Review
Intelligent Fault Diagnosis Methods for Hydraulic Piston Pumps: A Review

Yong Zhu 1,2, Qingyi Wu 1,3, Shengnan Tang 1,4,*, Boo Cheong Khoo 5 and Zhengxi Chang 6

Abstract: As the modern industry rapidly advances toward digitalization, networking, and intelligence, intelligent fault diagnosis technology has become a necessary measure to ensure the safe and stable operation of mechanical equipment and effectively avoid major disaster accidents and huge economic losses caused by mechanical equipment failure. As the “power heart” of hydraulic transmission systems, hydraulic piston pumps (HPPs) occupy an important position in aerospace, navigation, national defense, industry, and many other high-tech fields due to their high-rated pressure, compact structure, high efficiency, convenient flow regulation, and other advantages. Faults in HPPs can create serious hazards. In this paper, the research on fault recognition technology for HPPs is reviewed. Firstly, the existing fault diagnosis methods are described, and the typical fault types and mechanisms of HPPs are introduced. Then, the current research achievements regarding fault diagnosis in HPPs are summarized based on three aspects: the traditional intelligent fault diagnosis method, the modern intelligent fault diagnosis method, and the combined intelligent fault diagnosis method. Finally, the future development trend of fault identification methods for HPPs is discussed and summarized. This work provides a reference for developing intelligent, efficient, and accurate fault recognition methods for HPPs. Moreover, this review will help to increase the safety, stability, and reliability of HPPs and promote the implementation of hydraulic transmission technology in the era of intelligent operation and maintenance.

Keywords: hydraulic piston pump; fault diagnosis; intelligent operation and maintenance; research status; development trend

1. Introduction
Since the inauguration of “Industry 4.0” in Germany, “Made in China 2025”, “Industrial Internet” in America, and “Society 5.0” in Japan, the world has focused on the development of intelligent factories, production, electronic information and logistics, including human–computer interactions, high-end CNC machine tools and robotics, new energy vehicles, biomedicine, etc. These measures continue to strengthen the innovative applications of key digital technologies [1,2]. This is promoting digitization, networking, and intelligence in the manufacturing industry and an innovation-driven development path. Hydraulic transmission systems are widely used in the aforementioned engineering fields due to their advantages of stepless speed regulation, large speed regulation ranges, high load tolerance, and easy automation.
As the “power heart” of hydraulic transmission systems, hydraulic piston pumps have consistently attracted the attention of engineers and academia. Scholars and research institutions have achieved compelling research results in the study of fault diagnosis methods for various pumps. HPPs have occupied an important place and are widely used in high-tech fields, including aerospace, navigation, national defense, and industry, such as marine power drives, offshore wind power, oil-gas exploration, deep sea exploration, industrial machine tools, construction machinery, etc. [3]. However, a piston pump has numerous components, and its internal structure is rather complicated and often faces complex working conditions, such as high temperature, high pressure, and variable load. Thus, some typical failures of piston pumps often occur in extreme operating conditions. Once a fault occurs, it is difficult to quickly determine the cause and accurately locate and identify its location. This may lead to damage to the internal structure of the pump and eventually causes the pump and equipment to stop operation, resulting in economic losses and major accidents, such as system paralysis and production shutdown, even threatening the safety of the staff [4]. Therefore, fault diagnosis technology for HPPs is particularly important to guarantee the safety of the entire equipment and reduce the incidence of accidents.

In modern industry, HPPs are continuously evolving in higher precision, and their structures are becoming increasingly sophisticated and complex. This means that an efficient, accurate, and intelligent fault diagnosis technology has broad application prospects in both scientific research and engineering practice. With the rapid advancement of the big data era, the data presented by piston pumps have become important information sources that reflect the working statuses and fault manifestation processes, if any, of the pumps. The scale and interpretability of these data have also become an important part of current fault diagnosis technology [5]. However, due to the influence and interference of multiple factors in working environments, and the complexity and variability of work tasks, HPPs present many challenges in the process of fault identification.

The fault diagnosis approaches for HPPs mainly focus on collecting different types of signals to analyze and reflect their operating status. These signals mainly include vibration signals, sound signals, pressure signals, flow signals, etc. When an HPP runs at complex conditions, it generates a large number of complex signals, which reduces the purity of the original signal, increases the difficulty of signal feature extraction, and also increases the complexity of signal processing. Therefore, traditional fault recognition methods are difficult to achieve precise identification. Meanwhile, various intelligent fault identification or combined fault diagnosis approaches utilize intelligent algorithms for data mining and establishing fault identification models, and then complete the identification of different states. These methods have high accuracy and are more intelligent, and have become the mainstream of fault identification methods. In recent years, numerous experts and scholars have researched fault identification methods for HPPs, and several articles have provided an overview of the fault recognition methods for piston pumps [6,7]. They have summarized current fault identification methods from the view of different types of signals, but there are relatively few detailed classifications and comparative analyses for fault diagnosis approaches. Hence, a comprehensive summary to provide the latest research progress and application for intelligent fault diagnosis approaches of HPPs is urgently needed.

This work takes HPPs as the research object, and the common types and mechanisms of faults in HPPs are analyzed. Then, all kinds of existing fault diagnosis methods are summarized. Novelly, the various fault diagnosis methods are classified into traditional intelligent fault diagnosis methods, modern intelligent fault diagnosis methods, and combined intelligent fault diagnosis methods. Moreover, the achievements and application statuses of the HPP fault diagnosis methods are summarized. Finally, this work analyzes the aforementioned fault diagnosis methods and infers their development trends, and seeks to provide a theoretical reference for scientific research and engineering applications in this field.
2. Fault Types and Mechanisms of Hydraulic Piston Pumps

HPPs can be divided into radial piston pumps and axial piston pumps, according to their structural forms, and can be further divided into swashplate types and bent-axis types according to their structural characteristics. This paper uses the example of a swashplate-type HPP (Figure 1a) to introduce the structure of a piston pump. Multiple friction pairs have relative motion inside a piston pump, such as a piston ball head and slipper (Figure 1b), slipper and swashplate (Figure 1c), piston and piston hole (Figure 1d), and cylinder and valve plate (Figure 1e). In a continuous high-speed and high-pressure operational environment, HPP faults, such as a loose slipper, slipper wear, center spring failure, valve plate wear, piston wear, swashplate wear, and bearing damage, are prone to occur. Any of these faults may become a source of excitation, causing mechanical vibrations, among which a loose slipper, slipper wear, center spring failure, and valve plate wear are typical faults, as shown in Figure 2 and Table 1 [8].

![Figure 1. Schematic diagram of structural composition of piston pump. (a) Three-dimensional structural model of hydraulic piston pump. (b) Piston ball heads and slippers. (c) Slippers and swashplate. (d) Pistons and piston holes. (e) Cylinder and valve plate.](image-url)
Figure 2. Photos of typical fault components. (a) Loose slipper. (b) Slipper wear. (c) Center spring failure. (d) Valve plate wear.

Table 1. Summary of four typical faults.

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Fault Components</th>
<th>Fault Cause</th>
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<tbody>
<tr>
<td>Loose slipper</td>
<td>Slipper</td>
<td>Dust in the working environment enters the gap between the piston ball head and slipper. Less precise dimensions of piston ball head and slipper.</td>
</tr>
<tr>
<td>Slipper wear</td>
<td>Slipper</td>
<td>The supporting force of the swashplate on the slipper changes and makes the oil film thinner. The existence of a wedge-shaped clearance between the swashplate and the transmission shaft.</td>
</tr>
<tr>
<td>Center spring failure</td>
<td>Center spring</td>
<td>The long-term and high-intensity operation of the HPP causes fatigue wear and plastic deformation of the center spring.</td>
</tr>
<tr>
<td>Valve plate wear</td>
<td>Valve plate</td>
<td>The high-speed operation of an HPP increases the centrifugal force of the cylinder. Changes in the inclination angle of the swashplate change the thickness of the oil film.</td>
</tr>
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</table>

A loose slipper is caused by an excessive gap between the slipper and the piston ball head. When the slipper becomes severely loose to a certain extent, the slipper can fall off, which seriously affects the working state of the HPP [9]. There are two possible reasons for a loose slipper: (1) In the long-term operation of an HPP, dust in the working environment enters the gap between the piston ball head and slipper, causing the gap to increase due to the generated pressure. (2) In the manufacturing process, the assembly of a piston ball head and slipper may result in a large gap due to less precise dimensions.

Slipper wear refers to the wear fault caused by the relative friction between the slipper and the swashplate. During the operation of an HPP, the piston cavity performs oil absorption and discharge work. The hydraulic oil accompanies the reciprocating motion of the piston, enters the oil chamber along the cylinder, and forms an oil film between
the slipper and the swashplate to provide support and slow down wear. When the axial piston pump starts or stops running, the piston pressure on the slipper changes, causing a greater impact on the slipper. Moreover, the supporting force of the swashplate on the slipper changes, and the oil film becomes thinner, aggravating the wear of the slipper and the swashplate. Simultaneously, friction occurs between the edge of the slipper and the swashplate due to the existence of a wedge-shaped clearance between the swashplate and the transmission shaft, causing further slipper wear [10].

Center spring failure refers to the fatigue wear and plastic deformation of the center spring due to the long-term and high-intensity operation of the HPP. The center spring is responsible for providing preload to ensure the sealing effect between the slipper and the swashplate, as well as between the valve plate and the cylinder. Due to long-term pressure, the center spring may experience stress relaxation, which reduces its preload. When the preload generated by the center spring is less than the external load pressure it can bear, the sealing effect is lost, which results in oil leakage and affects the return process of the slipper and piston.

Valve plate wear refers to the wear fault caused by the relative friction between the valve plate and the cylinder. Valve plate wear is related to the thickness of the oil film, and the possible reasons for its occurrence include the following: (1) When an HPP operates at high speed, the centrifugal force of the cylinder increases, reducing the thickness of the oil film and exacerbating the wear between the valve plate and the cylinder. (2) Changes in the inclination angle of the swashplate change the thickness of the oil film, causing uneven pressure on the valve plate and resulting in valve plate wear [11].

3. Fault Diagnosis Methods

Fault diagnosis refers to analyzing the working status of mechanical equipment based on the obtained information, extracting feature elements from signals, combining relevant theoretical methods to determine the type of fault, and ultimately obtaining the fault result. At present, the fault identification approaches can be separated into the following three main types: traditional intelligent fault diagnosis methods, modern intelligent fault diagnosis methods, and combined intelligent fault diagnosis methods, as shown in Figure 3.

3.1. Traditional Intelligent Fault Diagnosis Methods

Knowledge-based recognition compares and analyzes real-time collected data with historical data to realize fault diagnosis. Such methods mainly include the expert system method, the oriented graph method, fault tree analysis, the fuzzy logic method, etc. This type of identification does not need a mathematical model to be established and can classify faults based on the knowledge, theory, and operating mechanism of a system to obtain fault results [12]. However, the evaluation criteria of knowledge-based identification are highly dependent on expert experience and theoretical knowledge, so its scalability and universality are relatively low.

Model-based methods identify the fault mode of mechanical equipment by constructing a correct mathematical model and identifying the deviation between the actual output and the expected output. These methods can achieve fault diagnosis based on a small amount of real-time data. This form of recognition mainly includes the Kalman filter method, the parameter estimation method, empirical dynamic modeling, the equivalent space method, the nonlinear observer method, the state estimation method, etc. Model-based recognition does not rely on the theoretical knowledge of experts and has high operability. However, mechanical equipment operates in an environment with typically a large number of interference signals, which affects real-time data collection. Moreover, a mathematical model is complex and difficult to accurately model, resulting in uncertainties and limitations in using model-based methods in complex and variable working conditions [13].
Figures 3. Classifications of fault diagnosis methods.

Traditional data-driven methods first preprocess the status signals of mechanical equipment to extract features, construct diagnostic models with data sets, and then analyze and identify fault patterns. The entire process is separated into two sections: feature extraction and pattern identification [14]. The feature extraction methods can be divided into frequency-domain analysis, time-domain analysis, and time–frequency-domain analysis. The methods of frequency-domain analysis include spectral analysis, among others. The methods of time-domain analysis include entropy theory, empirical mode decomposition, morphological signal analysis, etc. The methods of time–frequency-domain analysis include the wavelet transform, the wavelet packet transform, etc. The main methods of pattern recognition include support vector machines (SVMs), radial basis function (RBF) neural networks, k-nearest neighbor, backpropagation neural networks, hierarchical clustering algorithms, etc. Traditional machine learning has strong learning ability, nonlinear mapping ability, and robustness, but the accuracy of fault diagnosis still needs to be improved because the shallow learning model used in model recognition limits its ability to handle big data and complex nonlinear problems [15].
3.2. Modern Intelligent Fault Diagnosis Methods

Adaptive learning methods, such as deep learning (DL), transfer learning (TL), and reinforcement learning (RL), represent intelligent data-driven methods and are considered to be the mainstream modern intelligent fault recognition methods.

DL refers to a machine learning algorithm that preprocesses the collected data to perform feature extraction and fault classification, thereby realizing fault identification [16]. These methods mainly include convolutional neural networks (CNNs), recurrent neural networks (RNNs), deep belief networks (DBNs), automatic encoders, etc. DL can autonomously mine fault information hidden in original data, establish a mapping relationship between the original data and the working status of the mechanical equipment, and greatly eliminate the dependence on the manual diagnostic experience, thus improving the ability to classify and predict faults [17].

TL refers to a machine learning algorithm that realizes the process of knowledge and theoretical transfer via the correlation of tasks. The sample data are defined as the source domain data set, and the target domain data set is obtained from the measured data [18]. By extracting data from the target domain and the source domain data, the mapping function from the measured data to the sample data is established for fault classification and identification [19]. TL can be classified according to the target domain label and the migration method, as displayed in Figure 4. Such methods mainly include domain-adaptive neural networks, the TrAdaBoost algorithm, multi-task learning, the deep domain confusion model, etc. These methods can migrate the diagnostic task data to other tasks in the case of fewer fault samples and achieve high diagnostic accuracy when the measured data and sample data are different [20].

![Figure 4. Classification of transfer learning.](image)

Unlike other machine learning, RL poses a unique challenge in balancing exploration with utilization. After constructing the architecture for fault diagnosis, it can directly continue trial and error and accumulate the maximum reward, obtain the optimal action strategy, and identify its corresponding fault mode via raw data analysis [21]. Such methods include the SARSA algorithm, Q-learning algorithm, deterministic policy gradient algorithm, etc. RL can obtain long-term rewards from the original data, reduce the dependence on the environment, and enhance the speed and correctness of fault diagnosis [22].

3.3. Combined Intelligent Fault Diagnosis Methods

This pattern of identification refers to a combination of two or more knowledge-based methods, model-based methods, and data-driven methods. Typical approaches include deep Q-learning algorithms, methods combined with backpropagation neural networks, methods combined with entropy theory, methods combined with convolutional neural networks, etc. These methods can fully utilize the advantages of different algorithms, reduce the dimensionality and difficulty of intelligent fault diagnosis calculation, maintain high accuracy with small data samples, and obtain more comprehensive and high-precision diagnostic results.
4. Research Status of Fault Diagnosis for Hydraulic Piston Pumps

4.1. Traditional Intelligent Fault Diagnosis Methods

4.1.1. Model-Based Fault Diagnosis Methods

Model-based methods can utilize the obtained information to reduce their reliance on experimental data by constructing mathematical models. However, there is a level of difficulty in constructing a model required to accurately capture the dynamics of a system [23]. These mathematical models provide a deep understanding and analysis of the system characteristics and can accurately identify faulty patterns [24]. To improve the reliability and performance of HPPs, Ma et al. [25] explored a fault identification approach based on a nonlinear unknown input observer. This method can accurately diagnose the health status of an HPP and identify specific types of faults by considering the impacts of nonlinear factors. Tang et al. [26,27] investigated a fault recognition approach for HPPs under variable load conditions, wherein they constructed a virtual sample machine for a piston pump and analyzed the dynamics under different faults and loads, showing that this method increases the sensitivity of axial vibration signals to slipper faults. To target the problem of the serious wear caused by the slipper of a piston pump during high-speed operation, Chao et al. [28] proposed an integrated slipper-fixing mechanism to reduce the degree of wear between the slipper and the swashplate during high-speed operation. Tang et al. [29] established a rotor-bearing system model to explore the vibration characteristics of various faults and investigated the dynamic responses of mixed faults under different parameters.

In recent years, there were some research progresses in model-based fault diagnosis methods. Bedotti et al. [30] explored a swashplate dynamic modeling method for predicting and managing the health of mechanical systems that can monitor the working condition of an HPP in real time. Bensaad et al. [31] proposed an extended Kalman-filter-based method to identify leakage faults in HPPs to solve the issue of increased volume loss due to piston wear, which reduces the working efficiency of HPPs.

4.1.2. Data-Driven Fault Diagnosis Methods

With the development of advanced information technology, data-driven methods have gradually replaced model-based methods and have become an attractive research topic in the field of fault detection. Du et al. [32] considered the multiple faults that may occur simultaneously in an aircraft hydraulic pump during long-term operation and proposed a new hierarchical clustering algorithm that can effectively diagnose multiple faults occurring simultaneously in hydraulic pumps with high accuracy and reliability. Zheng et al. [33] addressed the problem of excessive frequency band decomposition obtained from Fourier amplitude spectra by exploring an improved feature extraction method based on the empirical wavelet transform, which can more accurately detect hydraulic pump fault signals. This method reduces the influence of external interference on frequency band acquisition and has a good decomposition effect on fault signals. Meng et al. [34,35] proposed a fault identification approach based on empirical mode decomposition to address the problem of the number of fault samples being less than the number of healthy samples in a civil aviation hydraulic pump. This method can enhance sample data and retain the inherent components of enhanced samples, ascribing the enhanced sample data and original data similar features and preventing overfitting.

Data analysis techniques are extensively used for fault recognition in HPPs by utilizing their fault information. Deng et al. [36] studied a Teager energy operator demodulation method based on extremum-field mean mode decomposition, which solved the issue of weak early failure characteristic signals in piston pumps. This method effectively filtered signals and extracted fault features from the frequency domain. Jiang et al. [37] studied an approach based on the balanced random forest algorithm under imbalanced data set conditions, which improved the accuracy of axial piston pump fault classification. Chao et al. [38] proposed an adaptive decision fusion method, which combines multiple sensors to increase the fault identification performance for HPPs using multi-channel
vibration signals. To enhance the reliability and stability of aviation HPPs, Lu et al. [39] put forward an evidence theory approach based on evidence similarity distance using multiple-source information fusion. Compared with failure detection approaches using single-source signals, this method has a higher fault diagnosis accuracy.

Traditional data-driven methods do not require the establishment of precise mathematical models. These methods use relevant signal-processing techniques to extract fault signal features and analyze data to achieve mechanical equipment fault identification and classification. Jiang et al. [40] explored a method based on mathematical morphology to realize fault identification in HPPs, thereby solving the problem of noise interfering with vibration signals, which leads to useful feature signals being covered up. This method can extract feature information from different fault modes. To target the problem of HPP fault signals presenting ambiguity and completeness in the failure detection procedure, a Bayesian network was used to fuse the multi-source information to identify the loose shoe and sliding shoe faults in a piston pump [41]. Zheng et al. [42] explored the log-SAM method based on complex signals to solve the problem of single-source signals possessing less feature information and formed an improved Autogram method, which was used for the fault diagnosis of slipper wear in HPPs. This approach can effectively suppress the impact of noise and has a strong feature extraction capability. A pressure feature signal extraction method based on Autogram was studied to address the issue of the fluctuation characteristics of other fluid flows in hydraulic pumps interfering with the fluctuation characteristics caused by central spring wear. This approach can more accurately extract the fault feature signals of central spring wear in hydraulic pumps [43]. A fault pattern recognition approach for HPPs based on adaptive multiple-scale morphological difference filtering was studied. This method can provide fault source signals for fault diagnosis and effectively filters out noise [44].

The feature extraction process may be affected by many external factors, so many researchers use various methods to suppress external interference and improve feature extraction capabilities. Gu et al. [45] studied a fault pattern recognition method based on instantaneous speed fluctuation signals, which are used to identify valve plate wear. This approach exhibits a strong anti-noise performance and can solve the problems of nonlinear and nonstationary signals. To address the issue of environmental noise and natural periodic pulses interfering with vibration signals, Gao et al. studied a Teager energy operator demodulation method based on L-kurtosis and an enhanced clustering segmentation algorithm, which effectively suppressed environmental noise and synchronously extracted weak fault features from environmental noise and natural periodic pulses [46,47]. A Walsh-transform-based Teager energy operator demodulation approach for quickly and effectively identifying faults in HPPs was explored. This approach can adaptively denoise the original signal and demonstrates good fault extraction and preprocessing capabilities [48]. As shown in Figure 5, Xiao et al. [49] studied an improved fast spectral correlation algorithm to identify bearing faults in HPPs using frequency band localization, responding to the problem of natural periodic pulses masking the fault excitation pulse from the piston pump bearing. This method uses kurtosis to enhance spectral entropy to locate the fault frequency band in an image, highlight the fault excitation pulse, and finally extract the feature frequency using the square-enhanced envelope spectrum to recognize the fault pattern. Research results indicated that Kurtosis enhanced spectral entropy is very sensitive to periodic pulses and can accurately extract weak fault excitation pulses. Square-enhanced envelope spectrum can enhance nonzero cyclic components by integrating complex values, improving the recognition accuracy of bearing faults. This improved algorithm enhances the ability to extract fault excitation pulses and can effectively prevent natural cycle pulse interference. Chao et al. [50] proposed an approach based on spectral characteristics to address the issue of the noise sensitivity of the vibration signals affecting the failure detection performance of a model. This method denoises time–frequency images and enhances the anti-interference capacity of the diagnostic model against noise and the recognition accuracy for the severity of cavitation in axial piston pumps.
Wang et al. [56] studied a failure identification approach based on a deep belief network, which uses data indicators to automatically extract fault features and detect faults in HPPs. This method can accurately extract effective fault features in complex fault classification.

Other data-driven methods have also been applied to failure detection in HPPs. Babikir et al. [51] proposed a model based on an improved artificial neural network to predict the noise generated by axial piston pumps with different valve materials. This method demonstrated that the main cause of noise generation was the speed of the piston pump, followed by the system pressure and valve material. Kumar et al. [52] studied a variational modal decomposition algorithm based on single-valued neutral entropy to extract feature information on different faults in plunger pumps. This algorithm is used to quantify the nonlinear connections between various faults and frequency bands, adaptively select sensitive frequency bands, and effectively identify the faulty components of axial piston pumps.

4.2. Modern Intelligent Fault Diagnosis Methods

To achieve intelligent fault identification, researchers have applied DL to the field of HPP fault diagnosis. DL can adaptively extract hidden fault information, avoiding dependence on human experience and theoretical knowledge. Fang et al. [53] studied a fault identification approach based on a semi-supervised neighborhood adaptive linear local tangent space arrangement algorithm using mixed vibration signal features, which improves the accuracy of HPP fault recognition. Gao et al. [54] explored a fault identification method based on a Siamese neural network for detecting wear faults in piston pumps, addressing the issue of underfitting and the low accuracy of traditional deep neural networks under small-sample conditions. Jiang et al. [55] studied a failure identification method based on full-vector data fusion-enhanced deep forest. The method combines full-spectrum technology with multi-scale scanning, enhances the feature extraction ability by inputting dual-channel signals, reduces feature disappearance and redundancy using feature-selection-cascaded residual forests, and hence increases the precision of fault identification, thus solving the problems of complex feature extraction and the high complexity of constructing DL network models in traditional fault identification processes. Wang et al. [56] studied a failure identification approach based on a deep belief network, which uses data indicators to automatically extract fault features and detect faults in HPPs. This method can accurately extract effective fault features in complex fault classification.

Figure 5. The flowchart of improved fast spectral correlation algorithm [49]. Reprinted with permission from Ref. [49]. Copyright 2021, Elsevier B.V.
Xiao et al. [57] studied an improved feature extraction algorithm based on adaptive minimum entropy deconvolution for failure identification in HPPs. It efficiently and accurately extracts weak periodic pulses from composite vibration signals with a good anti-aliasing performance. Zhu et al. [58] believed that manual feature extraction leads to a subjective experience affecting diagnostic results. The said researchers studied a stacked autoencoder, which exhibits good learning and representation capabilities and achieves automatic fault recognition in HPPs. Chen et al. [59] integrated a stacked sparse autoencoder into a deep neural network and extracted low-dimensional features to address the difficulty of identifying fault signals in HPPs. The stacked sparse autoencoder extracts high-dimensional features to detect different leakage states in hydraulic pumps.

A convolutional neural network has a powerful adaptive learning ability, which can extract hidden feature information from original data and realize the deep mining of feature data [60]. The model structure is described in Figure 6. Because the failure characteristics of an HPP can become submerged in the nonlinear interference caused by its components, Yan et al. [61] proposed an improved CNN, which simplifies the fault recognition procedure and improves precision and the ability to classify failure. Xu et al. [62] utilized a deep one-dimensional CNN to realize failure detection in HPPs, which solved the problems of the limited fault representation ability of shallow models and over-reliance on expert experience for feature extraction. The method optimizes fault recognition in HPPs and improves the accuracy of the diagnostic results. Tang et al. [63] used a new CNN model for intelligent failure detection in hydraulic plunger pumps. This approach can accurately classify various failure categories [64]. Addressing the deficiencies of traditional fault identification in raw data preprocessing and feature extraction, an improved CNN with an adaptive learning rate was studied for multi-source signal fault diagnosis in hydraulic plunger pumps. It overcomes the disadvantages of conventional fault diagnosis methods that rely heavily on expert experience and diagnostic knowledge [65]. In addition, a modified CNN model was established to target the problem of shallow machine learning models' heavy dependence on professional knowledge and experience. Bayesian optimization algorithms were used to model adaptive hyperparameter learning to preprocess acoustic signals. This method exhibits a strong fault classification ability, high accuracy, and robustness. To address the issue of difficult feature extraction and noise suppression when an HPP operates under variable speed conditions, Xu et al. [66] studied a failure detection approach using a one-dimensional convolutional long short-term memory neural network. This method can identify the cavitation level in a plunger pump.

Figure 6. Structural diagram of convolutional neural network model.

4.3. Combined Intelligent Fault Diagnosis Methods
4.3.1. Combined with Artificial Neural Networks

With the advancement of artificial intelligence, progress has been made in developing fault diagnosis methods combining data analysis technology with other technologies [67]. To increase the diagnostic efficiency for wear faults, Du et al. [68] proposed a fault recognition approach based on a probabilistic neural network and sensitivity analysis. This method summarizes the changes in the wear characteristic frequency in the piston pump via frequency spectrum analysis and improves the accuracy of fault diagnosis. Sun et al. [69] combined the intrinsic time-scale decomposition method with the Softmax regression
model. The different failure modes of HPPs are classified using the efficient and accurate signal time–frequency analysis capability of the intrinsic time-scale decomposition method. Wu et al. [70] addressed the difficulty of extracting the features of axial piston pumps under variable load conditions by combining chirplet transformation with variational mode decomposition to identify HPP bearing faults. He et al. [71] studied a multiple-signal fusion adversarial model based on TL and a residual network that weighted the vibrations and acoustic signals of HPPs. The dynamic adjustment ability was improved, and the problem of some deep learning algorithms’ failure due to unbalanced data distributions was solved. To address the issue of the fault feature distribution being too scattered after decomposing a vibration signal, Zheng et al. [72] proposed a method combining symplectic geometric mode decomposition and Autogram to identify swashplate wear in HPPs. Jin et al. [73] proposed a method based on variable pattern extraction and detrended fluctuation analysis. This method eliminates irrelevant interference information, such as noise in the diagnostic process, and effectively identifies and diagnoses failure signals in HPPs. Jin et al. [74] further combined dynamic mode decomposition and t-distribution random nearest-neighbor embedding clustering to identify different fault types in hydraulic pumps and enhance the precision of fault identification.

Artificial neural networks can abstractly simulate the way the human brain processes information, and they have strong generalization and self-learning abilities when combined with other methods. Du et al. [75] combined manifold learning and individual feature selection to extract the mixed features of vibration signals from multiple angles and used the sensitive features included in the feature set to achieve fault identification in HPPs. As revealed in Figure 7, Yu et al. [76] studied an algorithm that combines an improved empirical wavelet transform and the variance contribution rate. This method fuses the vibration signals of the three channels and decomposes them into a reasonable number of AM-FM components, which solves the complex spectrum decomposition problem found in the traditional empirical wavelet transform method. The researchers also proposed a density-based clustering application of noisy spaces to prevent the boundedness of full-scale space. The improved empirical wavelet transform solves the problem of unreasonable spectral segmentation, which was used to detect weak fault frequencies hidden in complex signal environments, including noise, inherent impulse frequency, and other periodic disturbances. The research results showed that it is more robust than the original empirical wavelet transform in different noise environments. This method effectively reduces the number of frequency bands related to noise and realizes the capability to identify weak faults in HPPs. To target the issue of the fault characteristics of HPP vibration signals being easily hidden, Jiang et al. [77] studied a failure signal demodulation approach that combines local mean decomposition and improved adaptive multi-scale morphology to effectively identify multiple fault modes in hydraulic pumps. Harnessing the ability of the Hilbert–Huang transform (HHT) to effectively deal with nonlinear and nonstationary signals, a fault identification approach combining HHT and the fuzzy C-means clustering algorithm was explored to improve the accuracy of failure identification in piston pumps [78]. Considering the problem of insufficient training samples for an algorithm, an artificial immune system and SVM were combined to accurately identify multiple failure modes in HPPs with loose boots and valve plate wear [79]. A fault recognition approach based on symmetrical polar images and the fuzzy C-means clustering algorithm was also studied. This method solves the issue of nonintuitive time-domain waveform failure signals in HPPs and intuitively reflects the difference between the failure type and the normal HPP type, as well as the characteristics of the fault state [80]. Liu et al. [81] presented a continuous learning model based on a combination of weight space meta-representation with a modified WaveletKernelNet. This model adapts to the dynamic changes in failure types and repeatedly updates the diagnostic model.
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Figure 7. The flowchart of improved empirical wavelet transform–variance contribution rate algorithm [76]. Reprinted with permission from Ref. [76]. Copyright 2020, Elsevier B.V.

4.3.2. Combined with Entropy Theory

Entropy theory can express the nonlinear and nonstationary dynamic characteristics of signals in feature extraction [82]. In recent years, many researchers have combined the entropy algorithm with other signal-processing techniques and applied it to the field of failure detection in piston pumps. Xiao et al. [83] used the method of fuzzy entropy-assisted singular spectrum decomposition to detect failure in an HPP and target the issue of noise interference in the vibration signals of the HPP bearing. The measurement data are adaptively decomposed into singular spectrum components, the components with fault information are screened via fuzzy entropy, and the soft threshold denoising algorithm is used for secondary filtering to reduce the interference of natural periodic pulses and suppress residual noise. This method exhibits improved robustness and can accurately extract fault excitation pulses with noise interference. Zhou et al. [84] proposed a novel tangent hyperbolic fuzzy entropy measure-based method, which can determine the highly sensitive frequency band and identify defective components in HPPs. Qu et al. [85] studied a fusion approach composed of variational mode decomposition and multi-scale scatter entropy to address the issue of low precision in the variational mode decomposition method. This method can efficiently and accurately identify sliding wear faults in piston pumps. Wang et al. [86] studied a method combining fast empirical mode decomposition and relative entropy for feature extraction from pressure signals. This method demonstrates an improved anti-interference ability in HPP fault identification. To improve the stability of multi-scale fluctuation discrete entropy, Zhou et al. [87] proposed an improved composite multi-scale fluctuation discrete entropy method. Particle swarm optimization, variational mode decomposition, and compound multi-scale fluctuation discrete entropy were combined to improve the fault identification accuracy in hydraulic pumps. To extract the weak fault signal of an HPP in a highly noisy environment, Liu et al. [88] explored an
approach based on adaptive noise for complete ensemble empirical mode decomposition and compound multi-scale–basic-scale entropy. The fault signal of an HPP is decomposed and quantified to acquire the failure symptoms in different states. The fault diagnosis algorithm combined with this method has a wider application range and higher precision. Zhao et al. [89] studied a method combining local mean decomposition sample entropy and an SVM for HPP fault feature extraction and classification. The method can accurately and efficiently identify multiple failure modes of HPPs. Zheng et al. [90] explored an approach combining power spectrum entropy and Autogram for HPPs that are seriously affected by Gaussian noise and non-Gaussian noise when slipper wear occurs. This method can suppress the noise and effectively identify the slipper wear in an HPP.

4.3.3. Combined with Convolutional Neural Network

As a deep learning algorithm, the local connection, weight-sharing, and pooling operations in a CNN improve its feature learning ability. Combining a CNN with other data analysis techniques produces a method with strong robustness and fault tolerance. Jiang et al. [91] studied a failure detection method based on the empirical wavelet transform and a one-dimensional CNN. This approach can effectively eliminate the noise components of HPP vibration signals and pressure signals. Tang et al. [92] explored an algorithm combining a CNN with the wavelet transform to realize fault identification in HPPs. A method combining DL and Bayesian optimization was studied to increase the precision of intelligent fault identification in HPPs [93]. Considering the complexity and concealment of fault pattern information, the authors [94] proposed an adaptive CNN based on pressure signals to realize automatic learning and fault pattern identification. A fault diagnosis method combining a deep self-adaptive normalized CNN and a synchronous compression wavelet transform was studied that can effectively increase the precision of HPP failure identification [95]. Zhu et al. [96] explored an approach combining wavelet analysis and an improved AlexNet CNN to achieve failure detection in HPPs. As shown in Figure 8, a method combining improved LeNet-5 and particle swarm optimization (PSO) hyper-parameter optimization was explored. This method improves the size and number of kernels in the standard LeNet-5 model and adds a batch normalization layer to the network framework. The improved LeNet-5 model can automatically adjust the hyperparameters through PSO, including learning rate, batch size, and the number of neurons in the full connection layer to overcome the uncertainty of manually adjusting parameters in the process of establishing the model. The new diagnostic model enhances the precision of HPP intelligent fault identification [97]. Considering that hyperparameters can effectively construct deep models, an adaptive neural network based on vibration signals was explored to diagnose the typical faults in HPPs without subjectivity and preprocessing [98]. The researchers combined an improved CNN and S transform to reduce data distribution differences to identify the multiple-source signals of HPP faults [99]. Based on the standard LeNet, an enhanced CNN model based on PSO was explored to achieve failure detection in HPPs via acoustic signals [100]. The researchers also analyzed the typical faults and wear in the important friction pairs in piston pumps and introduced the Bayesian algorithm for the adaptive optimization of an established deep learning model to overcome the low efficiency and time-consuming nature of traditional manual parameter tuning [101]. Targeting the problem of relying on manual feature extraction when diagnosing cavitation faults, Wei et al. [102] explored a fault recognition approach combining spectral analysis and a CNN. This method utilizes vibration signals to identify different levels of cavitation faults in HPPs. Wang et al. [103] studied an enhanced CNN based on minimum entropy deconvolution to address the difficulty of identifying the failure type in a piston pump due to the complex working environment. This CNN adopts the t-distribution random neighborhood embedding technology to visualize fault features and improve the fault classification ability. A minimum entropy deconvolution method based on a bandpass filter was studied for failure detection in HPPs [104].
4.3.4. Combined with Extreme Learning Machine

The extreme learning machine (ELM) is a classification algorithm based on a single-hidden-layer feedforward neural network. To improve the generalization performance of fault diagnosis methods, some researchers combined data analysis techniques with the ELM. Jiang et al. [105] investigated a recognition approach combining voiceprint features and the ELM for fault identification in HPPs. To address the difficulty of detecting failures in piston pumps, Li et al. [106] proposed a failure detection approach based on an improved ensemble empirical mode decomposition and wavelet kernel ELM. This method improves the recognition precision and speed of fault recognition. Lan et al. [107] utilized multiple-signal processing techniques, such as the wavelet packet transform, the local tangent space algorithm, empirical mode decomposition, and local mean decomposition, as a feature extraction approach for wear faults in HPPs. This method was combined with an SVM for slipper fault failure identification. Owing to the complexity of HPP structures and their impact on fault diagnosis, Zeng et al. [108] combined kernel functions with the ELM for fault identification in HPPs. The researchers successfully improved the diagnostic speed and precision. Li et al. [109] combined the ELM with the local S transform to effectively identify different degrees of shoe wear faults in piston pumps, thereby addressing the difficulty of extracting fault features due to weak fault signals. Aiming to overcome the difficulty of identifying faults due to noise interference, Cheng et al. [110] used multi-scale dispersion entropy and the ELM to diagnose weak faults in piston pumps. This method reflects the variation patterns in fault severity to a higher degree.

4.3.5. Combined with Three or More Algorithms

Currently, fault diagnosis methods that combine three or more algorithms have been adopted by some researchers. Such methods can fully integrate the advantages of different algorithms and achieve better fault diagnoses. Liu et al. [111] utilized the characteristics of the locally linear embedding algorithm to reduce algorithm dimensions and extract important feature information. A method comprising the wavelet transform, singular value decomposition, and locally linear embedding algorithm was proposed to achieve fault identification in submersible HPPs. Since the locally linear embedding algorithm cannot preprocess nonlinear signals, combining it with the wavelet transform and singular value decomposition enhanced its ability to extract significant features by decomposing and preprocessing nonstationary or noisy signals. Wang et al. [112] researched a fault diagnosis method that combines the wavelet packet transform, fuzzy entropy, and the linear local

![Figure 8. Structural diagram of improved LeNet-5 network model [97]. Reprinted with permission from Ref. [97]. Copyright 2021, Elsevier B.V.](image)
tangent space alignment algorithm. This method decomposed high-dimensional features into low-dimensional features with an improved classification performance. The difficulty of feature extraction was solved, and different fault types in HPPs were classified accurately. By integrating the probabilistic neural network with empirical mode decomposition and sensitivity analysis, Du et al. [113] identified the fault severity under different fault modes in piston pumps. This method can diagnose different failure modes and fault degrees in piston pumps with fewer training samples. Tian et al. [114] explored a fault pattern recognition approach based on the wavelet packet transform, singular value decomposition, and an SVM to acquire the transient failure data of piston pumps. The piston wear and swashplate wear were identified accurately and efficiently under small-sample conditions. Zhao et al. [115] aimed to address the nonlinear characteristics of the vibration signals in piston pumps and the issue of mode mixing in empirical mode decomposition. Based on complete ensemble empirical mode decomposition, short-time Fourier transform, time–frequency entropy, and a multi-classification SVM, a fault diagnosis method was proposed. This method was effective in improving feature extraction and failure classification capabilities. Ding et al. [116] focused on the problem of weak feature signals in hydraulic pumps when faults occur. A method combining the empirical wavelet transform, principal component analysis, and the ELM was explored. This method effectively obtained the fault features of HPPs. As shown in Figure 9, Zhu et al. [117] explored a new fault identification algorithm combining the synchrosqueezing wavelet transform, VGG11, and long short-term memory, which effectively identified the common fault categories in HPPs. The synchrosqueezing wavelet transform was employed to transform the state data into two dimensions in terms of time and frequency, and then the depth features of the time-frequency map were obtained. Then, the VGG11 was utilized to perform dimensionality reduction on time-frequency maps through deep feature mining. Moreover, the long short-term memory was used to increase the feature memory ability of the improved algorithm.

![Diagram of VGG-LSTM network](image)

**Figure 9.** Diagnostic flow chart of VGG–LSTM network [117].

### 4.4. Summary of Fault Diagnosis Methods for Hydraulic Piston Pumps

The research results on fault pattern recognition methods for HPPs have been summarized and organized herein, and the characteristics of various diagnostic methods are summarized and compared in Tables 2–4.
Table 2. Division of traditional intelligent fault diagnosis methods.

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>References</th>
<th>Fault Type</th>
<th>Method Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonlinear input observer</td>
<td>[25]</td>
<td>Leakage faults</td>
<td>Dynamic performance and high accuracy</td>
</tr>
<tr>
<td>Dynamic modeling</td>
<td>[26–30]</td>
<td>Sliding wear and swashplate wear</td>
<td>Increased sensitivity of characteristic signals to failure mode degrees</td>
</tr>
<tr>
<td>Kalman filter</td>
<td>[31]</td>
<td>Piston wear, valve plate wear, insufficent inlet pressure, bearing wear, swashplate eccentricity, increased piston, and slide clearance</td>
<td>Insensitivity to noise</td>
</tr>
<tr>
<td>Hierarchical clustering algorithm</td>
<td>[32]</td>
<td>Valve plate wear, insufficient inlet pressure, bearing wear, swashplate eccentricity, increased piston, and slide clearance</td>
<td>High accuracy with simultaneous diagnosis of multiple faults</td>
</tr>
<tr>
<td>Empirical wavelet transform</td>
<td>[33]</td>
<td>Sliding wear</td>
<td>Good interference resistance</td>
</tr>
<tr>
<td>Empirical modal reorganization</td>
<td>[34,35]</td>
<td>Wear, fatigue, corrosion, and deformation</td>
<td>Solves complex working conditions and small sample data problems</td>
</tr>
<tr>
<td>Teager energy operator demodulation</td>
<td>[36,46–48]</td>
<td>Cylinder faults and bearing faults</td>
<td>Good noise immunity and robustness</td>
</tr>
<tr>
<td>Random forest</td>
<td>[37]</td>
<td>Parts wear and loose slippers</td>
<td>Capable of handling high-dimensional data without having to perform feature selection</td>
</tr>
<tr>
<td>Adaptive decision fusion</td>
<td>[38]</td>
<td>Leakage faults</td>
<td>Improved classification accuracy and high precision</td>
</tr>
<tr>
<td>Theory of evidence</td>
<td>[39]</td>
<td>Piston wear, center spring failure, and swashplate wear</td>
<td>High accuracy, fast calculation speed, and high confidence level</td>
</tr>
<tr>
<td>Mathematical morphology</td>
<td>[40]</td>
<td>Sliding wear, loose slippers, and center spring failure</td>
<td>High noise immunity</td>
</tr>
<tr>
<td>Artificial neural networks</td>
<td>[41,51]</td>
<td>Loose slippers, sliding wear, and sliding corrosion</td>
<td>High accuracy</td>
</tr>
<tr>
<td>Improved Autogram</td>
<td>[42,43]</td>
<td>Sliding wear and center spring failure</td>
<td>Strong feature extraction ability and noise suppression ability</td>
</tr>
<tr>
<td>Shape difference filtering</td>
<td>[44]</td>
<td>Sliding wear, loose slippers, and center spring failure</td>
<td>Strong filtering ability and noise suppression ability</td>
</tr>
<tr>
<td>Based on instantaneous speed fluctuation signals</td>
<td>[45]</td>
<td>Valve plate wear</td>
<td>High noise immunity</td>
</tr>
<tr>
<td>Spectral characteristics</td>
<td>[49,50]</td>
<td>Bearing faults and cavitation faults</td>
<td>Prevention of natural cycle pulse interference and strong fault feature extraction capability</td>
</tr>
<tr>
<td>Variational modal decomposition</td>
<td>[52]</td>
<td>Piston wear and cylinder faults</td>
<td>Envelope decomposition of the appropriate frequency band</td>
</tr>
</tbody>
</table>

Table 3. Division of modern intelligent fault diagnosis methods.

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>References</th>
<th>Fault Type</th>
<th>Method Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial alignment algorithm</td>
<td>[53]</td>
<td>Loose slippers and sliding wear</td>
<td>High accuracy</td>
</tr>
<tr>
<td>Twin neural networks</td>
<td>[54]</td>
<td>Sliding wear and valve plate wear</td>
<td>Solves the problem of small sample data</td>
</tr>
<tr>
<td>Deep forest</td>
<td>[55]</td>
<td>Bearing faults</td>
<td>Strong feature extraction capability and high accuracy</td>
</tr>
<tr>
<td>Deep confidence network</td>
<td>[56]</td>
<td>Cylinder faults, valve plate wear, bearing faults, and piston faults</td>
<td>Improved fault classification capability</td>
</tr>
</tbody>
</table>
### Table 3. Cont.

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>References</th>
<th>Fault Type</th>
<th>Method Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum entropy deconvolution</td>
<td>[57]</td>
<td>Bearing faults</td>
<td>Extracts faint periodic pulses and reduces signal preprocessing time</td>
</tr>
<tr>
<td>Stacked self-encoder</td>
<td>[58]</td>
<td>Cylinder faults, valve plate wear, bearing faults, and piston wear</td>
<td>Solves the problem of small sample data and high accuracy</td>
</tr>
<tr>
<td>Sparse self-encoder</td>
<td>[59]</td>
<td>Leakage faults</td>
<td>Improved extraction of high-dimensional features and robustness</td>
</tr>
<tr>
<td>Convolutional neural network</td>
<td>[60–66]</td>
<td>Sliding wear, loose slippers, center spring failure, valve plate wear, and cavitation faults</td>
<td>Powerful adaptive learning capability, fault classification capability, good robustness, generalization capability, and high accuracy</td>
</tr>
</tbody>
</table>

### Table 4. Division of combined intelligent fault diagnosis methods.

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>References</th>
<th>Fault Type</th>
<th>Method Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probabilistic neural network–sensitivity analysis</td>
<td>[68]</td>
<td>Piston wear</td>
<td>High accuracy</td>
</tr>
<tr>
<td>Eigen time scale decomposition method–Softmax regression model</td>
<td>[69]</td>
<td>Loose slippers and valve plate wear</td>
<td>Capable of handling nonsmooth, nonlinear signals, and good robustness</td>
</tr>
<tr>
<td>Modal decomposition combinations</td>
<td>[70,72–74]</td>
<td>Bearing faults, impact faults, swashplate faults, and sliding wear</td>
<td>High signal-to-noise ratio, high precision, and strong feature extraction ability</td>
</tr>
<tr>
<td>Transfer learning–residual network</td>
<td>[71]</td>
<td>Sliding wear, valve plate wear, and piston wear</td>
<td>Adaptive extraction of fault information, high stability, and high generalization capability</td>
</tr>
<tr>
<td>Popular learning–feature selection</td>
<td>[75]</td>
<td>Sliding wear and loose slippers</td>
<td>High accuracy by excluding nonsensitive features in the mixed feature set</td>
</tr>
<tr>
<td>Empirical wavelet transform–variance contribution</td>
<td>[76]</td>
<td>Piston faults</td>
<td>High precision, low computational cost, and high noise suppression capability</td>
</tr>
<tr>
<td>Local mean decomposition–morphological analysis</td>
<td>[77]</td>
<td>Sliding wear, loose slippers, and center spring failure</td>
<td>Good noise immunity and adaptive demodulation</td>
</tr>
<tr>
<td>Fuzzy C-mean clustering algorithm combinations</td>
<td>[78,80]</td>
<td>Sliding wear, loose slippers, center spring failure, and swashplate wear</td>
<td>Accurately reflects fault characteristics, improves diagnostic accuracy, and visualizes fault types</td>
</tr>
<tr>
<td>Artificial immunity—support vector machine</td>
<td>[79]</td>
<td>Loose slippers and valve plate wear</td>
<td>Solves the problem of insufficient training samples and high accuracy</td>
</tr>
<tr>
<td>Weight space meta-representation–modified WaveletKernelNet</td>
<td>[81]</td>
<td>Valve plate wear, cylinder faults, swashplate wear, and rolling wear</td>
<td>Accommodates dynamic changes in fault types and repeatedly updates the diagnostic model</td>
</tr>
<tr>
<td>Entropy theory combinations</td>
<td>[83–90]</td>
<td>Sliding wear, loose slippers, valve plate wear, and bearing fault</td>
<td>Good robustness, strong noise immunity, high accuracy, and strong feature extraction</td>
</tr>
<tr>
<td>Convolutional neural network combinations</td>
<td>[91–104]</td>
<td>Cavitation faults, sliding wear, loose slippers, center spring failure, swashplate wear, and bearing faults</td>
<td>Good robustness, noise immunity, fault tolerance, and high accuracy</td>
</tr>
</tbody>
</table>
Table 4. Cont.

<table>
<thead>
<tr>
<th>Algorithm Type</th>
<th>References</th>
<th>Fault Type</th>
<th>Method Features</th>
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<tr>
<td>Ultimate learning machine combinations</td>
<td>[105–110]</td>
<td>Sliding wear, loose slippers, swashplate wear, valve plate wear, and center spring failure</td>
<td>Strong feature extraction capability, short computation time, and high accuracy</td>
</tr>
<tr>
<td>Wavelet transform–singular value decomposition–locally linear embedding algorithm</td>
<td>[111]</td>
<td>Bearing faults</td>
<td>Strong noise immunity and feature extraction capability</td>
</tr>
<tr>
<td>Wavelet packet transform–fuzzy entropy–linear local tangent space alignment algorithm</td>
<td>[112]</td>
<td>Sliding wear and loose slippers</td>
<td>Good dimensionality reduction and feature extraction capability</td>
</tr>
<tr>
<td>Empirical modal decomposition–sensitivity analysis–probabilistic neural network</td>
<td>[113]</td>
<td>Sliding wear, piston wear, and swashplate wear</td>
<td>Solves the problem of small sample data, high accuracy, and fast calculation speed</td>
</tr>
<tr>
<td>Wavelet packet transform–singular value decomposition–support vector machine</td>
<td>[114]</td>
<td>Piston wear and swashplate wear</td>
<td>Solves the problem of small sample data, and strong generalization ability</td>
</tr>
<tr>
<td>Fully integrated empirical modal decomposition–short-time Fourier transform–time/frequency entropy–multi-class support vector machine</td>
<td>[115]</td>
<td>Piston wear and swashplate wear</td>
<td>Strong feature extraction capability, good robustness, and high accuracy</td>
</tr>
<tr>
<td>Empirical wavelet transform–principal component analysis–extreme learning machine</td>
<td>[116]</td>
<td>Loose slippers and valve plate wear</td>
<td>Fast calculation speed, high generalization ability, and high accuracy</td>
</tr>
<tr>
<td>Synchrosqueezing wavelet transform–VGG11–long short-term memory</td>
<td>[117]</td>
<td>Sliding wear, loose slipper, swashplate wear, valve plate wear, and center spring failure</td>
<td>Self-adaptive feature extraction, blatant timing of fault signals, and high accuracy</td>
</tr>
</tbody>
</table>

5. Challenges and Trends in Fault Diagnosis of Hydraulic Piston Pumps

Fault diagnosis technology for HPPs will be combined with cutting-edge science via the continual improvements in signal acquisition technology and feature extraction methods, as well as the advancements in data analysis and processing techniques. Furthermore, this will promote the greening, precision, efficiency, and intelligence of diagnostic technology:

(1) Integrated intelligent fault diagnosis technology could improve the precision of fault pattern recognition in HPPs. The diagnostic results of traditional or single-fault diagnosis methods are often inaccurate when faced with nonlinear and adaptive feature extraction requirements. However, more comprehensive and intelligent fault diagnosis could be realized by combining multiple fault diagnosis techniques based on knowledge-based, model-based, and data-driven approaches. Integrating advanced data processing techniques with the different nonlinear features exhibited by HPPs in different fault modes could enable feature information in the time–frequency domain to be identified for multiple fault types, and fault classification and recognition could be accomplished rapidly and accurately. This provides ample room for the development of fault diagnosis technology.

(2) Establishing a knowledge-based database would enhance the intelligent reasoning levels of fault diagnosis in HPPs. Data serve as an important foundation and resource for fault pattern recognition research. With the development of artificial intelligence technology, a knowledge-based database could be established by integrating system diagnostic functions with expert knowledge. This approach would allow for
intelligent reasoning mechanisms based on this expert knowledge. Moreover, fault diagnosis would be enabled for HPPs without the need for model construction. Planning and establishing a knowledge-based database would have significant implications for technical innovations in fault diagnosis, revealing fault evolution mechanisms and supporting research work.

(3) Multi-source sensing technology could broaden the entry points of the fault diagnosis methods for HPPs. As a novel technology that is closely related to cutting-edge science, sensing technology could significantly enhance the capability to perceive and acquire multi-source fault information. This would achieve the multi-dimensional, multi-angle, and multi-level maintenance and monitoring of HPPs. With the increasing precision and complexity of HPP structures, intelligent fault diagnosis techniques are increasingly dependent on multi-dimensional and high-quality data. Integrating sensing technology with multiple sources of information could promote the diversification of fault diagnosis methods for HPPs and improve the accuracy of diagnostic results.

(4) Multi-angle and multi-level deep learning algorithms could enhance the intelligence and accuracy of the fault identification methods for HPPs. In addition, deep learning could simulate the learning process of the human brain and construct deep mathematical models. An end-to-end data-driven approach could be formulated to adaptively extract hidden feature information and fit the mapping relationship with the system. This would enrich the data content and improve the fault recognition accuracy. Establishing multi-angle and multi-level deep learning networks could enhance the intelligence and accuracy of fault diagnosis technology for HPPs and accomplish adaptive feature extraction processes and the automatic identification of fault modes in piston pumps.

(5) Establishing a remote fault diagnosis system could expand the application scenarios for HPPs. This system could realize fault diagnosis remotely by relying on intelligent control systems, computer technology, electronic information technology, etc., and combining the fault diagnosis process with data acquisition, feature signal extraction, and analysis. By effectively coordinating the working environment of the pump with the network environment of remote diagnosis, it will be possible to overcome environmental and spatial limitations and remotely achieve real-time perception, dynamic analysis, and failure identification in HPPs. This will expand the application scope of fault recognition.

(6) Incorporating visualization research into fault diagnosis methods could represent the health statuses of HPPs from multiple perspectives (as in digital twin). Visualization transforms data into images using image-processing techniques in an interactive visual manner. Furthermore, this would enable the understanding and interpretation of the intrinsic information of mechanical data. At present, feature extraction data signals and the visualization of fault diagnosis recognition results are used as research approaches. These approaches allow the relationship between fault modes and feature signals to be explored and deeply analyze the expression patterns of fault features in HPPs. Moreover, the health status of a piston pump could be intuitively reflected, and the faults could be accurately and efficiently classified, using these visualization results. This would promote the visualization and accuracy of fault diagnosis results for HPPs.

6. Conclusions

(1) In this review, the principles and types of fault diagnosis methods that have been developed in recent years were introduced and elaborated. Existing fault diagnosis methods were classified as traditional intelligent fault recognition methods, modern intelligent failure detection methods, or combined intelligent failure detection methods. In addition, existing fault recognition methods were divided into three categories: knowledge-based methods, model-based methods, and data-driven methods.
(2) The common types and mechanisms of faults in HPPs were briefly described, and detailed analyses were provided for four typical faults: loose slipper, slipper wear, center spring failure, and valve plate wear.

(3) From the perspectives of traditional intelligent fault recognition approaches, the modern intelligent fault pattern recognition methods, combined intelligent fault diagnosis methods, and recent research achievements in HPP fault diagnosis technology were comprehensively reviewed. The types, methods, and characteristics of the faults that have received attention in the field of fault diagnosis technology for HPPs were summarized.

(4) Based on the current research achievements in failure detection technology for HPPs, the development trends of fault recognition approaches were identified, including the following: combining intelligent fault diagnosis techniques could increase the precision of fault recognition; establishing knowledge-based databases could enhance the intelligent reasoning level of fault diagnosis; new sensing technologies could broaden the entry points for fault diagnosis techniques; multi-angle and multi-level deep learning algorithms could enhance the intelligence and accuracy of fault diagnosis methods; establishing remote fault diagnosis systems could expand the application scenarios for HPPs; and incorporating visualization research into fault diagnosis methods could present the health statuses of HPPs from multiple perspectives.

Achieving intelligent and accurate identification of typical failures in HPPs is crucial for ensuring the efficient, stable, and reliable operation of pumps and the entire machinery. The development, expansion, and application of novel intelligent fault diagnosis methods still require further exploration.

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**Nomenclature**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full name</th>
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<tbody>
<tr>
<td>HPP</td>
<td>Hydraulic piston pump</td>
</tr>
<tr>
<td>SVM</td>
<td>Support vector machine</td>
</tr>
<tr>
<td>RBF</td>
<td>Radial basis function</td>
</tr>
<tr>
<td>DL</td>
<td>Deep learning</td>
</tr>
<tr>
<td>TL</td>
<td>Transfer learning</td>
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<td>RL</td>
<td>Reinforcement learning</td>
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<tr>
<td>CNN</td>
<td>Convolutional neural network</td>
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<tr>
<td>RNN</td>
<td>Recurrent neural network</td>
</tr>
<tr>
<td>DBN</td>
<td>Deep belief network</td>
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<tr>
<td>HHT</td>
<td>Hilbert–Huang transform</td>
</tr>
<tr>
<td>ELM</td>
<td>Extreme learning machine</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle swarm optimization</td>
</tr>
<tr>
<td>AM-FM</td>
<td>Amplitude modulation–frequency modulation</td>
</tr>
</tbody>
</table>
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