Turn Short Circuit) fault occurs, a short circuit is introduced in the stator windings of phase C, which alters the system's behavior. The system then becomes unbalanced. Considering this short circuit, the system can be represented by a modified matrix equation.

Assuming that phase C is affected by the short circuit, the voltage relationship in the phases becomes:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \\ 0 \end{bmatrix} = \begin{bmatrix} v_0 \\ v_0 \\ v_0 \\ 0 \end{bmatrix} + \begin{bmatrix} R & 0 & 0 & -\sigma R \\ 0 & R & 0 & 0 \\ 0 & 0 & R & 0 \\ \sigma R & 0 & 0 & -\sigma R - R_{fc} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_{fc} \end{bmatrix} + \begin{bmatrix} L & M & M & -\sigma L \\ M & L & M & -\sigma M \\ M & M & L & -\sigma M \\ \sigma L & \sigma M & \sigma M & -\sigma^2 L \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_{fc} \end{bmatrix} + \begin{bmatrix} \varepsilon_a \\ \varepsilon_b \\ \varepsilon_c \\ \sigma\varepsilon_{fc} \end{bmatrix} \quad (3)$$

When the ISF fault develops, the short-circuit turn ratio σ influences the dynamics of the current i_{fc}, which is related to the variation of the magnetic flux ϕ and the angular speed ω_e. Considering that σ is a small variable and the back electromotive force (EMF) is much larger than the voltage drops, the expression for i_{fc} can be simplified to:

$$i_{fc} = -\frac{\sigma}{R_{fc}} \phi_f \omega_e \sin\theta_e \quad (4)$$

This shows that increasing μ or decreasing R_{fc} causes an increase in the amplitude of i_{fc}, and that as $\omega_e$increases, i_{fc} also increases.

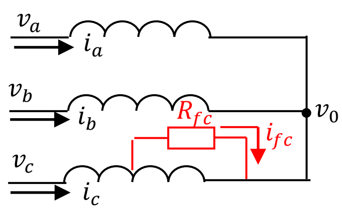


Fig.2. Insulation Fault (ISF) in Phase C

C. Zero-Sequence Voltage Detection

The zero-sequence voltage signal (v_0) in a Permanent Magnet Synchronous Motor (PMSM) with star-connected stator windings can be measured between the neutral point of a resistance network and the stator windings, as shown in Figure 2. The zero-sequence voltage, v_{0m}, is defined by an equation that includes terms related to resistance (R_i), inductance (L), mutual inductance (M), and the rate of change of the back electromotive force ($\varepsilon_a, \varepsilon_b, \varepsilon_c$) in the stator windings [2].

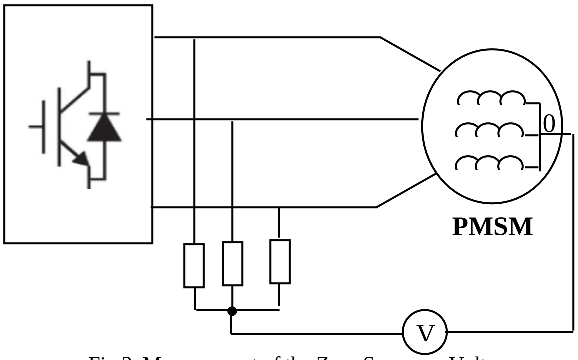


Fig.3. Measurement of the Zero-Sequence Voltage

It is noteworthy that the zero-sequence current could be measured if delta-connected stator windings are used in the PMSM [9].

In the case of a PMSM without an insulation fault (HS), where σ and i_{fc} are both zero, the zero-sequence voltage is solely determined by the variations in the sum of the stator winding voltages ($\varepsilon_a, \varepsilon_b, \varepsilon_c$).

$$v_{0m} = -\frac{1}{3}\frac{d(\varepsilon_a+\varepsilon_b+\varepsilon_c)}{dt} \qquad (5)$$

According to [12], when an Insulation Fault (ISF) occurs in the PMSM, additional harmonic components are introduced into v_{0m}, mainly the fundamental components as well as the third, fifth, and seventh harmonics.

The fundamental component of v_{0m} is typically used for insulation fault detection, and it is directly influenced by the insulation fault current (i_{fc}). An expression for the zero-sequence voltage under the ISF condition (v_{0mfon}) shows that it is related to the fundamental component of v_{0m} [3], v_{0m1}, which depends on both the resistance parameters and the rate of change of the insulation current (i_{fc}).

$$v_{0m1}=v_{0mfon} = \frac{1}{3}\sigma R i_{fc1} + \frac{1}{3}\sigma(L+2M)\frac{di_{fc1}}{dt} \qquad (6)$$

Where u_{0mfon} is the zero-sequence voltage under the ISF (Interference or Stator Fault) condition, and v_{0m1} is the fundamental component of v_{0mfon}.

In this study, the analysis of the mathematical models of the Permanent Magnet Synchronous Machine (PMSM) in two states healthy (HS) and inter-turn short-circuit fault (ISF) highlights significant differences as shown in equations (5) and (6). Specifically, the zero-sequence voltage signal in the ISF state contains new fundamental components that are absent in the healthy state. This suggests that the fault induces changes in the voltage signal, and these variations can be used to detect the presence of an inter-turn short-circuit fault.

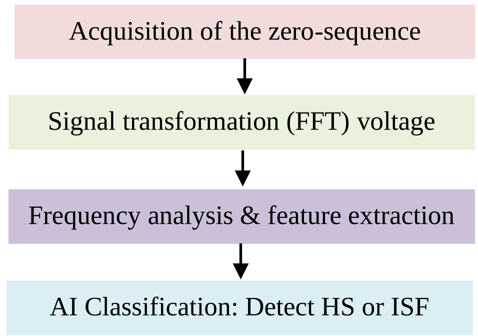


Fig.4. Algorithm for ISF Detection in PMSM

III. Method for Fault Detection

In this study, I developed a method for fault detection in PMSM machines. As shown in Figure 4, the process includes several key steps, from signal acquisition to classification of the states using Artificial Intelligence (AI).

A. Discrete Fourier Transform (FFT)

Dans le cadre de la détection de défauts ISF, la FFT permet une détection rapide des fréquences dominantes, telles que la fréquence fondamentale et ses harmoniques. Cependant, elle présente certaines limites. En raison de l'intégration globale du signal, la FFT peut générer des artefacts qui faussent l'interprétation de l'amplitude, la rendant moins réaliste. De plus, la FFT ne permet pas de localiser précisément les variations temporelles des fréquences, ce qui limite sa capacité à analyser des défauts complexes. Bien que la FFT soit efficace pour détecter les composants de fréquence généraux, elle a du mal à identifier précisément le moment des défauts transitoires ou localisés. Par conséquent, cette méthode est plus adaptée à la détection de problèmes en régime permanent, mais moins efficace pour détecter des défauts dynamiques et évolutifs.

The extracted features, such as fundamental amplitude and harmonic amplitudes, are used to detect faults. These features are intentionally perturbed with noise to simulate data variability, which helps test the robustness of fault detection under real-world conditions.

B. Intelligent Diagnosis

Artificial Intelligence (AI) [8] enables machines to simulate human capabilities such as learning and decision-making. In fault detection, especially for electric vehicles, AI automates the analysis of complex data from sensors and embedded systems, providing faster and more accurate solutions than traditional methods. Using supervised learning algorithms, it allows for signal classification, rapid anomaly detection, and proactive failure prediction, which is crucial for ensuring the long-term reliability and performance of electric vehicles [9].

In the context of ISF fault detection, Artificial Intelligence (AI) is used to improve the accuracy and automation of the classification process. I used a dataset of 2000 samples, evenly distributed between the healthy state (1000 samples) and the ISF fault state (1000 samples). These samples were divided into 1602 samples for training (about 80% of the data) and 400 samples for testing (about 20% of the data). This separation allows testing the robustness and generalization ability of the model on data it has not yet seen.

The features extracted from the signals, such as the fundamental amplitude and harmonic amplitudes, are perturbed by noise to simulate data variability. These features serve as input vectors for different supervised learning models. I used several AI algorithms for classification : Support Vector Machine (SVM), Decision Tree, and k-Nearest Neighbors (KNN). These models are capable of classifying the samples based on their membership in the healthy or defective (ISF) state.

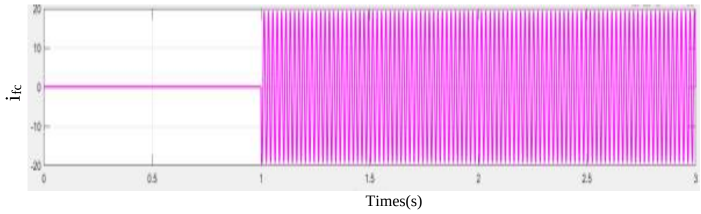
The training of these models is done on the 1602 samples, and their performance is then evaluated on the remaining 400 samples, allowing the efficiency and accuracy of each algorithm to be measured. The use of AI enables automatic fault detection by providing more precise analysis and reducing human errors. Moreover, these models, being capable of processing perturbed signals and handling complex variations, offer the robustness essential for reliable ISF fault detection in Permanent Magnet Synchronous Machines.

IV. Simulation Validation

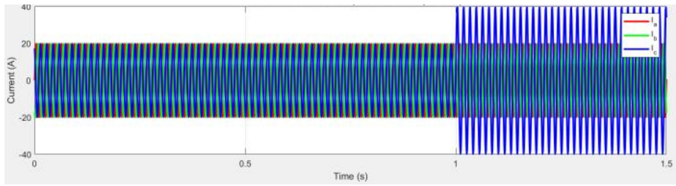
To test the proposed ITF diagnosis method, simulation validation is performed using MATLAB code.

In Figure 5, Figure 5(a) shows that the amplitude of i_{fc} remains constant at 0 during the HS phase of the PMSM. When the ISF occurs in the PMSM, i_{fc} takes the form of a periodic sine wave. In Figure 5(b), under normal operation, the currents in a three-phase motor are balanced and sinusoidal. During a short circuit in one phase (phase C), the current in that phase increases significantly, while the currents in phases A and B increase slightly to compensate. At t = 1 s, a short circuit in phase C causes a sharp increase in the current in that phase and a slight rise in the currents of phases A and B. These variations allow for the rapid and accurate detection of inter-turn short-circuit faults (ISF) in Permanent Magnet Synchronous Machines (PMSM).

In Figure 6, the analysis of amplitudes at 50 Hz (fundamental) and 100 Hz (second-order harmonic) reveals notable differences using the FFT method. At 50 Hz, the FFT method gives a high amplitude, which is an artifact resulting from the global integration of the magnitude over the entire duration of the signal. Regarding the amplitude at 100 Hz, it is lower. This shows that the second-order harmonic at 100 Hz is present, but its influence on the signal is relatively minor, without significant harmonic distortion. Thus, the fault in the system generates a fault current with a dominant component at 50 Hz, which is the fundamental frequency, while the second-order harmonic at 100 Hz is detectable but with negligible amplitude. The FFT proves useful for identifying the frequency components of the fault current, but it can overestimate the amplitude of the fundamental frequency, leading to potential misinterpretations.



(a)



(b)

Fig.5. Fault simulation results for Phase C. (a) Fault current i_{fc}. (b) Stator current.

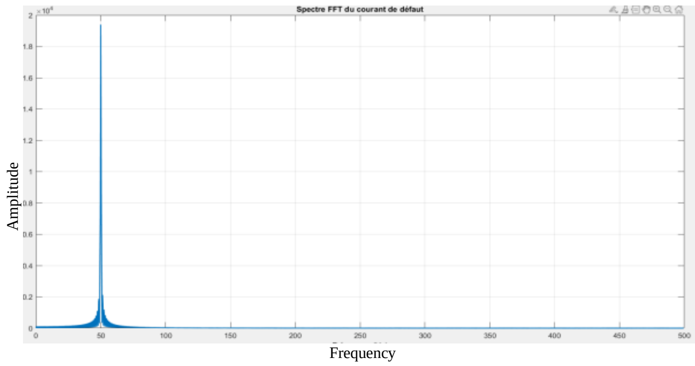
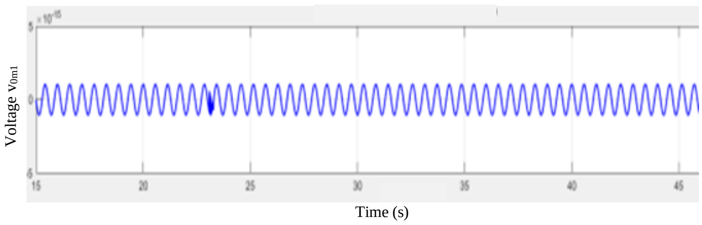
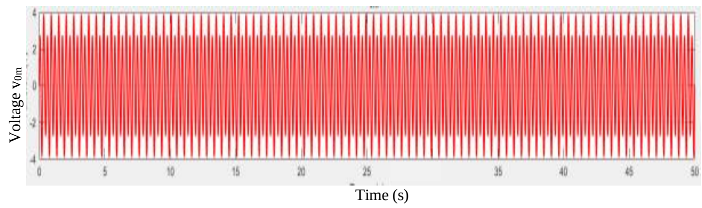


Fig.6. FFT Spectrum of Fault Current



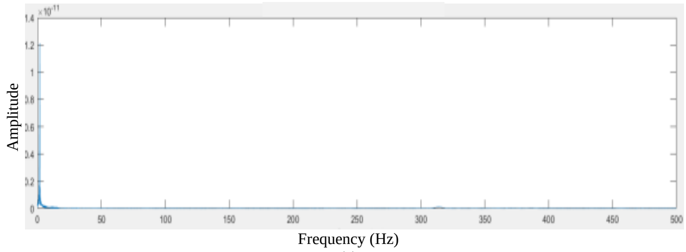
(a)



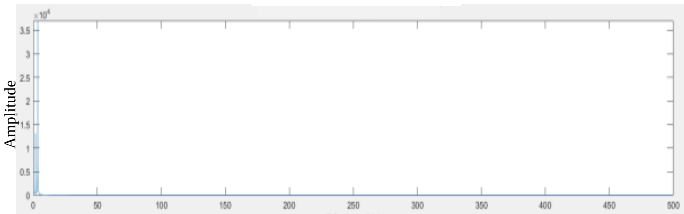
(b)

Fig.7. Simulation of v_{0m} Signal. (a) Healthy State; (b) ISF *Fault*

In Figure 7(a), the zero-sequence voltage v_{0m} under normal conditions shows values very close to zero, indicating the absence of faults or disturbances during normal operation. In contrast, in Figure 7(b), the zero-sequence voltage v_{0m1} under ISF fault (fundamental component) exhibits significant variations. The measured values at 5 seconds are 0.7796 V, at 10 seconds -0.0817 V, and at 15 seconds -0.7796 V, illustrating the notable fluctuations caused by the fault and confirming its impact on the machine.



(a)



Frequency (Hz)

(b)

Fig.8. Frequency Spectrum v_{0m}. (a) Healthy state, (b) ISF fault

The analysis of the fundamental frequency and amplitude under normal conditions and with an ISF fault reveals notable differences. In Figure 8(a), under normal conditions, the fundamental frequency is relatively low, with an extremely low amplitude, indicating normal operation without any faults. In contrast, in Figure 8(b), under the ISF fault condition, the fundamental frequency increases, and the amplitude reaches a very high value, suggesting a significant disturbance caused by the fault. The analysis of the harmonics and their amplitudes further shows that fault detection is much easier under the ISF condition, particularly for harmonic 3, which has an amplitude much higher than the values observed under normal conditions. In comparison, the harmonics under normal conditions are too weak to be easily detected. Thus, harmonic 3 under the ISF fault is the most detectable, as it has the highest amplitude among all harmonics, making it much easier to distinguish from noise or the healthy state.

Table I Algorithm Comparison

Model	***Accuracy***	***Precision***	***Recall***	***F1-score***
SVM	100%	100%	100%	100%
KNN	100%	100%	100%	100%
Decision Tree	99.5%	99.5%	99.5%	0.99485

Table I presents the performance of the three classification models (SVM, KNN, and Decision Tree) in terms of accuracy, precision, recall, and F1-score. It is interesting to note that the SVM and KNN models achieved exceptional performance, with 100% accuracy, precision, recall, and F1-score. This means they perfectly classified all samples into the correct categories, whether for the healthy state of the ISF defect. These results demonstrate their high efficiency in ideal conditions, where the data is clean, well-labeled, and sufficiently representative of both classes.

However, such performance is often achieved on well-prepared and balanced data. As shown by the analysis of the results, SVM and KNN are highly sensitive to the quality of the input data. Indeed, if the data is noisy, poorly labeled, or contains anomalies, these models risk losing precision, as they rely directly on the relationships between data points to determine classification boundaries (SVM) or neighbors (KNN).

The Decision Tree model, on the other hand, shows a slight difference with an accuracy of 99.5%, but its F1-score remains very close to the other models, at 0.99485. This indicates that even though the Decision Tree didn't reach the perfection of the other models in terms of accuracy, it remains highly effective and capable of handling data robustly. Decision trees have the advantage of being less sensitive to noisy data and can be more easily interpreted, making them an attractive option when model interpretability is important. However, they can suffer from overfitting in the tree is too deep.

While SVM and KNN are extremely powerful for ideal data, the Decision Tree offers an excellent alternative, being slightly less accurate but still highly competitive in terms of F1-score. This is especially useful when there is a need to balance precision and recall, particularly in situations where the data may be imperfect. All three models are effective, but the choice of model will largely depend on the quality of the data and the priorities in terms of performance, model understanding, and tolerance to noise.

V. Conclusions

In this work, this paper presents an innovative and effective method for detecting inter-turn short circuit (ISF) faults in Permanent Magnet Synchronous Machines (PMSMs). The use of zero-sequence voltage signals and Fast Fourier Transform (FFT) analysis, combined with Artificial Intelligence techniques such as SVM, KNN, and decision trees, improves the accuracy and reliability of fault detection. The results show that the SVM and KNN models are particularly effective, achieving perfect precision and recall. This combined approach not only allows for faster and more precise detection but also optimizes the overall performance of PMSMs by reducing failure risks and promoting predictive maintenance. This work represents a significant advancement in the field of intelligent maintenance for electrical machines, with potential applications in industry.

Therefore, future research could extend the current fault detection method to other machines and fault types, integrating advanced AI techniques like deep learning. Real-time monitoring and predictive maintenance systems would further improve performance and reliability, making industrial operations more efficient and cost-effective.

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