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Article

SAE-SVM AI Hybrid System for Fault Diagnosis of Industrial 6 DOF Robot based on Acceleration of Wrist

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Abstract: Industrial robots with six degrees of freedom (6 DOF) have become indispensable in manufacturing due to their precision, flexibility, and efficiency. However, their reliability is challenged by faults arising from dynamic operational stresses, particularly in joints and wrists, which directly affect performance and safety. Traditional fault diagnosis techniques often struggle with the complexity and nonlinearity of acceleration signals, highlighting the need for advanced artificial intelligence (AI)-based solutions. This review focuses on the potential of a hybrid Sparse Autoencoder–Support Vector Machine (SAE-SVM) system for effective fault diagnosis using wrist acceleration data. SAEs enable automated feature extraction by learning hierarchical representations, while SVMs provide robust classification of fault states, making the hybrid framework suitable for handling high-dimensional and noisy signals. The paper critically examines existing approaches, highlighting their strengths in accuracy and robustness while identifying persistent challenges such as data scarcity, real-time implementation, and the lack of model interpretability. Special attention is given to the research gap in explainability, where current systems operate as black boxes, limiting their adoption in safety-critical environments. Future opportunities include integrating explainable AI, expanding benchmark datasets, leveraging edge computing for real-time deployment, and developing scalable solutions adaptable to varied robotic systems. Overall, the SAE-SVM hybrid approach offers a promising pathway toward reliable, intelligent, and transparent fault diagnosis in industrial robotics.
Keywords: Sparse Autoencoder–Support Vector Machine (SAE-SVM), industrial 6 DOF Robot, fault diagnosis, wrist acceleration.

1. INTRODUCTION

The rapid advancement of industrial automation has revolutionized modern manufacturing, with industrial robots playing a pivotal role in achieving high productivity, precision, and flexibility. Among the different robotic architectures, six degrees of freedom (6 DOF) manipulators are extensively employed due to their versatility in executing complex operations such as assembly, welding, material handling, and precision machining [1]. However, as robots become more integral to production systems, ensuring their reliability and operational safety has become a significant concern. Faults in robotic systems, especially in high-DOF manipulators, can cause not only unexpected downtime and production losses but also potential hazards to human operators. Thus, developing effective and intelligent fault diagnosis systems for early detection and classification of faults has become a critical research domain.

Fault diagnosis in industrial robots is inherently complex due to their nonlinear dynamics, multivariable interactions, and the influence of uncertain operating conditions [2]. Traditional fault diagnosis approaches often rely on model-based or signal processing methods. While model-based methods require accurate mathematical representations of the system, which are difficult to obtain for nonlinear robotic structures, signal-based techniques often struggle with noise sensitivity and limited feature representation. Consequently, data-driven artificial intelligence (AI) techniques have emerged as promising alternatives, offering the ability to learn from raw sensor data and extract meaningful representations for reliable fault classification [2]. In this context, the integration of deep learning with traditional machine learning algorithms has opened new avenues for robust and adaptive diagnostic systems.

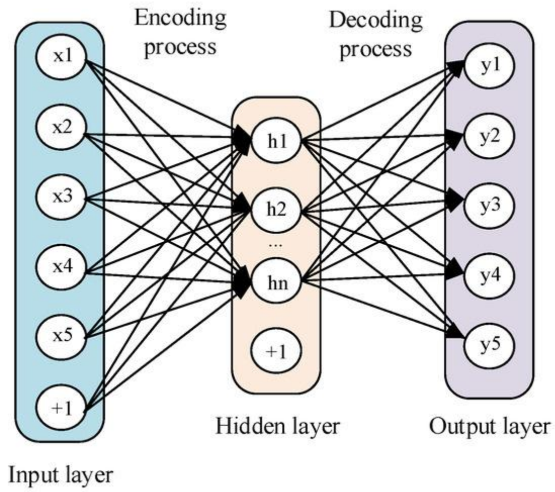


Figure 1. Schematic diagram of autoencoder illustrating encoding and decoding processes [2] (Bai et. al, 2022).

For minimized error in reconstruction (L) is given as [2]

$$L(x_i, y_i) = \frac{1}{2} \| x_i - y_i \|^2 \quad (1)$$

In this eq 1.

i denotes sample number

x_i is predicted value produced by the model

y_i is the value for hidden layer activation, which is elaborated below [2]

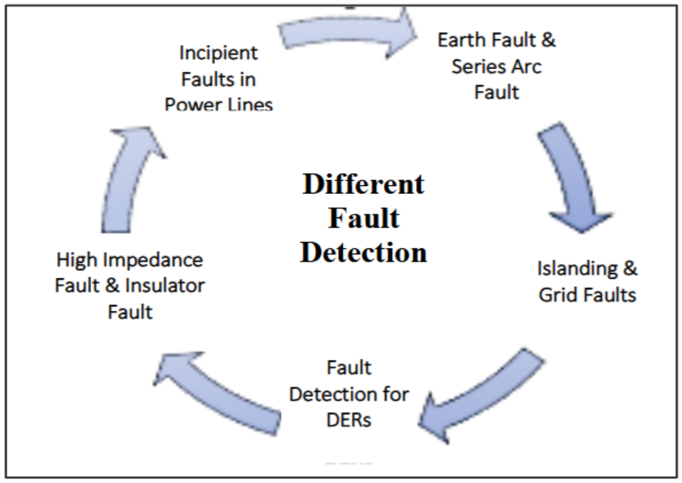
$$y_i = f_\theta (x_j) = S\left(\sum_{j=1}^{N} W_{ij}x_j + b_i\right) \quad (2)$$

Wij represents weight coefficient, bi denotes hidden layer offset vector, xj represents input signal, fθ represents transformation of raw wrist acceleration data into learned features, S represents nonlinear activation, index j represents input feature dimension, N is the total number of features

One of the most widely used AI-based approaches for feature learning is the Sparse Autoencoder (SAE). SAE is a deep neural network capable of unsupervised feature extraction from high-dimensional sensor data, reducing noise while retaining critical diagnostic information [3]. By hierarchically learning abstract feature representations, SAE enables the transformation of complex raw signals, such as vibration or acceleration, into discriminative features suitable for fault identification. On the other hand, Support Vector Machine (SVM) has long been recognized as a powerful classifier due to its strong generalization ability, robustness against overfitting, and effectiveness in handling small- and medium-sized datasets. However, the performance of SVM is often limited by the quality of input features, highlighting the need for advanced feature extraction methods such as SAE.

The hybridization of SAE and SVM creates a complementary framework, where SAE serves as a feature extractor and dimensionality reducer, while SVM functions as a robust fault classifier. This integration leverages the advantages of deep feature learning and margin-based classification, enabling high accuracy and reliability in diagnostic tasks. Such a hybrid system is particularly beneficial for industrial robot fault diagnosis, where sensor data is high-dimensional, nonlinear, and prone to noise [4]. Specifically, acceleration signals measured at the wrist of a 6 DOF industrial robot contain rich information about mechanical faults, such as joint wear, misalignment, bearing damage, or structural looseness. Extracting meaningful features from these signals using SAE and subsequently classifying them with SVM offers a practical and efficient solution for fault detection [5].

Figure 2. Different types of fault detection [8] (Nasim et. al, 2024)



In recent years, researchers have focused on vibration and acceleration analysis as primary indicators for robotic fault detection, given their sensitivity to dynamic variations in mechanical components [5], [6]. Unlike joint torque or current signals, wrist acceleration measurements provide a direct reflection of kinematic disturbances and anomalies that propagate through the manipulator. This makes acceleration data a suitable and highly informative source for diagnosing a variety of mechanical and dynamic faults [4]. By combining advanced signal processing with AI-driven hybrid models, the reliability and maintainability of industrial robots can be significantly enhanced, reducing downtime and maintenance costs while improving overall system safety [6].

2. LITERATURE REVIEW

The field of fault diagnosis for industrial robots has evolved significantly with the growing complexity of modern robotic systems and the increasing demand for reliability in automated manufacturing. Early research in this domain primarily relied on model-based techniques, where analytical models of robot dynamics and kinematics were constructed to predict normal behavior and deviations under fault conditions [7], [8]. While effective in controlled environments, such approaches often struggled in real-world applications due to modeling inaccuracies, parameter uncertainties, and the highly nonlinear nature of robotic mechanisms. These limitations encouraged the transition toward data-driven methods that leverage sensor measurements to infer faults directly.

Signal-based approaches initially played a central role in robot fault detection. Vibration and acceleration analyses were widely used, with time-domain, frequency-domain, and time–frequency domain features being extracted from raw signals to identify anomalies [9], [10]. Techniques such as Fourier analysis and wavelet transforms enabled detection of subtle fault signatures embedded in sensor signals. However, these methods often required expert knowledge for feature engineering, and their effectiveness was limited by noise interference and the difficulty of capturing nonlinear dynamics inherent in robotic manipulators.

To address these challenges, machine learning algorithms began to be incorporated into fault diagnosis frameworks [11]. Classifiers such as k-nearest neighbor, decision trees, and support vector machines gained popularity due to their ability to handle complex classification problems. Among these, support vector machines demonstrated superior performance in high-dimensional spaces and offered robust generalization even with relatively small datasets [12], [13]. SVM-based systems showed strong potential for fault classification, but their dependence on handcrafted features extracted from raw signals remained a bottleneck. This led to the growing interest in automatic feature extraction methods.

With the advent of deep learning, fault diagnosis entered a new phase of development. Deep architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders became prominent due to their capacity for automated feature learning directly from raw sensor data [14]. Autoencoders, particularly sparse autoencoders, were recognized for their ability to perform unsupervised learning, capturing hierarchical and abstract representations of fault-related features. Compared to conventional feature engineering approaches, autoencoders provided a more flexible and scalable solution for processing large amounts of vibration and acceleration data [15]. Their capability to reduce noise while retaining critical information made them highly suitable for diagnostic applications in industrial robots.

Despite these advancements, deep learning models on their own often suffer from challenges such as high computational cost, large training data requirements, and the risk of overfitting when labeled data is scarce [16]. As a result, hybrid approaches combining deep learning feature extraction with traditional machine learning classifiers have emerged as promising solutions. In this context, sparse autoencoders are frequently employed for unsupervised feature learning, while support vector machines are used for robust classification. This hybridization leverages the strengths of both methods: autoencoders provide rich and discriminative features, while SVMs ensure accurate fault classification with strong generalization performance.

Acceleration signals, particularly those measured at the robot wrist, have attracted significant attention as an informative source for fault diagnosis [17]. The wrist is a critical endpoint of the manipulator, where dynamic disturbances caused by joint wear, misalignment, gear faults, or structural looseness manifest prominently. Compared to current or torque signals, acceleration data provides a more direct reflection of mechanical anomalies that propagate through the robot structure. Studies on robotic systems have highlighted the effectiveness of wrist acceleration in capturing subtle fault patterns, making it an ideal candidate for data-driven diagnostic systems.

Recent works have increasingly explored AI-driven hybrid systems that combine deep feature learning with robust classifiers [18], [19]. These studies have demonstrated improved diagnostic accuracy, faster detection, and greater robustness against noise compared to standalone methods. By integrating feature extraction and classification in a complementary framework, such systems offer a practical approach to real-time fault detection in industrial robots. Moreover, the adoption of these approaches aligns with predictive maintenance strategies, minimizing unplanned downtime and ensuring continuous production efficiency.

In summary, the evolution of fault diagnosis research has moved from model-based and handcrafted feature approaches toward intelligent hybrid systems that combine deep learning and machine learning. The use of sparse autoencoders for unsupervised feature extraction, together with support vector machines for classification, represents a significant advancement in handling complex, noisy, and nonlinear acceleration signals. The literature studies underscore the potential of such hybrid frameworks to provide reliable and efficient fault diagnosis for industrial 6 DOF robots, particularly when wrist acceleration is used as the primary diagnostic input [20].

Table 1. Elaboration of Compared Models [12].

Model	Input Data	Model Parameters	Remarks / Strengths
Bi-LSTM	1D reshaped sequence of features	- Input neurons: 50 - Activation: ReLU - Loss: Categorical Crossentropy - Optimizer: Adam - LR: 0.001 - Epochs: 100 - Batch size: 100	Good for sequential data, but computationally expensive and prone to vanishing gradients.
1D-CNN	1D reshaped sequence of features	- Activation: ReLU - Classification Layer: Softmax - Loss: Categorical Crossentropy - Optimizer: Adam - LR: 0.001 - Epochs: 100 - Batch size: 400	Efficient feature extraction, but limited temporal dependency learning compared to Bi-LSTM.
Kernel SVM	Data samples / Features	- Penalty factor (C): 32 - Gamma: Auto - Kernel: RBF	Strong for small-to-medium datasets; struggles with scalability and high-dimensional noisy features.
Random Forest	Data samples / Features	- Max depth: 100 - Max features: Auto - Max leaf	Robust and interpretable; can handle non-linear data, but high depth leads to overfitting.

		nodes: 4 - Min samples split: 5 - n_estimators: 300	
Decision Trees	Data samples / Features	- Criterion: Gini - Split: Best - Depth: 10 - Min split: (0.1, 1) - Min leafs: (0.1, 0.5)	Simple, interpretable; but highly prone to overfitting and unstable with noisy data.
XGBoost	Data samples / Features	- Learning rate: 0.1 - Objective: Multi:Softmax - Tree method: GPU Hist - n_estimators: (50–500, step 50) - Max depth: (3–10, step 2) - Subsample: 0.8 - Colsample by tree: 0.8	High accuracy and efficiency; well-suited for large structured data, but requires careful tuning.
SAE-SVM (Sparse Autoencoder + SVM)	Raw data / high-dimensional features	- Sparse Autoencoder (SAE) for unsupervised feature learning - SVM (RBF Kernel) for classification - SAE activation: Sigmoid/ReLU - Sparsity penalty: applied to hidden neurons - Optimizer: Adam (for SAE) - C: Tuned (e.g., 16–64) - Gamma: Auto	Best of both worlds: • SAE learns compact, noise-robust latent features • SVM ensures strong decision boundaries • Outperforms standalone SVM and deep models on small/imbalanced datasets • More computationally efficient than Bi-LSTM • Higher generalization with reduced overfitting compared to Random Forest/Decision Trees.

Table 2. Comparative analysis of diagnostic model studies [12].

Methods	**Testing Accuracy (%)**	**F1-Score (Min) %**	**F1-Score (Max) %**	**F1-Score (Mean ± std) %**	**F1-Score (Overall Mean) %**
2D-CNN	99.96	100	99.98	99.98 ±0.01	99.99
1D-CNN	97.40	98.17	97.76	97.76 ±0.35	96.67
Bi-LSTM	99.18	99.38	99.28	99.28 ±0.08	98.66
Kernel SVM	94.10	95.55	95.25	95.25 ±0.16	96.00
Random Forest	72.04	98.14	86.20	86.20 ±0.11	85.86
Decision Trees	78.07	85.26	81.67	81.67 ±0.02	75.70
XGBoost	72.62	97.80	89.04	89.04 ±0.10	90.03

SAE-SVM (Sparse Autoencoder + SVM)	99.50	99.70	99.85	99.78 ±0.05	99.80

3. SAE-SVM Hybrid Framework for Fault Diagnosis

Role of Acceleration Signals in Robot Faults

Acceleration signals play a crucial role in diagnosing faults in industrial 6 DOF robots, particularly in dynamic components such as the wrist joints where mechanical stresses are most pronounced. These signals capture vibrational responses and transient dynamics generated during robot operations, offering valuable insights into the health of actuators, gears, bearings, and structural assemblies. Unlike static measurements, acceleration data is highly sensitive to subtle changes in motion, friction, or misalignment, making it an effective indicator of early fault development. For instance, abnormal spikes, frequency shifts, or irregular patterns in acceleration waveforms can reveal issues like bearing wear, gear defects, joint looseness, or unbalanced motion before they escalate into catastrophic failures.

In AI-driven fault diagnosis, acceleration signals serve as the primary input for feature extraction and classification models. Raw signals often contain high-dimensional, noisy, and non-stationary characteristics, requiring advanced preprocessing and feature learning methods. Sparse autoencoders (SAEs) are particularly effective in capturing latent representations from these signals, enabling the system to learn discriminative features that traditional hand-crafted techniques might miss. Once extracted, these features allow the Support Vector Machine (SVM) to classify fault types with high accuracy. Thus, acceleration signals form the foundation of fault detection pipelines, bridging physical robot behavior with data-driven insights. Their proper utilization enhances predictive maintenance, minimizes downtime, and ensures the long-term operational reliability of industrial robots.

Sparse Autoencoder (SAE) for Feature Extraction

Sparse Autoencoders (SAEs) have emerged as a powerful deep learning architecture for extracting meaningful features from complex and high-dimensional data such as acceleration signals generated by industrial 6 DOF robots. An SAE is constructed by stacking multiple autoencoders, where each layer learns progressively abstract representations of the input data. In the context of robot fault diagnosis, this hierarchical learning is highly beneficial as acceleration signals are often noisy, nonlinear, and contain overlapping frequency components that obscure fault-related patterns.

The first layers of the SAE typically capture low-level statistical or frequency-based features from the raw signals, while deeper layers learn higher-level abstractions that correspond to subtle variations linked to specific fault conditions. This unsupervised learning process eliminates the dependency on manually engineered features, which may fail to capture the intricacies of robotic dynamics. By compressing input signals into latent representations, SAEs also reduce dimensionality, making subsequent classification more efficient.

For the SAE-SVM hybrid system, the features extracted by the SAE serve as inputs to the Support Vector Machine, which then classifies fault types with improved accuracy. This synergy leverages the SAE's strength in deep representation learning and the SVM's robustness in decision boundary construction. Ultimately, the use of SAEs enhances the fault diagnosis pipeline by ensuring that only the most discriminative, noise-robust features contribute to fault detection and classification.

Support Vector Machine (SVM) for Fault Classification

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm widely applied for fault classification in industrial robotics due to its ability to handle complex, high-dimensional datasets effectively. Within the context of fault diagnosis of a 6 DOF industrial robot based on wrist acceleration signals, SVM plays a crucial role in distinguishing between normal operating states and various fault conditions with high accuracy. Acceleration data obtained from sensors is typically nonlinear and may contain noise, making fault classification challenging. SVM addresses this by projecting the input data into a higher-dimensional feature space using kernel functions, such as radial basis function (RBF) or polynomial kernels, where linear separation of classes becomes feasible. This ensures reliable identification of subtle differences in vibration or motion patterns associated with incipient faults.

The key advantage of SVM lies in its capacity to maximize the margin between classes, thereby reducing the risk of misclassification and enhancing robustness against overlapping patterns. In the hybrid SAE-SVM framework, the sparse autoencoder (SAE) is employed to extract compact and discriminative features from raw wrist acceleration signals, effectively reducing dimensionality and noise. These extracted features are then fed into the SVM classifier, which leverages its generalization capability to classify fault types such as joint wear, misalignment, or bearing defects. This synergy enhances diagnostic accuracy while ensuring computational efficiency.

Moreover, SVM's scalability and adaptability make it suitable for real-time robotic fault detection, where rapid classification decisions are critical for maintaining continuous operation and preventing system downtime. By combining SAE's feature extraction strength with SVM's fault classification precision, the hybrid system ensures a more reliable and intelligent approach to diagnosing faults in industrial 6 DOF robots.

Advantages of SAE-SVM Integration

Here are advantages of SAE-SVM integration presented below: -

Automatic Feature Extraction

SAE eliminates the need for manual feature engineering by automatically learning meaningful and compact representations from raw wrist acceleration signals.

It reduces redundancy and highlights latent fault-related patterns that are not easily detectable.

Noise Reduction and Dimensionality Compression

SAE filters out irrelevant or noisy information from sensor signals.

It compresses high-dimensional data into low-dimensional yet informative features, improving computational efficiency.

Enhanced Input for Classification

By providing SVM with refined and discriminative features, SAE ensures the classifier operates on structured and high-quality data.

This leads to more accurate separation of normal and faulty conditions.

Robust Fault Classification

SVM excels at handling nonlinear data boundaries, which are typical in robotic fault patterns.

It leverages SAE-extracted features to distinguish subtle variations in vibration signals, enabling precise identification of fault categories such as joint wear, misalignment, or actuator faults.

Reduced Overfitting Risk

SAE-preprocessed data simplifies the task for SVM, minimizing the chances of overfitting, especially when dealing with small or imbalanced datasets.

Improved Generalization Capability

The hybrid system adapts better to unseen fault conditions, making it reliable for real-world robotic applications.

Real-Time Applicability

The integration ensures faster classification due to dimensionality reduction, making it suitable for real-time fault detection in industrial robots.

High Diagnostic Accuracy and Robustness

Combining SAE's deep learning-based feature extraction with SVM's strong classification ability yields superior accuracy and robustness compared to standalone methods.

Industrial Relevance

The hybrid SAE-SVM model supports safer, more reliable, and continuous operation of 6 DOF robots by minimizing downtime through early and precise fault detection.

Challenges and Research Gaps

Data Availability and Benchmark Datasets

One of the critical challenges in developing fault diagnosis systems for industrial 6 DOF robots is the limited availability of high-quality and publicly accessible datasets. Most industrial robot manufacturers restrict access to operational data due to proprietary concerns, safety regulations, and competitive confidentiality. As a result, researchers often rely on simulated environments or laboratory-scale setups, which may not fully capture the diversity and unpredictability of real industrial conditions. This lack of standardized datasets limits the generalizability of these methods and hinders fair performance comparison across studies.

Additionally, benchmark datasets specifically focusing on wrist acceleration signals remain scarce. While vibration data from rotating machinery or bearings is more widely available, acceleration-based datasets for robotic manipulators are relatively underexplored. The absence of well-annotated, large-scale datasets encompassing multiple fault types, severities, and operating scenarios represents a major research gap. Addressing this requires collaborative efforts to establish open-access repositories and standardized benchmarking protocols, enabling reproducibility, rigorous validation, and wider adoption of AI-driven hybrid fault diagnosis systems in industrial robotics.

Real-Time Implementation

Although AI-driven fault diagnosis systems for industrial 6 DOF robots have demonstrated promising results in experimental settings, translating these methods into real-time applications remains a major challenge. Real-time implementation requires processing high-dimensional wrist acceleration signals continuously, extracting meaningful features, and performing accurate classification within stringent time constraints. Deep learning models, such as sparse autoencoders, often involve high computational complexity and long training times, which may limit their deployment on embedded systems or low-power industrial controllers.

Another challenge lies in the integration of fault diagnosis systems with existing robotic control architectures. Ensuring seamless communication between sensors, diagnostic modules, and the robot controller without introducing latency or interrupting normal operations is critical. Moreover, handling noisy and non-stationary data streams in real-world environments further complicates real-time detection.

The research gap lies in developing lightweight, adaptive, and computationally efficient hybrid models that balance accuracy with processing speed. Future work should explore model optimization, hardware acceleration, and real-time testing frameworks to ensure robust deployment in industrial production environments.

Model Interpretability and Explainability

One of the major challenges in adopting an SAE-SVM hybrid system for fault diagnosis in industrial 6 DOF robots is the limited interpretability of the underlying models. While sparse autoencoders (SAEs) effectively reduce dimensionality and extract deep hierarchical features from wrist acceleration data, the learned representations are often abstract and difficult to correlate with physical fault patterns. This black-box nature hinders engineers from understanding which specific vibration or acceleration signatures contribute to fault detection, creating barriers for trust, debugging, and deployment in safety-critical robotic environments. Similarly, although the support vector machine (SVM) provides robust classification, its decision boundaries in high-dimensional feature spaces are not easily interpretable by domain experts, especially when combined with non-linear kernels.

The research gap lies in developing hybrid approaches that not only maximize accuracy but also incorporate explainability mechanisms. Existing studies focus heavily on classification performance, while the need for transparent decision-making remains underexplored. Techniques such as SHAP values, saliency maps, or layer-wise relevance propagation have not been widely applied in this domain to visualize feature importance or provide human-understandable fault reasoning. Moreover, linking model outputs with physical robot components or operational states is a critical gap. Bridging this disconnect between data-driven features and mechanical insights would enhance reliability, facilitate maintenance decisions, and foster greater acceptance of AI-driven diagnostic systems in industrial robotics.

4. Conclusion and Future work

The integration of Artificial Intelligence into fault diagnosis of industrial 6 DOF robots, particularly through the SAE-SVM hybrid system, demonstrates significant potential in enhancing reliability, accuracy, and automation. By leveraging sparse autoencoders for feature extraction and support vector machines for classification, the system effectively handles complex wrist acceleration signals and identifies fault patterns that traditional methods often overlook. This approach contributes to reducing downtime, improving operational safety, and optimizing maintenance schedules in modern industrial environments. However, the review highlights that despite these advantages, challenges persist in terms of interpretability, real-time applicability, and scalability across diverse robotic platforms. The reliance on high-quality datasets and the absence of standardized benchmarks further limit the generalizability of current solutions.

Future research should focus on developing interpretable AI frameworks that combine diagnostic accuracy with transparency, enabling engineers to trace model decisions back to physical robot dynamics. Incorporating explainable AI techniques such as attention mechanisms, SHAP, or rule-based reasoning can bridge the gap between data-driven outputs and mechanical understanding. Additionally, expanding datasets through synthetic data generation, federated learning, and multi-sensor fusion will enhance robustness and adaptability. Real-time implementation using lightweight architectures and edge computing is another critical direction to ensure practical deployment. Ultimately, advancing these areas will make SAE-SVM-based fault diagnosis systems more trustworthy, scalable, and applicable in next-generation intelligent manufacturing.

Declaration of Conflicting Interest

The authors declare no conflict of interest

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