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A Hierarchical Multi-Source Condition Monitoring and Fault Diagnosis Framework for LNG Submersible Centrifugal Pumps in Marine Energy Transportation Systems

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Abstract

Liquefied natural gas (LNG) submersible centrifugal pumps are critical components in marine energy transportation systems, and fault-induced degradation may threaten operational safety, transfer reliability, and maintenance efficiency. However, condition monitoring and fault diagnosis often rely on heterogeneous multi-source data, where redundant information, unequal channel sensitivity, and inter-signal coupling may obscure discriminative fault features. To address this challenge, this paper proposes a hierarchical multi-source condition monitoring and fault diagnosis framework for LNG submersible centrifugal pumps by integrating an Entropy-Weighted Sensor Selection Method (EWSSM) with a hybrid convolutional neural network (CNN)–Transformer model. Functional information is used for front-end abnormality screening, while selected response signals are used for fault category recognition. EWSSM evaluates channel contribution and suppresses redundant inputs to construct a compact fault-sensitive input space. The CNN–Transformer model combines local feature extraction with global dependency modeling to identify complex fault patterns. A laboratory-scale fault simulation platform was established, and vibration, acoustic, internal pressure-pulsation-related response information, and operating parameter data were collected under ten operating states. Experimental results show that the proposed framework achieves effective abnormality screening and accurate fault diagnosis, with an average classification accuracy of 98.73% over repeated experiments. Covariance-difference analysis further provides interpretable evidence for condition assessment by revealing fault-related multi-source response redistribution. The proposed framework provides an effective, intelligent monitoring and diagnosis solution for LNG submersible centrifugal pumps and supports reliability-oriented operation and maintenance of marine energy transportation equipment.



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1. Introduction

As a clean and efficient energy source, liquefied natural gas (LNG) is playing an increasingly important role in the global transition toward low-carbon and sustainable energy

systems [1–3]. In LNG transportation and storage systems, submersible centrifugal pumps serve as critical equipment for cryogenic fluid delivery, and their operational safety and reliability directly affect system stability, transport efficiency, and economic performance [4–7]. In marine LNG storage and transportation scenarios, such pumps are often required to operate continuously under cryogenic, submerged, and safety-critical conditions. Unexpected degradation may affect LNG transfer reliability, cargo handling safety, and maintenance scheduling. Figure 1 shows typical component-level failure modes of submersible centrifugal pumps, highlighting the need for reliable condition monitoring and fault diagnosis under demanding service conditions. Due to long-term operation under cryogenic temperatures, high pressure, and liquid-immersion conditions, these pumps are exposed to harsh service environments and considerable maintenance challenges. Previous studies have shown that complex hydraulic phenomena, including cavitation, pressure pulsation, and flow instability, may induce structural vibration and performance degradation in centrifugal pumps, which can further lead to efficiency loss, intensified noise, and even severe operational risks [8–12]. Therefore, effective condition monitoring and fault diagnosis of submersible centrifugal pumps are of great engineering importance for ensuring operational safety, reducing maintenance costs, extending service life, and enabling predictive maintenance of critical energy infrastructure [13,14].

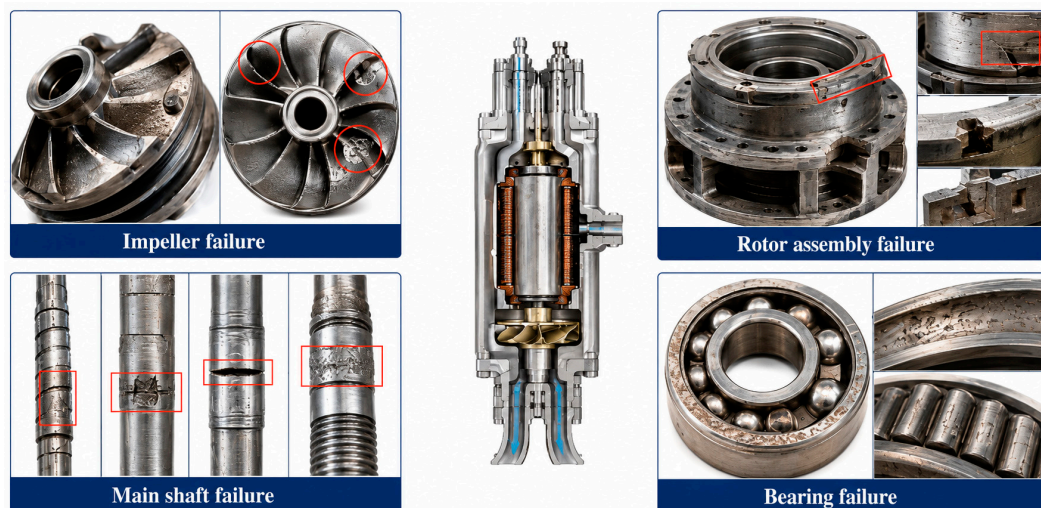


Figure 1. Typical component-level failure modes of submersible centrifugal pumps [15–17].

With the rapid development of sensing and data-acquisition technologies, condition monitoring of centrifugal pumps and other rotating machinery has gradually evolved from single-signal observation to multi-source information analysis [18,19]. Vibration-based monitoring has been extensively investigated because vibration signals are highly sensitive to mechanical impacts and structural response variations [20,21]. Meanwhile, pressure-pulsation analysis has been widely employed to characterize internal hydraulic disturbances, particularly under cavitation, flow instability, and impeller-related fault conditions [22,23]. In addition to vibration and pressure signals, acoustic emission, motor current, and power signals have also been introduced in recent years as supplementary information sources for abnormal-state identification [24,25]. Compared with single-source monitoring strategies, several studies have reported that multi-source information fusion can significantly improve the completeness of system state perception and enhance the reliability of fault identification [26–28]. However, the effective utilization of heterogeneous monitoring signals remains a challenging task in practical applications.

A major difficulty lies in the fact that different monitoring channels do not contribute equally to fault discrimination. Existing multi-sensor diagnostic studies have shown that certain channels are highly sensitive to specific fault types, whereas others may contain limited diagnostic information or even introduce noise and redundancy [29,30]. To address this issue, various sensor-selection, feature-selection, and dimensionality-reduction techniques have been explored to improve diagnostic efficiency and reduce redundant inputs [31,32]. Hu et al. [33] demonstrated that interpretable feature selection can effectively reduce redundant information and enhance the robustness of centrifugal pump fault identification. Tao et al. [34] further indicated that selecting fault-sensitive sensor channels helps improve diagnostic efficiency and real-time performance in multi-sensor systems. In addition, Ullah et al. [35] confirmed that discriminative feature evaluation and dimensionality reduction are beneficial for strengthening the separability of fault categories in multistage centrifugal pumps. However, fault diagnosis is more challenging for submersible centrifugal pumps because their response characteristics are affected by hydraulic excitation, structural vibration transmission, and submerged operating conditions. Different faults may appear in vibration, acoustic, and pressure-pulsation-related signals with unequal intensity and distinct coupling patterns. Therefore, it is difficult to directly identify the most fault-sensitive information sources from multi-source signals. Many existing methods are designed for general multi-sensor classification tasks and are not specifically adapted to the response characteristics of submersible centrifugal pumps. Directly fusing all channels may increase input dimensionality and model complexity. This can increase computational burden, raise overfitting risk, and reduce diagnostic performance.

In condition monitoring of LNG submersible centrifugal pumps, multi-source information refers to monitoring data acquired from different sensor types, measurement locations, and acquisition approaches. These signals differ in physical meaning, data structure, sampling characteristics, and fault sensitivity, but they jointly reflect the operating condition and health status of the pump. In existing studies, condition monitoring and fault diagnosis are often treated as relatively independent tasks. Some studies focus on performance monitoring or anomaly detection using operational parameters, whereas others concentrate on fault-category recognition using vibration or other response signals [36–38]. In practical applications, however, abnormality screening and detailed fault-category recognition are closely related. Functional information is more suitable for front-end state evaluation, whereas response information is more informative for detailed fault identification. Without a coordinated framework to integrate these two levels of information, the monitoring process may become inefficient, and the subsequent diagnosis may lack targeted information support. Therefore, a hierarchical monitoring and diagnosis framework that links abnormality screening with downstream fault classification is needed to improve the utilization efficiency of multi-source monitoring data.

Meanwhile, deep-learning-based methods have demonstrated strong capability in complex signal analysis for rotating machinery. Convolutional neural networks (CNNs) have been widely applied to machinery fault diagnosis due to their effectiveness in extracting local temporal and structural patterns from raw monitoring signals [39–41]. More recently, Transformer-based architectures have attracted increasing attention because of their ability to model long-range dependencies and global contextual relationships in time-series data [42,43]. Some recent studies have attempted to integrate CNN and Transformer modules to jointly exploit local feature extraction and global dependency modeling capabilities [44,45]. Nevertheless, directly feeding high-dimensional multi-source signals into deep neural networks may still lead to redundant feature learning and inefficient information utilization. These limitations restrict the practical application of intelligent condition monitoring methods in marine LNG equipment. For practical marine equipment monitoring, the

diagnostic framework should not only pursue high classification accuracy but also reduce redundant sensing information and provide compact, interpretable monitoring evidence for maintenance decisions. Consequently, combining effective sensor-selection mechanisms with deep feature learning provides a promising strategy for improving the fault-diagnosis performance of submersible centrifugal pumps.

To address these issues, this study proposes a hierarchical multi-source diagnosis framework for submersible centrifugal pumps by integrating an Entropy-Weighted Sensor Selection Method (EWSSM) and a hybrid CNN–Transformer model. In the proposed framework, functional information and response information are coordinated in a progressive manner. Front-end condition monitoring is first performed for abnormality screening. Then, a detailed fault-category diagnosis is conducted using selected multi-source response signals. EWSSM is used to evaluate the relative importance of candidate channels and remove redundant inputs. This process retains compact and fault-sensitive response information for subsequent diagnosis. The CNN–Transformer model is then used to extract local fault features and global temporal dependencies from the selected signals, enabling accurate fault classification under different fault conditions. In this way, the proposed framework improves diagnostic performance and provides an interpretable basis for condition assessment and maintenance-oriented analysis of submersible centrifugal pumps.

The fundamental novelty of this study lies in the development of a hierarchical multi-source condition monitoring and fault diagnosis framework specifically for LNG submersible centrifugal pumps, rather than in simply applying a general multi-sensor fusion model. The EWSSM and CNN–Transformer are two key technical components within this framework: EWSSM constructs a compact and fault-sensitive multi-source input space, while the CNN–Transformer model performs downstream fault classification based on the selected channels. The main contributions of this study are summarized as follows:

1. A hierarchical abnormality-screening and fault-classification framework is established for LNG submersible centrifugal pumps in marine energy transportation systems. Different from conventional approaches that directly fuse all available monitoring signals for classification, the proposed framework coordinates functional information and response information according to their diagnostic roles, thereby linking front-end condition monitoring with downstream fault diagnosis.
2. A fault-specific entropy-weighted sensor selection method with global aggregation is introduced to quantify the discriminative contribution of heterogeneous response channels. The proposed method considers the unequal sensitivity of different channels under different fault conditions and generates a compact fixed channel subset for practical diagnosis, thereby reducing redundant multi-source inputs while preserving representative fault-sensitive information.
3. A CNN–Transformer-based diagnostic model is developed for fault-category recognition using the selected multi-source channels. The CNN module extracts local temporal fault patterns, whereas the Transformer module captures global dependencies and inter-channel relationships. In addition, covariance-difference analysis is used as supplementary interpretable evidence to support condition assessment and maintenance-oriented discussion.

The remainder of this paper is organized as follows. Section 2 introduces the proposed methodology. Section 3 describes the hierarchical multi-source fault diagnosis case for the LNG submersible centrifugal pump, including the experimental setup and diagnostic procedure. Section 4 presents the results and discussion. Finally, Section 5 summarizes the main conclusions and future work.

2. Methodology for Multi-Source Condition Monitoring and Fault Diagnosis

Condition monitoring and fault diagnosis of submersible centrifugal pumps are closely related, but they serve different purposes. Condition monitoring aims to comprehensively characterize the operating state of the equipment by integrating multi-source information, whereas fault diagnosis focuses on accurately identifying specific fault categories using informative and compact diagnostic inputs. Consequently, there exists a practical need to balance information completeness and diagnostic efficiency. Excessive input dimensionality may increase computational burden and introduce redundant information, while overly simplified inputs may weaken fault-sensitive feature representation.

To address this issue, this study proposes a hierarchical multi-source diagnosis framework for LNG submersible centrifugal pumps. In the proposed framework, front-end condition monitoring and downstream fault diagnosis are organized in a coordinated manner. Functional information and response information are first processed according to their different diagnostic roles to perform abnormality screening. Subsequently, the candidate diagnostic channels are evaluated using an entropy-weighted sensor selection mechanism to retain informative inputs and reduce redundancy. On this basis, a hybrid CNN–Transformer model is constructed for detailed fault-category recognition. Through this framework, the proposed method aims to improve fault diagnosis performance while maintaining effective utilization of heterogeneous monitoring information.

The overall framework of the proposed method is illustrated in Figure 2 and consists of three main stages:

1. **Condition monitoring stage:** The acquired multi-source information is divided into functional information (e.g., rotational speed, flow-related parameters, and pressure-related operating variables) and response information (e.g., vibration, internal pressure-pulsation-related responses, and acoustic signals). A hierarchical evaluation mechanism is then used to assess the operating condition of the pump and determine whether an abnormality is present.
2. **Information screening stage:** An entropy-weighted sensor selection mechanism is introduced to evaluate the relative importance of candidate response channels. The most informative channels for fault discrimination are retained, while redundant and weakly informative inputs are removed, thereby improving the effectiveness of subsequent diagnosis.
3. **Diagnostic modeling stage:** The selected key channels are fed into a hybrid model integrating a convolutional neural network (CNN) and a Transformer architecture. The CNN is used to extract local fault-related features, whereas the Transformer captures long-range dependencies and global contextual relationships, enabling accurate fault category recognition of the submersible centrifugal pump.

2.1. Hierarchical Condition Monitoring and Evaluation

During the operation of a submersible centrifugal pump, state-related information can be obtained from multiple sources. According to their physical meanings and diagnostic roles, this information can be broadly divided into functional information and response information. These two categories differ in diagnostic sensitivity, information content, and application stage. Therefore, a hierarchical condition monitoring and evaluation framework is established in this study to coordinate front-end state assessment and subsequent abnormality screening.

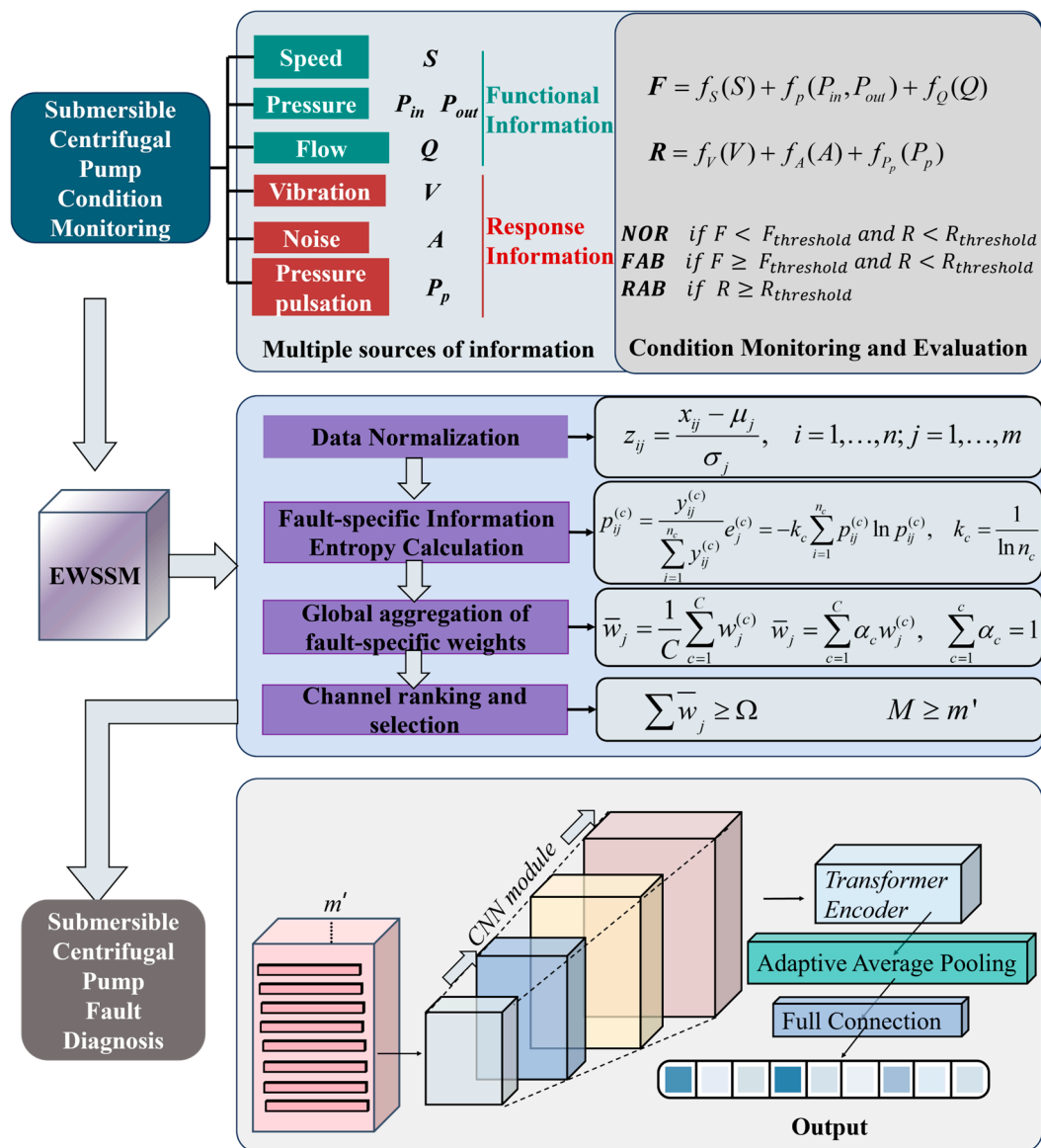


Figure 2. Proposed hierarchical multi-source condition monitoring and fault diagnosis framework.

2.1.1. Information Classification

Functional information mainly refers to the operating parameters directly related to the designed working performance of the submersible centrifugal pump, such as motor rotational speed, inlet and outlet pressures, and flow-related variables. These parameters can directly reflect whether the pump operates within its expected working range and whether its basic hydraulic performance remains stable. Therefore, functional information is mainly used for front-end evaluation of the overall operating condition and functional integrity of the pump.

Response information refers to the dynamic responses generated during pump operation, including external vibration signals, acoustic noise, and internal pressure-pulsation-related responses. Compared with functional information, response information is generally more sensitive to local disturbances, structural variations, and fault evolution. Therefore, it can provide more fault-sensitive evidence for identifying abnormal dynamic behavior and potential fault characteristics of the equipment.

2.1.2. Logical Hierarchy and State Evaluation

Based on the two categories of monitoring information described above, a logic-based hierarchical evaluation method is established to perform multi-level judgment of the health condition of the submersible centrifugal pump.

At the functional level, the operating condition of the pump is preliminarily evaluated according to key operating parameters and their allowable ranges. This level focuses on whether the equipment satisfies the expected working conditions from the perspective of system performance. A functional evaluation index is constructed as

$$F = f_S(S) + f_p(P_{in}, P_{out}) + f_Q(Q) \quad (1)$$

where F denotes the functional evaluation result, S denotes rotational speed, P_{in} and P_{out} denote inlet and outlet pressures, respectively, and Q denotes flow-related information. The functions $f_S(S)$, $f_p(P_{in}, P_{out})$, and $f_Q(Q)$ characterize the contributions of the corresponding variables to functional-state evaluation. By comparing these variables with predefined thresholds or empirical operating ranges, a coarse-grained assessment of the functional condition of the pump can be achieved.

At the response level, feature statistics and trend analysis are used to characterize the fluctuation and stability of dynamic response signals, including vibration, acoustic, and internal pressure-pulsation-related information. This level focuses on whether the response characteristics deviate from the normal operating pattern. A response evaluation index is defined as

$$R = f_V(V) + f_A(A) + f_{P_p}(P_p) \quad (2)$$

where R denotes the response evaluation result, V denotes vibration-related information, A denotes acoustic/noise-related information, and P_p denotes internal pressure-pulsation-related information. The functions $f_V(V)$, $f_A(A)$, and $f_{P_p}(P_p)$ are used to quantify the corresponding contributions of different response sources to abnormality evaluation.

Finally, the functional-level and response-level results are integrated through a hierarchical logical reasoning mechanism to determine the health state of the submersible centrifugal pump. The operating condition is classified into three levels: Normal (**NOR**), Functional Abnormality (**FAB**), and Response Abnormality (**RAB**). When a response abnormality is detected, the downstream fault diagnosis module is activated for detailed fault category recognition, thereby providing a basis for subsequent data screening and intelligent diagnosis. The detailed algorithm of the hierarchical condition monitoring and graded evaluation is provided in Appendix A.

In practical implementation, the threshold values $F_{threshold}$ and $R_{threshold}$ were determined based on normal-condition statistics and the allowable operating ranges of the pump. Specifically, $F_{threshold}$ was set according to the acceptable deviation limits of key functional parameters, including rotational speed, inlet/outlet pressure, and flow-related variables, with respect to the expected operating condition. $R_{threshold}$ was determined from the statistical fluctuation boundaries of vibration, acoustic, and pressure-pulsation-related response indicators under normal operation. In this way, the front-end screening module provides preliminary normal/abnormal discrimination before detailed fault-category recognition and establishes the decision basis for the graded states **NOR**, **FAB**, and **RAB**.

2.2. Entropy-Weighted Sensor Selection Method (EWSSM)

In the fault diagnosis of submersible centrifugal pumps, multiple response channels are used to acquire heterogeneous information such as vibration, internal pressure-pulsation-related responses, and acoustic noise. However, different channels do not contribute equally to fault discrimination, and their sensitivity may vary across different fault categories. Some

channels are highly responsive to certain fault-induced dynamic changes and contain strong discriminative information, whereas others may provide limited useful information or even introduce redundancy and noise. Directly using all candidate channels as diagnostic inputs may therefore increase model complexity, aggravate computational burden, and impair diagnostic performance. To address this issue, an Entropy-Weighted Sensor Selection Method (EWSSM) is adopted in this study to evaluate channel importance and identify informative diagnostic inputs.

Unlike a single global ranking strategy, the proposed method considers that different fault categories may exhibit different channel sensitivities. Therefore, channel importance is first analyzed separately for different fault conditions during model development, and the resulting fault-specific channel weights are then aggregated to obtain a global channel ranking. Based on this ranking, a compact subset of informative channels is selected as the fixed input for the downstream fault diagnosis model. In this way, the proposed method preserves fault-sensitive channel information while avoiding the ambiguity of online channel selection when the fault category is still unknown.

Assume that the diagnosis system contains m candidate channels, and n samples are collected under different operating states or fault conditions. The corresponding data matrix can be expressed as

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \quad i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (3)$$

where x_{ij} represents the observation value of the j -th sensor channel in the i -th sample.

2.2.1. Data Normalization

Because different channels may exhibit significant differences in magnitude and scale, normalization is first performed to improve inter-channel comparability. In this study, Z-score normalization is adopted as a preprocessing step:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \quad i = 1, \dots, n; j = 1, \dots, m \quad (4)$$

where μ_j and σ_j denote the mean value and standard deviation of the j -th sensor channel, respectively. After normalization, the data from each channel have a mean of zero and a variance of one, thereby eliminating the influence of dimensional inconsistencies and enhancing the comparability among channels. To ensure valid entropy calculation, the normalized channel features are further transformed into a non-negative form before probability construction. On this basis, the relative distribution of each channel can be used for entropy evaluation.

2.2.2. Fault-Specific Information Entropy Calculation

To reflect the fact that different fault categories may have different channel sensitivities, entropy evaluation is performed separately for each fault category during model development. Let $c \in \{1, 2, \dots, C\}$ denote the fault category, where C is the number of

fault categories considered in diagnosis. For the j -th channel under fault category c , the normalized probability distribution is defined as

$$p_{ij}^{(c)} = \frac{y_{ij}^{(c)}}{\sum_{i=1}^{n_c} y_{ij}^{(c)}} \quad (5)$$

where $y_{ij}^{(c)}$ denotes the non-negative transformed value of the normalized feature for the j -th channel under the i -th sample of fault category c , and n_c denotes the number of samples associated with that category in the fault-specific analysis.

The information entropy of the j -th channel for fault category c is then calculated as

$$e_j^{(c)} = -k_c \sum_{i=1}^{n_c} p_{ij}^{(c)} \ln p_{ij}^{(c)}, \quad k_c = \frac{1}{\ln n_c} \quad (6)$$

where k is a constant ensuring that $e_j^{(c)} \in [0, 1]$. The entropy $e_j^{(c)}$ reflects the uncertainty of the j -th channel with respect to fault category c . A lower entropy value indicates that the channel exhibits stronger variation and richer fault-related information under the corresponding fault condition. In contrast, a higher entropy value indicates weaker discriminative capability for that fault category.

2.2.3. Fault-Specific Weight Determination and Relation to Fault Classification

From the perspective of fault classification, the entropy value of a channel is closely related to its potential discriminative capability. If the response distribution of a channel differs significantly under a certain fault category, the uncertainty of that channel is relatively low, indicating that it contains more structured fault-related information and is more conducive to class separation. Conversely, if the channel responses remain similar across fault states, the corresponding entropy tends to be high, suggesting limited discriminative value for downstream diagnosis.

Accordingly, the fault-specific discriminative contribution of the j -th channel under fault category c can be interpreted as being positively related to $1 - e_j^{(c)}$, i.e.,

$$D_j^{(c)} \propto 1 - e_j^{(c)} \quad (7)$$

where $D_j^{(c)}$ denotes the potential contribution of the j -th channel to the recognition of fault category c . After normalization, the fault-specific channel weight is defined as

$$w_j^{(c)} = \frac{1 - e_j^{(c)}}{\sum_{j=1}^m (1 - e_j^{(c)})} \quad (8)$$

where $w_j^{(c)}$ denotes the relative contribution of the j -th channel to discriminating fault category c . A larger $w_j^{(c)}$ indicates that the corresponding channel is more informative for identifying that fault condition.

2.2.4. Global Aggregation of Fault-Specific Weights

Although fault-specific channel weights can reveal the sensitivity of different channels to different fault categories, the fault type is unknown before diagnosis in practical applications. Therefore, a unified channel subset is still required for downstream classification. To

achieve this, the fault-specific weights are further aggregated to obtain a global channel importance score.

A simple and effective aggregation strategy is adopted in this study, in which the global channel weight is calculated as the average of the fault-specific weights across all fault categories:

$$\bar{w}_j = \frac{1}{C} \sum_{c=1}^C w_j^{(c)} \quad (9)$$

where $w_j^{(c)}$ denotes the importance of the j -th channel under fault category c , C is the total number of fault categories, and $\bar{w}_j$ represents the aggregated global importance score of the j -th channel. More generally, if different fault categories are assigned different priorities according to practical requirements, the aggregation process can be extended to a weighted form:

$$\bar{w}_j = \sum_{c=1}^C \alpha_c w_j^{(c)}, \quad \sum_{c=1}^C \alpha_c = 1 \quad (10)$$

where α_c denotes the aggregation coefficient associated with fault category c . In the present study, equal weighting is adopted because all fault categories are treated uniformly during model development.

The aggregated weight $\bar{w}_j$ can be interpreted as a global estimate of the stable discriminative contribution of the j -th channel across representative fault conditions. In this way, the proposed method preserves the fault-sensitive information revealed by category-specific analysis while providing a fixed and practically applicable channel ranking for subsequent diagnosis.

2.2.5. Channel Ranking and Selection

After the aggregated channel weights are obtained, all candidate channels are ranked in descending order according to $\bar{w}_j$.

The final selected subset is defined as the smallest top-ranked channel set that satisfies two conditions: its cumulative global weight reaches the threshold Ω , and the number of retained channels is not smaller than the minimum retained-channel constraint m' . Therefore, Ω controls the required amount of preserved aggregated fault-discriminative information, whereas m' serves as a lower-bound constraint to prevent excessive channel compression.

In this study, the threshold parameters were determined based on validation performance, cumulative information preservation, and engineering considerations. Specifically, the selected channel subset was required to preserve sufficient fault-discriminative information while maintaining representative multi-source coverage and avoiding unnecessary input redundancy. The detailed algorithm of the fault-specific entropy-weighted sensor selection with global aggregation is provided in Appendix B.

2.3. CNN–Transformer-Based Fault Diagnosis Model

To effectively characterize fault patterns in multi-source monitoring signals, a CNN–Transformer-based diagnosis model is developed in this study. The design of the model is motivated by the complementary strengths of convolutional and attention-based architectures.

Specifically, convolutional layers are well suited for extracting local temporal patterns, transient impulses, and short-range periodic structures from multi-channel signals, whereas Transformer encoders are advantageous in modeling long-range dependencies and global contextual relationships in the reduced feature space. Based on this consideration, the proposed model adopts a cascaded architecture consisting of three components: local

feature extraction, global dependency modeling, and classification prediction. The overall structure is shown in Figure 3.

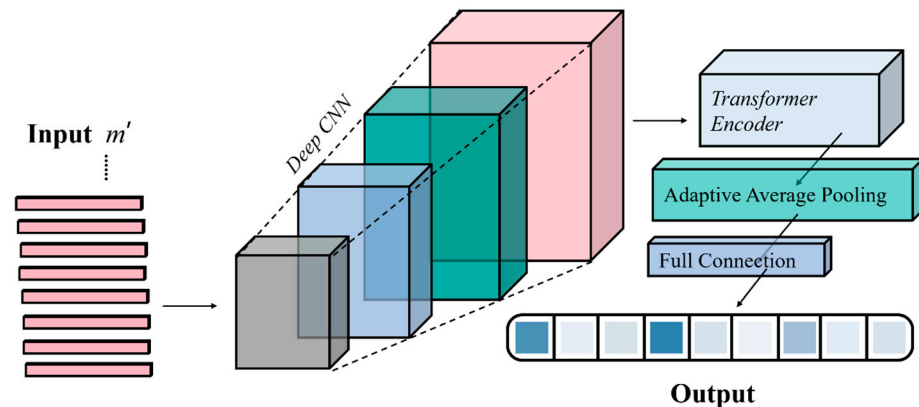


Figure 3. CNN–Transformer Model structure diagram.

2.3.1. CNN Module for Local Feature Extraction

After preprocessing and entropy-weighted channel selection, the retained multi-source time-series data are organized into an input tensor:

$$\mathbf{X} \in \mathbb{R}^{B \times K \times L} \quad (11)$$

where B is the batch size, K is the number of selected channels, and L denotes the temporal sequence length.

The CNN front-end is designed to extract local fault-sensitive patterns from the input signals and to reduce the temporal resolution before attention-based encoding. Let $H^{(0)} = \mathbf{X}$ denote the model input. For the l -th convolutional block, the feature extraction process can be expressed as

$$H^{(l)} = \sigma(BN(Conv1D(\tilde{H}^{(l-1)}))) \quad (12)$$

$$\tilde{H}^{(l)} = MaxPool1D(H^{(l)}) \quad (13)$$

where $Conv1D$ denotes the one-dimensional convolution operation, BN denotes batch normalization, σ denotes the nonlinear activation function, and $MaxPool1D$ denotes the max-pooling operation. Through this stacked structure, the model gradually enlarges the channel-wise feature dimension while compressing the temporal dimension. After the final convolutional block, the local feature tensor is obtained as

$$F_{CNN} \in \mathbb{R}^{B \times C' \times L'} \quad (14)$$

where C' denotes the output feature dimension of the CNN module, and L' denotes the compressed temporal length. In this study, the temporal dimension is reduced to one-sixteenth of the original sequence length. This design not only captures local impulses, short-term fluctuations, and periodic fault signatures but also reduces the sequence burden of the subsequent Transformer encoder.

2.3.2. Transformer Encoder for Global Dependency Modeling

Although convolutional operations are effective in local pattern extraction, they are limited in describing long-range temporal dependencies and global interactions among multi-source features. To enhance the representation capability of the extracted features, Transformer encoder layers are introduced after the CNN module.

Before entering the Transformer module, the CNN feature tensor is rearranged into a sequence representation:

$$Z \in \mathbb{R}^{B \times L' \times C'} \quad (15)$$

where each temporal position is associated with a multi-dimensional feature embedding. The Transformer encoder then models dependencies among these embeddings through Multi-Head Self-Attention (MHSA) and a position-wise Feed-Forward Network (FFN). For each encoder layer, the transformation process can be written as

$$Z' = \text{LN}(Z + \text{MHSA}(Z)) \quad (16)$$

$$Z'' = \text{LN}(Z' + \text{FFN}(Z')) \quad (17)$$

where LN denotes layer normalization. Residual connections are used to stabilize feature propagation and facilitate gradient flow during training. Through this design, the Transformer module can capture long-range temporal dependencies and global contextual relations in the compressed feature space, thereby complementing the locality of the CNN front-end.

2.3.3. Feature Aggregation and Classification

After global dependency modeling, an adaptive average pooling operation is applied along the temporal dimension to obtain a compact representation of the encoded sequence:

$$g = \text{AdaptiveAvgPool1D}(Z'') \quad (18)$$

where g denotes the aggregated global feature vector of the input sample.

The pooled feature vector is then mapped to the target category space by a fully connected layer, and the final class probability distribution is obtained by the *Softmax* function:

$$\hat{y} = \text{Softmax}(W_g g + b_g) \quad (19)$$

where W_g and b_g denote the weight matrix and bias vector of the classification layer, respectively, and $\hat{y}$ denotes the predicted probability distribution.

Overall, the proposed CNN–Transformer model follows a clear feature-processing logic: the CNN module extracts local fault-related patterns and performs temporal compression, the Transformer encoder models global dependencies and inter-feature interactions, and the classification layer maps the learned representation to fault categories. Through this cascaded architecture, the model is able to provide an effective solution for multi-source fault diagnosis of submersible centrifugal pumps.

3. Experimental Validation on an LNG Submersible Centrifugal Pump

3.1. Experimental System and Sensor Layout

To verify the effectiveness of the proposed entropy-weighted sensor selection method (EWSSM) and the CNN–Transformer-based diagnosis model, a laboratory-scale fault diagnosis platform for a submersible centrifugal pump was established. The platform was designed to reproduce representative operating conditions and typical fault states of submersible pump operation, thereby enabling controlled acquisition and storage of multi-source monitoring data for subsequent analysis. The overall experimental procedure, including platform construction, representative fault simulation, multi-source signal acquisition, and subsequent diagnostic validation, is illustrated in Figure 4.

The overall experimental platform consisted of three main subsystems:

1. A mechanical subsystem, which reproduced the basic operating structure and fluid-delivery process of a submersible centrifugal pump;
2. A sensor and data-acquisition subsystem, which was responsible for multi-channel measurement and synchronous signal acquisition;
3. A fault simulation subsystem, which was used to generate representative mechanical and hydraulic fault conditions for diagnostic validation.

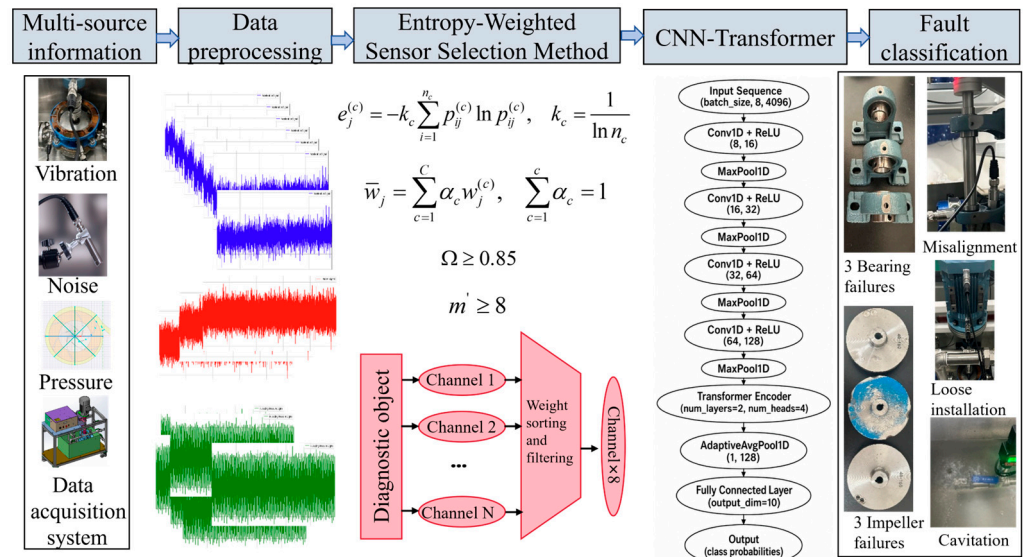


Figure 4. Experimental procedure flowchart.

3.1.1. Mechanical System and Test Object

The laboratory-scale experimental platform used in this study is shown in Figure 5. Its core component was a submersible centrifugal pump with a rated flow rate of 4 m³/h and a rated head of 32 m. The pump was driven by an electric motor, and its rotational speed was regulated by a variable frequency drive (VFD). The pipeline system was equipped with inlet and outlet valves, allowing flexible adjustment of flow-related and pressure-related operating conditions. This configuration enabled the simulation of normal operation as well as representative abnormal states under controlled laboratory conditions.

3.1.2. Sensor Configuration and Channel Layout

To comprehensively capture the operating condition of the pump, multiple types of sensors were arranged at representative positions of the pump body and the pipeline system. According to their different roles in the proposed framework, the acquired information can be divided into functional monitoring variables and diagnostic response channels.

- Rotational-speed information, used to characterize the basic operating condition of the pump;
- Vibration Sensors (Accelerometers): Mounted on the bearing housing and pump casing to capture high-frequency features associated with bearing and rotor-related faults;
- Pressure Sensors: Installed at the inlet and outlet to monitor internal pressure fluctuations within the pump chamber and to identify cavitation characteristics;
- Acoustic Sensors (Noise Sensors): Placed on the exterior surface of the pump casing to detect abnormal acoustic emissions;
- Flow Sensors: Used to monitor operating parameters such as flow rate, providing auxiliary information for analyzing energy conversion and cooling performance;
- Internal pressure-pulsation-related channels: Used to characterize internal pressure-related dynamic responses for subsequent diagnosis.

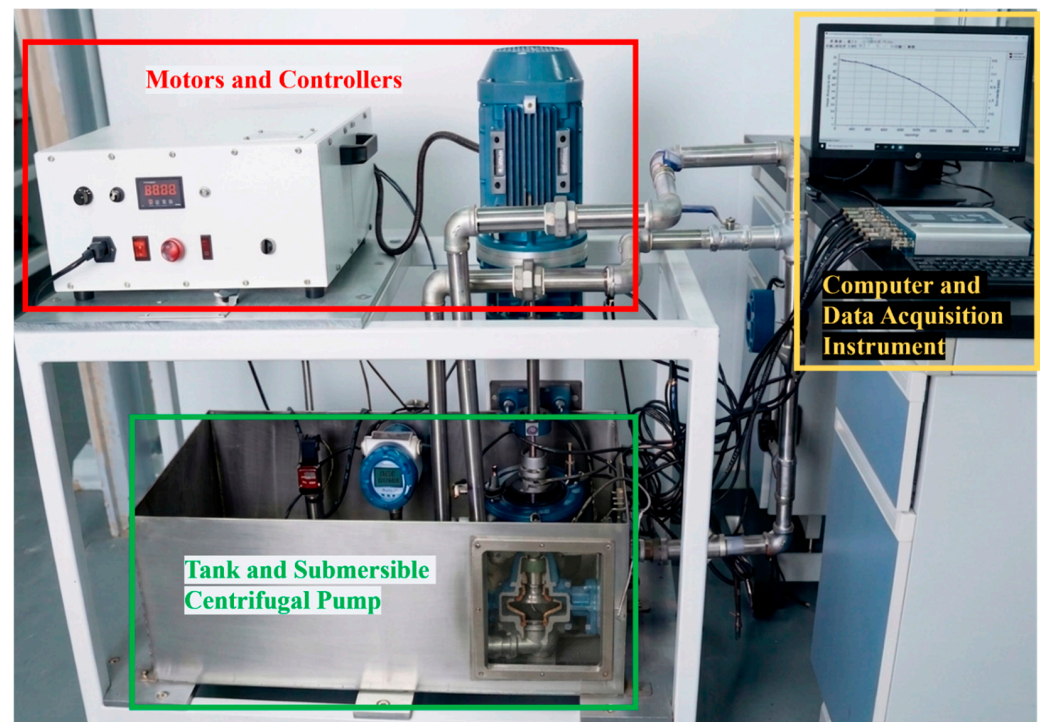


Figure 5. Experimental system of the submersible centrifugal pump.

In this study, 16 response channels were selected for fault diagnosis, comprising 10 vibration channels, 3 internal pressure-pulsation-related channels, and 3 acoustic channels. The corresponding sensor arrangement is presented in Figure 6. The internal pressure-pulsation-related information was obtained through a dedicated signal-processing procedure based on vibration measurements and incorporated into the subsequent multi-source diagnosis framework. In addition, rotational speed, inlet and outlet pressures, and flow-related variables were used as functional information in the front-end condition-monitoring stage.

The experiments were conducted on a laboratory water-medium platform under controlled operating conditions. The sampling frequency of the dynamic response channels was set to $f_s = 10$ kHz to ensure sufficient coverage of the characteristic frequency range relevant to fault diagnosis of the submersible centrifugal pump.

It should be noted that the present laboratory platform was designed to reproduce representative mechanical and hydraulic fault-response characteristics of a submersible centrifugal pump under safe, controllable, and repeatable conditions, rather than to fully replicate all cryogenic LNG operating conditions. The use of water as the working medium enables controlled fault-simulation experiments and multi-source signal acquisition, which is suitable for validating the proposed hierarchical monitoring framework, EWSSM-based channel selection, and CNN–Transformer-based fault classification under representative fault states.

However, several differences exist between the laboratory platform and practical LNG submersible pump applications. The cryogenic temperature and thermophysical properties of LNG, practical pressure boundary, complex vapor–liquid behavior, submerged installation, tank constraints, limited accessibility, and long-term marine service effects were not fully reproduced in this study. Therefore, the experimental results should be interpreted as validation of the proposed diagnostic methodology under controlled and representative fault-simulation conditions. Further validation under cryogenic LNG environments and field operating conditions is required before direct engineering deployment.

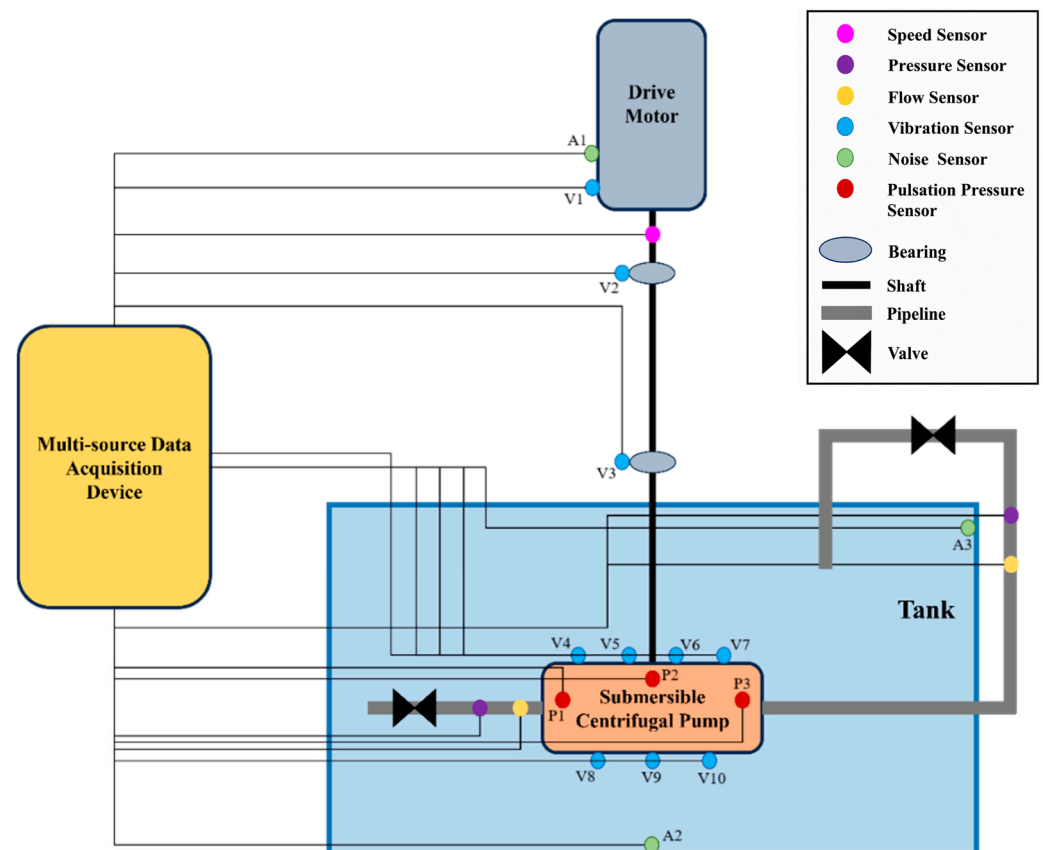


Figure 6. Schematic diagram of the sensor deployment.

3.2. Experimental Conditions and Dataset Construction

3.2.1. Fault Simulation and Operating Conditions

To construct a representative dataset for failure-related condition identification, the experimental platform was designed to simulate several typical fault types of the submersible centrifugal pump. The simulated fault conditions are summarized as follows (Figure 7):

- **Bearing Faults:** These faults were introduced by replacing the bearings with defective ones containing specific fault types, including inner-race fault (IRF), outer-race fault (ORF), and rolling-element fault (REF).
- **Impeller Faults:** These faults were simulated by installing impellers with different defect conditions, including impeller wear (IW), impeller deformation (ID), and impeller hole defect (IHD).
- **Misalignment:** Misalignment faults were generated by intentionally adjusting the shaft alignment to produce abnormal axial and radial alignment conditions.
- **Loose Installation:** Structural looseness was simulated by manually loosening the motor foundation bolts to reproduce installation-related instability.
- **Cavitation Condition:** Cavitation was induced by regulating the inlet valve to change the suction pressure and generate cavitation-related hydraulic disturbances.

For each fault condition, data from all monitoring variables and diagnostic response channels were synchronously acquired to construct a multi-source fault diagnosis database. In this study, the experiments were conducted under controlled laboratory operating conditions to ensure consistent comparison among different fault categories. In total, ten operating states were considered, including one normal condition and nine representative fault types. To avoid class imbalance bias, the number of samples for different operating states was kept approximately balanced.



Figure 7. Schematic diagram of simulated fault types in the submersible centrifugal pump.

3.2.2. Data Processing and Channel Selection

The experimental data were acquired on the submersible centrifugal pump test platform using a multi-channel synchronous acquisition system. The collected information included vibration signals, acoustic noise, internal pressure-pulsation-related information, and operating parameters.

The dataset covered ten operating states, including one normal condition and nine representative fault types. These states were designed to cover typical mechanical, hydraulic, and installation-related abnormalities of submersible centrifugal pumps, including bearing faults, impeller faults, rotor-related faults, structural looseness, and cavitation. For each operating state, response signals were continuously collected for 3 min at a sampling frequency of 10 kHz. Each sample segment consisted of 4096 consecutive data points, and the step size was set to 1024 points. To clarify the data-splitting strategy and reduce the risk of information leakage caused by overlapping windows, the raw time-series signal of each operating state was first divided along the time axis into training, validation, and testing subsets with a ratio of 8:1:1. Sliding-window segmentation was then performed independently within each subset. In this way, highly correlated windows generated from the same continuous signal segment were not assigned to different subsets. The training subset was used for model optimization, the validation subset was used for hyperparameter selection and early stopping, and the testing subset was used only for the final performance evaluation. Under this setting, each operating state generated 1403 training

samples, 172 validation samples, and 172 testing candidate samples. For the final confusion-matrix evaluation, 150 samples were selected from the independent testing subset of each operating state to maintain a balanced evaluation protocol across all classes. The remaining testing candidate samples were not used for model training, validation, hyperparameter tuning, or model selection. All operating states were tested under the same controlled laboratory-scale operating conditions, with a rotational speed of 2900 r/min, a rated flow rate of 4 m³/h, and a rated head of 32 m. For the cavitation condition, the inlet pressure was reduced to induce cavitation while maintaining the same basic operating setting. Since the acquisition duration, sampling frequency, window length, and step size were identical for all operating states, the dataset was balanced across different categories. Therefore, no additional over-sampling or under-sampling operation was required. The detailed dataset composition is summarized in Table 1.

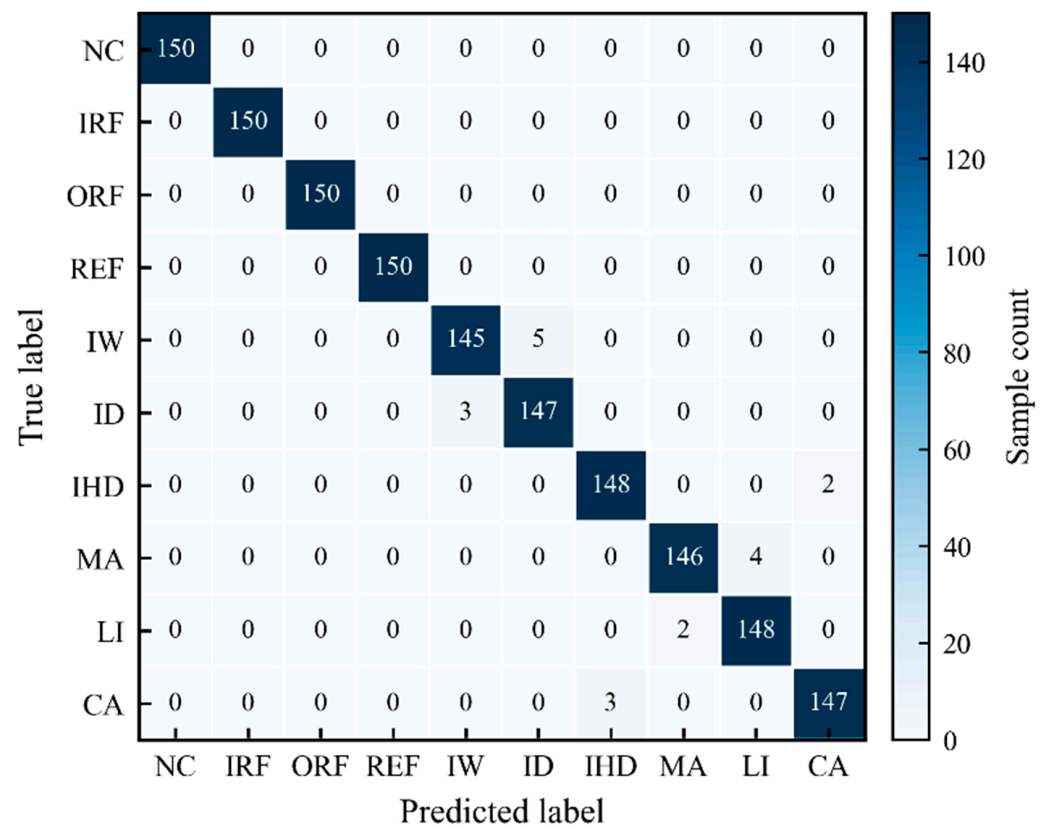
Table 1. Summary of operating states, dataset split, operating condition, and relevance to practical LNG submersible pump faults.

Operating State	Fault Category	Training/Validation/Testing Samples	Operating Condition	Relevance to Practical LNG Submersible Pump Faults
Normal condition/NC	Normal	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Baseline healthy operation under stable hydraulic and mechanical conditions
Inner-race fault/IRF	Bearing fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents localized bearing degradation caused by long-term operation or lubrication deterioration
Outer-race fault/ORF	Bearing fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents bearing support damage related to casing load transmission and installation stress
Rolling-element fault/REF	Bearing fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents rolling-contact damage that may induce periodic impacts and vibration amplification
Impeller wear/IW	Impeller fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents hydraulic-component degradation caused by erosion, cavitation, or particle-induced wear
Impeller deformation/ID	Impeller fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents impeller geometric distortion that may alter hydraulic loading and rotor balance
Impeller hole defect/IHD	Impeller fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents local impeller material loss or perforation caused by severe erosion or cavitation damage
Misalignment/MA	Rotor-related fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents shaft-line assembly deviation or installation-induced rotor misalignment

Table 1. Cont.

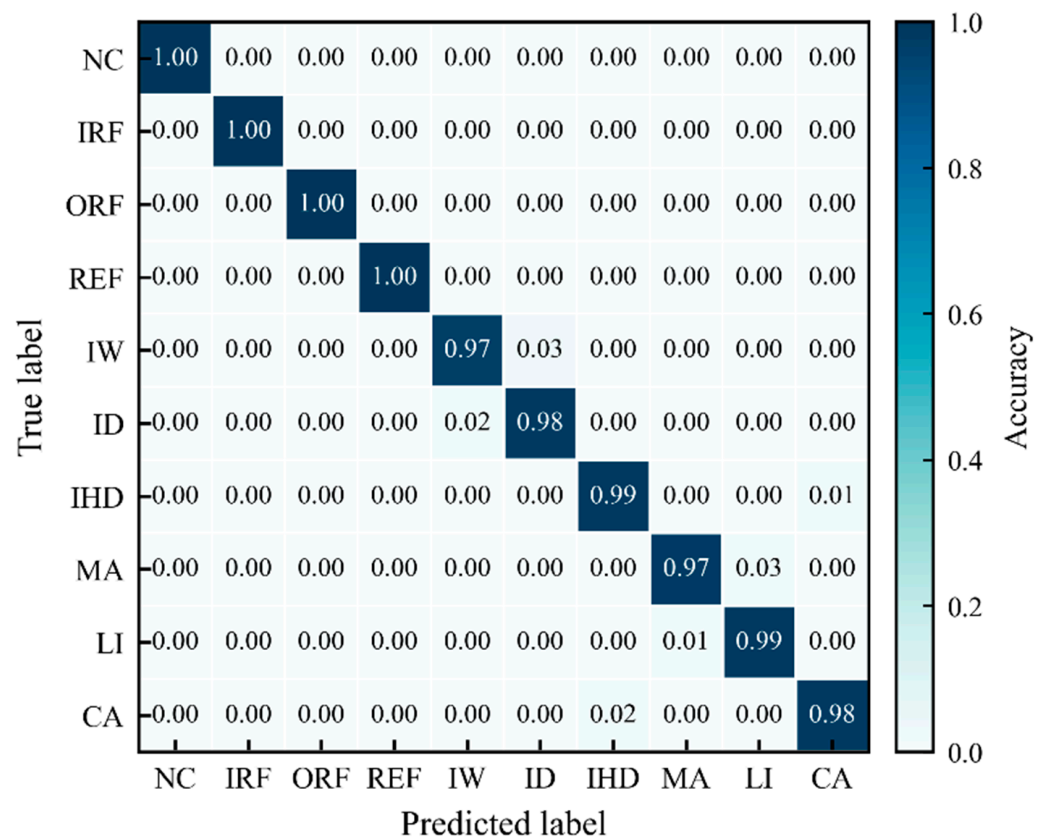
Operating State	Fault Category	Training/Validation/Testing Samples	Operating Condition	Relevance to Practical LNG Submersible Pump Faults
Loose installation/LI	Structural looseness	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m	Represents insufficient fastening or support looseness under long-term vibration and marine operation
Cavitation/CA	Hydraulic fault	1403/172/172	2900 r/min, 4 m ³ /h, H = 32 m (reduced inlet pressure)	Represents suction-pressure fluctuation and vapor-pocket formation under unfavorable inlet conditions

Notes: For all operating states, the raw response signals were continuously collected for 3 min at a sampling frequency of 10 kHz. The window length and step size were 4096 and 1024 points, respectively. The raw signal of each operating state was first divided along the time axis into training, validation, and testing subsets with a ratio of 8:1:1, and sliding-window segmentation was then independently performed within each subset. The independent testing subset generated 172 testing candidate samples for each operating state, among which 150 samples were used for the confusion-matrix evaluation in Figure 8. The simulated fault states represent controlled single-fault conditions for diagnostic-method validation and are not intended to cover complete degradation processes or multiple severity levels.



(a) Original confusion matrix for ten-class fault diagnosis.

Figure 8. Cont.



(b) Row-normalized confusion matrix for ten-class fault diagnosis.

Figure 8. Confusion matrix for multi-class fault diagnosis results.

All raw signals were first standardized using Z-score normalization. Subsequently, the proposed fault-specific entropy-weighted sensor selection method with global aggregation was applied to the 16 candidate diagnostic channels, and the top informative channels were retained as the final model inputs. This selection strategy reduced input dimensionality and redundant information while preserving fault-sensitive response characteristics for downstream diagnosis.

The threshold selection in EWSSM follows a three-step logic. First, the minimum retained-channel constraint m' is introduced to avoid excessive compression of heterogeneous response information. Since the fault responses of submersible centrifugal pumps may appear simultaneously in vibration, pressure-pulsation-related, and acoustic channels, the selected subset should retain representative multi-source coverage rather than only the highest-ranked single-source channels. Therefore, m' was used as a lower-bound constraint to prevent under-selection.

Second, the cumulative-weight threshold Ω is used to determine how much aggregated fault-discriminative information should be preserved. The channels are ranked in descending order of their global EWSSM weights, and the cumulative weight is calculated sequentially. In this study, the first eight channels reached a cumulative weight of 0.851, which means that they preserved 85.1% of the aggregated discriminative contribution of all 16 candidate channels. In addition, a clear decrease in channel contribution appeared after the eighth channel: the eighth-ranked channel A3 had a weight of 0.091, whereas the ninth-ranked channel V5 had a much lower weight of 0.036. This indicates that the first eight channels form the main informative subset, while the subsequently ranked channels provide only limited additional contribution.

Third, the candidate thresholds were checked using the validation subset. When $\Omega \leq 0.85$ with $m' = 8$, the final retained subset remained unchanged because the minimum retained-channel constraint required at least eight channels. When Ω was increased beyond 0.85, additional lower-ranked channels were included, but the validation performance did not improve. Instead, the input dimensionality and computational burden increased. Therefore, $\Omega = 0.85$ was selected because it corresponds to the natural cumulative-weight boundary of the main informative channel subset and provides a favorable balance between information preservation and redundancy suppression.

Accordingly, $\Omega = 0.85$ and $m' = 8$ were adopted in this study. Under this configuration, eight channels were finally retained, namely V3, V2, V6, V4, P2, P1, V9, and A3. While V5, V7, P3, V8, V10, V1, A2, and A1 were not retained because of their lower global EWSSM weights. The aggregated ranking and selection status of all candidate channels are summarized in Table 2. As shown in Table 3, the retained subset includes vibration, pressure-pulsation-related, and acoustic channels, indicating that the proposed method preserves representative multi-source fault information while suppressing redundant inputs.

Table 2. Global ranking of the candidate diagnostic channels obtained by EWSSM.

Rank	Channel	Signal Type	Global Weight $\bar{w}_j$	Cumulative Weight	Selection Status
1	V3	Vibration	0.127	0.127	Selected
2	V2	Vibration	0.119	0.246	Selected
3	V6	Vibration	0.112	0.358	Selected
4	V4	Vibration	0.105	0.463	Selected
5	P2	Pressure-pulsation-related	0.102	0.565	Selected
6	P1	Pressure-pulsation-related	0.098	0.663	Selected
7	V9	Vibration	0.097	0.760	Selected
8	A3	Acoustic	0.091	0.851	Selected
9	V5	Vibration	0.036	0.887	Not selected
10	V7	Vibration	0.029	0.916	Not selected
11	P3	Pressure-pulsation-related	0.023	0.939	Not selected
12	V8	Vibration	0.019	0.958	Not selected
13	V10	Vibration	0.016	0.974	Not selected
14	V1	Vibration	0.011	0.985	Not selected
15	A2	Acoustic	0.009	0.994	Not selected
16	A1	Acoustic	0.006	1.000	Not selected

Table 3. Physical composition of the final eight-channel subset.

Order	Channel	Signal Type	Main Physical Significance
1	V3	Vibration	Upstream structural transmission response
2	V2	Vibration	Upstream structural transmission response
3	V6	Vibration	Pump-body vibration response
4	V4	Vibration	Pump-body vibration response
5	P2	Pressure-pulsation-related	Internal hydraulic excitation response
6	P1	Pressure-pulsation-related	Internal hydraulic excitation response
7	V9	Vibration	Lower pump-body vibration response
8	A3	Acoustic	External acoustic radiation response

The selected channels also exhibit clear physical interpretability. V3 and V2 were ranked highest, suggesting that upstream structural transmission responses contain strong fault-discriminative information in the present system and are sensitive to fault-induced vibration propagation, especially for bearing-related defects. V6, V4, and V9 provide complementary vibration responses from different structural regions, which are useful for

capturing mechanical faults, misalignment, loose installation, and distributed structural responses. In addition, P2 and P1 preserve essential hydraulic information associated with internal unsteady excitation, impeller disturbance, and cavitation-related pressure fluctuation, while A3 provides supplementary acoustic information related to external acoustic radiation. In contrast, the discarded channels generally showed lower discriminative contribution or partial redundancy with the retained channels under the tested conditions. Therefore, the retained subset shows both source heterogeneity and spatial complementarity and can be regarded as the most fault-sensitive compact channel subset for downstream diagnosis.

The sensitivity analysis of Ω is summarized in Table 4. With fixed $m' = 8$, the retained subset remained unchanged when $\Omega \leq 0.85$ because the minimum retained-channel constraint already required the first eight ranked channels to be retained. The corresponding accuracy and Macro-F1 remained stable. When Ω was increased to 0.88, 0.90, and 0.95, additional lower-ranked channels were introduced. However, these additional channels had relatively small global weights and did not improve the diagnosis performance. This result confirms that the channels beyond the eighth rank mainly introduced redundant or weakly informative inputs.

Table 4. Sensitivity analysis of Ω with fixed $m' = 8$.

Ω	Final Retained Channel Number	Accuracy (%)	Macro-F1 (%)	Computational Burden
0.75	8	98.73	98.61	Moderate
0.80	8	98.73	98.61	Moderate
0.85	8	98.73	98.61	Moderate
0.88	9	98.60	98.45	Moderate-high
0.90	10	98.40	98.22	Higher
0.95	12	98.07	97.85	High

The sensitivity analysis of m' is summarized in Table 5. With fixed $\Omega = 0.85$, the final retained subset remained unchanged when $m' \leq 8$, because eight channels were already required to reach the cumulative-weight threshold. When m' was increased above 8, the minimum retained-channel constraint forced additional lower-ranked channels to be included, which increased the input dimensionality but did not improve the diagnostic performance. Therefore, $m' = 8$ served as an appropriate lower-bound constraint that ensured representative multi-source coverage without introducing unnecessary redundancy.

Table 5. Sensitivity analysis of m' with fixed $\Omega = 0.85$.

m'	Final Retained Channel Number	Accuracy (%)	Macro-F1 (%)	Computational Burden
4	8	98.73	98.61	Moderate
5	8	98.73	98.61	Moderate
6	8	98.73	98.61	Moderate
7	8	98.73	98.61	Moderate
8	8	98.73	98.61	Moderate
9	9	98.53	98.36	Moderate-high
10	10	98.40	98.22	High

3.2.3. Model Training Parameters

The proposed EWSSM-CNN-Transformer model was trained using the selected eight-channel response signals obtained after EWSSM-based channel selection. The training, validation, and testing subsets were generated according to the time-axis-based data-splitting strategy described above. The training subset was used for model optimization,

the validation subset was used for hyperparameter selection and early stopping, and the testing subset was used only for the final performance evaluation. To improve the reproducibility of the proposed model, the main architectural configuration is summarized in Table 6.

Table 6. Main architectural configuration of the proposed EWSSM-CNN-Transformer model.

Module	Main Configuration	Feature Size
Input	8 EWSSM-selected channels; sequence length ($L = 4096$)	($C = 8, L = 4096$)
CNN block 1	Conv1D: ($C_{in} = 8, C_{out} = 16, k = 3, p = 1$); ReLU; MaxPool1D: ($s = 2$)	($C = 16, L = 2048$)
CNN block 2	Conv1D: ($C_{in} = 16, C_{out} = 32, k = 3, p = 1$); ReLU; MaxPool1D: ($s = 2$)	($C = 32, L = 1024$)
CNN block 3	Conv1D: ($C_{in} = 32, C_{out} = 64, k = 3, p = 1$); ReLU; MaxPool1D: ($s = 2$)	($C = 64, L = 512$)
CNN block 4	Conv1D: ($C_{in} = 64, C_{out} = 128, k = 3, p = 1$); ReLU; MaxPool1D: ($s = 2$)	($C = 128, L = 256$)
Transformer encoder	($N = 2$) encoder layers; ($h = 4$) attention heads; ($d_{model} = 128$); ($d_{ff} = 512$)	($L = 256, d = 128$)
Feature aggregation	AdaptiveAvgPool1D	($C = 128, L = 1$)
Classifier	Fully connected layer; output dimension = 10	10 classes

Notes: (C) denotes the number of channels, (L) denotes the temporal sequence length, (k) denotes the convolutional kernel size, (p) denotes padding, (s) denotes the pooling stride, (N) denotes the number of Transformer encoder layers, (h) denotes the number of attention heads, (d_{model}) denotes the embedding dimension, and (d_{ff}) denotes the feed-forward dimension. The total number of trainable parameters is approximately (4.31×10^5).

The input of the model is the selected eight-channel response signal with a sequence length of 4096. The CNN module consists of four one-dimensional convolutional blocks with filter numbers of 16, 32, 64, and 128, respectively. Through four MaxPool1D operations, the temporal sequence length is progressively reduced from 4096 to 256, corresponding to one-sixteenth of the original sequence length. Before entering the Transformer encoder, the CNN feature tensor is rearranged into a sequence representation. The Transformer encoder contains two encoder layers with four attention heads in each layer. The embedding dimension is set to 128, and the feed-forward dimension is set to 512. After AdaptiveAvgPool1D, the extracted representation is fed into a fully connected layer for ten-class fault classification. The total number of trainable parameters is approximately (4.31×10^5).

This configuration was selected to balance feature-learning capability and model complexity. The CNN module extracts local fault-sensitive temporal patterns and compresses the original sequence before the attention-based modeling stage. The Transformer encoder then captures long-range dependencies and contextual relationships in the compressed feature space produced by the CNN front-end. Therefore, the proposed configuration is suitable for the present signal length and dataset size while avoiding unnecessary parameter expansion.

The main training parameters are summarized in Table 7. The main hyperparameters of the CNN-Transformer model were determined based on preliminary validation trials and training stability. The learning rate was selected from typical candidate values of 0.0001, 0.0005, and 0.001, and 0.001 provided stable convergence without obvious oscillation. The batch size was set to 64 to balance gradient stability and computational efficiency. Dropout was introduced to reduce overfitting, and a value of 0.5 was adopted because it provided better validation stability than smaller dropout settings in preliminary trials. The maximum number of epochs was set to 200, while early stopping with a patience of 15 epochs was used to terminate training when the validation accuracy no longer improved. Therefore, the final model configuration was selected according to validation performance and convergence behavior rather than testing-set performance.

Table 7. Training parameters of the proposed CNN–Transformer model.

Parameter	Value	Description
Batch Size	64	Number of samples per batch
Learning Rate	0.001	Initial learning rate and schedule
Optimizer	Adam	Adaptive gradient optimization
Loss Function	Cross-Entropy Loss	Multi-class classification loss
Dropout	0.5	Regularization to prevent overfitting
Epochs	200	Maximum training iterations
Early stopping patience	15	Stop training if validation accuracy does not improve

3.2.4. Performance Evaluation Metrics

To quantitatively evaluate the diagnostic performance of the proposed model, the overall classification accuracy (Acc) was used as the primary metric, which is defined as

$$Acc = \frac{N_{correct}}{N_{total}} \quad (20)$$

where $N_{correct}$ denotes the number of correctly classified samples and N_{total} denotes the total number of samples.

In addition to the overall classification accuracy, precision, recall, and F1-score were used to evaluate the diagnostic performance for each fault category [46]. For the k -th class, these metrics are defined as follows:

$$Precision_k = \frac{TP_k}{TP_k + FP_k} \quad (21)$$

$$Recall_k = \frac{TP_k}{TP_k + FN_k} \quad (22)$$

$$F1_k = \frac{2 \times Precision_k \times Recall_k}{Precision_k + Recall_k} \quad (23)$$

where TP_k , FP_k , and FN_k denote the numbers of true-positive, false-positive, and false-negative samples for the k -th class, respectively. To further evaluate the balanced diagnostic performance across different categories, the macro-averaged F1-score is calculated as

$$Macro-F1 = \frac{1}{K} \sum_{k=1}^K F1_k \quad (24)$$

where K is the total number of classes. In this study, $K = 10$, including one normal condition and nine representative fault conditions. In addition, to provide a more intuitive representation of the recognition performance for different fault categories, a confusion matrix was constructed. This visualization facilitates the analysis of class-wise recognition results and the discriminative capability of the proposed model in the multi-class fault diagnosis task.

4. Results and Discussion

4.1. Front-End Abnormality Screening Results

To validate the hierarchical condition screening strategy described in Section 2.1, front-end abnormality screening was conducted before downstream fault-category recognition. Functional information was used for coarse-grained evaluation of the operating condition, whereas response information was used to detect abnormal dynamic-response patterns. According to Appendix A, each operating state was preliminarily classified as Normal

(*NOR*), Functional Abnormality (*FAB*), or Response Abnormality (*RAB*). The screening results are summarized in Table 8.

Table 8. Functional-level and response-level screening outcomes for different operating states.

Operating State	Functional-Level Screening	Response-Level Screening	Final Screening Result
NC	Normal	Normal	<i>NOR</i>
IRF	Normal	Abnormal	<i>RAB</i>
ORF	Normal	Abnormal	<i>RAB</i>
REF	Normal	Abnormal	<i>RAB</i>
IW	Normal	Abnormal	<i>RAB</i>
ID	Normal	Abnormal	<i>RAB</i>
IHD	Normal	Abnormal	<i>RAB</i>
MA	Normal	Abnormal	<i>RAB</i>
LI	Normal	Abnormal	<i>RAB</i>
CA	Normal	Abnormal	<i>RAB</i>

Note: Bold italic terms indicate the self-defined screening state abbreviations.

The normal condition was correctly identified as *NOR*, while the representative fault conditions were mainly screened as *RAB*, indicating that the proposed front-end module can effectively distinguish normal and abnormal states before detailed diagnosis. Accordingly, only the samples screened as response abnormalities were forwarded to the downstream EWSSM–CNN–Transformer model for fault-category recognition.

4.2. Classification Performance and Confusion Matrix

To evaluate the effectiveness of the proposed method in the multi-class fault diagnosis task, a confusion matrix was constructed to visualize the classification performance over ten operating states, including one normal condition and nine representative fault types, as shown in Figure 8. The confusion matrix was calculated using 150 independent testing samples for each operating state. The main observations can be summarized as follows:

- Normal condition: The normal condition achieved a recognition rate of 100%, indicating that the proposed model can reliably distinguish healthy operation from faulty conditions.
- Bearing faults (IRF, ORF, and REF): All three bearing fault categories were identified with an accuracy of 100%. This result indicates that the proposed model can effectively capture the discriminative features associated with bearing-related faults under the present experimental conditions.
- Impeller faults (IW, ID, and IHD): The impeller-related fault categories were all recognized with high accuracy. Specifically, impeller wear, impeller deformation, and impeller hole defect achieved accuracies of 96.67%, 98.00%, and 98.67%, respectively. A small degree of confusion was observed between impeller wear and impeller deformation, which is likely due to their partially similar hydraulic disturbance mechanisms and related response characteristics.
- Cavitation condition: The cavitation state was recognized with an accuracy of 98.00%. Minor confusion was observed between cavitation and impeller hole defect, suggesting that both conditions may induce partially similar pressure-fluctuation-related or hydraulic instability responses in some cases.
- Misalignment and loose installation: Misalignment and loose installation achieved accuracies of 97.33% and 98.67%, respectively. Although slight confusion existed between these two fault categories, the results indicate that the proposed model still has good discriminative capability for structurally related faults with partially similar dynamic response patterns.

Overall, the proposed model achieved consistently high class-wise recognition accuracy under the present experimental setting. The confusion matrix demonstrates that the CNN–Transformer-based diagnosis framework can effectively distinguish representative fault categories of the submersible centrifugal pump, even for fault pairs with partially similar response characteristics, thereby providing reliable support for multi-class condition diagnosis. This result indicates that the selected multi-source response channels can provide sufficient diagnostic evidence for representative mechanical and hydraulic faults of LNG submersible centrifugal pumps.

4.3. Feature Representation Visualization (t-SNE)

To further illustrate the feature extraction capability of the proposed model, the latent feature vectors extracted immediately before the final classification layer were visualized using t-distributed stochastic neighbor embedding (t-SNE), as shown in Figure 9. The projection results provide the following observations:

- Distinct clustering patterns are formed in the two-dimensional feature space, with relatively clear inter-class boundaries and compact intra-class distributions.
- Bearing faults, including inner-race fault, outer-race fault, and rolling-element fault, remain well separable in the feature space, despite their physical similarity and partially overlapping signal characteristics.
- The impeller fault categories appear relatively close to each other in the projected space but still maintain distinguishable cluster structures, indicating that the proposed model is able to capture subtle response differences associated with different impeller-related defects.
- The normal condition is clearly separated from all faulty conditions, which is consistent with the confusion-matrix results and further supports the discriminative effectiveness of the learned feature representation.

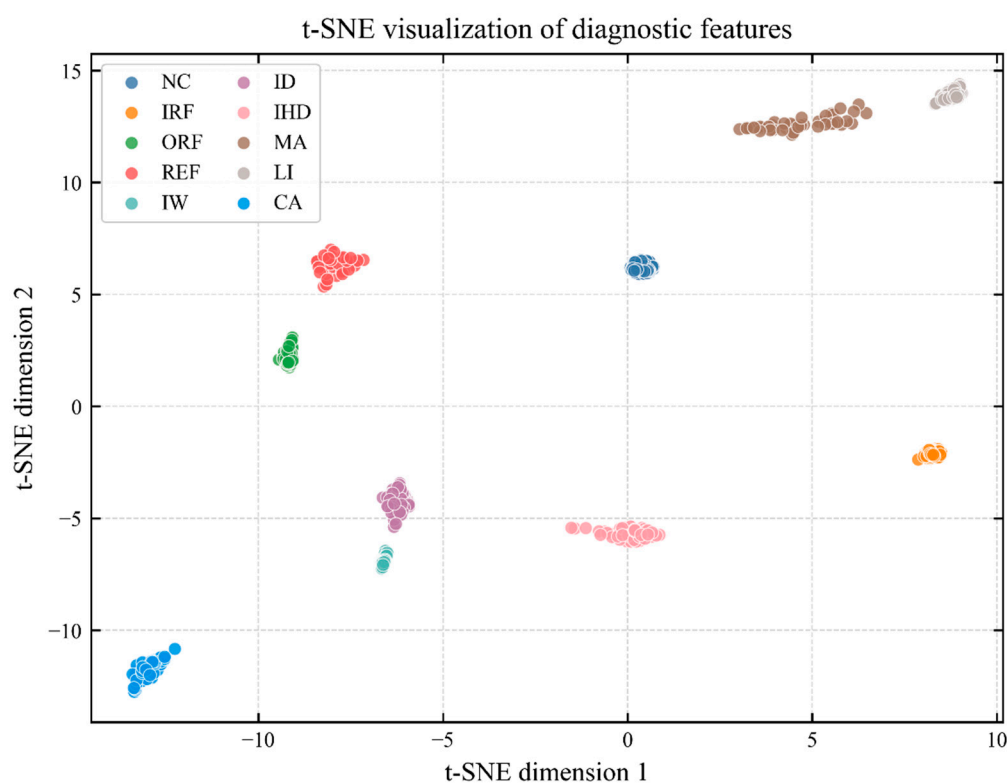


Figure 9. t-SNE visualization illustrating feature separability among different fault categories.

It should be noted that the t-SNE visualization serves as an intuitive supplementary illustration of feature separability rather than a standalone quantitative performance measure. Nevertheless, the observed clustering pattern is consistent with the classification results and provides additional evidence for the effectiveness of the proposed feature-learning framework.

4.4. Covariance-Based Interpretation for Condition Assessment

To further interpret the statistical differences among fault categories, covariance analysis was performed on the selected multi-source response features. This analysis is intended to provide interpretable supplementary evidence for differentiating fault-related multi-source response patterns, rather than direct root-cause identification of failure mechanisms. Unlike single-channel statistics, which mainly describe the variation intensity of individual signals, covariance analysis characterizes the joint fluctuation relationships among channels and thus provides supplementary evidence for identifying fault-induced changes in inter-channel coupling structures. In submersible centrifugal pumps, different faults may not only modify the local response level of vibration, acoustic, and internal pressure-pulsation-related signals but may also redistribute their statistical coupling patterns through different mechanical transmission paths and hydraulic disturbance mechanisms.

For a given fault category c , let the corresponding feature matrix of the selected channels be denoted by

$$X^{(c)} \in \mathbb{R}^{N_c \times d} \quad (25)$$

where N_c denotes the number of samples under fault category c , and d denotes the number of selected diagnostic channels or extracted feature dimensions. The covariance matrix under fault category c is defined as

$$\Sigma^{(c)} = \frac{1}{N_c - 1} (X^{(c)} - \bar{X}^{(c)})^T (X^{(c)} - \bar{X}^{(c)}) \quad (26)$$

where $\bar{X}^{(c)}$ is the mean vector of the corresponding feature matrix. To highlight the fault-induced redistribution of inter-channel coupling relative to the normal condition, the covariance-difference matrix is further defined as

$$\Delta\Sigma^{(c)} = \Sigma^{(c)} - \Sigma^{(Normal)} \quad (27)$$

where $\Sigma^{(Normal)}$ denotes the covariance matrix under the normal condition. The matrix $\Delta\Sigma^{(c)}$ reflects the relative enhancement or reduction in statistical coupling among selected channels caused by fault condition c .

To further interpret the fault-related statistical differences retained by EWSSM, covariance analysis was performed on the final selected channel subset, namely V3, V2, V6, V4, P2, P1, V9, and A3. Five representative states, including the normal condition, bearing inner-race fault, impeller wear, cavitation, and loose installation, were selected for comparative analysis. Unlike single-channel statistics, covariance analysis describes joint fluctuation relationships among channels and provides supplementary evidence for understanding fault-related changes in multi-source response coupling.

For covariance-difference analysis, the selected channels were first normalized using the same preprocessing strategy as the model inputs. For each operating state, a covariance matrix was calculated from the segmented samples. The normal-state covariance matrix was then used as the reference baseline, and the covariance-difference matrix of each fault condition was obtained by subtracting this baseline from the corresponding fault-state covariance matrix. Therefore, the covariance-difference matrix reflects changes in inter-channel coupling rather than absolute amplitude variations in individual channels. The

robustness of this analysis is supported by signal normalization and covariance estimation over multiple segmented samples, which help reduce the influence of scale differences and random fluctuations. In addition, the interpretation focuses on consistent covariance redistribution patterns among selected channels instead of isolated changes in individual covariance elements. Nevertheless, covariance-difference analysis may still be affected by strong environmental noise, sensor drift, or severe operating-condition changes. Therefore, it is used here as supplementary interpretive evidence rather than as an independent diagnostic criterion.

As shown in Figure 10, the selected channels exhibit fault-dependent covariance variation patterns. Under normal conditions, the overall covariance redistribution remains weak, indicating relatively stable inter-channel relationships. For the bearing inner-race fault, covariance enhancement is mainly concentrated among vibration channels, such as V3 and V2, suggesting a mechanically transmitted response. For impeller wear and cavitation, stronger covariance redistribution appears between vibration channels and pressure-pulsation-related channels, indicating coupled structural–hydraulic interactions. For loose installation, broader covariance redistribution across multiple vibration channels reflects a spatially distributed influence on system dynamic stability.

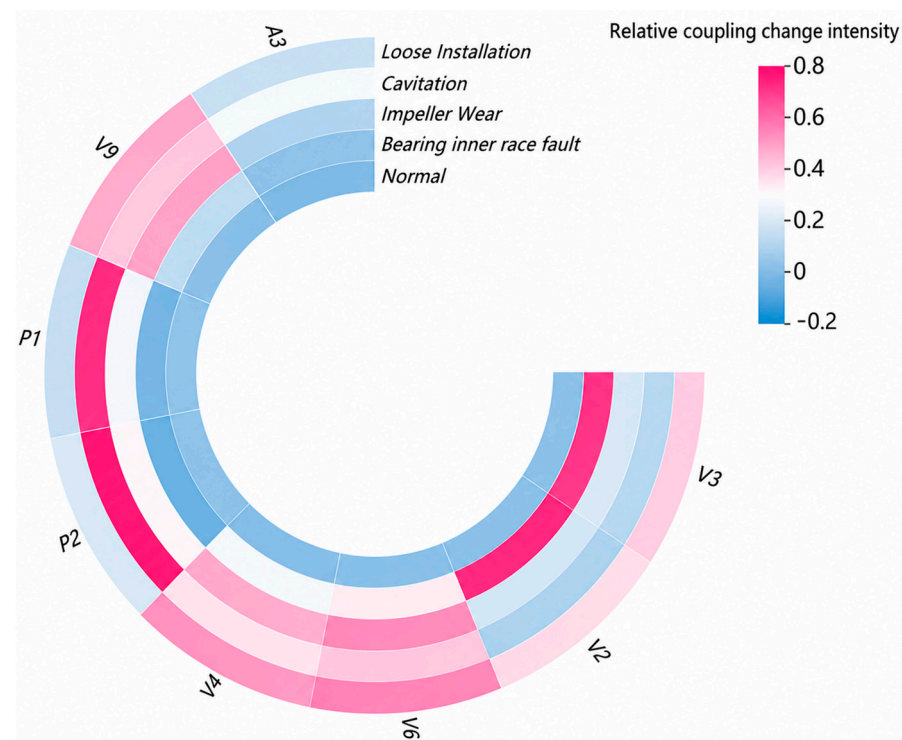


Figure 10. Covariance-difference patterns of selected channels under four representative fault conditions relative to the normal condition.

From the perspective of monitoring-channel analysis, covariance-difference results can help explain why certain channels provide complementary condition information. Channels that repeatedly participate in fault-dependent covariance redistribution, such as V3, V2, V6, V4, P2, P1, and A3, are consistent with the EWSSM-selected subset and should be prioritized in a compact monitoring configuration under the tested conditions. In contrast, channels with weak covariance variation and low EWSSM weights may be less critical for real-time diagnosis. Therefore, EWSSM ranking identifies channels with strong discriminative contribution, whereas covariance-difference analysis provides auxiliary evidence for understanding their coupling relationships and physical complementarity. It should be noted that covariance analysis is not intended to replace fault classification

or provide an independent root-cause conclusion, but to support the interpretation of multi-source response coupling and monitoring-point optimization.

4.5. Model Comparison

Figure 11 compares the diagnostic accuracy of the proposed EWSSM–CNN–Transformer model with several representative baseline models, including traditional machine learning models (SVM and DNN) and deep learning models (DNN and CNN), over ten independent experiments. All baseline models were trained and tested using the same sample construction and data split strategy. As shown in Figure 12, the traditional SVM and DNN models achieved relatively limited performance, with average accuracies of approximately 66.2% and 72.1%, respectively. These models show insufficient capability in extracting discriminative representations from high-dimensional time-series data and are less effective in capturing the nonlinear dynamic characteristics of submersible centrifugal pump fault signals.

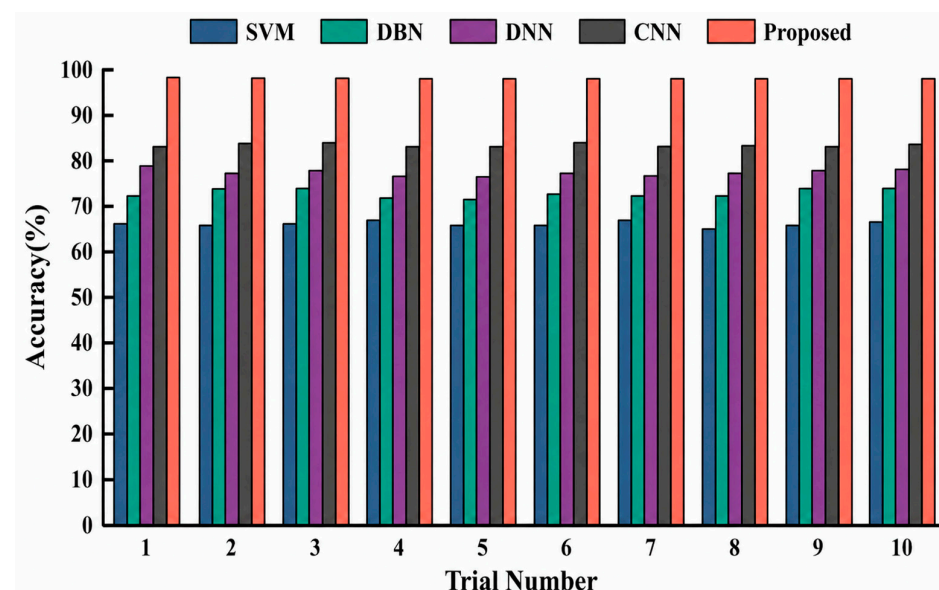


Figure 11. Comparison of diagnostic accuracy for different models over ten independent trials.

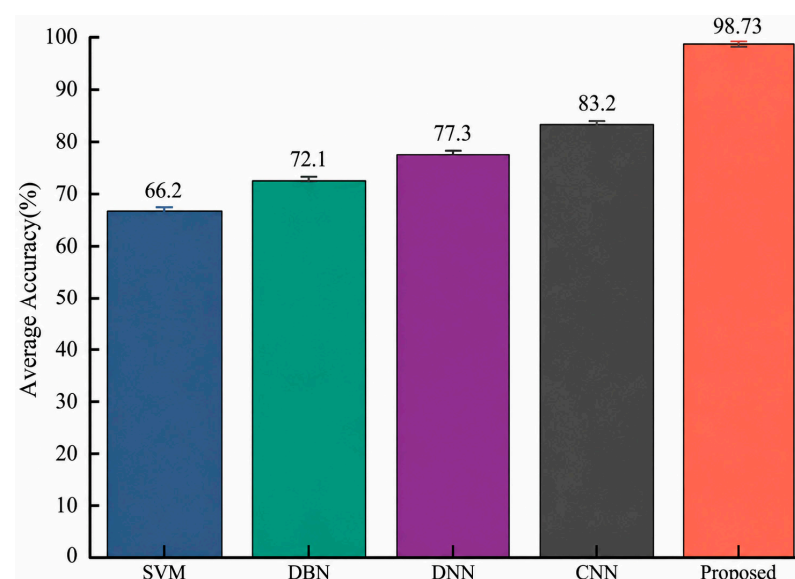


Figure 12. Average diagnostic accuracy of different models over ten independent trials.

In contrast, the DNN and CNN models exhibited improved performance, with average accuracies of 77.3% and 83.2%, respectively. The DNN benefits from multilayer nonlinear feature mapping, while the CNN is more effective in extracting local impulse patterns and short-term temporal structures from the multi-source input. However, the CNN still shows limited ability in modeling long-range dependencies and global interactions among multi-source features, which may restrict its discrimination capability for more complex fault patterns.

The proposed EWSSM–CNN–Transformer model consistently achieved the highest accuracy across all ten experiments, with an average accuracy of 98.73%. This value was obtained from repeated trials under the same independent data-splitting protocol rather than from a single random run. In addition to accuracy, precision, recall, F1-score, and the confusion matrix were used for comprehensive performance evaluation. These results demonstrate the stable diagnostic performance of the proposed framework under controlled laboratory conditions, although further validation under field operating conditions and more complex degradation scenarios is still required, as discussed in Section 5.2. EWSSM was treated as a dedicated component of the proposed framework and was not embedded into the baseline models. The superior performance of the proposed model can be attributed to the combined effect of entropy-weighted channel selection, local feature extraction by CNN, and global dependency modeling by the Transformer encoder. Specifically, EWSSM reduces redundant inputs and retains informative channels, CNN extracts local fault-sensitive patterns, and the Transformer encoder captures long-range dependencies and contextual interactions in the compressed feature space.

Overall, the proposed EWSSM–CNN–Transformer model outperformed both traditional models and single-structure deep learning models in terms of average diagnostic accuracy and overall consistency across repeated experiments. These results support the effectiveness of combining entropy-weighted channel screening with local and global feature learning for multi-source fault diagnosis of submersible centrifugal pumps. More importantly, the superior performance of the proposed model indicates that representative failure-related response characteristics can be more effectively identified when fault-sensitive channel screening and cross-source dependency modeling are jointly considered.

4.6. Ablation Study and Convergence Speed

As shown in Table 9, the eight-channel subset provided the most favorable balance between diagnosis performance and input compactness. When only four channels were retained, the diagnosis result was clearly limited because the selected subset contained only vibration information and lacked hydraulic and acoustic responses. After adding P2 and P1, the diagnosis performance improved noticeably, indicating the importance of preserving hydraulic fault-related information.

When V9 and A3 were further included, the accuracy increased to 98.73%, suggesting that additional spatially complementary vibration information and heterogeneous acoustic information were beneficial for fault discrimination. In contrast, retaining more than eight channels did not lead to further improvement. Instead, the additional lower-ranked channels mainly introduced redundancy, causing the diagnosis performance to slightly decline. These results confirm that the proposed EWSSM can effectively suppress redundant inputs while preserving the main fault-sensitive characteristics required for reliable diagnosis.

To verify the independent contributions and combined effects of different modules in the proposed framework, five model configurations were designed for ablation experiments: CNN, Transformer, EWSSM–CNN, CNN–Transformer, and EWSSM–CNN–Transformer. For a fair comparison, all variants were trained and evaluated using the same dataset and evaluation protocol, including the same time-axis-based training/validation/testing

split, sample length of 4096, training and testing subsets, and evaluation metrics. The CNN baseline evaluates the effect of local temporal feature extraction alone, while the Transformer baseline examines global dependency modeling without the CNN front-end. EWSSM–CNN evaluates the contribution of channel selection combined with local convolutional feature extraction. CNN–Transformer uses all candidate channels as inputs and thus represents the model without EWSSM. EWSSM–CNN–Transformer denotes the complete proposed framework.

Table 9. Comparison of diagnostic performance under different retained channel numbers.

Retained Channel Number	Representative Channel Composition	Accuracy (%)	Macro-F1 (%)	Input Compactness	Assessment
4	V3, V2, V6, V4	93.82	93.23	Very high	Excessive compression; hydraulic and acoustic information missing
6	V3, V2, V6, V4, P2, P1	96.35	95.12	High	Improved performance after preserving hydraulic information
8	V3, V2, V6, V4, P2, P1, V9, A3	98.73	98.61	Balanced	Best trade-off between informativeness and compactness
10	V3, V2, V6, V4, P2, P1, V9, A3, V5, V7	98.60	98.45	Moderate	Slight redundancy introduced, with no further gain
12	V3, V2, V6, V4, P2, P1, V9, A3, V5, V7, P3, V8	98.20	98.02	Lower	Additional weakly informative channels reduce compactness
16	All channels	97.87	97.65	Lowest	Highest redundancy, with no clear performance advantage

Figure 13 shows the training convergence curves of the five model variants. All models gradually reached stable performance, but their convergence rates and final accuracies differed clearly. The CNN model achieved relatively limited final accuracy, indicating that local convolutional features alone are insufficient to fully characterize the complex multi-source dynamic responses of the submersible centrifugal pump. The Transformer-only model achieved higher final accuracy than CNN, suggesting the benefit of global dependency modeling for multi-source fault diagnosis. However, its early-stage convergence was slower, and its final performance remained lower than that of CNN–Transformer. This indicates that direct attention-based modeling without CNN-based local feature extraction and temporal compression is less effective for the present long time-series signals.

After incorporating entropy-weighted channel selection, the EWSSM–CNN model converged rapidly in the early training stage and achieved improved performance compared with CNN, demonstrating that optimized channel selection can enhance the effectiveness of diagnostic inputs. When the Transformer encoder was added, the CNN–Transformer model further improved the ability to capture long-range dependencies and global feature interactions. Since this model used all candidate channels as inputs, it also reflects the performance of the CNN–Transformer structure without EWSSM. Finally, the proposed EWSSM–CNN–Transformer model achieved the highest validation performance and the most stable convergence, indicating that the proposed configuration provides the most effective balance among informative input selection, local feature extraction, global dependency modeling, and training stability.

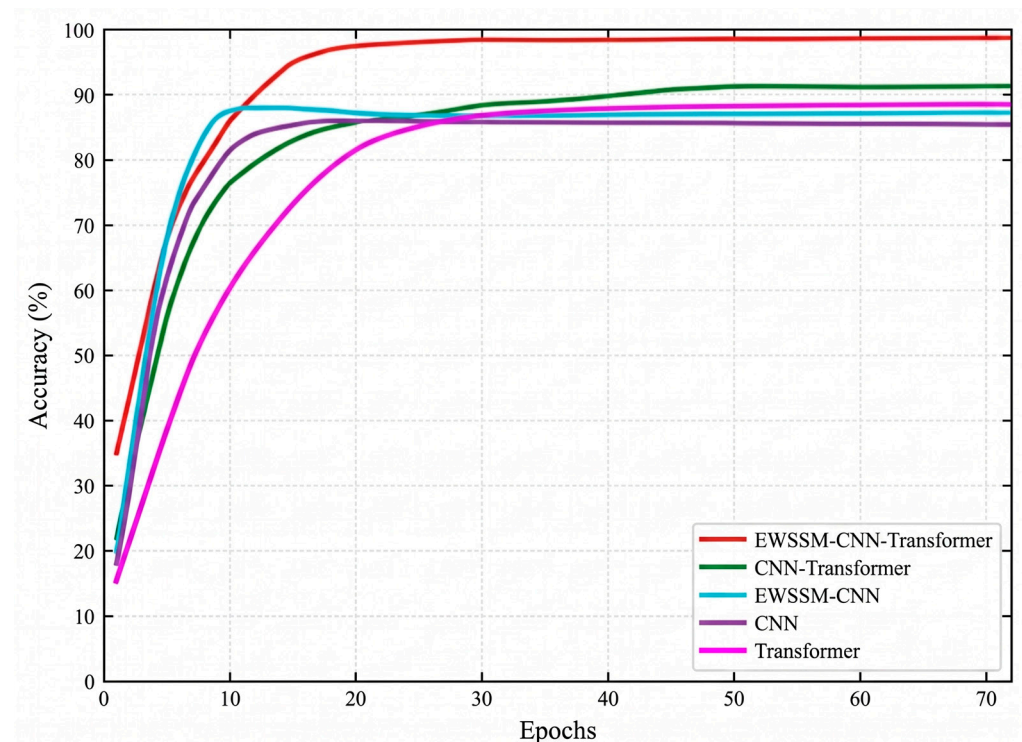


Figure 13. Training convergence curves of different diagnostic models under the same dataset and evaluation protocol.

Overall, Figure 13 also provides additional evidence for evaluating the overfitting risk of the proposed CNN–Transformer-based model. In the revised comparison, a Transformer-only baseline was further added, and all model variants were trained and evaluated under the same dataset and evaluation protocol. The proposed EWSSM–CNN–Transformer model reached stable convergence after approximately 25 epochs, and no obvious oscillation or unstable divergence was observed during training. In addition, the ablation comparison with CNN, Transformer, EWSSM–CNN, and CNN–Transformer shows that the performance improvement was not caused by a single complex module alone, but by the combined effects of EWSSM-based channel selection, CNN-based local feature extraction, and Transformer-based global dependency modeling. It should also be noted that the present dataset does not fully cover unseen operating conditions or multiple fault-severity levels. Therefore, further validation under variable loads, progressive degradation, and field operating conditions are still required, as discussed in Section 5.2.

5. Conclusions

5.1. Main Conclusions

In this study, a hierarchical multi-source condition monitoring and fault diagnosis framework was proposed for LNG submersible centrifugal pumps in marine energy transportation systems. The framework integrates an entropy-weighted sensor selection method and a CNN–Transformer diagnostic model to address the challenges of heterogeneous information utilization, redundant monitoring channels, and complex fault-feature representation. Its effectiveness was validated using experimental data from a laboratory-scale submersible centrifugal pump test platform. The main conclusions are summarized as follows:

1. A hierarchical monitoring and diagnosis framework was established by coordinating functional information and response information. Functional information was used for front-end condition assessment and abnormality screening, while selected

response information was used for downstream fault-category recognition. This design provides a structured route for linking operating-state evaluation with detailed fault diagnosis.

2. An entropy-weighted sensor selection method was developed to quantify the contribution of different monitoring channels and reduce redundant multi-source inputs. The selected channel subset retained representative vibration, pressure-pulsation-related, and acoustic information, indicating that fault-sensitive heterogeneous responses can be effectively preserved while improving the compactness of diagnostic inputs. In addition, covariance-difference analysis provided supplementary evidence for understanding inter-channel response variations among the selected channels under different fault conditions.
3. A CNN–Transformer-based diagnostic model was constructed to learn fault-related representations from the selected multi-source response signals. The CNN module enhanced local temporal feature extraction, whereas the Transformer module improved the modeling of global temporal dependencies and inter-channel relationships. The proposed framework achieved an average diagnostic accuracy of 98.73% over repeated trials, demonstrating its effectiveness and stability for the considered fault categories.

Overall, this study demonstrates that effective fault diagnosis of LNG submersible centrifugal pumps can be achieved by combining hierarchical multi-source monitoring, fault-sensitive channel selection, and hybrid deep feature learning. The proposed framework improves the utilization efficiency of heterogeneous monitoring data, reduces redundant channel inputs, and retains representative fault-sensitive response information. The covariance-based analysis further provides auxiliary interpretive evidence for understanding inter-channel response variations, but it is not intended to serve as an independent diagnostic or maintenance-decision criterion.

5.2. Limitations and Future Work

Several limitations of the present study should be acknowledged. First, the experiments were conducted on a laboratory water-medium platform under controlled operating conditions, and actual cryogenic LNG conditions were not directly reproduced. In practical LNG submersible pump applications, cryogenic temperature, submerged installation, sealing requirements, and restricted maintenance accessibility may affect sensor sensitivity, mounting stiffness, cable performance, and signal transmission stability. Therefore, although the proposed framework showed promising performance under the tested conditions, further validation under cryogenic LNG environments is still required before large-scale engineering deployment.

Second, the present dataset mainly covers representative discrete fault states, including bearing faults, impeller faults, misalignment, loose installation, and cavitation. However, real LNG submersible pumps may experience progressive long-term degradation rather than abrupt fault transitions. Fault signatures may evolve gradually over long service periods, and distribution shifts may occur between laboratory data and field data. In addition, compound-fault scenarios, such as bearing degradation coupled with misalignment, impeller erosion coupled with cavitation, or structural looseness coupled with hydraulic excitation, were not fully considered in this study. Future work should therefore include long-term degradation monitoring, incipient-fault characterization, and compound-fault diagnosis to improve robustness under practical operating conditions.

Third, the framework was validated on one specific laboratory-scale submersible centrifugal pump platform. Although the proposed EWSSM procedure and CNN–Transformer model provide a general methodological framework, the trained model and selected channel subset should not be directly assumed to be universally applicable to other pump types,

pump sizes, installation boundaries, or marine LNG systems. Changes in pump geometry, hydraulic design, structural stiffness, support condition, sensor layout, and operating range may alter the multi-source response characteristics and the relative importance of diagnostic channels. Therefore, for practical transfer, the EWSSM channel weights should be recalibrated using data from the target pump, and the diagnostic model may require fine-tuning or transfer learning with target-domain data. Future work will focus on cross-platform validation and transfer-learning strategies for adapting the proposed framework to different pump sizes and marine LNG operating scenarios.

Finally, real-time deployment requires further evaluation of computational cost, sampling requirements, and hardware implementation. In this study, EWSSM was mainly used during model development to determine a fixed diagnostic channel subset, and the online diagnosis stage only requires the selected eight channels as model inputs. This design helps reduce input dimensionality and computational burden. With the sampling frequency of 10 kHz and the sample length of 4096 used in this study, each diagnostic window corresponds to approximately 0.4096 s of signal duration. In addition, the CNN front-end compresses the temporal length from 4096 to 256 before the Transformer encoder, which helps reduce the computational cost of attention-based modeling. The proposed model contains approximately (4.31×10^5) trainable parameters, indicating a moderate model size for potential deployment on industrial monitoring computers or edge-computing devices. Nevertheless, shipboard or terminal monitoring systems may still face constraints related to inference latency, data storage, edge-computing resources, sensor synchronization, data transmission, long-term channel reliability, and environmental robustness. Future work will further explore lightweight deployment and online monitoring under long-term marine LNG operating conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

LNG	Liquefied Natural Gas
EWSSM	Entropy-Weighted Sensor Selection Method
CNN	Convolutional Neural Network
NOR	Normal
FAB	Functional Abnormality
RAB	Response Abnormality
IRF	Inner Race Fault
ORF	Outer Race Fault
REF	Rolling Element Fault
IW	Impeller Wear

ID	Impeller Deformation
IHD	Impeller Hole Defect
MA	Misalignment
LI	Loose Installation
CA	Cavitation
SVM	Support Vector Machine
DBN	Deep Belief Network
DNN	Deep Neural Network

Appendix A

Algorithm A1. Hierarchical condition monitoring and graded evaluation

Input: $F, R, F_{threshold}, R_{threshold}$

- 1: Compute the functional evaluation result F
- 2: Compute the response evaluation result R
- 3: **If** $R \geq R_{threshold}$ **then**
- 4: Graded assessment results = RAB
- 5: **Else if** $F \geq F_{threshold}$ **then**
- 6: Graded assessment results = FAB
- 7: **Else**
- 8: Graded assessment results = NOR
- 9: **End if**

Output: Graded assessment results

Appendix B

Algorithm A2. Fault-Specific Entropy-Weighted Sensor Selection with Global Aggregation

Input: Candidate diagnostic channels X

1. Construct the multi-channel data matrix X
2. Perform Z-score normalization on each channel
3. Transform the normalized channel features into non-negative form
4. For each fault category c :
 - 4.1 Construct the fault-specific channel subset
 - 4.2 Compute the probability distribution $p_{ij}^{(c)}$
 - 4.3 Calculate the entropy $e_j^{(c)}$ of each channel
 - 4.4 Compute the fault-specific channel weight $w_j^{(c)}$
5. Aggregate the fault-specific weights to obtain the global channel weight $\bar{w}_j$
6. Rank all channels in descending order by $\bar{w}_j$
7. Determine Ω and m' according to validation results and task requirements
 - 7.1 Set m' to avoid under-selection
 - 7.2 Compute the cumulative global weights
 - 7.3 Identify the main contribution boundary
 - 7.4 Validate candidate Ω and m' settings
 - 7.5 Select the setting with stable performance and low redundancy
8. Retain the top κ channels satisfying the cumulative-weight threshold and minimum retained-channel constraint

Output: Selected channel indices and corresponding channel data

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