New Developments in Intelligent Diagnostic Methods for Hydraulic Piston Pumps Faults

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Abstract: *As industries increasingly embrace digital transformation, the need for effective fault diagnosis in hydraulic piston pumps (HPPs) has grown in importance. HPPs are critical components across various sectors, including aerospace and manufacturing, where their reliability directly impacts system performance. The reliability of these pumps affects not only operational productivity but also the safety of the entire system. As a result, the development of diagnostic methods for identifying and addressing faults in HPPs has become a crucial area of research. This article explores the latest advancements in intelligent diagnostic techniques for fault detection in HPPs, highlighting their effectiveness and limitations. By providing insights into these advancements, this review aims to contribute to safer and more reliable hydraulic systems in modern operational environments.*

Keywords: *Diagnostic methods, hydraulic piston pump, intelligent maintenance, intelligent fault detection and diagnosis*

1. Introduction

Hydraulic systems are essential to industrial production and manufacturing, and mathematical modeling and simulation of these systems provide valuable insights into their performance [1-4]. At the heart of these systems, the hydraulic pump plays a critical role by converting mechanical energy into hydraulic energy to deliver pressurized oil throughout the system [5-7].

Hydraulic piston pumps (HPPs) are crucial components in various industrial applications, including construction, manufacturing, and automotive systems, where they are utilized to convert mechanical energy into hydraulic energy [8]. The fundamental principle of operation for HPPs lies in the movement of pistons within cylinders, which creates pressure through the displacement of hydraulic fluid. This mechanism allows for efficient power transmission over considerable distances, making HPPs an essential element in hydraulic systems.

HPPs consist of numerous intricate components, including valves, drive mechanisms, cylinders and pistons, seals and gaskets, fluid ports, and a supporting structure. Recent developments in materials technology, along with innovations in precision machining techniques, contemporary design processes, and simulation methods, have greatly improved the performance, durability, and resistance of hydraulic piston pumps to wear and corrosion. On the other hand, these pumps operate under challenging conditions characterized by high temperatures, significant pressure levels, and fluctuating loads, which can put considerable stress on their internal components. These extreme operational environments often lead to typical failures that are difficult to diagnose quickly, as pinpointing the exact cause and location of faults can be complex. Common issues include wear and tear, cavitation, leakage, and contamination of the hydraulic fluid. These faults can lead to significant downtime, reduced performance, and increased maintenance costs.

As the industry advances, HPPs are being designed with greater precision and increasingly intricate structures, underscoring the need for efficient, accurate, and intelligent fault diagnosis technologies. However, challenges remain in fault identification due to environmental influences, multiple interfering factors, and the inherent complexity of various operational tasks. Traditional diagnostic methods often relied on visual inspections and routine maintenance checks; however, these approaches can be time-consuming and may not detect early signs of failure. Recent advancements in diagnostic technologies have introduced new methodologies and innovations that enhance the ability to detect and diagnose faults in HPPs.

Over the past few decades, a multitude of studies have focused on reviewing and analyzing the methodologies employed in the recognition of faults within hydraulic piston pumps (HPPs). These studies have made significant strides in categorizing fault diagnosis approaches according to the various types of signals utilized, including vibration, acoustic, thermal, and pressure signals. Despite this progress, there is a notable deficiency in detailed classifications and comparative analyses that critically evaluate the efficacy and applicability of these diagnostic methods across different contexts, as well as delineate the strengths and weaknesses of current diagnostic techniques. In light of these considerations, this review aims to provide a comprehensive overview of the latest developments in intelligent diagnostic techniques for HPPs, examining existing methodologies, evaluating their effectiveness in various operational contexts, and discussing future directions for research and implementation.

2. Research methodology

Hydraulic piston pumps (HPPs) can be categorized based on their structural designs into two primary types: radial piston pumps and axial piston pumps [8,9]. Within these broad classifications, axial piston pumps are of two types namely swash plate type and bent axis type (fig. 1). This classification highlights the variations in design and function that influence the performance and application of HPPs across various industrial contexts. A survey was conducted on diagnostic methods for hydraulic piston pump faults in the scientific literature from 2011 to 2024.

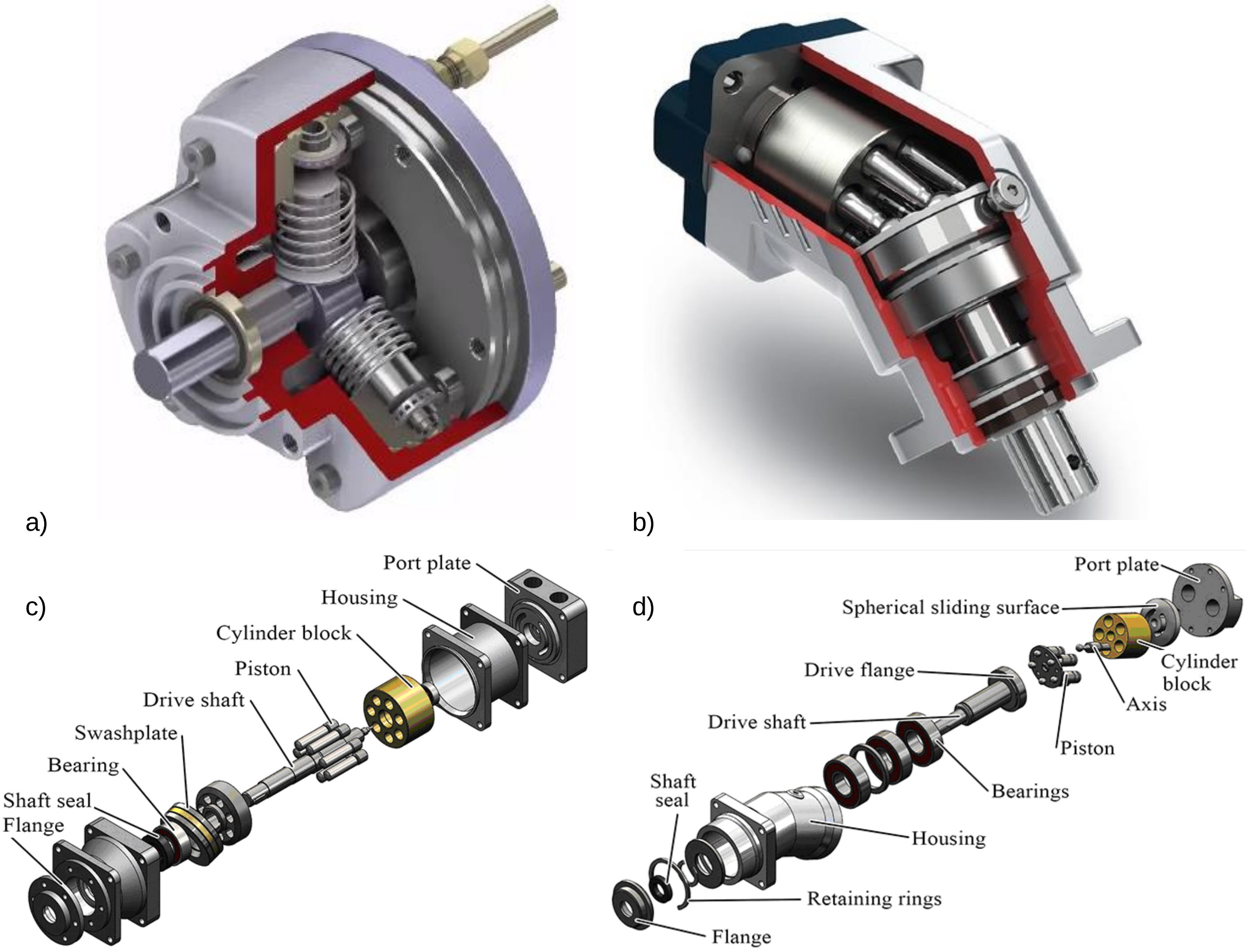


Fig. 1. a) Radial piston pump, b) axial piston pump, c) axial piston pump - swash plate type, d) axial piston pump – bent axis type.

2.1 The fault diagnosis methods of hydraulic piston pumps

Fault diagnosis methods for hydraulic piston pump faults focus on identifying, classifying, and evaluating various types of pump malfunctions by analyzing the system's signals and operating data. Currently, fault identification methods can be divided into three main categories: a) traditional intelligent fault diagnosis methods; b) modern intelligent fault diagnosis methods; and c) combined intelligent fault diagnosis methods [9].

a) Traditional intelligent fault diagnosis method rely on well-established techniques that often use physical models, statistical analysis, and signal processing to identify faults [9,10-13]. Key approaches include: vibration analysis, acoustic emission, pressure signal analysis, thermal analysis. Traditional methods often use threshold-based decision-making, where measurements are compared to predefined limits. Deviations beyond these thresholds trigger alerts for potential faults. While effective, these methods may have limitations in detecting complex faults, particularly when multiple faults are present [14-17].

b) Modern intelligent fault diagnosis methods harness advanced computing power and data analytics, using machine learning, deep learning, and artificial intelligence (AI) to enhance fault detection and diagnosis accuracy [18-20]. Some key techniques include: machine learning algorithms, deep learning techniques, data-driven models, signal feature extraction and processing. Modern methods can recognize intricate fault patterns and adapt over time as new data becomes available. However, they require large datasets and computational resources, and implementation can be complex [21-24].

c) Combined intelligent fault diagnosis methods integrate traditional and modern techniques to improve fault diagnosis accuracy and robustness. By combining the strengths of physical models with data-driven approaches, these methods offer a balanced solution [25-29]. Some key techniques include: model-based and data-driven fusion, multi-sensor data fusion, ensemble learning, adaptive thresholding. Combined methods are particularly valuable in situations where high fault-diagnosis accuracy is required but data availability or computational resources are limited. They offer a comprehensive approach by leveraging both theoretical knowledge and real-world data, making them suitable for complex fault scenarios in hydraulic piston pumps [30-34].

2.2 Advanced techniques for intelligent fault detection and diagnosis of hydraulic piston pumps

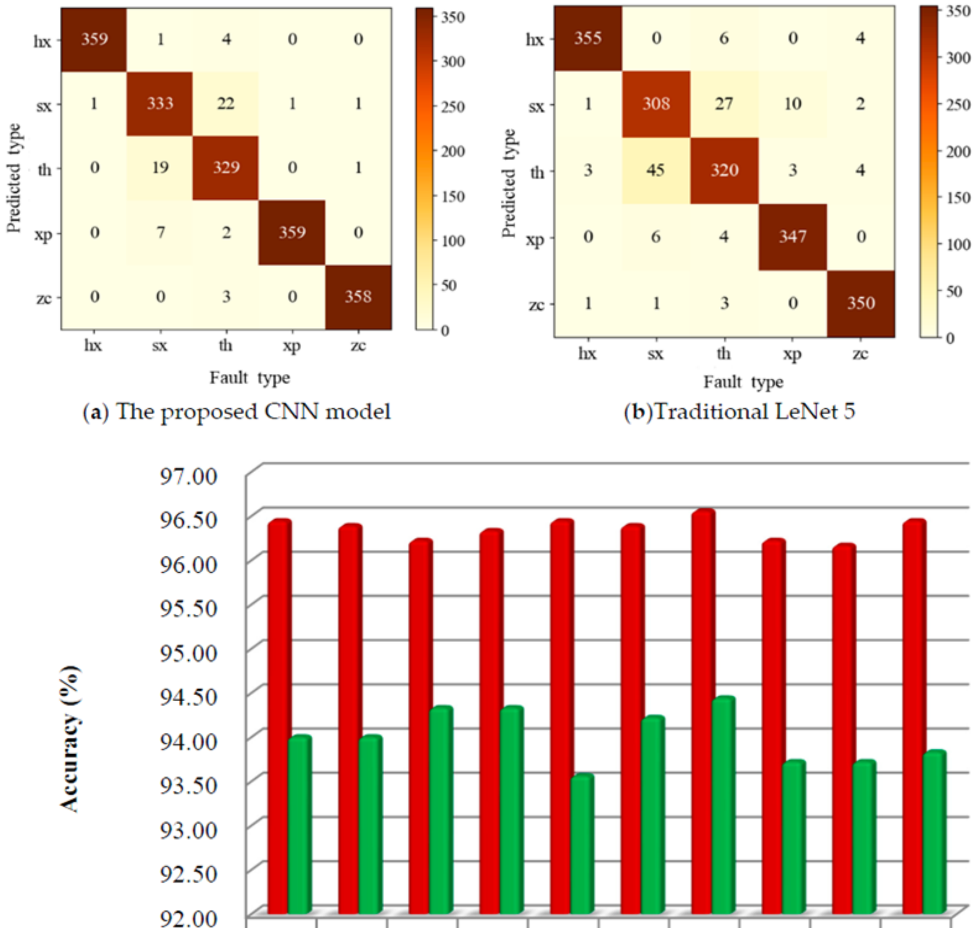
Intelligent fault detection and diagnosis methods, leveraging deep learning and machine learning algorithms, enable the automatic identification of faults in hydraulic piston pumps through the analysis of complex signal data. With capabilities like adaptive learning, feature extraction, and model optimization, these methods enhance diagnostic accuracy and reliability, even in challenging conditions such as small sample sizes and noisy environments.

The fault diagnosis method utilizing Siamese neural networks proposed by Gao et al. [20] aimed to overcome the challenges of low accuracy and underfitting often encountered in traditional deep neural networks, particularly when applied to small sample sizes. The Siamese subnetwork was constructed with convolutional and pooling layers, automatically extracting meaningful low-dimensional features from the raw vibration signals. By using Euclidean distance to quantify the similarity between input sample pairs, this method effectively augmented the training dataset, facilitating the training of the SNN model to differentiate accurately among health states, and improving diagnostic accuracy even in scenarios with limited data.

Wang et al. [19] introduced a fault detection method based on Deep Belief Networks (DBNs) to enhance reliability in axial piston pumps, specifically targeting the complex issue of identifying multiple, often ambiguous fault types. This approach begins by processing raw signal data from the time, frequency, and time-frequency domains, enabling the extraction of robust features for both training and testing samples. These samples are then classified using DBNs, which are constructed from stacked Restricted Boltzmann Machines (RBMs) designed to automatically learn intricate fault features. By using this deep learning structure, the method reduces reliance on manually engineered features, allowing for more accurate fault pattern recognition in challenging diagnostic conditions. The classification results demonstrated a high accuracy rate of 97.40%, which significantly outperformed conventional models such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN). This approach proved effective in cases where the underlying fault mechanisms were poorly understood, showcasing its potential as a robust tool for complex fault detection in hydraulic systems.

Xiao et al. [24] proposed an innovative hybrid approach, Multipoint Optimal Minimum Entropy Deconvolution Adjusted - Teager Energy Operator (MOMEDA-TEO) method, specifically developed to isolate fault impulses from axial piston pump bearings, where periodic vibrations often mask fault signals. This method enhances periodic impulses through an optimized MOMEDA framework, enabling fault frequency extraction via Teager Energy Operator (TEO) demodulation. On the other hand, MOMEDA has been adopted for its ability to directly yield an optimal filter solution without requiring iterative procedures. Unlike Maximum Correlated Kurtosis Deconvolution (MCKD), MOMEDA employs a maximum D-norm rule, allowing it to analyze vibration signals with a non-integer fault period, thus eliminating the need for resampling. Experimental validation indicated that this hybrid approach significantly improved both accuracy and processing speed compared to traditional techniques, demonstrating its effectiveness in extracting fault impulses and advancing fault diagnostics in hydraulic systems.

Tang et al. [21] proposed a novel integrated intelligent method for fault diagnosis of hydraulic axial piston pumps. The approach begins with the transformation of vibration signals into time-frequency images using continuous wavelet transform (CWT), which enables the effective extraction of key features. These transformed images serve as the input for a newly designed deep Convolutional Neural Network (CNN) model aimed at accurately classifying fault types. To better understand the potential learning dynamics within the various layers of the CNN, t-distributed stochastic neighbor embedding (t-SNE) was applied to visualize the reduced features, offering insights into the relationships between fault patterns captured by the network. Experimental testing validated the proposed method's effectiveness and stability, showing high accuracy in identifying various fault types in hydraulic axial piston pumps.



	1	2	3	4	5	6	7	8	9	10
Proposed CNN	96.44	96.39	96.22	96.33	96.44	96.39	96.56	96.22	96.17	96.44
Traditional LeNet 5	94.00	94.00	94.33	94.33	93.56	94.22	94.44	93.72	93.72	93.83

Fig. 2. The confusion matrix of the testing samples on CNN in the seventh trial: a) The proposed CNN model, b) Traditional LeNet 5. c) The comparison between the proposed CNN and traditional LeNet 5. Reprinted from ref. [21] with permission of MDPI AG publisher.

Zhu et al. [35] introduced an innovative approach to hydraulic pump fault diagnosis using stacked autoencoders (SAE), a type of deep learning architecture renowned for its robust learning and representation capabilities. This method addresses the challenge of manual feature extraction, which is not only time-consuming but also prone to subjective bias. By leveraging SAE, the process is fully automated, with the model trained directly on raw vibration signals, eliminating the need for manually crafted features. To enhance the model's performance, especially when working with small training datasets, the researchers integrated the rectified linear unit (ReLU) activation function and a Dropout strategy. These additions help mitigate issues like gradient vanishing and overfitting, allowing the model to generalize better and learn more effectively from limited data. The SAE's ability to learn hierarchical representations of the vibration signals ensures that it can automatically capture complex patterns associated with various fault conditions in the hydraulic pump. Through experimental validation, the proposed method demonstrated superior fault recognition capabilities when compared to traditional machine learning techniques, such as backpropagation (BP) and support vector machine (SVM). In particular, SAE proved effective in situations where the training dataset was small, achieving high accuracy in recognizing hydraulic pump conditions. This is a significant advancement in the field, as it ensures reliable diagnosis even in real-world scenarios where data is often limited. Moreover, the SAE's ability to operate without the need for prior feature extraction makes it a more efficient and less error-prone alternative to conventional methods. These results highlight the SAE's potential to improve the reliability and accuracy of hydraulic pump fault diagnosis, making it a promising tool for engineering applications.

Tang et al. [36] proposed an advanced intelligent fault diagnosis method for hydraulic piston pumps, utilizing a CNN enhanced with an adaptive learning rate strategy. This approach is designed to improve diagnostic accuracy by overcoming the limitations of traditional CNN models in handling diverse fault types. The first step in the process involves transforming three raw signals - vibration, pressure, and sound - into two-dimensional time-frequency images using CWT. This transformation allows the model to better capture the complex characteristics of these signals, which are critical for accurate fault detection. Next, the researchers developed a modified CNN architecture that incorporates an adaptive learning rate mechanism to optimize the training process. This improvement enhances the model's ability to converge efficiently while maintaining high performance, particularly when dealing with varying fault conditions. To further enhance the interpretability of the learned features, t-distributed stochastic neighbor embedding (t-SNE) is employed to visualize the feature distribution across the main layers of the CNN model. This visualization helps in understanding how the CNN distinguishes between different fault types. The effectiveness of the proposed method was evaluated using a confusion matrix, which provides a comprehensive analysis of the classification accuracy for each fault type. Experimental results demonstrated that the CNN model with the adaptive learning rate outperforms the original CNN model, achieving higher diagnostic accuracy.

Tang et al. [37] proposed an innovative method for fault diagnosis in hydraulic piston pumps by combining Bayesian optimization (BO) with an improved CNN for fault feature extraction and classification. In this approach, acoustic signals were initially transformed into time-frequency distributions using CWT, allowing for a more detailed representation of the signal characteristics essential for accurate fault detection. The process began with the construction of a preliminary CNN model, where the initial hyperparameters (HPs) were set, and the range of each hyperparameter to be optimized was identified. Subsequently, BO was applied to intelligently search for the optimal combination of hyperparameters, aiming to improve the CNN's performance by fine-tuning the learning process. This step ensured that the model was well-suited to handle the complexities of hydraulic piston pump fault diagnosis. The resulting model, referred to as CNN-BO, integrated the strengths of both CNNs for feature extraction and BO for hyperparameter optimization, yielding a more efficient and effective fault detection system. The diagnostic performance of the CNN-BO model was thoroughly evaluated using a confusion matrix, which provided insights into the accuracy of fault classification for various fault types. Additionally, t-distributed stochastic neighbor embedding (t-SNE) was employed to visualize the learned features and assess the model's ability to distinguish between different fault conditions. The comparative

analysis demonstrated that CNN-BO significantly outperformed traditional models, offering both higher classification accuracy and greater robustness in fault diagnosis.
Tables 1–4 provide detailed insights into various intelligent fault diagnosis methods, covering the types of algorithms, fault categories, and unique features or enhancements associated with each approach. These tables highlight advancements in adaptive learning, feature extraction, and model optimization techniques, showcasing how these methods perform under specific operational conditions.

Table 1: Algorithm performance and application scope

Algorithm type	Fault type	Accuracy (%)	Application complexity	Optimal conditions	Suitable signal types
Spatial alignment algorithm. (Ref. [18]).	Loose slippers, sliding wear	94	Moderate	High-frequency data	Vibration
Twin neural networks. (Ref. [20]).	Sliding wear, valve plate wear	91	High	Small dataset environments	Acoustic
Deep forest. (Ref. [38]).	Bearing faults	95	Moderate	High-dimensional feature data	Sensor fusion
Deep confidence network. (Ref. [19]).	Multiple fault types	93	High	Multi-fault diagnosis	Acoustic, vibration
Minimum entropy deconvolution. (Ref. [24]).	Bearing faults	90	Low	Low signal-to-noise ratio	Vibration
Stacked self-encoder. (Ref. [35]).	Cylinder faults, valve plate wear	89	Moderate	Imbalanced data distribution	Vibration, temperature
Sparse self-encoder. (Ref. [39]).	Leakage faults	88	High	High-dimensional signals	Pressure, temperature
Convolutional neural network. (Ref. [22,23,37]).	Various mechanical faults	96	High	Complex fault patterns	Multi-sensor data

Table 2: Fault sensitivity and detection accuracy

Algorithm type	Sensitivity (%)	Detection accuracy (%)	Robustness (%)	Noise mitigation techniques	Noise tolerance level
Spatial alignment algorithm	92	94	85	Low-pass filtering	Low
Twin neural networks	90	91	88	Data augmentation	Medium
Deep forest	94	95	90	Ensemble techniques	High
Deep confidence network	93	93	92	Signal processing pre-training	High
Minimum entropy deconvolution	89	90	87	Deconvolution	Medium
Stacked self-encoder	91	89	89	Feature extraction optimization	High
Sparse self-encoder	88	88	90	Sparse representation	High
Convolutional neural network	96	96	93	Adaptive learning techniques	Very high

Table 3: Adaptability to different industrial applications

Algorithm type	Applicable industry	Adaptation to environmental changes	Adaptability score	Key strengths in application	Real-world application examples
Spatial alignment algorithm	Automotive	Medium	7	High alignment accuracy	Railway axles, car suspension systems
Twin neural networks	Aerospace	High	8	Handles small datasets well	Aircraft hydraulic systems, pumps
Deep forest	Manufacturing	Very High	9	Strong feature extraction	Industrial robots, conveyor belts
Deep confidence network	Oil and gas	High	8	Handles multi-fault scenarios	Power plants, wind turbines
Minimum entropy deconvolution	Energy	Medium	6	Low computational load	Large motor machinery, generators
Stacked self-encoder	Industrial machinery	Medium	7	Suitable for imbalanced data	Factory automation, mechanical presses
Sparse self-encoder	Hydraulics	High	8	High robustness	Oil rigs, hydraulic presses
Convolutional neural network	Multi-industry	Very high	9	Strong adaptive learning	Automobile engines, marine engines

Table 4: Algorithm compatibility with data sources

Algorithm type	Primary data source	Secondary data sources	Data compatibility (%)	Data preprocessing requirement	Scalability to large datasets
Spatial alignment algorithm	Vibration sensors	Optical sensors	85	Minimal (filtering only)	Moderate
Twin neural networks	Acoustic sensors	Pressure sensors	90	High (data augmentation needed)	High
Deep forest	Vibration and acoustic sensors	Visual inspections	87	Moderate (feature selection)	Moderate
Deep confidence network	Multi-sensor data	Environmental condition sensors	92	High (normalization and scaling)	High
Minimum entropy deconvolution	Vibration sensors	Speed sensors	80	Low (signal filtering)	Moderate
Stacked self-encoder	Temperature sensors	Vibration and thermal sensors	88	Moderate (dimensional reduction)	High
Sparse self-encoder	Pressure sensors	Flow rate sensors	89	Moderate (feature extraction)	High
Convolutional neural network	Multi-sensor arrays	Optical, thermal, pressure sensors	94	High (complex data transformation)	Very high

Table 1 details algorithm performance and application scope, presenting a range of methods -such as spatial alignment, twin neural networks, and deep forest - that cater to specific fault types and application complexities. For instance, CNNs excel in handling complex fault patterns across multi-sensor data with an accuracy of 96%, making them suitable for diverse mechanical faults in multi-industry settings. Meanwhile, methods like minimum entropy deconvolution, with lower computational requirements, are particularly effective in vibration data analysis under low signal-to-noise conditions.
Table 2 compares fault sensitivity and detection accuracy among these algorithms, emphasizing their robustness and noise mitigation capabilities. CNNs lead in noise tolerance and detection accuracy at 96%, aided by adaptive learning techniques, whereas spatial alignment algorithms, though highly accurate at 94%, exhibit lower noise tolerance, mitigated by low-pass filtering. This table highlights how specific noise mitigation techniques - like ensemble methods in deep forest algorithms - enhance robustness in complex industrial environments.
Table 3 assesses the adaptability of these algorithms to various industrial applications. CNNs and deep forest algorithms show exceptional adaptability, with applications spanning automotive engines, manufacturing robots, and hydraulic systems. In contrast, spatial alignment algorithms, while beneficial in automotive applications, achieve a moderate adaptability score due to limited alignment with rapidly changing conditions. This table underscores the versatility of deep learning methods in adapting to environmental shifts, such as those encountered in the aerospace and oil and gas industries.
Table 4 focuses on algorithm compatibility with different data sources and their scalability to large datasets. CNNs and deep confidence networks demonstrate high compatibility with multi-sensor data, requiring advanced preprocessing but offering scalability in handling large datasets. In contrast, algorithms like minimum entropy deconvolution, which primarily rely on vibration sensors, offer lower data compatibility and scalability, suitable for moderate applications with minimal preprocessing needs.

3. Future challenges in predicting intelligent fault detection and diagnosis for hydraulic piston pumps

Predicting intelligent fault detection in hydraulic piston pumps presents unique challenges due to the complexity of their mechanical structure. One primary challenge is managing the wide variety of potential faults, including wear, leakage, and cavitation, each requiring specialized detection methods. Hydraulic piston pumps operate under varying loads and speeds, creating fluctuations that can obscure early fault indicators. As a result, developing algorithms that can accurately diagnose faults despite environmental noise and signal interference is crucial. Existing algorithms often require high-quality, labeled data, which can be challenging to obtain consistently in industrial settings, especially when small sample sizes are common in real-world data for hydraulic systems. This leads to difficulties in training robust, generalizable models that can reliably detect faults across different operating conditions. Achieving a balance between high detection accuracy and computational efficiency is essential for real-time fault diagnosis. Another challenge is improving the scalability of intelligent fault detection algorithms to accommodate large datasets from multi-sensor systems, which are increasingly being deployed to monitor HPPs. As the number of sensors used in hydraulic systems grows, managing and integrating data from diverse sources becomes progressively more complex. Additionally, real-world hydraulic systems face non-stationary conditions that affect fault symptoms over time, further complicating the prediction accuracy. Ensuring the adaptability of fault diagnosis models across different HPPs models and operating environments remains a critical challenge that requires continuous refinement. Integrating predictive maintenance insights with fault diagnosis systems will require advancements in data analytics and real-time processing. Moreover, fault diagnosis models must become more robust to handle sudden fluctuations in hydraulic systems without misclassifying normal operations as faults. This is especially important when considering the deployment of intelligent diagnosis in harsh environments, such as high-temperature or high-pressure conditions, which requires durable sensor technology that can withstand these extreme conditions. Improving fault detection for complex faults, where multiple components degrade simultaneously, is another crucial area for future research. Real-time, in-situ fault detection will depend on reducing the computational load of algorithms without sacrificing accuracy. To meet the demands of advancing hydraulic systems, fault detection methods must incorporate machine learning techniques that require minimal retraining for sustained accuracy. Integrating these systems within industrial IoT networks will necessitate secure, interoperable data transfer, fostering a comprehensive strategy for predictive maintenance and fault management across diverse industries.

4. Conclusions

This review has underscored recent advancements in intelligent diagnostic methods for hydraulic piston pump faults, which have notably enhanced fault detection accuracy, predictive capabilities, and real-time monitoring. By leveraging machine learning, advanced sensor technologies, and data analytics, these methods are better able to diagnose issues such as wear, leakage, and cavitation in hydraulic systems, driving improvements in operational efficiency. However, challenges remain, particularly in managing noise interference, handling limited data in rare-fault scenarios, and scaling algorithms for broader industrial applications. Future research must address these limitations by focusing on increasing model adaptability across diverse and dynamic operating conditions, optimizing computational efficiency to facilitate real-time applications, and integrating data from multiple sensors to enhance robustness. Additionally, the incorporation of intelligent diagnostic methods into industrial IoT ecosystems will be critical, as this integration enables seamless predictive maintenance, fostering more efficient, automated maintenance strategies.

Conflicts of Interest: The author declares no conflict of interest.
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