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# A neuro-fuzzy approach with hypergraph convolution for fault diagnosis in industrial devices

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**Abstract**

Fault diagnosis of industrial systems is essential for maintaining intelligent maintenance in a big data environment. Existing methods typically leverage deep learning and statistical modeling to extract informative features from data, where information transmission involves cascading and interactive processes. However, previous work characterizes complex information cascades by constructing simplistic connections with fixed weights, which introduces significant uncertainty into the diagnostic outcomes. Additionally, the interpretability of these models remains insufficiently addressed. To address these limitations, a neuro-fuzzy framework incorporating hypergraph convolution is proposed to comprehensively capture the semantic representation of information cascades through fuzzy rules. Specifically, a fuzzy rule-driven hypergraph construction framework is designed to induce dynamic cascading behaviors derived from diverse input feature subsets for hypergraph fusion. In other words, the weight fuzzy module dynamically adjusts hypergraph connection weights, thereby enhancing semantic propagation between interconnected nodes. Furthermore, a novel heterogeneous embedding strategy is developed, namely multi-layer perception hybrid embedding, which effectively mitigates

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knowledge dispersion within the graph structure. To validate the superiority of the proposed methodology, comprehensive evaluations on an industrial platform have been conducted. Experimental results demonstrate that the proposed approach achieves state-of-the-art performance in diagnostic tasks.

Keywords: deep neuro-fuzzy approach, industrial systems, diesel engine, fault diagnosis, data fusion, hypergraph convolution network

## 1. Introduction

Industrial devices may experience faults that lead to substantial financial losses. To prevent potential risks associated with such failures (Ni *et al* 2023), intelligent diagnosis has become a core component of intelligent maintenance strategies (Han and Li 2022). Industrial devices can provide intelligent diagnostics with big data generated by the operation of devices (Li *et al* 2019). Currently, the focus of industrial device is primarily on the development of hardware and software for tracking the health of monitored system components. Accurate fault diagnosis can effectively accelerate the development of these monitoring systems.

Existing diagnosis methods are broadly categorized into two paradigms: statistical model-based fault identification (Yan *et al* 2023) and machine learning-driven fault detection (Ren *et al* 2023). The former employs statistical techniques to extract discriminative feature vectors from raw data and utilizes classifiers for differentiation (Wang *et al* 2021). Statistical features include entropy, kurtosis, mean, spectrum, etc. These methods require advanced analysis based on *a priori* knowledge and may lose many rich features in the process. Moreover, the accuracy of fault diagnosis is closely related to the manually extracted features, which exert significant and uncontrollable influence on the final diagnostic results.

To improve diagnosis accuracy, deep neural networks have attracted increasing research interest (Qin *et al* 2023). These methods aim to develop mapping structures with deep nonlinearities that enable gradient computation for a given complex problem (Li *et al* 2023). In other words, an iterative training process is established using big data streams to facilitate knowledge extraction (Yang *et al* 2023). An *et al* (2024) proposed projecting the features learned from the two operating conditions into a common auxiliary distribution, thus enabling bearing fault diagnosis under variable operating conditions. Feng *et al* (2023) proposed a globally-localized multi-source domain adaptation neural network for cross-domain fault diagnosis. Generally, the interpretability of such deep models is extremely weak (Zhao *et al* 2022). Improving model interpretability allows for a deeper understanding of the working mechanisms of deep models, thereby facilitating the design of more rational model structures (An *et al* 2022). Zhang *et al* (2025) proposed a novel intelligent big data-driven method for electric aircraft, which offers a new insight for battery data analysis. The results show promising industrial application prospects of the cutting-edge method for prognosis. Fortunately, many researchers (Abid *et al* 2020) have noticed this issue and are beginning to address it. Recently, some studies have started to integrate deep neural networks into fuzzy systems using the stacked generalization principle (Zhang *et al* 2018). Different architectures are used to create deep neuro-fuzzy structures, with the aim of leveraging the interpretability of fuzzy rules to complement the deep models (Eristi 2013). Rajabi *et al* (2022) evaluated the condition of bearings using a neuro-fuzzy inference system classifier with a multi-output adaptive attribute. Although deep neuro-fuzzy approaches are developing rapidly, the problem of processing neuro-fuzzy rules in industrial data streams remains an open issue in the literature. The goal of this work is to apply the neuro-fuzzy approach to industrial data by enhancing the fuzzy rules.

One issue that remains to be further considered is how to deal with information cascades in industrial data streams. In the information cascade, different inputs may inject uncertainty into the information interaction. Also, the semantic correlation between different inputs is susceptible to many factors, such as variations in fault evolution, signal acquisition inaccuracies, and information loss during signal conversion. Most of the state-of-the-art models use underlying data fusion, and feature fusion to deal with such problems. However, a simple weighted fusion of data or features may not cope with this uncertainty. In other words, it is not sufficient to rely on a simple fully-connected layer to model complex semantic correlations using fixed weights. Thus, designing a model to capture the information cascade between different inputs is critical. Inspired by fuzzy theory, we propose a novel hypergraph convolution mechanism to model data fusion in this paper. Meanwhile, we also note the shortcomings demonstrated by graph convolution, i.e., knowledge dispersion. To mitigate this problem, the graph convolution is also appropriately adapted.

To solve the above problems, this paper proposes a neuro-fuzzy approach with hypergraph convolution for implementing fault diagnosis tasks in industrial systems. This method aims to model information cascading in data fusion by combining fuzzy theory and hypergraph convolution. Specifically, a fuzzy rule-driven hypergraph construction approach is first designed to induce cascading behaviors from two different input feature subsets and facilitate data fusion in the hypergraph. A weight fuzzy module is designed to adjust the weights in the hypergraph, thus enhancing the semantic transfer between graphs. Also, a multi-layer perceptual hybrid embedding is developed to suppress knowledge dispersion in graph structures. Finally, an evaluation of an industrial diesel engine platform is conducted. The effectiveness of the model is demonstrated by extensive experiments.

The main contributions of this work are summarized as follows:

(1) A neuro-fuzzy approach with hypergraph convolution is proposed as a framework for fault diagnosis of industrial systems, which is successfully applied to diagnosis tasks.
(2) A fuzzy rule-driven hypergraph construction approach is developed to induce cascading behaviors from two different input feature subsets and data fusion in the graph. The weight fuzzy module adjusts the edge weights in the graph, enhancing the semantic transfer between graphs. Specifically, a weight fuzzy module is used to adjust the weights in the graph, thus enhancing the semantic transfer between graphs.
(3) A novel feature encoding is designed to generate heterogeneous embeddings, i.e., multilayer perceptual hybrid embeddings, for suppressing knowledge dispersion in graph structures.

The rest of the paper is organized as follows. Section 2 describes the related work in detail. Section 3 outlines the proposed neuro-fuzzy methodology, and section 4 presents the industrial dataset and discusses the experimental results. Section 5 gives the conclusion.

## 2. Related works

### 2.1. Neuro-fuzzy theory

Neuro-fuzzy theory (Zhang *et al* 2010) offers a promising solution for researchers to explore the 'black box' problem in deep neural networks. Fuzzy inference is an interpretable rule-based concept (Rajabi *et al* 2022). Combining it with a deep neural network results in a deep neuro-fuzzy system. Subbaraj *et al* (2014) discussed the design and development of adaptive neuro-fuzzy inference system for fault detection and diagnosis for pneumatic valves. Shah *et al* (2022) proposed a new evolutionary neuro-fuzzy classifier for real-time gear system fault diagnosis. Zio *et al* (2009) proposed a neuro-fuzzy approach for obtaining easily interpretable classification models. Neuro-fuzzy approaches can be utilized as a component of deep learning models by selecting fuzzy parameters or training parameters in fuzzy logic. In other words, fuzzy values are generated by utilizing neuro-fuzzy methods, thereby guiding the training of deep neural networks. This novel neuro-fuzzy approach shows the possibility of automatically extracting fuzzy rules. Fuzzy rules (Eristi 2013) are a mathematical technique for expressing fuzzy and imprecise concepts, quantifying preferences in feature extraction and feature decision-making based on available data. To construct the graph nodes appropriately, a fuzzy weight module is designed to enhance the information transfer in the graph by mapping the interactions under the guidance of fuzzy weights.

### 2.2. Graph convolution networks (GCNs)

Graph neural networks aim to utilize the connections between nodes and edges in a graph for information transfer (Chen *et al* 2022), thus effectively capturing features among data. Li *et al* (2021) note that most GCNs are constructed on unweighted graphs, treating the importance of nodes as equal a scenario that is not realistic. Zhao *et al* (2021) designed a new adaptive local graph learning method to construct graph relations using labeled and unlabeled samples. These methods described above effectively utilize the intrinsic semantic links between nodes. Gao *et al* (2022) state that the connections between these graph nodes are limited to neighboring nodes and cannot capture correlations between multiple nodes at the same time. Zhang *et al* (2022) construct hypergraph structures applicable to the current signal to form complex interrelationships and obtain interrelationships for higher-order data for representation learning. Thus, a new graph operation has evolved from ordinary graphs, where each edge in the new graph can connect more than two nodes, thus describing the relationship between multiple nodes. Shi *et al* (2023) converted unlabeled vibration signals into hypergraphs to mine higher-order structural information from raw unlabeled data. Although these graph structures (Zhao *et al* 2023) can perform well in fault diagnosis, further studies and investigations are needed regarding graph structures in multi-data fusion. In this paper, we improve graph convolution using fuzzy rules to explore an approach from a neuro-fuzzy perspective that fully understands the information transfer between different inputs, leading to more robust diagnosis results.

## 3. Methodology

### 3.1. Overview

Aiming at the shortcomings of fault diagnosis of industrial systems under deep learning, a neuro-fuzzy method with hypergraph convolution is proposed for industrial fault diagnosis, as shown in figure 1. Data acquisition is first performed and hypergraph construction is realized by constructing the time-frequency representation (TFR) and vibration signals into their respective graph nodes and hyperedges. Next, the weight fuzzy module is utilized to perform the data fusion across different input graphs. Finally, a fuzzy inference hypergraph convolutional network with multilayer perceptual hybrid embedding is designed to suppress knowledge dispersion in graph structures. A detailed description is given as follows.

### 3.2. Fuzzy inference hypergraph convolution modeling

***1) Formula definition:*** The proposed neuro-fuzzy approach can be considered as a multi-class task, aiming to learn a classifier through the fuzzy inference graph convolutional training that utilizes the information cascade between different inputs to predict fault labels. Formally, let $\mathcal{C} = \{c^1, c^2, \cdots, c^m\}$ be the fault dataset, where $c^i$ is the $i$th class of faults and $m$ is the number of fault classes. Each fault class is defined as $c^i = \{x_1^i, x_2^i, \cdots, x_{N_i-1}^i\}$, where $x_j^i$ refers to the $j$th vibration data slice or TFR and $N_i$ denotes the amount of data. The hypergraph is defined as $\mathcal{G}^i = (\mathcal{V}^i, \mathcal{E}^i, \mathcal{W}^i)$, where $\mathcal{V}^i = \{v_1^i, v_2^i, \cdots, v_n^i\}$ represents the set of nodes of the hypergraph, $\mathcal{W}^i = \text{diag}\left(w_1^i, w_2^i, \cdots, w_n^i\right)$ referring to the set of

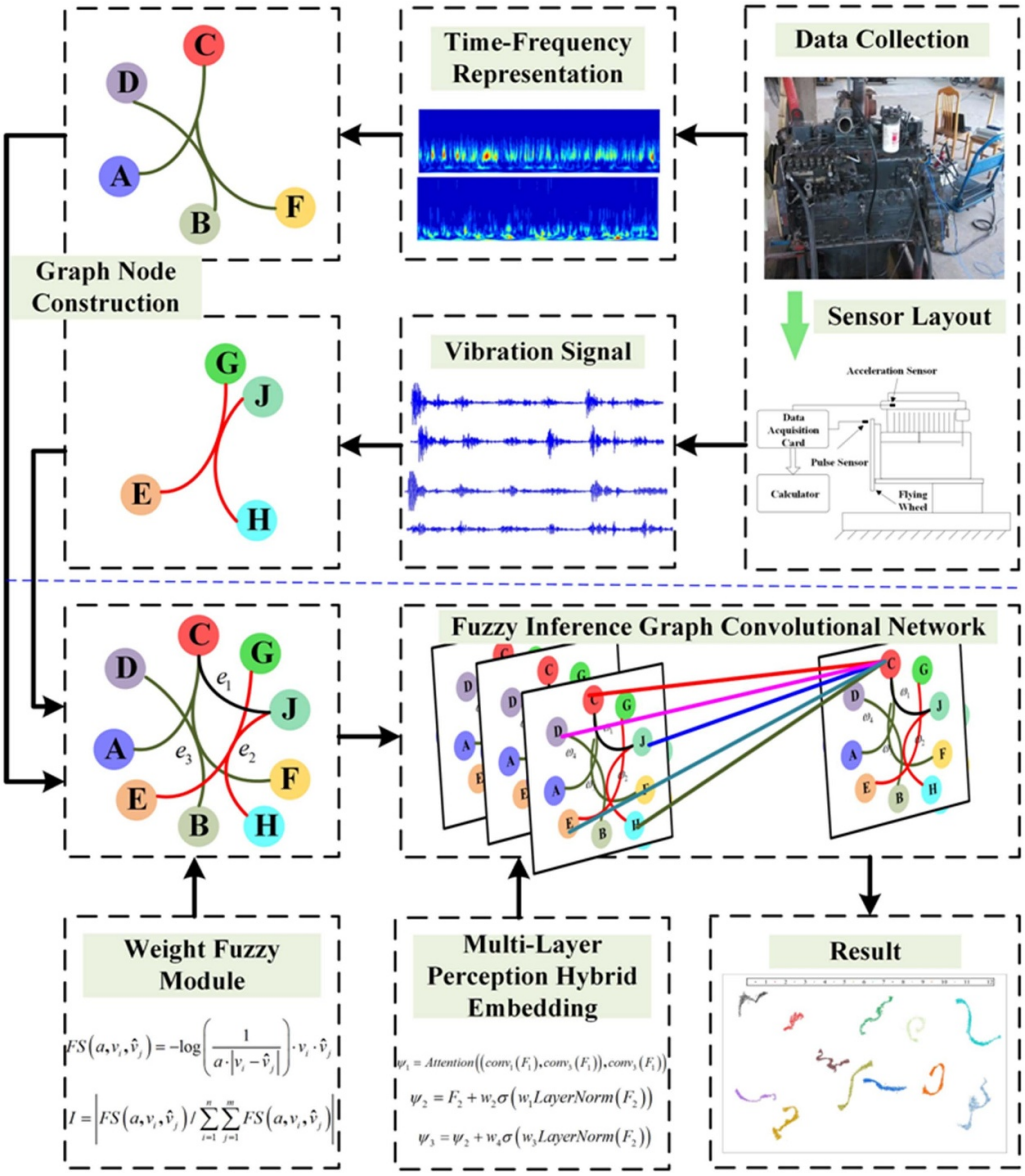



**Figure 1.** Framework of the proposed methodology.

directed hyperedges, and $\mathcal{W}^i = \text{diag}\left(w_1^i, w_2^i, \cdots, w_n^i\right)$ denotes the weights assigned to the hyperedges.

***2) Graph construction***: The larger the value in the weight matrix $\mathcal{W}$, the greater the influence of the corresponding hyperedges. For any hyperedge is a subset of the set $\mathcal{V}$ of nodes. In a hypergraph, the degree of a node is defined as follows:

$$d(v_j) = \sum_{\{e \in \mathcal{E}\}} w(e_j) H(v_j, e_j). \tag{1}$$

For a hyperedge $e_j \in \mathcal{E}$, the degree of the hyperedge is defined as follows:

$$\delta(e_j) = \sum_{\{v_j \in \mathcal{V}\}} H(v_j, e_j) \tag{2}$$

where $H$ denotes is a $|\mathcal{V}| \times |\mathcal{E}|$ dimensional node-hyperedge association matrix. In an association matrix, if a node $e$ is on a hyperedge $v$, then $H(v,e) = 1$, otherwise $H(v,e) = 0$, as shown in figure 2. Set the diagonal matrices $D_v$ and $D_e$ to denote the degree matrices of the nodes and hyperedges, where the elements on the diagonal are the degrees of each node/hyperedge, i.e., $d(v)$ or $\delta(e)$. The adjacency matrix of a hypergraph represents the connectivity between nodes, where the adjacency matrix $A$ of a hypergraph is defined as follows:

$$A = H^T \mathcal{W} D_e^{-1} H. \tag{3}$$

The value of each element of the matrix is represented as follows:

$$\begin{aligned} &a_{i,j} = w(e_n) \\ &v_i, v_j \in e_n \end{aligned} \tag{4}$$

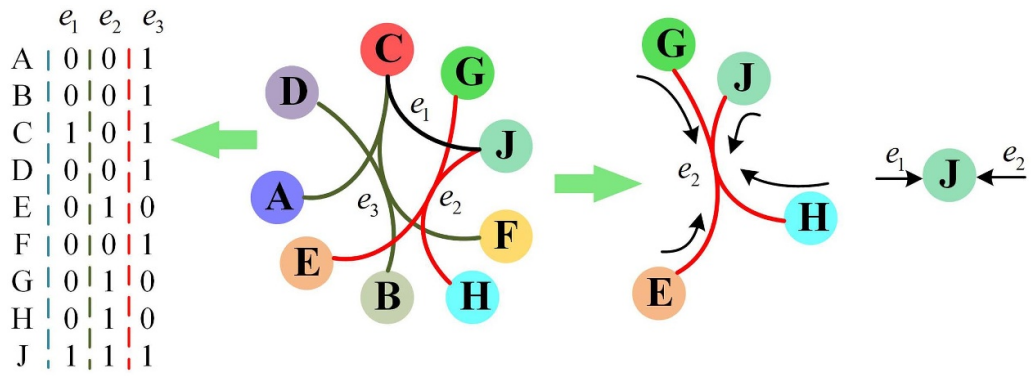



**Figure 2.** Instruction for the graph construction.

where $w(e_n)$ denotes the average of the heat kernel distances between any two nodes on the hyperedge,

$$w(\mathrm{e}_n) = \frac{1}{\delta(\mathrm{e})(\delta(\mathrm{e})-1)} \sum_{\{v_i,v_j\}\in\mathcal{V}} \mathrm{e}^{\frac{\|x_i-x_j\|^2}{u}}. \tag{5}$$

The Laplace matrix according to the hypergraph can be expressed as:

$$L = D_v - H\mathcal{W}D_e^{-1}H^T. \tag{6}$$

Thus, the optimization of hypergraphs can be translated into solving for the feature vector corresponding to the smallest eigenvalue of a matrix bundle $(L,A)$. The minimum non-negative feature vector can be computed:

$$\Delta = I - D_v^{-\frac{1}{2}}H\mathcal{W}D_e^{-1}H^TD_v^{-\frac{1}{2}} \tag{7}$$

where $I$ refers to the unit matrix. Further, the information transfer of the hypergraph convolutional neural network is defined as follows:

$$X^l = \sigma_{\theta^{l-1}}\left(\left(D_v^{-\frac{1}{2}}H\mathcal{W}D_e^{-1}H^TD_v^{-\frac{1}{2}}\right)X^{l-1}\right) \tag{8}$$

where $X^l$ and $X^{l-1}$ denote the inputs and outputs of the hypergraph convolution, $\theta^{l-1}$ refers to the parameters of the model, and $\sigma(\cdot)$ denotes the rectified linear units activation function. To handle the challenge of data fusion with different inputs, it is crucial to utilize graph structures to construct information cascades for information transfer. In this study, different graph structures are constructed based on different inputs, and a fusion graph structure guided by a fuzzy weight module is used to characterize the information cascade. The fuzzy weight module is described in detail in the next section.

***3) Training modeling:*** Each fault class $c^i$ is labeled with a ground-truth label $y^i \in \mathcal{Y}$. The constructed fuzzy inference hypergraph convolutional network aims to learn a classifier from a labeled dataset, i.e. $f: C \to \mathcal{Y}$. The label probabilities of all classes are computed through a fully connected layer and a softmax function. This process can be defined as follows:

$$\hat{y} = \mathrm{softmax}(\boldsymbol{w}_C\boldsymbol{F} + \boldsymbol{b}_C) \tag{9}$$

where $\{\boldsymbol{w}_C, \boldsymbol{b}_C\}$ denotes the learnable parameters of the classifier, $\boldsymbol{F}$ refers to the final feature representation, and $\hat{y}$ represents the predicted label. For the training process, the cross-entropy function is employed as the loss function for measuring the discrepancy between the predictions and ground-truth values. The loss is defined as follows:

$$\mathcal{L}_C = \sum_{i=1}^{N} y^i \log\hat{y}^i. \tag{10}$$

### 3.3. Weight fuzzy module

Hypergraph fusion between different inputs is the key to this work. How to implement information cascades across graphs for performing information transfer remains to be further explored. To achieve this, we design a fuzzy weight module to guide the fusion between two graphs, aiming to compute a score representing their similarity by means of a fuzzy entropy metric. This module is utilized to generate dynamic fuzzy rules to determine the correlation strength between individual nodes in the two graphs as strong or weak. Specifically, given a hypergraph $\mathcal{G}_1 = (\mathcal{V}^i, \mathcal{E}^i, \mathcal{W}^i)$ constructed from vibration signals and a hypergraph $\mathcal{G}_2 = (\hat{\mathcal{V}}^i, \hat{\mathcal{E}}^i, \hat{\mathcal{W}}^i)$ constructed from TFRs, the fuzzy entropy of the nodes between the two graphs is computed sequentially. The specific calculations are as follows:

$$FS(a, v_i, \hat{v}_j) = -\log\left(\frac{1}{a\cdot|v_i - \hat{v}_j|}\right)\cdot v_i \cdot \hat{v}_j \tag{11}$$

where $a$ denotes the adjustment factor. This fuzzy rule is considered by adding the fuzzy affiliation $FS(a, v_i, \hat{v}_j)$ as a guide for calculating the weights. The fuzzy rule is represented as follows:

$$I = \left| FS(a, v_i, \hat{v}_j) \Big/ \sum_{i=1}^{n}\sum_{j=1}^{m} FS(a, v_i, \hat{v}_j) \right| \tag{12}$$

where $I$ denotes the score, with a value ranging from 0 to 1. The relationship between two nodes can be determined to be strong or weak based on scores and fuzzy rules. If the correlation is strong, the two nodes are connected through a hyperedge, otherwise, no connection exists. The specific fuzzy rules are represented as follows:

$$R = \begin{cases} 1, & I \geqslant \xi \\ 0, & I < \xi \end{cases} \tag{13}$$

where 1 means strong, 0 means weak, and $\xi$ refers to a predefined threshold, with a value of 0.5. The entropy of the two graph nodes, i.e., their semantic relevance, is emphasized by the fuzzy weight module. In hypergraph fusion, more critical nodes are prioritized to establish connections, replacing the initial node connections. This enables the most critical semantics of the two graphs to be transferred to the final constructed hypergraph.

### 3.4. Multi-layer perception hybrid embedding

The behavior of knowledge divergence may occur during graph convolution, as discussed in the introduction. This issue warrants attention because it affects the final prediction results. Thus, a multi-layer perception hybrid embedding is proposed, aiming at constructing the dependencies by the self-attention mechanism of the features $F_1$ output from the hypergraph convolution of the first layer. It is represented as follows:

$$\psi_1 = \text{Attention}\left(\left(\text{conv}_1\left(F_1\right), \text{conv}_3\left(F_1\right)\right), \text{conv}_3\left(F_1\right)\right) \tag{14}$$

where $\text{conv}\left(\cdot\right)$ denotes the convolution operation. After self-attention, the feature $F_2$ generated from the convolutional output of the final second hypergraph layer is linearly transformed. Two MLP blocks are created, both consisting of multiple layers of the same size. In the first MLP block, $F_2$ is mapped,

$$\psi_2 = F_2 + w_2\sigma\left(w_1\text{LayerNorm}\left(F_2\right)\right) \tag{15}$$

where $\sigma\left(\cdot\right)$ is the unitary nonlinear Gaussian error linear unit. In the second MLP block, $F_2$ and $\psi_2$ are mapped.

$$\psi_3 = \psi_2 + w_4\sigma\left(w_3\text{LayerNorm}\left(F_2\right)\right). \tag{16}$$

Multi-layer perception hybrid embedding is constituted by equations (14)–(16). The dimension alignment of $\psi_1$, $\psi_2$, and $\psi_3$ is first performed, and then, the embedding vectors are completed after the feedforward combination,

$$F_e = \psi_1^T \cdot \psi_2 + \psi_1^T \cdot \psi_3. \tag{17}$$

To avoid knowledge dispersion in graph convolution, the embedding vectors are used as inputs to the last layer of hypergraph convolution, thereby ensuring that initial knowledge is preserved and aggregated in the last layer.

## 4. Case study

### 4.1. Preliminary

***1) Dataset description:*** The industrial data were collected on a diesel engine platform for testing, where the main technical parameters are shown in table 1. The cylinder head vibration signals of the diesel engine are collected using an ICP 356A26 accelerometer sensor, where the sampling frequency is 25 kHz. A photoelectric speed sensor is used to measure the engine stop signal, which is used for the analysis and feature extraction of the vibration signal to enable time localization. The experimental platform mainly consists of a Komatsu diesel engine, a multi-channel data acquisition system, and a computer, as shown in figure 3. The acceleration sensor is mounted on the sixth cylinder head. Reflective labels are affixed to the flywheel and the stop signal of the diesel engine is measured using a photoelectric speed sensor. Twelve common faults in the diesel engine fuel system and valve actuation mechanism are simulated, including fuel system faults and valve actuation mechanism faults. These faults include excessive and insufficient lubrication advance angles, misfire faults and poor combustion faults, abnormal intake valve clearances, and abnormal exhaust valve clearances. The test speed is set to approximately 950 rpm at idle and the engine is unloaded. The waveforms of the vibration signals for normal and fault conditions are shown in figure 4. Using a sliding window to divide the raw data into consecutive time blocks in chronological order, ensuring that the time order of the training, validation, and testing sets does not overlap. The number of samples in normal state is 500, and the number of samples for each fault is 500.

***2) Evaluation metrics:*** Accuracy (Acc), Matthew correlation coefficient (MCC), and $F1$ Score are chosen as evaluation measures (Zhu *et al* 2020). Accuracy represents the probability of correctly diagnosing a fault. MCC is a comprehensive evaluation metric that reflects the reliability of the algorithm. $F1$ Score combines precision and recall, serving as a weighted average evaluation metric.

### 4.2. Ablation study

***1) Baseline network analysis***: To verify the effectiveness of the proposed fuzzy inference hypergraph convolutional model for fault feature extraction, six baseline networks are used for comparative analysis, including TCN, GCN, GRU, LSTM, CNN-1d, and Transformer-1d. Note that CNN-1d and Transformer-1d employ the 1D convolution operation. The baseline network of the proposed method is replaced by these basic models and retrained and tested to perform the diagnosis task. The test results for different backbone networks are shown in figure 5, which illustrates the average accuracy for all fault classes. The proposed model significantly outperforms to the other models. In addition, the fuzzy inference hypergraph convolutional network can obtain diagnosis stability and error compactness second only to TCNs. Except for GCN, the diagnosis performance that can be achieved

**Table 1.** Description of test conditions.

| Description | Setting | Description | Setting |
|---|---|---|---|
| Number of cylinders | 6 | Maximum output power | 112 KW |
| Cylinder arrangement | Inline | Rated power speed | 1950 rpm |
| Engine displacement | 5.9 l | Minimum fuel consumption rate at full load | 85 $mm^3$ $s^{-1}$ |
| Firing order | 1–5–3–6–2–4 | Intake valve lash | 0.25 mm |
| Intake form | Supercharged intercooler | Exhaust valve lash | 0.5 mm |
| Fault types | 1. Normal; 2. Intake valve lash large 0.1 mm; 3. Intake valve lash large 0.2 mm;<br>4. Exhaust valve lash large 0.1 mm; 5. Exhaust valve lash large 0.2 mm;<br>6. Clogged air intake filter; 7. Clogged exhaust pipe;<br>8. Lubrication advance angle reduced by 3°; 9. Lubrication advance angle increased by 3°;<br>10. Misfire in cylinder 5; 11. Improper combustion in cylinder 6;<br>12. Severe work on cylinder 6 | | |

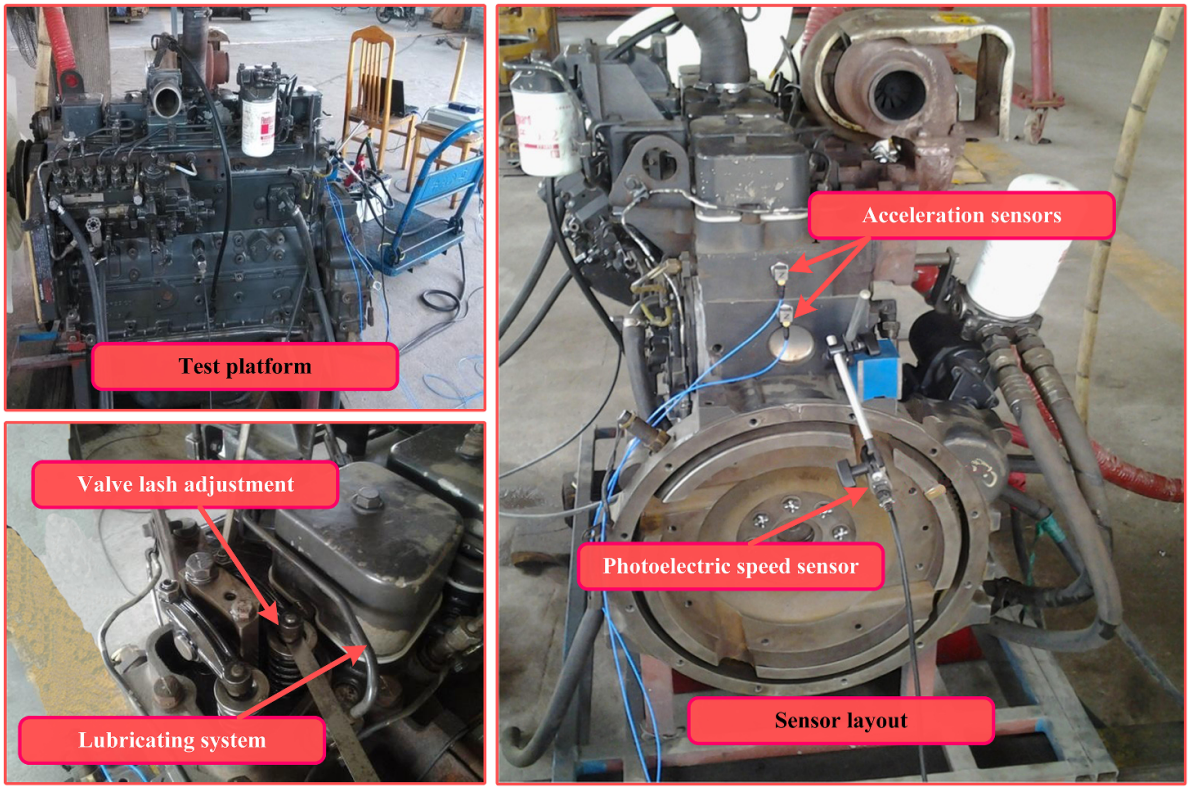



**Figure 3.** Diesel engine test platform.

by other models mainly ranges from 0.75 to 0.90. Typically, these accuracies are insufficient for diagnosis in industrial scenarios, where LSTM achieves the worst results, CNN-1d and TCN have more stable diagnostic performance, and Transformer-1d and GRU exhibit insufficient performance stability. Compared to GCN, incorporating fuzzy rule embedding significantly enhances model robustness and be more sensitive to fault diagnosis. In addition, table 2 shows the computational complexity and statistical significance tests of different methods. It can be observed that all baseline methods have $p$-values less than 0.05 compared to the proposed model, indicating that the proposed model has a statistically significant advantage in performance. In terms of time complexity, the proposed model has a time complexity of $O(n^2)$, which is between CNN-1d and GRU/LSTM, indicating a good balance in computational efficiency. In terms of spatial complexity, the proposed model has a spatial complexity of $O(n)$, which is lower than Transformers-1d, GCN, GRU, and LSTM, indicating that it is more efficient in use.

***2) Comparative analysis of different modules:*** The weight fuzzy module is designed to adjust the weights across two graphs, thus enhancing the semantic transfer between graphs. The multi-layer perception hybrid embedding aims to suppress knowledge dispersion in graph structures. To verify the feasibility of the two proposed modules, ablation analysis

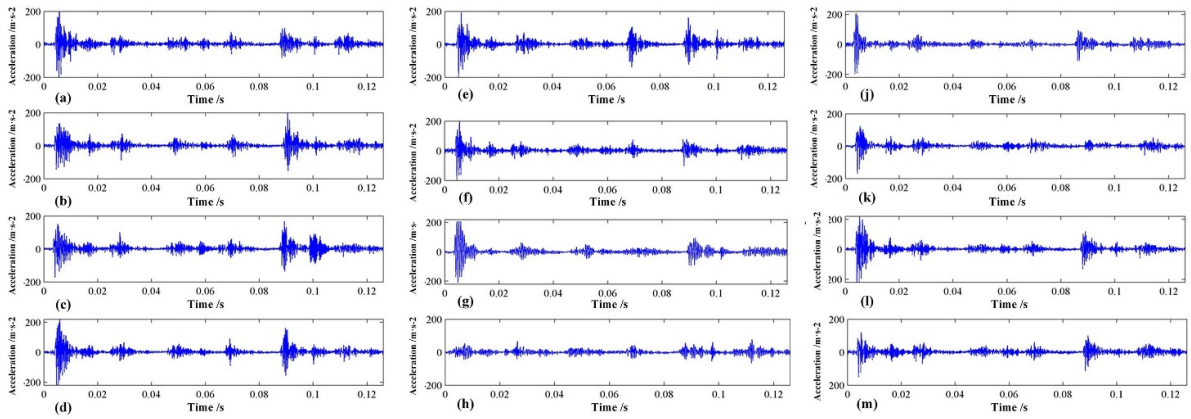



**Figure 4.** Different fault signal waveforms. (a) Normal 1, (b) fault 2, (c) fault 3, (d) fault 4, (e) fault 5, (f) fault 6, (g) fault 7, (h) fault 8, (j) fault 9, (k) fault 10, (l) fault 11, and (m) fault 12.

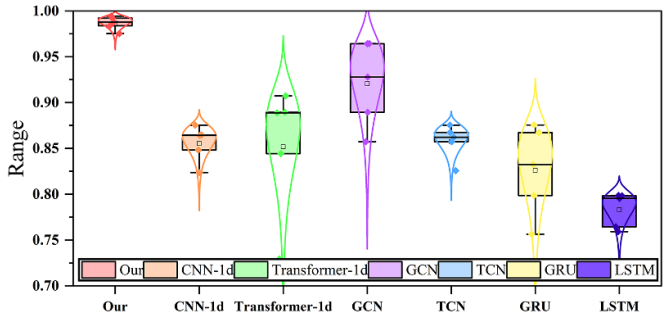



**Figure 5.** Results of different backbone networks.

is performed on these modules, where the ablation results are reported in figure 6. In the absence of the multi-layer perception hybrid embedding, the model performance exhibits a degradation trend. We suspect that the features attached to different graph nodes are different, and without properly integrating such nodes, the acquired fault knowledge does not converge towards the center node, which prevents the model from capturing fault features. The multi-layer perception hybrid embedding models feature interaction through multi-layer nonlinear transformations and concentrating knowledge through attention mechanisms. This modeling method can effectively suppress the interference of redundant nodes and concentrate knowledge in the fault related areas.

Furthermore, removing the weight fuzzy module significantly affects the model, resulting in more pronounced diagnostic fluctuations. Weights in graphs greatly influence diagnostic outcomes, and uncontrolled weight generation may lead to unfavorable semantic transfer, thereby inhibiting accurate diagnosis. The weight update process of traditional graph neural networks is usually black box, while the weight fuzzy module converts the relationships between nodes into fuzzy rules by introducing the fuzzy rule function. This fuzzification process interprets the basis for weight allocation, such as the similarity of fault data. Specifically, a hypergraph convolution embedded with fuzzy rules maps the weight changes of different graph nodes to specific faults. When the weight of node A significantly increases in the visualization node, it may correspond to abnormal intake valve clearances, providing traceable diagnostic basis and interpretability of fuzzy rules.

### *4.3. Modeling analysis*

***1) Model training analysis:*** The proposed deep neuro-fuzzy approach is essentially a deep model incorporating fuzzy inference. Thus, the magnitude of change in each optimization iteration can be analyzed in terms of the learning rate. A series of training analyses are performed using different learning rates as a reference, as shown in figure 7. In $Lr = 0.005$ and 0.001, the model requires more iterations to converge, potentially exceeding 800 epochs for stable convergence. It suggests that the lower the learning rate the more computational time is needed to converge, which leads to lower efficiency. When $Lr = 0.05$, the higher learning rate causes the model to experience abnormal loss fluctuations after convergence, resulting in instability. At $Lr = 0.001$, the model achieves stable convergence through consistent iterative computation. Additionally, it is observed that all training runs exhibit a convergence trend after 500 iterations, despite potential loss fluctuations at different learning rates. This indicates that the model consistently moves toward a convergent state.

***2) Parameter setting analysis:*** This section discusses the parameter values of the most critical adjustment factor $\alpha$ in this work, and the results are shown in figure 8. In the weight fuzzy module, the value range of adjustment factor $\alpha$ is [0.1, 1.5], which is used to control the sensitivity of weight allocation among nodes. We can observe that as the adjustment factor increases from 0.5 to 1.0, the accuracy of the model gradually increases and stabilizes at $\alpha = 0.8$. Further increasing $\alpha$ will lead to a decrease in accuracy, which may be due to excessive smoothing of weight allocation suppressing the transmission of key fault features. In addition, when removing the weight

**Table 2.** Calculation complexity and significance test of various methods.

| | *P*-value of *T*-test | Time complexity | Space complexity |
|---|---|---|---|
| Our | # | O($n^2$) | O($n$) |
| CNN-1d | 0.002 | O($n$) | O($n$) |
| Transformer-1d | 0.001 | O($n^2$) | O($n^2$) |
| GCN | 0.01 | O($n^2$) | O($n^2$) |
| TCN | 0.03 | O($n$) | O($n$) |
| GRU | 0.005 | O($n^3$) | O($n^2$) |
| LSTM | 0.0005 | O($n^3$) | O($n^2$) |

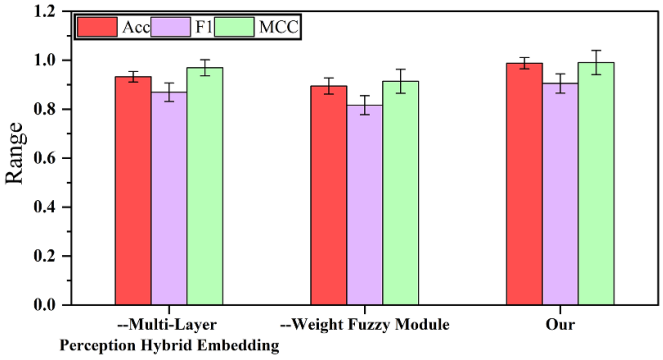



**Figure 6.** Results of different modules.

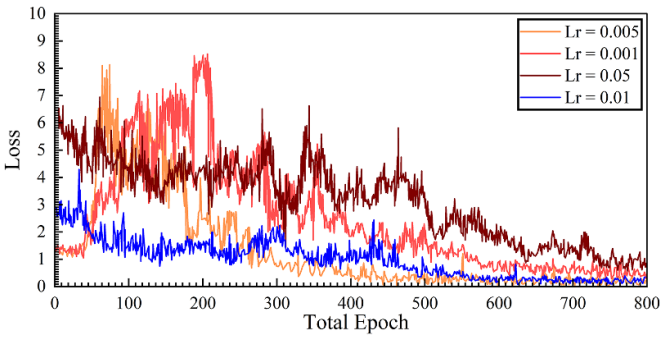



**Figure 7.** Result measurement of each epoch.

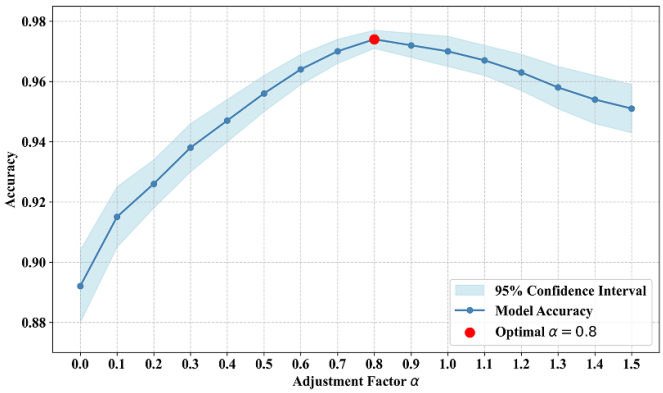



**Figure 8.** Adjustment factor trend.

fuzzy module (i.e., $\alpha = 0$), the model performance significantly decreases, verifying the necessity of adjusting factors in semantic transfer.

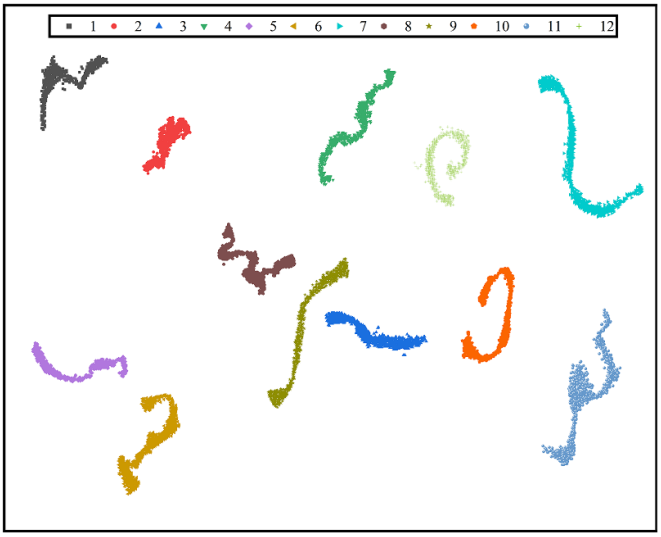


**Figure 9.** Visualization of feature distribution.

### *4.4. Results of the experiment*

***1) Fault diagnosis***: In this subsection, fault diagnosis is evaluated using the proposed method. To further visualize the final classification results, the t-SNE algorithm (Xiao *et al* 2023) is employed as a visualization tool, and its feature distribution is shown in figure 9. In addition, the diagnosis results are summarized in a confusion matrix, demonstrating the best and worst results, as shown in figure 10. It can be seen that the twelve fault classes are correctly identified by the proposed method. Meanwhile, the confusion matrix shows that most fault classes achieve perfect classification in the best-case scenario. In the worst-case confusion matrix, only a small number of instances are misclassified. Overall, the proposed method demonstrates satisfactory diagnostic accuracy. The confusion matrix further enables quantitative measurement of diagnostic accuracy for each fault class. The diagnostic accuracy for each fault category exceeds 0.96, and some fault classes achieve perfect identification. The MCC and $F1$ Score for each fault class also attain satisfactory levels, further reflecting the model's reliability.

***2) Comparison with other related methods***: To further analyze the superiority of the proposed method, it is necessary to compare it with recent and relevant diagnosis techniques. In this subsection, three fault diagnosis methods closely related

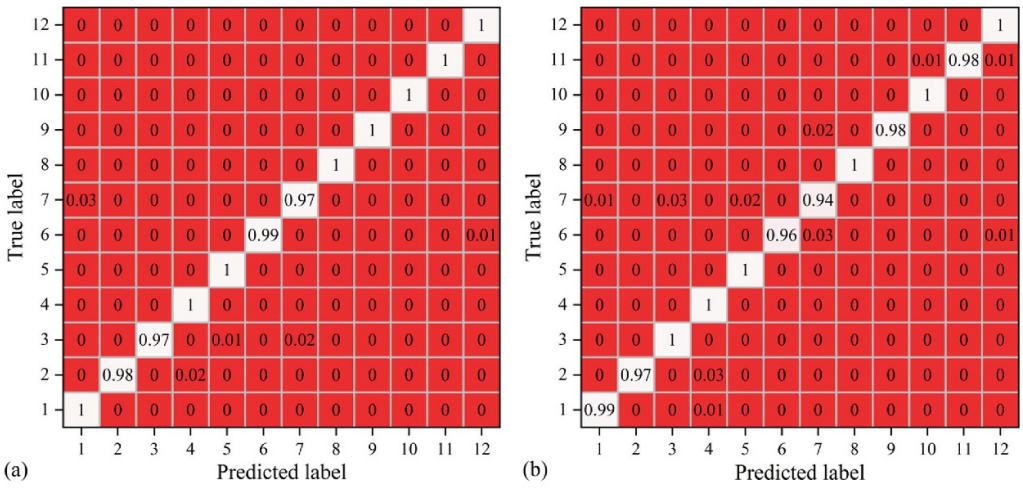



**Figure 10.** Confusion matrix of results. (a) The best diagnosis results and (b) the worst diagnosis results.

**Table 3.** Measurement results of different methods.

| | 1-Fold | | | 2-Fold | | | 3-Fold | | | 4-Fold | | | 5-Fold | | | Average | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Acc | *F*1 | MCC | Acc | *F*1 | MCC | Acc | *F*1 | MCC | Acc | *F*1 | MCC | Acc | *F*1 | MCC | Acc | *F*1 | MCC |
| Our | 0.994 | 0.920 | 0.996 | 0.982 | 0.916 | 0.991 | 0.972 | 0.895 | 0.981 | 0.985 | 0.913 | 0.993 | 0.974 | 0.896 | 0.985 | **0.981** | **0.908** | **0.989** |
| Method 1 | 0.938 | 0.874 | 0.965 | 0.953 | 0.889 | 0.980 | 0.894 | 0.829 | 0.921 | 0.952 | 0.885 | 0.977 | 0.917 | 0.852 | 0.941 | **0.931** | **0.866** | **0.957** |
| Method 2 | 0.822 | 0.766 | 0.861 | 0.788 | 0.719 | 0.822 | 0.790 | 0.741 | 0.838 | 0.802 | 0.748 | 0.854 | 0.853 | 0.793 | 0.872 | **0.811** | **0.753** | **0.849** |
| Method 3 | 0.964 | 0.903 | 0.980 | 0.973 | 0.911 | 0.983 | 0.967 | 0.904 | 0.980 | 0.968 | 0.906 | 0.979 | 0.977 | 0.905 | 0.988 | **0.970** | **0.906** | **0.982** |

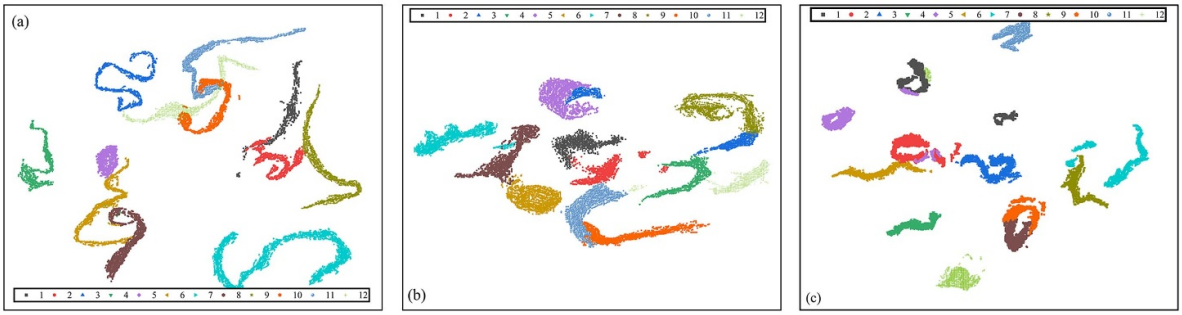



**Figure 11.** Feature distribution of different methods. (a) Results of Method 1, (b) Results of Method 2, and (c) Results of Method 3.

to and representative of our research work are used to conduct comparative experiments. These methods include Method 1 (Li *et al* 2021), Method 2 (Zhao *et al* 2023), and Method 3 (Chen *et al* 2022), where Method 1 and Method 3 are based on traditional graph convolution methods, while Method 2 is based on hypergraph convolution.

Note that 5-fold cross-validation is employed to evaluate the generalization performance of the different methods, in which all the samples are divided into 5 equal subsets, and one of the subsets is randomly taken as the test set and the rest as the training set. Table 3 reports the quantitative metrics of the different methods under cross-validation. Also, the feature visualization of these comparison methods is shown in figure 11. In the distribution of the various fault features, Method 2 exhibits misclassification across almost all fault classes, with some classes being completely misidentified. The diagnosis performance of Method 1 is second only to that of Method 3. In Method 1, although most fault classes are fully recognized, the decision boundaries for some classes are blurred. In Method 3, most faults are diagnosed satisfactorily, with only a few classes showing slightly ambiguous margins. Meanwhile, as shown in table 2, the diagnosis stability of Method 3 is comparable to that of the proposed method. In contrast, Method 2 exhibits significant diagnosis fluctuations. Collectively, these results demonstrate that the proposed method achieves superior diagnostic performance across the twelve fault classes.

### *4.5. Noise testing*

To illustrate the noise immunity of the diagnosis, Gaussian white noise with different signal-to-noise ratios (SNRs) is

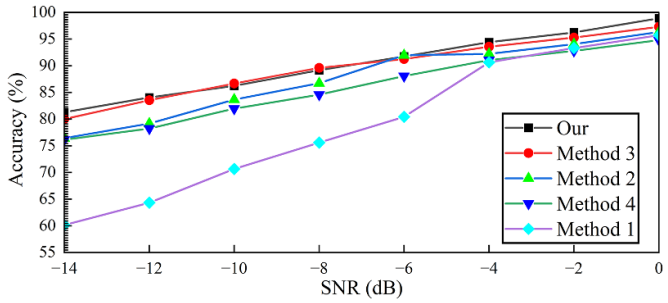



**Figure 12.** Test results in a noisy environment.

added to the industrial dataset. This simulates fault diagnosis in real industrial systems under noisy conditions, as shown in figure 12. The noise immunity of each method can be assessed by their performance under varying SNR levels. In figure 12, a degradation trend is evident for all the diagnosis methods as the noise intensity increases. In other words, the negative impact on the diagnosis performance worsens progressively with increasing noise intensity. Overall, these methods exhibit varying degrees of diagnosis degradation and declining fault recognition rates. Specifically, Method 1 experiences a sharp drop in its diagnostic performance at SNR $= -6$, indicating that the method is not robust to stronger white noise when SNR falls below $-6$. The decrease in diagnosis accuracy for Methods 2, 3, and the proposed method is more gradual as the noise increases, demonstrating that these methods are relatively robust to varying degrees of random noise. Method 1 fails to maintain a stable decline in the noise immunity test, indicating poor robustness against noise interference. Furthermore, the proposed method also exhibits a stable and relatively small degradation trend. As the noise intensity increases, its diagnosis accuracy remains within an acceptable range. In general, the proposed method demonstrates noise robustness comparable to other diagnosis methods.

## 5. Conclusion

In this paper, a neuro-fuzzy approach with hypergraph convolution is proposed for fault diagnosis in industrial systems. A diagnosis framework for industrial systems is constructed based on fuzzy logic and hypergraph convolution to mine hidden fault features in industrial big data and to fully understand the semantic representation of information cascades guided by fuzzy rules. Specifically, a fuzzy rule-driven graph construction approach is designed to map different subsets of input features and induce cascading behaviors. The developed weight fuzzy module is utilized to adjust the weights across the two graphs to enhance semantic transfer between them. Next, multi-layer perception hybrid embedding is utilized to suppress knowledge dispersion in the graph structure. Extensive diagnosis experiments using diesel engine data in industrial scenarios were conducted to validate the effectiveness of the proposed methodology. The experimental results show that the proposed method is highly competitive. Moreover, ablation studies on different modules and backbone networks further corroborate the design choices.

Although the fuzzy rule provides partial interpretability, the hidden layers of hypergraph convolution and multi-layer perceptual embedding still have a 'black box' problem, making it difficult to directly explain the causal chain of fault diagnosis. In addition, although hypergraph construction and multi-layer perceptual embedding mechanisms have improved semantic transfer efficiency, their computational complexity is high, making it difficult to meet the strong demand for real-time diagnosis in industrial scenarios. Therefore, future research will combine causal graph models to explicitly associate fuzzy rules with causal relationships, and introduce dynamic graph sparsity techniques to reduce the computational scale of hypergraphs by pruning redundant hyperedges or nodes.

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