

DEEP LEARNING-BASED FAULT DIAGNOSIS AND INTELLIGENT OPERATION OF CENTRIFUGAL PUMPS: MODELS, CHALLENGES, AND PERSPECTIVES

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Abstract: As one of the most critical power devices in industrial systems, the operational status of centrifugal pumps directly affects system safety, reliability, and economic efficiency. To address the limitations of traditional diagnostic methods—such as reliance on manual feature extraction and poor generalization—this paper provides a comprehensive review of recent advances in deep learning-based fault diagnosis and intelligent operation and maintenance (O&M) of centrifugal pumps. It first outlines the theoretical foundations and representative deep learning models, including convolutional neural networks (CNN), recurrent neural networks (RNN/LSTM/GRU), residual networks (ResNet), graph neural networks (GCN), and Transformers, and discusses their applications in cross-condition diagnosis, remaining useful life (RUL) prediction, and intelligent O&M. Furthermore, it summarizes the progress in key enabling technologies such as multi-sensor data fusion, transfer learning, self-supervised and meta-learning, physics-informed feature alignment, and digital twins, which significantly enhance diagnostic accuracy, robustness, and generalization. Studies indicate that deep learning-based approaches outperform traditional methods in automatic feature extraction, domain adaptation, and decision optimization, thus enabling the shift from passive monitoring to proactive maintenance. Nevertheless, challenges remain regarding data scarcity and labeling difficulty, limited model interpretability and generalization, and real-time computational constraints. Future research directions include: developing few-shot and self-supervised learning to alleviate data dependency; integrating physical knowledge with deep learning to improve interpretability and trustworthiness; designing lightweight models suitable for edge deployment; and advancing digital twin-driven lifecycle management and predictive maintenance. This review provides a systematic reference and future outlook for research and industrial applications of intelligent fault diagnosis and maintenance of centrifugal pumps.

Keywords: Deep learning; Centrifugal pump fault diagnosis; Transfer learning; Multi-source data fusion; Intelligent operation and maintenance; Digital twin

1 INTRODUCTION

Centrifugal pumps are critical power equipment widely used across industrial systems, serving as essential components for fluid transportation and energy conversion in sectors such as energy, chemical engineering, manufacturing, aerospace, and petroleum extraction. Their operational status is directly related to the safety, stability, and efficiency of the entire industrial system. However, under complex operating conditions, prolonged continuous service, and the influence of external environmental factors, centrifugal pumps are prone to various failures, including bearing wear, cavitation, and seal degradation. These failures not only reduce operational efficiency but, in severe cases, may lead to unplanned shutdowns or even safety accidents. Therefore, achieving efficient and accurate fault diagnosis and intelligent maintenance of centrifugal pumps is of great theoretical and engineering significance for ensuring the safe and reliable operation of industrial systems.

Traditional fault diagnosis methods for centrifugal pumps primarily rely on expert knowledge, signal processing techniques, and feature analysis methods [1]. Typically, these approaches extract fault features through time-domain, frequency-domain, or time–frequency-domain analysis and employ machine learning algorithms for classification and identification. However, such methods face notable limitations: the feature extraction process depends heavily on manual expertise, the models often lack generalization capability, and the diagnostic accuracy is constrained. Consequently, they fail to meet the increasing demands of modern industry for intelligent and automated systems [2-3]. With the rapid advancement of artificial intelligence, particularly deep learning, data-driven intelligent fault diagnosis methods have become a major research focus [2-4]. Deep learning achieves hierarchical feature learning through multilayer neural networks, enabling the automatic extraction of high-dimensional representations directly from raw signals. This end-to-end mapping from data to fault types significantly enhances the automation level and accuracy of fault diagnosis [5-9].

In recent years, deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) and their variants, residual networks (ResNets), graph neural networks (GNNs), and Transformer models have been widely applied to centrifugal pump fault diagnosis. These models demonstrate remarkable performance in feature extraction and classification, showing great potential in tasks such as cross-condition diagnosis, remaining useful life (RUL) prediction, and intelligent maintenance. Furthermore, the integration of multi-source information fusion and

transfer learning technologies has further improved the flexibility and comprehensiveness of deep learning applications in centrifugal pump fault diagnosis, offering new perspectives for addressing practical challenges such as data scarcity and variable operating conditions.

In the field of intelligent operation and maintenance (O&M), the application of deep reinforcement learning and adaptive optimization algorithms is driving a paradigm shift from traditional “passive monitoring” to “active decision-making.” By integrating real-time monitoring, condition assessment, and decision optimization, intelligent O&M systems can effectively extend equipment lifespan, reduce energy consumption, and improve operational efficiency—thereby providing crucial support for the intelligent management of industrial equipment [10].

In this context, this paper systematically reviews the fundamental theories and key methodologies of deep learning in centrifugal pump fault diagnosis. It further summarizes the fault characteristics and diagnostic strategies of various centrifugal pump types and explores recent advances in multimodal signal processing, transfer learning, and intelligent O&M. The objective is to provide a comprehensive theoretical reference and technical outlook for future research in this field.

2 DEEP LEARNING FOUNDATIONS FOR CENTRIFUGAL PUMP FAULT DIAGNOSIS

2.1 Convolutional Neural Networks and Variants

With its hierarchical architecture, deep learning technology is capable of simulating the information-processing mechanisms of the human brain, enabling automatic learning and extraction of high-level features from raw data. This capability has demonstrated significant advantages in the field of centrifugal pump fault diagnosis. Compared with traditional diagnostic methods, deep learning eliminates the need for complex manual signal processing and feature engineering. Through an end-to-end learning approach, it directly establishes complex nonlinear mappings between monitoring data and fault categories [11]. This automated feature learning ability substantially enhances both the accuracy and robustness of fault diagnosis [12].

Among various deep learning models, convolutional neural networks (CNNs) are among the most widely applied architectures in centrifugal pump fault diagnosis. The core strengths of CNNs—namely local connectivity, weight sharing, and subsampling—enable them to efficiently capture spatial correlations within signals. In centrifugal pump diagnostics, CNNs are frequently used to process time–frequency representations of vibration or acoustic signals for recognition and classification tasks [13]. Studies have shown that CNNs can simultaneously perform feature extraction and classification when dealing with high-dimensional mechanical monitoring data, thereby improving diagnostic efficiency. To further optimize model performance, researchers have introduced adaptive learning rate strategies that dynamically adjust network parameters, leading to enhanced fault classification accuracy [22].

As an advanced evolution of CNNs, the residual network (ResNet) effectively addresses the problems of gradient vanishing and model degradation encountered in deep network training through the introduction of residual learning mechanisms. ResNet has demonstrated superior performance in centrifugal pump fault diagnosis. Zheng et al. proposed a two-stage multi-channel deep learning model based on Robust-ResNet, which incorporates a step-size factor to improve model robustness and adaptability for mechanical fault detection tasks. The enhanced model achieved accuracy rates of 99.96% and 99.53% in fault detection and remaining useful life (RUL) prediction tasks, respectively—significantly outperforming other state-of-the-art methods [14]. Through its deep network architecture, ResNet is capable of learning more complex fault feature representations, offering new insights for the in-depth application of deep learning in centrifugal pump fault diagnosis [15].

2.2 Recurrent Neural Networks and Variants

Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), possess distinctive advantages in time-series data analysis, making them particularly suitable for temporal signal modeling in centrifugal pump fault diagnosis. These models can effectively capture temporal dependencies within signals, enabling precise modeling of fault evolution processes. For instance, LSTM and GRU networks have demonstrated higher accuracy than traditional RNNs in Remaining Useful Life (RUL) prediction tasks, allowing for more reliable estimation of equipment lifespan.

Furthermore, researchers have developed hybrid deep learning architectures that integrate the strengths of Convolutional Neural Networks (CNNs) and LSTMs. In such models, CNNs are employed to extract spatial features, while LSTMs are used to capture temporal characteristics. This synergistic combination significantly enhances the overall performance of centrifugal pump fault diagnosis and prognostics, improving both detection precision and predictive capability [16–17].

2.3 Transformers and Self-Attention Mechanisms

The Transformer model, which initially achieved remarkable success in the field of natural language processing (NLP), has in recent years been increasingly applied to centrifugal pump fault diagnosis. Its core innovation lies in the self-attention mechanism, which enables the dynamic capture of long-range dependencies within sequential data and demonstrates clear advantages when processing complex and non-stationary signals. Unlike Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the Transformer does not rely on fixed receptive fields or

recursive structures, allowing it to process sequence data in parallel and thereby greatly improving computational efficiency.

In centrifugal pump fault diagnosis, the Transformer effectively captures global dependencies within monitoring signals and exhibits outstanding performance under varying operating conditions and rotational speeds. When combined with physics-informed feature alignment methods, the Transformer can better adapt to distributional shifts across different operating regimes, thereby enhancing the model's generalization capability and robustness in real-world diagnostic applications [18].

2.4 Hybrid Deep Learning Models

In recent years, hybrid deep learning models have emerged as an effective strategy for enhancing the performance of centrifugal pump fault diagnosis. Such models integrate different deep learning architectures—such as Convolutional Neural Networks (CNNs) combined with Long Short-Term Memory (LSTM) networks or Transformers—to achieve complementary advantages and improve diagnostic accuracy. For instance, in centrifugal pump fault diagnosis tasks, CNNs are capable of efficiently extracting spatial features from time–frequency representations, while LSTM networks or Transformers focus on capturing the temporal dependencies of the signals. Through this synergistic design, hybrid models provide more robust diagnostic and prognostic capabilities under multi-condition and multimodal environments [19]. Notably, the careful design of hybrid architectures also strengthens model generalization, enabling greater adaptability in complex and dynamic industrial scenarios [20], see Table 1.

Table 1 Comparison of Major Deep Learning Models for Centrifugal Pump Fault Diagnosis

Model Type	Core Features	Applicable Data Types	Typical Applications	Advantages	Limitations
Convolutional Neural Network (CNN)	Local connectivity, weight sharing, spatial feature extraction	Time–frequency images, 2D signals	Fault type classification, automatic feature extraction	Automated feature learning; robust to translational variations	Difficult to directly process long sequential time-series data
Recurrent Neural Network (RNN)	Memory capability, captures temporal dependencies	Time-series data	RUL prediction, dynamic process modeling	Effective for sequential data; models dynamic processes	Susceptible to vanishing/exploding gradients; high training complexity
Transformer	Self-attention mechanism, captures long-range dependencies	Time-series, sequential data	Cross-condition diagnosis, long-sequence signal processing	High parallel computing efficiency; strong global dependency modeling	High computational resource consumption; large data requirements
Residual Network (ResNet)	Residual blocks, mitigates network degradation	Deep network structures, images/signals	Complex fault pattern recognition, deep feature learning	Enables very deep networks; alleviates gradient vanishing	Relatively large number of model parameters
Hybrid Models	Combines strengths of multiple architectures	Multimodal, spatiotemporal data	Comprehensive fault diagnosis and prediction	Simultaneously extracts spatial and temporal features; improved performance	Complex architecture; challenging training and hyperparameter tuning

In summary, the theoretical framework of deep learning–based centrifugal pump fault diagnosis has evolved from single-model approaches toward multi-architecture integration, exhibiting both contrasting and complementary characteristics, as illustrated in Table 1. CNNs excel at extracting spatial features and efficiently identifying signal structures in the time–frequency domain; Recurrent Neural Networks (RNNs), including LSTMs and Gated Recurrent Units (GRUs), emphasize temporal sequence modeling and effectively capture the dynamic evolution of faults; Transformers, empowered by self-attention mechanisms, overcome the limitations of RNNs in long-sequence modeling, offering stronger capabilities in global dependency representation and parallel processing. Hybrid models, through the collaborative fusion of CNNs, LSTMs, and Transformers, enable complementary extraction of spatial and temporal features, thereby significantly improving robustness and generalization across varying operating conditions and multimodal scenarios.

Overall, the development trend of deep learning in centrifugal pump fault diagnosis is shifting from single-structure feature learning toward multi-model collaborative intelligence [17] [19]. This transition provides a more comprehensive, efficient, and adaptive solution for fault identification and prognostics in centrifugal pump systems [21].

3 KEY TECHNICAL APPROACHES FOR CENTRIFUGAL PUMP FAULT DIAGNOSIS

3.1 Advanced Signal Preprocessing and Feature Extraction Methods

Time–frequency analysis methods serve as essential techniques in signal processing and feature extraction, playing a crucial role in centrifugal pump fault diagnosis. These methods can effectively capture time-varying characteristics in

non-stationary signals by transforming one-dimensional time-domain data into two-dimensional time–frequency representations. This transformation provides deep learning models with richer feature information and significantly enhances diagnostic accuracy.

Among various time–frequency analysis techniques, the Continuous Wavelet Transform (CWT) is one of the most widely applied in centrifugal pump fault diagnosis. By employing scalable mother wavelet functions for multi-resolution analysis, CWT simultaneously provides localized information in both the time and frequency domains. In fault diagnosis, CWT is commonly used to convert raw vibration signals into time–frequency representations for subsequent image-based feature extraction [22]. This approach effectively preserves transient and periodic characteristics of the signal, making it particularly suitable for identifying complex mechanical fault patterns. Studies have demonstrated that converting vibration, pressure, and acoustic signals into two-dimensional time–frequency images and feeding them into improved deep Convolutional Neural Networks (CNNs) enables accurate identification of multiple fault types in centrifugal pumps [23]. Moreover, CWT can be combined with methods such as the Stockwell Transform (ST) to generate detailed time–frequency scale maps, where Sobel filtering enhances feature visibility and provides higher-quality inputs for downstream deep learning models [22].

The Hilbert–Huang Transform (HHT) is another powerful time–frequency analysis technique that has shown excellent performance in centrifugal pump fault diagnosis. Based on Empirical Mode Decomposition (EMD) and Hilbert spectral analysis, HHT adaptively decomposes nonlinear and non-stationary signals, making it particularly suitable for complex mechanical vibration data. In monoblock centrifugal pump fault detection, HHT has been employed to convert vibration signals into HHT-based images, which are then classified using pre-trained deep networks with high accuracy. Compared with the traditional Fourier Transform, HHT provides superior capability in capturing localized signal characteristics, offering unique advantages for detecting early-stage faults and weak signals. In drilling pump diagnostics, HHT has been applied to extract time–frequency features from denoised strain signals, which are then fed into parallel Deep Neural Networks (DNNs) and fused with other features to improve diagnostic precision [24].

Essentially, time–frequency analysis methods perform a secondary level of signal feature representation by transforming one-dimensional signals into two-dimensional time–frequency images. Taking CWT as an example, it computes wavelet coefficients across different scales and positions to generate an energy distribution map on the time–frequency plane, where the horizontal axis represents time, the vertical axis denotes frequency, and color or grayscale encodes energy intensity. This two-dimensional representation not only preserves temporal characteristics of the original signal but also reveals its frequency components and their temporal evolution. Similarly, HHT decomposes the signal into a series of Intrinsic Mode Functions (IMFs) via EMD and then performs Hilbert Transform on each IMF to obtain instantaneous frequency and amplitude, ultimately constructing a Hilbert spectrum. These time–frequency images provide deep learning models with richer and more intuitive feature representations, enabling more effective learning and discrimination between subtle fault patterns [24].

Case studies have shown that the integration of time–frequency analysis with deep learning significantly improves fault diagnosis accuracy in centrifugal pumps. For example, one study proposed a dual-scale image approach that combines convolutional autoencoders with Artificial Neural Networks (ANNs), achieving accuracies of 100%, 99.2%, and 98.8% across three datasets—substantially outperforming traditional methods [4]. Similarly, applying HHT to transform vibration signals into images and incorporating transfer learning techniques has successfully enabled accurate diagnosis of monoblock centrifugal pump faults, providing new insights for equipment condition monitoring and maintenance strategies.

In centrifugal pump fault diagnosis, feature selection and dimensionality reduction play a pivotal role in enhancing both diagnostic efficiency and accuracy. With the rapid advancement of sensor technologies and the proliferation of monitoring data, high-dimensional features often contain redundant information. Thus, extracting the most effective subset of features has become an important research focus.

Principal Component Analysis (PCA), as a classical dimensionality reduction technique, is widely used in centrifugal pump fault diagnosis. PCA performs linear transformation to convert original data into a set of uncorrelated representations, effectively extracting dominant feature components. It is often employed as an initial dimensionality reduction tool prior to deep learning model training. For instance, in the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm, PCA is first used to reduce high-dimensional features to a lower dimension before nonlinear mapping and visualization.

t-SNE, a nonlinear dimensionality reduction technique, is particularly effective for visualizing high-dimensional data. Unlike PCA, t-SNE preserves local structures within the data, ensuring that similar samples remain close in the low-dimensional space. In centrifugal pump fault diagnosis, t-SNE is widely used to visualize the feature distributions learned at different layers of deep neural networks, thereby helping to reveal the internal learning mechanisms of the models. Studies have shown that as network depth increases, features progressively evolve from mixed states to well-separated clusters, vividly illustrating the CNN's ability to automatically extract and optimize features.

Convolutional Autoencoders (CAEs) also serve as important tools for feature selection and dimensionality reduction in centrifugal pump fault diagnosis. One approach employs dual CAEs to process different types of time–frequency images, providing comprehensive and discriminative feature representations for each input modality. Through the encoder–decoder architecture, autoencoders learn the most efficient data representations while effectively removing noise and redundancy.

Feature selection and dimensionality reduction techniques significantly enhance both the efficiency and accuracy of centrifugal pump fault diagnosis. By eliminating redundant information and focusing on the most discriminative

features, these techniques reduce computational costs and improve model generalization under varying operating conditions. Experimental results indicate that adopting appropriate feature selection and dimensionality reduction strategies can substantially improve diagnostic accuracy, with some approaches achieving near-perfect performance on specific datasets [4]. Looking forward, as deep learning technologies continue to advance, feature selection and dimensionality reduction will remain key areas of innovation, offering more efficient and accurate solutions for centrifugal pump fault diagnosis.

3.2 Diagnostic Enhancement via Multi-Source Data Fusion

In centrifugal pump fault diagnosis, multi-sensor data fusion techniques have been demonstrated to significantly enhance diagnostic accuracy and reliability by integrating information from diverse sensor types. Fault-related information generated during pump operation is often distributed across multiple physical signals, and single sensors are typically only capable of capturing local features, making it difficult to comprehensively reflect the operational state of the equipment. Multi-sensor data fusion effectively consolidates signals from vibration, pressure, acoustic, and current sensors, leveraging the complementary characteristics of different sensor modalities to achieve a more complete representation of fault features.

Commonly employed sensors in centrifugal pump diagnostics include accelerometers, pressure sensors, acoustic sensors, and current sensors. Accelerometers effectively capture vibration signals, exhibiting high sensitivity to mechanical faults such as bearing damage and rotor imbalance. Pressure sensors monitor variations in hydraulic systems or fluid pipelines, offering good detectability for blockages and leaks. Acoustic sensors capture sound signals generated during operation, providing unique advantages for identifying friction, cavitation, and other acoustic-related faults. Current sensors reflect variations in motor load, indirectly indicating pump operational conditions [25]. The distinct physical characteristics and complementary information provided by these sensors form the foundation for multi-source data fusion.

Multimodal feature fusion constitutes a core technique in multi-sensor data integration, aiming to combine features from different sensors or feature extraction methods into more discriminative representations. Studies have shown that fusing graphical features from indicator diagrams with Fourier descriptor features can substantially improve feature robustness. This approach first extracts features from single-modal inputs using two separate backbone networks, then employs an interactive fusion module to jointly learn from both indicator diagram and Fourier descriptor information. The fused features are subsequently used for classification, achieving an accuracy of 97.24%, which is significantly higher than using only graphical features (82.33%) or only Fourier descriptor features (94.22%).

Weighted fusion is another effective strategy for multi-sensor data integration. By assigning appropriate weights to different sensor signals, it allows for dynamic adjustment and optimization of the information. For axial piston centrifugal pumps under varying operating conditions, researchers have designed a multi-signal fusion module that dynamically allocates weights to vibration and acoustic signals, enhancing the method's adaptability [26]. The module embeds a residual network (ResNet) within a shared feature generation framework to extract rich representations and achieved an average accuracy of 98.5% across nine transfer scenarios, demonstrating excellent cross-domain fault detection performance. Compared with single-sensor signals, weighted fusion provides richer fault information and reduces the stochastic variability of diagnostic outcomes.

A representative application of multi-sensor data fusion is the diagnosis of inlet pipeline blockage in centrifugal pumps. Research indicates that combining accelerometer, pressure, and motor current signals significantly improves the accuracy of blockage level identification. Experiments show that diagnostic models using multi-sensor combinations can achieve near-100% accuracy, far exceeding single-sensor approaches. Notably, the combination of accelerometers and current sensors achieves very high precision across all blockage levels. The study also indicates that increasing the number of sensors further enhances classification accuracy; for instance, using two accelerometers and one pressure sensor outperforms a configuration using only two accelerometers, highlighting the importance of multi-source data collection in centrifugal pump diagnostics.

For drilling pumps operating under variable-speed conditions, an innovative method combining physics-driven feature alignment with dynamic distribution adaptation has been proposed. This approach aligns signal amplitude, angular sampling frequency, and pulse phase, effectively reducing discrepancies between samples collected under different rotational speeds. Furthermore, Dynamic Distribution Adaptation (DDA) dynamically adjusts marginal and conditional distributions during domain adaptation, improving cross-domain feature matching. Experimental results demonstrate that this method outperforms existing state-of-the-art approaches in fault diagnosis under variable-speed conditions [27].

Overall, multi-sensor data fusion offers significant advantages in enhancing the accuracy and robustness of centrifugal pump fault diagnosis. By integrating data from diverse sensors, it provides a more comprehensive depiction of fault information, compensating for the limitations of individual sensors. Additionally, multi-sensor fusion enhances model adaptability to environmental variations and operational fluctuations, improving generalization performance. It also reduces the impact of noise and interference, increasing the reliability of fault feature extraction. By employing appropriate fusion strategies and weight allocation, the complementary strengths of different sensors can be fully exploited, achieving a synergistic "1+1>2" effect and significantly improving diagnostic accuracy. In summary, multi-sensor data fusion provides powerful technical support for intelligent centrifugal pump fault diagnosis and is a key approach for enhancing equipment operational reliability and safety.

3.3 Transfer Learning and Domain Adaptation for Real-World Operating Conditions

In centrifugal pump fault diagnosis, variations in operating conditions—such as changes in rotational speed, load fluctuations, and temperature or pressure variations—often lead to significant differences in the data distributions collected by sensors. Such variations can substantially degrade the performance of conventional deep learning models when applied across different operating conditions. The distributional differences induced by changing conditions are primarily reflected in the signal features; for example, vibration signal amplitude, frequency, and phase characteristics vary significantly at different rotational speeds, making models trained under one condition difficult to directly apply to new conditions.

To address the problem of cross-condition fault diagnosis, various transfer learning-based approaches have been proposed, with domain adaptation and adversarial training being two primary strategies. Domain adaptation methods improve model generalization by reducing the distribution discrepancy between the source domain (existing conditions) and the target domain (new conditions). Physics-driven feature alignment is an effective domain adaptation strategy that leverages the physical properties of the equipment to align signal features, such as amplitude, angular sampling frequency, and pulse phase, thereby reducing physical distribution differences across operating conditions. Dynamic distribution adaptation (DDA) further improves domain adaptation by dynamically adjusting the weights of marginal and conditional distributions, avoiding over-reliance on a single distribution and extracting more robust domain-invariant features [28].

Adversarial training constitutes another important transfer learning strategy for cross-condition diagnosis. Typically, adversarial-based transfer learning frameworks comprise a feature extractor, a classifier, and a domain discriminator. The domain discriminator's task is to distinguish whether features originate from the source or target domain, while the feature extractor aims to generate features that "fool" the discriminator, thereby learning domain-invariant representations. By combining transfer learning with residual networks (ResNets), researchers have proposed multi-signal fusion adversarial models that dynamically assign weights to vibration and acoustic signals, enhancing model adaptability across operating conditions. Experimental results indicate that this approach achieves an average accuracy of 98.5% across nine transfer scenarios for axial piston centrifugal pumps, demonstrating excellent cross-domain fault detection performance.

Beyond these methods, additional transfer learning strategies have been explored to improve cross-condition adaptability. Frequency-aware networks, which employ frequency-sensitive convolutional architectures, simultaneously consider time-domain and frequency-domain features, overcoming the limitations of conventional convolution operations under variable conditions. Self-supervised learning approaches, particularly those based on CutMix, have also been applied to cross-condition fault diagnosis, effectively enhancing model robustness and generalization under varying conditions and equipment variations. The overarching goal of these methods is to leverage knowledge and models from existing conditions to rapidly construct high-performance diagnostic models for new conditions, reducing reliance on large volumes of labeled data.

Feature representation learning is a critical component in cross-condition fault diagnosis. Studies indicate that appropriate signal processing and feature extraction methods can substantially enhance model adaptability to condition changes. For example, Continuous Wavelet Transform (CWT) can convert one-dimensional time-domain signals into two-dimensional time–frequency representations, better capturing the time–frequency characteristics of the signals and improving feature extraction performance under varying conditions. Furthermore, attention mechanisms can enable models to automatically focus on domain-invariant, fault-relevant features while filtering out condition-specific noise, further improving cross-condition diagnostic performance, see Table 2.

Table 2 Summary of Transfer Learning and Domain Adaptation Methods for Practical Operating Conditions

Method Category	Core Idea	Key Techniques	Primary Function
Domain Adaptation	Reduce the data distribution discrepancy between source and target domains	Physics-driven feature alignment, Dynamic Distribution Adaptation (DDA)	Align signal features under different operating conditions to improve model generalization
Adversarial Training	Learn domain-invariant features	Domain discriminator, Gradient Reversal Layer	Ensure extracted features are unaffected by changes in operating conditions, enhancing robustness
Self-Supervised Learning	Learn general representations from unlabeled data	CutMix-based pretraining, Contrastive Learning	Reduce dependence on labeled data and learn transferable, robust features
Frequency-Enhanced Network	Perform feature alignment and enhancement in the frequency domain	Frequency-aware convolutional architecture	Overcome the limitations of traditional convolution in extracting frequency-domain features and improve cross-condition performance

Extensive experimental studies have validated the effectiveness of transfer learning for cross-condition centrifugal pump fault diagnosis. For instance, under variable-speed conditions in three-cylinder drilling pumps, methods combining physics-driven feature alignment with dynamic distribution adaptation significantly outperformed traditional deep learning and other transfer learning approaches. These results confirm that transfer learning methods can

effectively enhance model generalization and adaptability.

Despite the significant progress achieved, several challenges remain. First, the design of more efficient domain adaptation strategies to handle complex distributional shifts under varying operating conditions requires further research. Second, incorporating domain knowledge to guide the transfer learning process for improved model interpretability and reliability remains an important direction. Finally, achieving effective cross-condition transfer under few-shot or zero-shot scenarios represents a core challenge for future research. Overall, transfer learning provides an effective pathway for addressing cross-condition fault diagnosis in centrifugal pump systems. By leveraging domain adaptation, adversarial training, and related techniques, it enables rapid construction of high-performance diagnostic models suitable for new operating conditions, reduces dependency on large labeled datasets, and substantially enhances model generalization and adaptability. As research continues, transfer learning is expected to play an increasingly critical role in intelligent centrifugal pump fault diagnosis.

4 FROM DIAGNOSIS TO PROGNOSIS: REMAINING USEFUL LIFE ESTIMATION AND INTELLIGENT MAINTENANCE OF CENTRIFUGAL PUMPS

4.1 Remaining Useful Life Prediction Techniques

In recent years, significant progress has been made in deep learning-based remaining useful life (RUL) prediction for centrifugal pumps, with the CNN-CBAM-Transformer parallel channel method representing a state-of-the-art approach. This method employs a dual-channel parallel architecture to extract degradation-related features from both time-domain and time-frequency-domain signals, thereby significantly improving prediction accuracy.

During signal preprocessing, the raw strain signals are first denoised using a wavelet thresholding algorithm. Specifically, a sym10 wavelet is selected for three-level wavelet decomposition, and the wavelet coefficients are estimated using a soft-threshold function before reconstructing the signal, effectively removing noise. The denoised signal is then split into two streams for the extraction of time-domain and time-frequency-domain features.

For time-domain feature extraction, twelve commonly used features—including standard deviation, root mean square, peak value, maximum value, and kurtosis—are extracted from the denoised strain signal. These features are serialized with a time-series step length of 10 to address input requirements for the Transformer model in RUL prediction. Time-domain features capture the direct variations during pump operation and serve as important indicators for assessing equipment degradation.

In the time-frequency domain, Hilbert-Huang Transform (HHT) is applied to the denoised signal. Notably, Ensemble Empirical Mode Decomposition (EEMD) replaces conventional EMD to better handle nonlinear and non-stationary signals. Time-frequency features reveal the temporal evolution of energy distribution across frequencies, which is critical for detecting early signs of centrifugal pump degradation.

Following feature extraction, the proposed CA-Transformer model employs a parallel structure to process time-domain and time-frequency features independently. One channel utilizes a CNN-CBAM architecture, while the other leverages a Transformer. This parallel design effectively mitigates information interference and enhances overall model performance.

The CNN-CBAM channel primarily extracts spatial features. In conventional CNNs, all features are often treated equally, which may lead to the inclusion of redundant or irrelevant features. To address this, a convolutional block attention module (CBAM) is incorporated to weight deep features according to their importance, enabling the model to focus on key degradation-related characteristics [29].

In contrast, the Transformer channel is dedicated to temporal feature extraction. Traditional RNNs and LSTMs perform poorly on long sequences and cannot process time series in parallel, increasing computational complexity. The Transformer, leveraging a self-attention mechanism, independently captures both long-term and short-term dependencies in sequence data, efficiently extracting relevant temporal features regardless of the distance between data points.

The Transformer model consists of four main components: positional encoding, encoder, decoder, and fully connected layers. For RUL prediction, only positional encoding and the encoder are required. Positional encoding captures intrinsic sequential information, while the multi-head attention mechanism extracts temporal dependencies [30].

After feature extraction and sequence modeling, the deep features independently learned by the two channels are fused through a merging layer and passed to fully connected layers, where the mean squared error (MSE) is used to evaluate discrepancies between predicted and actual RUL values. Model training is optimized using backpropagation combined with the Adam optimizer.

During training, RUL percentages are used as regression labels. For example, if a drilling pump has a total lifespan of 240,000 seconds and has operated for 192,000 seconds, its normalized RUL is 0.24. This normalization improves prediction precision.

The method has demonstrated excellent performance in practice. Validation using operational data from four drilling pumps shows that this approach outperforms several state-of-the-art methods, providing reliable support for safe pump operation and cost reduction.

For pumps operating under different conditions, transfer learning-based improvements have also been proposed. Frequency standardization via resampling, phase identification using short-term autocorrelation, and segmentation into uniform-phase intervals effectively reduce distribution differences between source and target domains, addressing the

generalization limitations of single models across multiple operating conditions.

In internal gear pumps, a two-stage multi-channel method based on Robust-ResNet has been proposed for RUL prediction. This method improves prediction performance by integrating pressure pulsation and vibration signals. The first stage identifies the pump's fault type, while the second stage predicts RUL, offering a novel framework for health assessment in complex systems.

Furthermore, combining signal demodulation with deep learning has yielded promising results in centrifugal pump monitoring. By extracting characteristic frequencies of modulation components and inputting the preprocessed data into an integrated MBConv-based deep learning model, cavitation state recognition rates of 89.44% have been achieved [31]. This approach provides a new pathway for early fault detection and RUL prediction.

In summary, deep learning-based RUL prediction methods for centrifugal pumps leverage multiple signal processing techniques and neural network models to effectively extract key degradation-related features from both time-domain and time-frequency-domain signals. The CNN-CBAM-Transformer parallel channel method, with its dual-channel architecture, significantly enhances prediction accuracy and represents the forefront of technological development in this field, offering critical support for intelligent pump maintenance and operational decision-making.

4.2 Intelligent Maintenance Decision-Making and Optimization

In the field of intelligent operation and maintenance (O&M) and optimization decision-making for centrifugal pump systems, deep reinforcement learning (DRL) has demonstrated significant potential. Traditional O&M approaches often rely on fixed rules and human expertise, which are insufficient to cope with complex and dynamic operating conditions. In contrast, DRL-based intelligent O&M systems can autonomously learn optimal strategies through environment interaction and trial-and-error learning, enabling adaptive control and optimization of centrifugal pump operations.

The core advantage of DRL in intelligent O&M lies in its ability to construct self-optimizing control systems. These systems interact continuously with the pump operating environment, learning the mapping between state-action pairs and long-term rewards to gradually develop efficient decision-making policies.

The development of an intelligent O&M system typically involves several key steps. First, the state space, action space, and reward function must be defined to form a complete reinforcement learning framework. The state space should include operational parameters of the pump (e.g., pressure, flow rate, temperature, vibration), historical states, and environmental factors. The action space encompasses potential maintenance operations (e.g., start/stop control, parameter adjustments, maintenance scheduling). The reward function should integrate multiple objectives, such as efficiency improvement, energy consumption reduction, and extended equipment lifespan. A carefully designed reward mechanism enables the system to balance short-term gains with long-term benefits, thereby learning optimal operational strategies.

From a model architecture perspective, deep neural networks are widely used for value function approximation and policy optimization in DRL. Studies have shown that adaptive convolutional neural networks combined with Bayesian optimization (CNN-BO) can effectively handle complex pump operating conditions. By autonomously optimizing network hyperparameters, CNN-BO significantly enhances fault diagnosis accuracy and robustness. Similarly, semi-supervised graph learning models leverage large amounts of unlabeled data for pretraining and fine-tune on limited labeled samples, reducing dependence on annotated data while providing higher interpretability, which is crucial for engineering O&M decisions [32].

The trial-and-error learning process of intelligent O&M systems typically integrates offline training with online optimization. In the offline phase, the system is pretrained on historical operational data to learn basic maintenance patterns. In the online phase, real-time states guide strategy adjustments, with experience replay mechanisms continually refining the decision network. For example, in submersible pump performance prediction, researchers successfully captured the nonlinear relationships between input parameters—such as flow rate, viscosity, and gas-liquid ratio—and pump output performance (e.g., pressure differential) using machine learning, enabling accurate performance predictions under complex conditions [33-34].

Application of intelligent O&M systems brings substantial economic benefits and safety improvements. In terms of efficiency, the system dynamically adjusts operational parameters in real time, ensuring pumps operate within optimal efficiency ranges. In cost reduction, predictive maintenance and precise control minimize unnecessary energy consumption and maintenance expenses. Regarding safety, the system can proactively identify potential faults and implement preventive measures, effectively preventing severe equipment damage and production interruptions. Studies indicate that deep learning-based fault diagnosis and performance optimization methods, when applied to single centrifugal pumps, significantly reduce fault handling time and resource consumption through automated detection and diagnostic workflows.

Future intelligent O&M systems are expected to evolve toward greater autonomy, collaboration, and interpretability. Autonomy refers to the system's capability to independently complete monitoring, diagnosis, and decision-making. Collaboration involves information sharing and coordinated strategies among multiple pumps, achieving system-level optimization. Interpretability enhances operator trust and understanding of intelligent decisions, ensuring reliability in critical applications. With continued advancements in DRL, intelligent O&M and optimization decision-making for pump systems are poised to achieve broader and more impactful applications.

5 CHALLENGES AND LIMITATIONS IN CURRENT RESEARCH

5.1 Data-Related Challenges

In the field of industrial centrifugal pump fault diagnosis, deep learning (DL) methods have been increasingly applied; however, they commonly face significant challenges related to data dependency and annotation difficulty. Traditional DL models typically require large volumes of labeled data to achieve accurate fault identification and classification. In practical industrial settings, obtaining sufficient fault samples is both challenging and costly. This is especially true for critical components such as centrifugal pumps, where faults are often hidden or sudden, making sample acquisition more complex. Such data scarcity severely limits the practical application of DL models in real-world industrial environments.

Several factors contribute to the difficulty of obtaining labeled data. First, the enclosed structure of centrifugal pumps and the unpredictability of faults make direct observation of fault features challenging, hindering the acquisition of high-quality labeled samples. Second, in real production environments, fault samples are often unevenly distributed, with some fault types represented by very few instances, making it difficult to meet the balanced data requirements of traditional machine learning. For example, in a well field of the Daqing Oilfield, 5,053 sets of fault diagnosis data for pumping units were collected; after data cleaning, only 3,502 valid samples remained, with significant differences in the number of samples across fault types. Additionally, the accumulation of fault data generally requires a long time, further exacerbating the difficulty of data acquisition.

Another critical challenge arises from data distribution differences under variable operating conditions. In practice, centrifugal pumps often operate under different working conditions, such as load fluctuations or changes in fluid properties, leading to substantial distribution shifts in the collected data. These shifts make it difficult to directly apply models trained under specific conditions to other conditions, often necessitating the collection of new labeled data for each operating scenario, which substantially increases the data demand. Studies indicate that under variable operating conditions, distribution differences between training and test data can significantly degrade the performance of existing fault diagnosis models, particularly when only limited samples are available.

The inherent data sensitivity of DL models further exacerbates this issue. Although deep neural networks, such as feedforward networks, can effectively capture complex nonlinear relationships, their performance is highly sensitive to training data volume and parameter settings. Even minor parameter variations can lead to substantial fluctuations in model performance, necessitating more labeled data to ensure stability and generalization. Furthermore, DL models typically require large datasets to avoid overfitting, which, if unaddressed, may result in poor generalization and potential misdiagnosis, posing safety risks [44].

To address these challenges, various strategies have been proposed. Semi-supervised learning leverages a large amount of unlabeled data along with limited labeled samples, effectively mitigating the scarcity of labeled data. For instance, data augmentation-based consistency regularization in semi-supervised learning generates new samples consistent with the original feature distribution, expanding the labeled feature space across different operating conditions. Transfer learning strategies transfer rich labeled knowledge from a source domain to a target domain, alleviating insufficient labeled data in the latter. Few-shot learning and meta-learning techniques aim to achieve effective fault diagnosis with minimal labeled samples, showing significant potential in industrial scenarios where data are extremely limited.

These approaches offer promising solutions to the challenges of data dependency and annotation in centrifugal pump fault diagnosis. Nevertheless, practical industrial implementation still faces many obstacles. For example, improving the robustness of few-shot learning and optimizing the generalization capability of transfer learning models under dynamic operating conditions remain open research questions. Therefore, while these methods provide strong support for DL-based centrifugal pump fault diagnosis, further technical advancements are required to enable large-scale deployment in real-world industrial applications.

5.2 Model-Related Challenges

In the field of centrifugal pump fault diagnosis, although deep learning (DL) models often perform well under the training data distribution corresponding to specific operating conditions, their performance frequently deteriorates when faced with new working conditions, equipment variations, or environmental changes. This limited generalization capability poses a significant constraint on the reliability of DL techniques in practical industrial applications.

Studies indicate that real-time adjustments in centrifugal pump operating conditions, particularly for mud pumps used in drilling operations, require continuous tuning of operational parameters according to drilling depth. Such variations make it challenging for conventional DL methods to maintain stable diagnostic performance across different conditions. Similarly, when centrifugal pumps operate under varying temperature conditions, vibration signal characteristics can change, leading to fluctuations in the accuracy of cavitation state recognition. For rod pumping systems, performance diagrams from different oilfields are influenced by geographical conditions, sensor devices, and acquisition software, exhibiting environment-specific characteristics that single-model diagnostic approaches struggle to accommodate.

In centrifugal pump fault diagnosis, fluctuations in working conditions inevitably introduce distribution differences between training and testing data. This issue is especially pronounced in scenarios with limited sample sizes, where distribution shifts can lead to substantial declines in model performance. For instance, when a model trained under one operating condition is applied to another, significant differences in fault features between conditions can cause a sharp

drop in diagnostic accuracy.

To address these challenges, several approaches have been proposed to enhance model generalization. Transfer learning has been shown to be an effective solution, particularly when similar datasets are unavailable or when data must be transferred across domains. By transferring network parameters, models can maintain robust generalization even after extensive adaptation to the target task.

Feature fusion is another strategy for improving generalization. Studies demonstrate that combining Fourier descriptor features with graphical features from performance diagrams enhances feature robustness and improves diagnostic accuracy. For example, the diagnostic accuracy of a fused-feature model increased from 82.33% to 97.24%, significantly outperforming models using individual feature sets. This approach leverages the complementary relationships among features, effectively enhancing the generalization capability of the diagnostic model.

Data augmentation techniques are also widely employed to improve model robustness under variable conditions. By generating diverse training samples through transformations such as rotation, translation, shear, scaling, and flipping, models can better adapt to different operating scenarios. For example, in centrifugal pump cavitation state recognition, augmenting data with rotations of $\pm 20^\circ$, translations of $\pm 20\%$, and shearing of $\pm 20\%$ substantially enhanced the model's ability to generalize across varying conditions.

Furthermore, meta-learning methods have been applied to address generalization under limited-sample scenarios. By embedding prior knowledge into meta-learning strategies, models can simulate diverse operating conditions and adaptively capture domain-invariant features. For instance, segmenting time-frequency images into grids and utilizing positional information to construct self-supervised loss functions enables the model to learn cross-domain invariant representations, thereby improving generalization across different working conditions.

Despite these advances, centrifugal pump fault diagnosis in practical industrial applications still faces significant challenges. Key research directions include further enhancing model adaptability to unknown conditions, reducing reliance on extensive labeled datasets, and improving model stability in complex and variable environments.

5.3 System-Level Challenges

Deep learning (DL) models have demonstrated significant potential in centrifugal pump fault diagnosis; however, their practical application still faces two major challenges: insufficient interpretability and limited real-time performance. These limitations substantially hinder the widespread adoption of DL techniques in industrial environments and affect engineers' trust in these methods.

Insufficient interpretability is the primary issue in applying DL to fault diagnosis. Since DL models are typically regarded as "black boxes," their internal decision-making processes are difficult for humans to understand and explain. This lack of transparency makes it challenging for engineers to trust and rely on model predictions, particularly in critical equipment monitoring scenarios. Studies have highlighted that conventional DL methods cannot establish a direct mapping between raw sensor data and corresponding fault modes, making diagnostic performance heavily dependent on the quality of feature extraction. When misdiagnoses occur, engineers are unable to trace the decision rationale, which impedes effective fault analysis and system improvement. Moreover, neural network architecture design and parameter optimization often require extensive manual tuning and expert knowledge, further restricting model applicability and generalization.

Limited real-time performance constitutes another critical barrier to industrial deployment. Complex DL models typically incur significant computational overhead, making it difficult to meet the real-time diagnostic requirements of industrial operations. In centrifugal pump systems, faults must often be detected and identified at an early stage to prevent severe consequences. However, existing DL algorithms frequently underperform under variable-speed and other complex operating conditions, with low computational efficiency. Additionally, training such models usually requires considerable time and computational resources, which is particularly challenging in resource-constrained industrial environments.

To address these challenges, several strategies have been proposed. One approach introduces an interpretable semi-supervised graph learning model that incorporates a feature reconstruction module. By fitting and explaining the learned features with nonlinear surrogate models, this method enhances interpretability during training and accelerates model convergence. Another approach combines DL with reinforcement learning to construct an end-to-end fault diagnosis framework, directly mapping raw fault data to corresponding fault modes. Methods integrating physics-driven feature alignment with dynamic distribution adaptation have also been developed, leveraging physical knowledge to improve model performance and enhance cross-operating-condition adaptability. Frequency-enhanced networks, which jointly consider time-domain and frequency-domain features and incorporate CutMix-based self-supervised learning, have demonstrated robust generalization across varying operating conditions. Transfer learning has been effectively applied to mitigate issues of insufficient labeled data and imbalanced data distributions, improving model performance under data-constrained scenarios.

Despite these advances, further research is needed to develop models that maintain high diagnostic accuracy while simultaneously improving interpretability and computational efficiency. In particular, designing transparent yet efficient DL models for industrial deployment is critical to promoting the broader adoption of intelligent fault diagnosis technologies in centrifugal pump systems.

6 FUTURE RESEARCH DIRECTIONS AND PERSPECTIVES

6.1 Few-Shot and Self-Supervised Learning

Few-shot learning (FSL) and self-supervised learning (SSL) have demonstrated significant potential in centrifugal pump fault diagnosis, providing effective solutions to the data scarcity problem commonly encountered in industrial settings. In this domain, obtaining large-scale labeled datasets is often costly and challenging. FSL and SSL can leverage limited labeled data alongside abundant unlabeled data to enhance model diagnostic performance and generalization ability [35].

In few-shot learning, model-agnostic meta-learning (MAML) algorithms offer a novel approach for centrifugal pump fault diagnosis. Through an inner-loop and outer-loop gradient update process, the model can rapidly adapt to new tasks using only a small number of labeled samples [36]. Specifically, tasks are divided into a support set and a query set. The support set, typically containing 1–5 samples, is used to quickly adjust model parameters, while the query set evaluates model performance. This strategy enables the model to learn generalizable feature representations applicable across varying operating conditions, effectively addressing the performance degradation caused by distribution shifts in centrifugal pump data under different working conditions [37].

Self-supervised learning exhibits unique advantages in this field. Unlike traditional supervised methods, SSL can learn meaningful feature representations from unlabeled data, reducing reliance on annotated samples. One effective approach involves feature-level differential updates in graph convolutional networks (GCNs), ensuring that the feature extractor preserves maximal fault-related information. Specifically, constructed graph data are fed into a GCN model, where neighbor information is aggregated and node features are iteratively updated to produce nonlinear feature matrices. Feature-level loss is then computed to update model parameters. This SSL pretraining process allows the model to capture intrinsic data structures and relationships, providing high-quality feature representations for subsequent fault diagnosis tasks.

Data augmentation techniques play a critical role in mitigating data scarcity. Considering that centrifugal pump monitoring data are typically 1D time-series signals, improved symplectic geometric data augmentation (ISGDA) methods generate new samples with feature distributions similar to the original data. By introducing controlled perturbations to time-series signals, these methods enrich the feature space of labeled samples, improving diagnostic performance under limited data conditions. ISGDA also effectively suppresses overfitting during training and enhances model robustness. Furthermore, the introduction of consistency regularization further improves model performance. The supervised loss function ensures consistency between augmented labeled samples and their true labels, while the unsupervised loss reduces distribution discrepancies between augmented and unlabeled samples [32].

Meta-learning frameworks demonstrate substantial advantages in few-shot scenarios. A prior-knowledge-embedded meta-learning vision transformer (PKMLVIT) represents an innovative approach for few-shot fault diagnosis. This method integrates wavelet transform, meta-learning, self-supervised learning, and vision transformer architectures to extract domain-invariant features transferable across varying operating conditions. Initially, a modified ViT-based feature extractor captures global–local fused features from time–frequency spectrograms. Subsequently, a meta-learning strategy incorporating prior knowledge simulates the generalization scenario of centrifugal pump devices under changing conditions, adaptively learning domain-invariant representations. Experimental results indicate that PKMLVIT achieves superior robustness and accuracy under limited samples and variable operating conditions, outperforming existing approaches [42].

Despite the potential of FSL and SSL in centrifugal pump fault diagnosis, several challenges remain. First, the quality of pseudo-labels directly affects model performance, and pseudo-label generation may be influenced by model errors, noise, bias, or outliers in the data. Second, distribution shifts across different operating conditions can degrade model performance, particularly when sample sizes are limited. Finally, careful tuning of model parameters and regularization strategies is essential to prevent overfitting, requiring a balance between model complexity and generalization ability, see Table 3.

Table 3 Correspondence between Challenges and Future Directions in Intelligent Fault Diagnosis of Centrifugal Pumps

Challenge Category	Core Challenges	Corresponding Future Research Directions
Data Level	Data scarcity and labeling difficulties; distribution shifts under varying operating conditions	Few-shot learning, self-supervised learning, advanced data augmentation techniques
Model Level	Limited generalization capability; insufficient interpretability	Integration of physical mechanisms with deep learning, explainable AI (XAI), meta-learning
System Level	Limited real-time performance; high computational resource demands; low system integration	Lightweight models, edge computing, digital twin-based full lifecycle management

In the future, few-shot learning (FSL) and self-supervised learning (SSL) will continue to offer broad research opportunities in the field of centrifugal pump fault diagnosis. On one hand, more advanced data augmentation techniques can be explored, particularly those tailored for 1D time-series signals, to generate more representative samples. On the other hand, improvements and optimizations in meta-learning algorithms will further enhance model performance in few-shot scenarios, for example, by incorporating additional prior knowledge or designing more effective task-generation strategies. Moreover, integrating self-supervised learning with explainable methods can improve model transparency and reliability, providing more valuable support for industrial decision-making.

In summary, FSL and SSL provide effective solutions to the data scarcity problem in centrifugal pump fault diagnosis. By leveraging limited labeled data alongside abundant unlabeled data, and combining advanced data augmentation techniques with meta-learning frameworks, more efficient and robust diagnostic models can be developed. The integration of these technologies offers strong support for health monitoring and maintenance of industrial centrifugal pump systems, thereby advancing the development of intelligent operation and maintenance systems.

6.2 Integration of Physical Mechanisms and Deep Learning

The integration of physical information with deep learning represents a cutting-edge research direction in centrifugal pump fault diagnosis. By combining physical models and mechanistic knowledge with deep learning, the model's performance under extreme conditions and its interpretability can be significantly enhanced. This fusion approach not only leverages the powerful feature extraction capabilities of deep learning but also utilizes physical knowledge to provide prior constraints, ensuring that the model outputs adhere more closely to actual physical laws.

Physical-driven feature extraction is a key aspect of integrating physical information with deep learning. Studies have shown that converting raw signals into time-frequency images using continuous wavelet transform can effectively capture the time-frequency characteristics of centrifugal pump faults. This method simultaneously captures variations in both time and frequency domains, providing richer input features for deep learning models [38]. Moreover, for fault diagnosis under varying operating conditions, physical-driven feature alignment methods adjust signal amplitude, angular sampling frequency, and pulse phase to reduce discrepancies between samples from different conditions. This physically-informed feature alignment enables deep learning models to better adapt to fault diagnosis tasks under variable operating conditions.

Physics-informed neural networks (PINNs) exemplify the deep integration of physical models with deep learning. In centrifugal pump fault diagnosis, researchers have developed frequency-enhanced networks that employ frequency-aware convolutional architectures to consider both time-domain and frequency-domain features, overcoming limitations of traditional convolution operations in frequency feature extraction. Additionally, adaptive convolutional neural network models constructed based on the intrinsic knowledge of centrifugal pumps can automatically optimize critical hyperparameters through Bayesian optimization. Experimental results indicate that such physics-guided adaptive models achieve a maximum accuracy of 99.78%, representing a 5.45% improvement over the traditional LeNet-5 model.

Multi-source information fusion is another effective approach for integrating physical knowledge with deep learning. By fusing the diagnostic outputs of multiple single models, the accuracy and robustness of fault diagnosis can be substantially improved. Studies show that after combining multiple deep learning models, the final diagnostic accuracy can reach 99.98%, which is 9.09% higher than the average accuracy of individual models. Introducing reliable evidence during the fusion process can further enhance performance. For instance, fusing the 1-DPCA-AE model with other models (e.g., Models 1, 4, 8, 9) increased accuracy by 13.53%, while combining the AE model with Models 2 and 4 improved accuracy by 10.45%. Such multi-source information fusion methods significantly enhance the recognition accuracy of diaphragm pump fault types [39].

To improve generalization across varying operating conditions, researchers have developed hybrid methods incorporating dynamic distribution adaptation. These methods dynamically adjust marginal and conditional distributions during domain adaptation, improving cross-domain feature matching. Additionally, CutMix-based self-supervised learning achieves robust generalization under different operating conditions and equipment variations. These approaches perform well in diagnosing pump faults across varying temperature, pressure, and speed conditions.

Regarding interpretability, integrating physical information with deep learning substantially enhances model transparency. Visualization techniques such as t-SNE can reveal the feature learning process at different CNN layers, improving understanding of the model's decision-making mechanisms. Furthermore, health indicators developed using Mahalanobis distance and Fisher discriminant ratio contribute to stabilizing high-dimensional latent representations during model training. Such interpretability methods provide more transparent and reliable support for fault diagnosis, increasing confidence in diagnostic outcomes.

In the future, research on the integration of physical information and deep learning is expected to deepen further, particularly in the following areas: first, developing more refined physical models to more accurately embed centrifugal pump operating mechanisms into deep learning frameworks; second, exploring more effective multi-source information fusion strategies to further improve diagnostic accuracy; third, investigating adaptive optimization methods to enhance model performance under complex and variable operating conditions; and finally, strengthening research on model interpretability to improve transparency and reliability of diagnostic results. These research directions will advance centrifugal pump fault diagnosis toward more intelligent and precise methodologies.

6.3 Explainable AI and Trustworthy Fault Diagnosis

In the field of industrial pump fault diagnosis, while deep learning techniques have demonstrated remarkable performance, their "black-box" nature and high computational demands limit practical deployment in industrial environments. The integration of explainable AI (XAI) and edge computing offers a promising solution to these challenges.

The primary goal of explainable AI is to render the decision-making process of deep learning models transparent,

thereby enhancing user trust in diagnostic results. Traditional deep learning models in fault diagnosis face two major challenges: reliance on large amounts of labeled data and lack of interpretability. To address these issues, researchers have proposed various explainability methods, including Class Activation Mapping (CAM), Gradient-weighted CAM (Grad-CAM), Shapley Additive Explanations (SHAP), and Local Interpretable Model-agnostic Explanations (LIME). Specifically, LIME generates locally interpretable models to explain how predictions are made, rendering the decision process of complex models more transparent. An innovative approach involves incorporating an interpretable feature reconstruction module, which uses nonlinear surrogate models to fit and interpret learned features and embeds interpretability scores into the feature representations. This method not only enhances model transparency during training but also accelerates convergence.

On the other hand, edge computing addresses the high computational resource demands of deep learning models. By deploying data, applications, and computing capabilities closer to the data source, edge computing significantly reduces latency and meets industrial requirements for real-time processing. In centrifugal pump fault diagnosis, containerized edge AI inference frameworks have shown excellent performance by deploying Docker container services near sensors, providing an efficient and low-latency data analysis pipeline.

To enable real-time diagnosis on edge devices, researchers have proposed model compression and lightweight design techniques. Various lightweight model architectures, such as CNNs tailored for rolling bearing fault diagnosis, have been developed. For edge deployment, Docker container technology is widely used to encapsulate and deploy AI models, allowing them to run on resource-constrained devices. Studies indicate that utilizing different container runtimes (e.g., CRI-O, Docker, Containerd) across platforms (e.g., x64 and ARM) optimizes resource utilization and improves computational efficiency on edge devices [40].

Looking forward, integrating physical knowledge with deep learning models offers an effective way to enhance both model performance and interpretability. For example, employing wavelet packet decomposition and information entropy-based feature extraction to capture physical characteristics of signals, combined with CNN models incorporating attention mechanisms, can significantly improve diagnostic accuracy. Furthermore, physics-driven feature alignment methods that adjust signal amplitude, angular sampling frequency, and pulse phase can reduce inter-sample discrepancies and enhance model generalization across varying operating conditions [41].

In summary, the combination of explainable AI and edge computing is poised to play an increasingly important role in centrifugal pump fault diagnosis. By developing transparent deep learning models and efficient edge deployment strategies, it is possible to improve the reliability of diagnostic outcomes while satisfying the stringent real-time requirements of industrial settings, thereby promoting the widespread adoption of intelligent fault diagnosis technologies.

6.4 Digital Twin and Full-Life-Cycle Intelligent Management

Digital twin technology provides a revolutionary solution for the full lifecycle management of centrifugal pump equipment. By creating a virtual replica of the physical pump and integrating deep learning algorithms, digital twin systems enable a seamless transition from fault diagnosis to remaining useful life (RUL) prediction, laying a solid foundation for predictive maintenance. These models can reflect the real-time operational status of centrifugal pumps, and through multi-source data fusion and deep analysis, provide scientific support for maintenance decision-making.

In constructing digital twins for centrifugal pumps, deep learning models have demonstrated outstanding performance. Studies indicate that neural network models outperform traditional polynomial fitting and mechanical modeling methods in predicting submersible pump performance, especially under complex flow conditions. Deep learning models can accurately capture nonlinear relationships and overcome the limitations of traditional approaches in complex operating environments. To address overfitting during neural network training, researchers have employed early stopping strategies, effectively avoiding non-physical pump performance curves caused by excessive training. Moreover, the choice of activation function significantly affects prediction accuracy and must be optimized for specific applications [33].

In volumetric pump wear-state classification, deep learning methods have also shown strong performance. Research demonstrates that a neural network with 5 input neurons, 12 hidden neurons, and 3 output neurons can effectively classify three pump states: normal operation, end-of-life, and wear. By precisely adjusting the number of hidden neurons, based on empirical formulas and key parameters such as the number of input neurons and constants, classification performance is significantly enhanced [43].

Significant breakthroughs have been achieved in RUL prediction using deep learning. For example, a parallel-channel method combining convolutional neural networks (CNNs), convolutional block attention modules (CBAM), and Transformer networks has been proposed for drilling pump RUL prediction [44]. The model extracts both time-domain and time-frequency features from strain signals via two parallel channels, followed by feature fusion to predict RUL accurately. Experimental results indicate that deep learning models consistently outperform traditional machine learning approaches for monitoring-based RUL prediction. In particular, models incorporating CBAM modules achieve high accuracy across all drilling pump evaluation metrics, demonstrating their effectiveness in predicting RUL.

Vibration-based intelligent fault diagnosis is a crucial component of digital twin systems. A proposed deep hybrid model considers frequency, time, and spectral information from vibration signals, including spectrograms obtained via short-time Fourier transform and scalograms derived from continuous wavelet transform [13]. Experimental evaluations show that this deep hybrid model significantly outperforms conventional machine learning methods, such as k-nearest

neighbors, support vector machines, logistic regression, and random forests, enabling automatic detection of submersible pump faults from operational vibration data [33].

Predictive maintenance strategies rely on accurate fault diagnosis and RUL prediction provided by digital twin systems. Accurate RUL predictions guide pump operation and maintenance, reducing unplanned downtime and production interruptions caused by improper maintenance, thereby improving overall operational efficiency [45]. Additionally, precise fault forecasting enhances safety measures, minimizing risks such as blowouts or worker injuries caused by pump failures. By optimizing test matrices to balance prediction accuracy with testing cost, the economic benefits of predictive maintenance can be further improved.

Future research should focus on the real-time updating and adaptive capability of digital twin models, particularly in the effective fusion of multi-source heterogeneous data. Probabilistic prediction methods, such as Gaussian process regression, offer advantages in assessing model uncertainty but face high computational costs with large-scale datasets, necessitating algorithmic efficiency improvements [46]. Furthermore, integrating digital twin systems with the Internet of Things (IoT) and edge computing will enhance the real-time accuracy of predictive maintenance, supporting a shift from reactive maintenance to proactive prevention.

7 CONCLUSION

This paper systematically reviews the current research, key technologies, and future development trends of deep learning in centrifugal pump fault diagnosis and intelligent operation and maintenance (O&M). Studies indicate that deep learning, with its powerful automatic feature extraction and nonlinear modeling capabilities, provides an effective solution to the limitations of traditional methods—such as strong feature dependence, limited diagnostic accuracy, and poor adaptability across operating conditions—thereby significantly advancing both theoretical research and engineering applications for intelligent pump management.

At the model and methodology level, deep architectures—including convolutional neural networks (CNNs), recurrent neural networks (RNNs) and their variants, residual networks, graph neural networks (GNNs), and Transformers—demonstrate notable advantages in feature extraction, temporal modeling, and complex signal recognition. Techniques such as transfer learning, adversarial training, and dynamic distribution adaptation effectively mitigate cross-condition data distribution differences, enhancing model generalization. Multi-source information fusion strategies integrate vibration, acoustic, pressure, and current signals to achieve high-precision sensing and robust diagnostics of pump operating states. Furthermore, combining deep reinforcement learning with remaining useful life (RUL) prediction models enables centrifugal pump systems to evolve from “reactive maintenance” toward “proactive operation,” significantly improving operational safety and economic efficiency.

However, several challenges remain. First, high-quality labeled data in industrial scenarios are scarce, leading to strong model dependency and pronounced sample imbalance issues. Second, the lack of interpretability and limited cross-condition generalization of deep learning models constrain their reliable application in complex environments. Additionally, high model complexity and challenges related to real-time performance and edge deployment remain key bottlenecks for practical intelligent O&M implementation.

Future research should focus on the following directions:

1. Few-shot and self-supervised learning: Develop methods to alleviate data scarcity and reduce dependence on labeled samples.
2. Integration of physical mechanisms with deep learning: Construct physically constrained, interpretable models to enhance transparency and trustworthiness of diagnostic results.
3. Multi-modal fusion and multi-task coordination: Achieve integrated intelligent management combining fault diagnosis, health assessment, and RUL prediction.
4. Reinforcement learning-based adaptive O&M strategies: Enable systems to transition from “monitoring and identification” toward “autonomous decision-making.”
5. Edge computing and digital twin integration: Implement real-time diagnosis and full lifecycle management of pump equipment.

In summary, the introduction of deep learning provides a new theoretical framework and technical support for centrifugal pump fault diagnosis and intelligent O&M. Its deep integration with physical modeling, industrial IoT, and intelligent decision-making technologies will be a key driving force for advancing industrial equipment toward intelligent, autonomous, and trustworthy operation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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