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# Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery Based on Multisensor Data Fusion

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## ABSTRACT

*To address the issues of incomplete condition information in single-sensor monitoring, the disconnection between fault diagnosis and remaining useful life (RUL) prediction, and the insufficient utilization of multisource data in rotating machinery under complex operating conditions, this paper proposes a multisensor data fusion method for fault diagnosis and RUL prediction of rotating machinery. First, multisource monitoring signals are uniformly preprocessed and organized into samples, and sensor-specific feature extraction modules are employed to learn local condition features from different sensor channels. Then, an adaptive multisensor fusion module is designed to dynamically weight and effectively integrate multisource information, thereby constructing a shared health representation that characterizes the machinery health evolution process. Based on this representation, a dual-task joint learning framework for fault diagnosis and RUL prediction is further established to collaboratively optimize current fault-state recognition and future degradation trend modeling. Experimental results demonstrate that the proposed method outperforms single-sensor methods, simple feature concatenation methods, and representative deep learning baselines in terms of diagnostic accuracy, RUL prediction error, and robustness under noisy environments. Ablation studies further verify the effectiveness of multisensor input, adaptive fusion strategy, and dual-task joint learning in improving the overall model performance. The results indicate that the proposed method can provide a more comprehensive characterization of rotating machinery health conditions and offers effective technical support for predictive maintenance and intelligent operation.*

**KEYWORDS**
*rotating machinery, multisensor data fusion, fault diagnosis, remaining useful life prediction*

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## INTRODUCTION

Rotating machinery is a fundamental component in modern industrial systems and is widely used in aerospace, rail transportation, energy production, and intelligent manufacturing [1, 2]. Its operating condition is closely associated with the safety, reliability, and economic efficiency of the overall system. In practical applications, rotating machinery often operates under high speed, heavy load, and complex working conditions for extended periods, during which critical components such as bearings, gears, and rotors inevitably undergo performance degradation and may eventually develop faults or fail completely [3, 4]. Therefore, accurate condition identification, timely fault diagnosis, and reliable remaining useful life (RUL) prediction have become essential tasks in the fields of prognostics and health management and predictive maintenance [5, 6]. Conventional condition monitoring methods are mainly based on single-sensor signals. However, due to the nonlinear, nonstationary, and weakly manifested characteristics of fault-related information in rotating machinery, a single sensor is often insufficient to fully characterize the complex health evolution process, which limits the accuracy and robustness of both fault diagnosis and life prediction [7, 8].

In recent years, with the rapid development of intelligent sensing, signal processing, and deep learning techniques, multisensor data fusion has emerged as a promising solution for intelligent health monitoring of rotating machinery [9]. By collecting operational information from different locations, modalities, and physical mechanisms, multisensor monitoring provides richer and more complementary data for fault identification and degradation modeling [10]. Existing studies have demonstrated that multisensor fusion can effectively improve diagnostic accuracy, enhance noise immunity, and increase adaptability under complex operating conditions. Nevertheless, several challenges remain. On the one hand, many existing methods rely on straightforward data concatenation or feature stacking, without sufficiently exploring the intrinsic correlations and complementary relationships among different sensors. On the other hand, fault diagnosis and RUL prediction are still commonly treated as two separate tasks, lacking a unified health representation framework that can jointly support state discrimination and degradation trend modeling. In addition, the generalization capability and stability of current methods under noise interference, varying operating conditions, and sensor inconsistency still require further improvement [11].

To address these issues, this paper proposes a multisensor data fusion method for fault diagnosis and remaining useful life prediction of rotating machinery. First, a unified preprocessing and sample construction strategy is developed for multisource monitoring signals, and sensor-specific feature extraction modules are employed to learn local condition information from each sensor channel. Then, an adaptive multisensor fusion module is designed to effectively integrate complementary information from different sensors and generate a shared health representation that characterizes the underlying degradation trajectory of the machinery. Based on this shared representation, a joint framework for fault diagnosis and RUL prediction is further constructed, where classification and regression tasks are collaboratively optimized to achieve unified modeling of the current fault state and future degradation trend. Experimental results on representative rotating machinery datasets demonstrate that the proposed method achieves competitive performance in diagnostic accuracy, RUL prediction error, and model robustness, indicating its potential for practical intelligent health management of rotating machinery.

## PROBLEM FORMULATION AND PRELIMINARIES

### Health Degradation Process of Rotating Machinery

During long-term operation, key components of rotating machinery are continuously subjected to alternating loads, frictional wear, lubrication degradation, impact vibration, and environmental disturbances, which gradually degrade their performance and may eventually lead to explicit faults or even functional failure. This process usually evolves from a normal state to an incipient degradation state, then to a detectable fault state, and finally to a severe failure state. Such a degradation trajectory exhibits strong stage-wise characteristics, nonlinearity, and time-varying behavior [12]. For typical components such as bearings, gears, and rotors, the early stage of degradation is often characterized by weak and localized abnormal signatures. As damage accumulates, fault-related features become increasingly pronounced and can be observed more clearly in the time domain, frequency domain, and time-frequency domain. Therefore, the health condition of rotating machinery should not be regarded as a static discrete label, but rather as a dynamic evolution process that changes continuously over time.

From the perspective of machinery health management, fault diagnosis and remaining useful life (RUL) prediction correspond to two different yet closely related tasks within the health degradation process. Fault diagnosis aims to identify the current health condition or fault type of the machinery based on present monitoring data, with emphasis on accurate recognition of the current state. In contrast, RUL prediction estimates the remaining operational time from the current moment to the failure point according to historical observations and degradation trends, thereby focusing on continuous inference of the future state. Although these two tasks are generally formulated as classification and regression problems, respectively, they both fundamentally rely on an accurate characterization of the machinery health evolution pattern. Therefore, from the viewpoint of unified health state modeling, integrating fault diagnosis and RUL prediction into a common analytical framework is beneficial for comprehensively describing the entire process from early degradation to final failure.

## Multisensor Monitoring Mechanism

To accurately characterize the complex operating conditions of rotating machinery, relying solely on a single sensor type or a single sensor location is often insufficient [13]. Different sensors are sensitive to different aspects of the machinery condition according to their underlying physical mechanisms. For example, vibration signals are effective in capturing mechanical impacts, structural looseness, and periodic fault-related patterns; acoustic emission signals are more sensitive to crack initiation, localized friction, and weak incipient damage; current signals can reflect load-related variations, while temperature signals are more suitable for characterizing thermal accumulation, lubrication deterioration, and long-term degradation trends. Even for sensors of the same type, different installation positions may lead to different responses to local fault propagation paths and signal attenuation characteristics. As a result, multisensor monitoring can provide richer operational information from multiple modalities, spatial positions, and physical scales, offering a more comprehensive data basis for machinery health condition analysis.

Nevertheless, multisensor data cannot be directly exploited through simple aggregation [14, 15]. On the one hand, signals collected from different sensors may differ significantly in sampling frequency, physical scale, magnitude range, and noise distribution. On the other hand, the information carried by different sensors contains not only redundant descriptions of the same health condition but also complementary representations of localized fault characteristics. If multisource information is fused merely by straightforward concatenation, redundant information may accumulate, critical features may be obscured, and model generalization may be weakened. Therefore, the key to multisensor fusion lies not in increasing the amount of information itself, but in effectively modeling the correlations, complementarities, and importance differences among sensors so as to construct a more discriminative and continuous health representation. Based on this understanding, this paper develops an adaptive fusion mechanism to effectively integrate multisource monitoring information and provide a unified feature basis for subsequent fault diagnosis and RUL prediction.

## Problem Definition

Assume that a rotating machinery system is monitored by $M$ sensors simultaneously during operation. For the $m$ -th sensor, the raw signal collected within a given time window can be represented as:

$$\mathbf{x}^{(m)} \in \mathbb{R}^L, m = 1, 2, ..., M \tag{1}$$

where $L$ denotes the window length. By combining the signals acquired from all sensors within the same time instant or the same time window, the multisensor input sample can be expressed as:

$$\mathbf{X} = \left[\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, ..., \mathbf{x}^{(M)}\right] \tag{2}$$

For the fault diagnosis task, let the corresponding label be $y^c \in \{1, 2, ..., C\}$ , where $C$ denotes the total number of fault categories. For the RUL prediction task, let the corresponding label be $y^r \in \mathbb{R}$ , which represents the remaining useful life value at the current time. Accordingly, the objective of this study is to learn a mapping from the multisensor input to the dual-task outputs:

$$f : \mathbf{X} \to (y^c, y^r) \tag{3}$$

where the mapping function $f(\cdot)$ is expected to simultaneously support fault-state discrimination and degradation tendency modeling.

To achieve this objective, it is further assumed that there exists a latent shared health representation $\mathbf{h}$ embedded in the multisensor input, which can comprehensively reflect the machinery operating condition observed by different sensors and simultaneously support both classification and regression tasks. Formally, the process can be defined as:

$$\mathbf{h} = \phi(\mathbf{X}) \tag{4}$$

$$\hat{y}^c = g_c(\mathbf{h}), \hat{y}^r = g_r(\mathbf{h}) \tag{5}$$

where $\phi(\cdot)$ denotes the multisensor feature encoding and fusion process, and $g_c(\cdot)$ and $g_r(\cdot)$ represent the fault diagnosis branch and the RUL prediction branch, respectively. Based on this formulation, the following sections focus on how to construct a high-quality shared health representation through sensor-specific feature extraction and adaptive fusion, and how to further achieve collaborative modeling of fault diagnosis and remaining useful life prediction for rotating machinery.

## PROPOSED METHOD

### Overall Framework

To achieve collaborative modeling of fault diagnosis and remaining useful life (RUL) prediction for rotating machinery, this paper proposes a dual-task learning framework based on multisensor data fusion. The proposed framework consists of six main components: multisensor data input, data preprocessing and sample construction, sensor-specific feature extraction, adaptive multisensor fusion, shared health representation learning, and dual-task prediction. First, multiple sensors synchronously acquire machinery operating signals within the same time instant or time window, and the collected signals are transformed into structurally consistent input samples through unified preprocessing. Then, sensor-specific feature extraction modules are constructed for different sensor channels to learn independent representations of local health conditions. Based on these local features, an adaptive fusion mechanism is introduced to perform dynamic weighting and interactive modeling of multisource information, thereby generating a compact representation of the current health state.

Finally, the shared representation is simultaneously fed into the fault diagnosis branch and the RUL prediction branch, and the classification and regression tasks are jointly optimized to achieve unified modeling of the current fault state and future degradation trend. Let the preprocessed multisensor input sample be denoted as:

$$\mathbf{X} = \left[\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, ..., \mathbf{x}^{(M)}\right] \tag{6}$$

where $x^{(m)}$ denotes the input signal from the $m$ -th sensor and $M$ is the total number of sensors. First, a sensor-specific feature extraction module is used to obtain the local feature representation for each channel:

$$\mathbf{f}^{(m)} = \mathcal{E}^{(m)}\left(\mathbf{x}^{(m)}\right), m = 1, 2, ..., M \tag{7}$$

where $\mathcal{E}^{(m)}(\cdot)$ denotes the feature encoder for the $m$ -th sensor. Then, all local features are fed into the adaptive fusion module to generate the shared health representation:

$$\mathbf{h} = \mathcal{F}\left(\mathbf{f}^{(1)}, \mathbf{f}^{(2)}, ..., \mathbf{f}^{(M)}\right) \tag{8}$$

where $\mathcal{F}(\cdot)$ denotes the multisensor fusion process. Finally, the fused representation $\mathbf{h}$ is passed to the fault diagnosis branch and the RUL prediction branch to produce the fault category prediction $\hat{y}^c$ and the life prediction $\hat{y}^r$ , respectively:

$$\hat{y}^c = \mathcal{C}(\mathbf{h}), \hat{y}^r = \mathcal{R}(\mathbf{h}) \tag{9}$$

where $\mathcal{C}(\cdot)$ and $\mathcal{R}(\cdot)$ denote the classifier and regressor, respectively. By using the shared health representation as a bridge, the entire framework unifies fault diagnosis and life prediction within a common modeling paradigm, thereby enhancing the model's ability to characterize machinery health evolution.

**Data Preprocessing and Sample Construction**

Raw multisensor monitoring signals usually exhibit inconsistencies in sampling frequency, physical scale, noise contamination, and amplitude range. Directly feeding such signals into the model may adversely affect subsequent feature extraction and fusion. Therefore, unified data preprocessing and sample construction are required before model training. First, the raw signals collected from different sensors are aligned according to their acquisition time stamps and synchronously segmented within the same physical time window, so that all channels in one input sample correspond to the same operating interval rather than being forced into point-by-point correspondence. When different sampling frequencies or response characteristics are involved, resampling or unified window mapping is performed in a channel-wise manner to construct structurally consistent inputs, while preserving the local temporal patterns of each sensor as much as possible. Specifically, transient-sensitive high-frequency signals, such as vibration and acoustic emission signals, are first segmented at their native sampling resolution before being mapped to a fixed input length, whereas low-frequency or slowly varying signals are aligned at the window level to avoid unnecessary loss of degradation-related information. Subsequently, each sensor channel is standardized through operations such as mean removal and normalization in order to reduce the influence of scale differences and amplitude bias.

In the sample construction stage, a sliding-window strategy is adopted to extract local segments of length $L$ from continuous monitoring signals, and samples are generated with a fixed step size $S$ . For the $i$ -th sample, the input corresponding to the $m$ -th sensor can be expressed as:

$$\mathbf{x}_i^{(m)} = \left[x_{i,1}^{(m)}, x_{i,2}^{(m)}, \ldots, x_{i,L}^{(m)}\right] \in \mathbb{R}^L \tag{10}$$

Accordingly, the multisensor sample can be formulated as:

$$\mathbf{X}_i = \left[\mathbf{x}_i^{(1)}, \mathbf{x}_i^{(2)}, ..., \mathbf{x}_i^{(M)}\right] \tag{11}$$

For the fault diagnosis task, each sample is associated with a fault category label $y_i^c$ ; for the RUL prediction task, each sample is associated with a life label $y_i^r$ . To improve the stability of RUL model training, the life label is usually normalized as:

$$\tilde{y}_i^r = \frac{y_i^r}{y_{\max}} \tag{12}$$

where $y_{\max}$ denotes the maximum life value in the training set. After these procedures, the original multi-source monitoring data are transformed into a unified sample format suitable for deep learning models, providing a consistent basis for subsequent feature extraction and joint modeling.

### Sensor-Specific Feature Extraction

Since different sensors perceive machinery health conditions from different physical mechanisms, their signal patterns, spectral structures, and degradation-sensitive features often differ significantly. Therefore, before multisensor fusion, it is necessary to independently encode each sensor channel so as to fully extract its sensor-specific local condition information. To this end, this paper constructs relatively independent yet structurally consistent feature extraction modules for different sensors. Through parallel learning within a unified framework, the initial representation of machinery health conditions can be obtained from each sensor channel.

Let $\mathbf{x}^{(m)}$ denote the input signal of the $m$ -th sensor. After feature extraction, the output representation can be written as:

$$\mathbf{f}^{(m)} = \mathcal{E}^{(m)}\left(\mathbf{x}^{(m)}\right) \tag{13}$$

where $\mathbf{f}^{(m)} \in \mathbb{R}^d$ denotes the $d$ -dimensional feature vector extracted from the $m$ -th sensor. In this work, the encoder is composed of one-dimensional convolutional layers, nonlinear activation functions, and pooling operations to perform hierarchical feature learning on raw signals. Specifically, convolution operations are used to capture local impulsive patterns, periodic fluctuations, and degradation-related structural information, while pooling operations compress the feature dimension and enhance the robustness of the representation. The $l$ -th convolutional feature can be formulated as:

$$\mathbf{z}_l^{(m)} = \sigma\left(\mathbf{W}_l^{(m)} * \mathbf{z}_{l-1}^{(m)} + \mathbf{b}_l^{(m)}\right) \tag{14}$$

where $*$ denotes the convolution operation, $\mathbf{W}_l^{(m)}$ and $\mathbf{b}_l^{(m)}$ denote the kernel weight and bias of the $l$ -th convolutional layer, respectively, and $\sigma(\cdot)$ is a nonlinear activation function.

Through the above feature extraction process, the model can learn local health-related patterns from different sensor channels individually, thereby providing effective inputs for subsequent multisensor fusion. It should be noted that the purpose of this stage is not to directly accomplish classification or regression, but to preserve the differentiated perception capability of different sensors toward machinery conditions, so that the subsequent fusion module can further explore the complementary relationships among multisource information at a higher semantic level.

**Adaptive Multisensor Fusion for Shared Health Representation**

After obtaining local features from different sensors, the effective integration of multisource information becomes the key to high-quality health modeling. Although direct feature concatenation can preserve information from each channel, it cannot explicitly distinguish the importance differences of different sensors under varying operating states, nor can it sufficiently model the correlations and complementarities among multisource features. To address this issue, this paper develops an adaptive multisensor fusion module, which dynamically learns the contribution weights of different sensor features so as to selectively enhance informative signals and suppress redundant information, thereby generating a more discriminative and continuous shared health representation.

First, the features extracted from all sensors are mapped and concatenated to construct the fusion input:

$$\mathbf{F} = \left[\mathbf{f}^{(1)}; \mathbf{f}^{(2)}; \ldots; \mathbf{f}^{(M)}\right] \tag{15}$$

Then, to characterize the relative importance of different sensors with respect to the current machinery condition, an attention-based weighting mechanism is introduced to assign an adaptive weight $\alpha^{(m)}$ to each sensor. For the feature vector $\mathbf{f}^{(m)} \in \mathbb{R}^d$ extracted from the $m$ -th sensor, the corresponding attention score is calculated as:

$$e^{(m)} = \mathbf{q}^\top \tanh\bigl(\mathbf{W}_a \mathbf{f}^{(m)} + \mathbf{b}_a\bigr) \tag{16}$$

$$\alpha^{(m)} = \frac{\exp\bigl(e^{(m)}\bigr)}{\sum_{j=1}^{M} \exp\bigl(e^{(j)}\bigr)} \tag{17}$$

where $\mathbf{W}_a \in \mathbb{R}^{d_a \times d}$ , $\mathbf{b}_a \in \mathbb{R}^{d_a}$ , and $\mathbf{q} \in \mathbb{R}^{d_a}$ are learnable parameters, and $d_a$ denotes the hidden dimension of the attention layer. The $\tanh(\cdot)$ activation therefore produces a $d_a$ -dimensional hidden attention representation for each sensor feature. The softmax operation in Eq. (17) is applied over the sensor dimension to normalize the importance weights of all $M$ sensors. In this study, no additional temperature scaling is applied to the softmax function. All attention parameters are initialized together with the network parameters and optimized end-to-end through backpropagation under the joint loss function in Eq. (24).

$$\mathbf{h} = \sum_{m=1}^{M} \alpha^{(m)} \mathbf{f}^{(m)} \tag{18}$$

This representation can adaptively emphasize more informative sensor features and suppress redundant or noisy channels under different operating conditions and degradation stages.

Furthermore, to enhance the nonlinear expressive capability of the shared representation, the weighted fusion result is fed into a fully connected projection layer to obtain the final shared health representation:

$$\mathbf{h}_s = \psi(\mathbf{W}_s \mathbf{h} + \mathbf{b}_s) \tag{19}$$

where $\mathbf{W}_s$ and $\mathbf{b}_s$ are projection parameters and $\psi(\cdot)$ is a nonlinear transformation function. Different from simple feature stacking, the proposed fusion strategy extracts a unified semantic representation for the overall machinery health state from multisource local representations, which serves as the common feature basis for both fault diagnosis and RUL prediction.

### Joint Modeling of Fault Diagnosis and Remaining Useful Life Prediction

Based on the learned shared health representation, this paper further constructs a joint learning framework for fault diagnosis and RUL prediction so as to collaboratively optimize classification and regression tasks. In this framework, the shared representation $\mathbf{h}_s$ generated by the fusion module is simultaneously fed into two task-specific branches. The fault diagnosis branch is responsible for identifying the current fault category of the machinery, while the RUL prediction branch estimates the remaining operational time from the current moment to the failure point. Although the two branches correspond to different objectives, they are both built upon the same shared health representation and can therefore mutually benefit each other during joint training.

For the fault diagnosis branch, a fully connected classifier is used to output the predicted probability distribution over all fault categories:

$$\hat{\mathbf{y}}^c = \mathrm{Softmax}\ (\mathbf{W}_c \mathbf{h}_s + \mathbf{b}_c) \tag{20}$$

where $\hat{\mathbf{y}}^c \in \mathbb{R}^C$ denotes the predicted probability distribution over $C$ fault categories, and $\mathbf{W}_c$ and $\mathbf{b}_c$ are the classifier parameters. For the RUL prediction branch, a regressor is employed to output the continuous life estimation:

$$\hat{y}^r = \mathbf{W}_r \mathbf{h}_s + \mathbf{b}_r \tag{21}$$

where $\hat{y}^r$ denotes the predicted normalized RUL value, and $\mathbf{W}_r$ and $\mathbf{b}_r$ are the regressor parameters.

The essence of joint learning lies in connecting current state recognition and future trend estimation through a shared feature layer, such that the model simultaneously possesses strong discriminative capability and degradation perception capability. In essence, fault diagnosis improves the model’s ability to distinguish between different health condition boundaries, while RUL prediction enhances its ability to capture the continuous evolution pattern of machinery degradation. By integrating the two tasks within a shared representation framework, the learned features become not only discriminative for classification but also continuous for degradation modeling, thereby improving the overall health assessment performance.

### Loss Function and Training Strategy

To jointly optimize fault diagnosis and RUL prediction, a multitask objective function composed of a classification loss and a regression loss is constructed. For the fault diagnosis task, the cross-entropy loss is adopted to measure the discrepancy between the predicted category distribution and the true label:

$$\mathcal{L}_c = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{C} y_{i,k}^{c} \log \hat{y}_{i,k}^{c} \tag{22}$$

where $N$ denotes the number of training samples, $y_{i,k}^{c}$ denotes the ground-truth label of the $i$ -th sample for the $k$ -th category, and $\hat{y}_{i,k}^{c}$ denotes the corresponding predicted probability.

For the RUL prediction task, the mean squared error loss is employed to constrain the deviation between the predicted life value and the true life label:

$$\mathcal{L}_r = \frac{1}{N}\sum_{i=1}^{N} (\hat{y}_i^{r} - y_i^{r})^2 \tag{23}$$

Accordingly, the total loss is formulated as a weighted combination of the two losses:

$$\mathcal{L} = \lambda_c \mathcal{L}_c + \lambda_r \mathcal{L}_r \tag{24}$$

where $\lambda_c$ and $\lambda_r$ denote the weight coefficients for the classification task and the regression task, respectively, and are used to balance their contributions during training.

During training, the entire model is optimized in an end-to-end manner, enabling the feature extraction module, fusion module, and task-specific branches to be updated collaboratively under a unified objective. Through this strategy, the model is able to learn local condition characteristics from different sensors, adaptively determine the fusion pattern of multisource information, and finally obtain a shared health representation suitable for both fault diagnosis and RUL prediction. In summary, the proposed framework integrates sensor-specific feature extraction, adaptive multisensor fusion, and dual-task optimization into a unified modeling procedure. Based on this formulation, the following section evaluates the proposed method through fault diagnosis, RUL prediction, ablation studies, and robustness analysis.

## EXPERIMENTS AND RESULTS

### Dataset Description and Experimental Settings

Following the methodological framework described above, experiments were conducted to evaluate the effectiveness of the proposed method in both fault diagnosis and remaining useful life (RUL) prediction of rotating machinery. The experiments were performed on the public University of Ottawa Rolling-element Bearing Vibration and Acoustic Fault Signature Dataset under Constant Load and Speed Conditions. In the experiments, accelerometer vibration signals and microphone acoustic signals were selected as the primary monitoring inputs to characterize the dynamic response and localized damage evolution of the machinery under different operating conditions. According to the dataset description, the vibration signals were acquired using an accelerometer mounted on the bearing test rig, while the acoustic signals were collected using a microphone arranged near the tested bearing. Each raw signal record was sampled at 42,000 Hz with a duration of 10 s. For the fault diagnosis task, the samples were labeled according to different health states and fault categories. For the RUL prediction task, each sample was labeled according to the remaining life from the current operating time to the failure point. To ensure consistency among different sensor channels within the same time window, the raw monitoring signals were first synchronized, normalized, and segmented using a sliding-window strategy. The processed samples were then divided into training, validation, and test sets for model training and performance evaluation.

In terms of experimental settings, the proposed method was compared with single-sensor models, simple feature concatenation methods, and representative deep learning baselines so as to comprehensively evaluate the effectiveness of multisensor fusion and the joint learning mechanism.

For the RUL prediction task, MAE, RMSE, and Score were employed. MAE and RMSE were used to evaluate the average prediction error and the overall deviation between the predicted and true RUL values. Different from the asymmetric exponential scoring function used in some PHM data challenges, the Score metric in this study is defined as a normalized absolute prediction-error score to provide a scale-independent comparison among different methods. Specifically, it is calculated as

$$Score = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\mid \hat{y}_i^r - y_i^r \mid}{y_{\max}}\right) \tag{25}$$

where $N$ denotes the number of test samples, $\hat{y}_i^r$ and $y_i^r$ denote the predicted and true RUL values of the $i$ -th sample, respectively, and $y_{\max}$ is the maximum RUL value used for normalization. A lower Score value indicates better RUL prediction performance.

**Baseline Methods and Evaluation Metrics**

To comprehensively evaluate the proposed method, the following categories of baseline methods were considered: (1) Single Vibration-CNN / Single Vibration-GRU, which use only vibration signals for diagnosis or life prediction; (2) Single AE-CNN / Single AE-GRU, which rely solely on acoustic emission signals; (3) Feature Concatenation, which directly concatenates multisensor features before feeding them into downstream task modules; (4) CNN-LSTM / CNN-GRU, which represent typical deep sequence modeling approaches; (5) Attention Fusion, which introduces an attention-based multisensor fusion strategy but does not employ the shared health representation and dual-task collaborative learning proposed in this study; (6) Proposed Method, i.e., the adaptive multisensor fusion and shared-health-representation-based joint modeling framework proposed in this paper.

Tables 1 and 2 present the experimental results for the fault diagnosis task and the RUL prediction task, respectively. It can be observed that as the information source evolves from single-sensor input to multisensor input, and further from simple concatenation to adaptive fusion, the model performance exhibits a consistent improvement trend. This indicates that complementary information indeed exists among different sensors, and that an appropriate fusion strategy can effectively enhance the representation capability of machinery health conditions.

Table 1. Comparison of fault diagnosis performance

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Single Vibration-CNN | 93.4 | 92.9 | 93.1 | 93.0 |
| Single AE-CNN | 91.8 | 91.2 | 91.5 | 91.3 |
| Feature Concatenation | 95.6 | 95.1 | 95.3 | 95.2 |
| CNN-LSTM | 96.1 | 95.7 | 95.8 | 95.7 |
| Attention Fusion | 97.3 | 97.0 | 97.1 | 97.0 |
| Proposed Method | 98.4 | 98.1 | 98.2 | 98.1 |

Table 2. Comparison of RUL prediction performance

| Method | MAE | RMSE | Score |
|---|---|---|---|
| Single Vibration-GRU | 12.84 | 16.92 | 0.312 |
| Single AE-GRU | 14.21 | 18.15 | 0.338 |
| Feature Concatenation | 10.37 | 13.64 | 0.267 |
| CNN-GRU | 9.74 | 12.81 | 0.243 |
| Attention Fusion | 8.96 | 11.57 | 0.219 |
| Proposed Method | 7.48 | 9.86 | 0.181 |

As shown in Table 1, the proposed method achieves the best performance in terms of Accuracy, Precision, Recall, and F1-score for the fault diagnosis task. Compared with the single-vibration model, the proposed method improves Accuracy by 5.0 percentage points. Even compared with the simple feature concatenation strategy, an improvement of 2.8 percentage points is still observed. These results indicate that a single sensor is insufficient to fully characterize complex fault patterns, whereas the proposed adaptive fusion mechanism can more effectively exploit complementary multisource information and thus improve fault identification performance.

Table 2 further shows that the proposed method also outperforms all comparison methods in the RUL prediction task and yields the lowest MAE, RMSE, and Score values. Compared with the single-vibration model, the RMSE decreases from 16.92 to 9.86, indicating a substantial reduction in prediction error. Even when compared with the attention-fusion baseline, further improvement is still achieved. This suggests that the proposed shared health representation is not only suitable for current-state recognition but is also capable of better capturing degradation trends, thereby providing more stable feature support for life prediction.

Figure 1 illustrates the Accuracy comparison among different methods for the fault diagnosis task. It can be more intuitively observed that the performance of single-sensor models is relatively limited. Although multi-sensor feature concatenation improves performance, it is still inferior to the proposed method. In contrast, the proposed framework achieves higher classification accuracy while maintaining a compact model structure, demonstrating the effectiveness of adaptive fusion and dual-task shared representation learning in enhancing state discrimination capability.

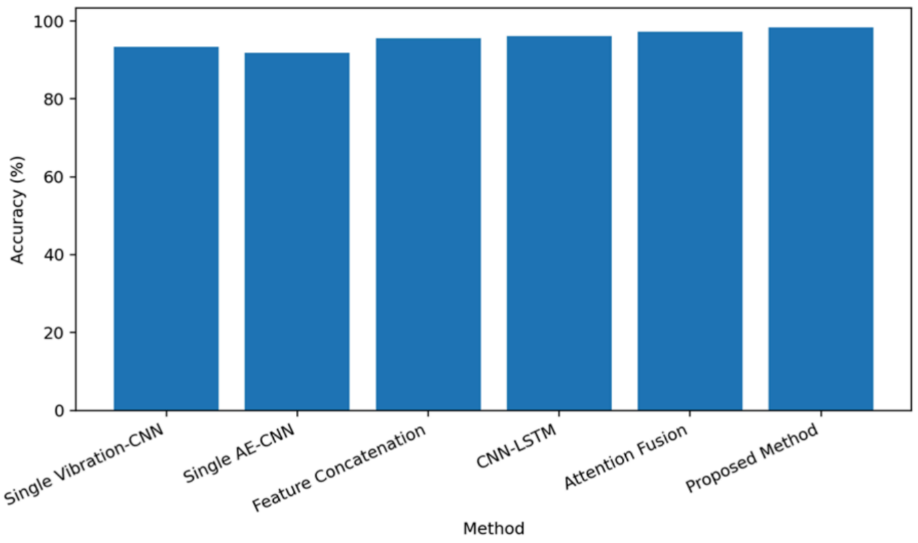

Figure 1. Diagnosis Accuracy

### Fault Diagnosis Results

To further analyze the recognition capability of the model for different fault categories, Fig. 2 presents the confusion matrix of the proposed method on the test set. It can be observed that most samples are correctly classified, and the diagonal entries are significantly larger than the off-diagonal ones, indicating strong discrimination ability across different health states and fault categories. Only a small number of misclassifications occur between a few similar fault categories, which is typically caused by similar local dynamic characteristics, close fault propagation paths, or weak signatures in the early degradation stage.

Overall, the proposed method exhibits relatively balanced classification performance across all categories, without obvious bias toward a specific class. This indicates that the shared health representation is capable of sufficiently preserving fault-discriminative information under the joint contribution of different sensor channels. In addition, the limited category confusion further suggests that the adaptive fusion mechanism can effectively suppress redundant information and noise interference, enabling the model to focus on the key sensor features that contribute most to classification. This property is of practical significance for state recognition in complex rotating machinery fault scenarios.

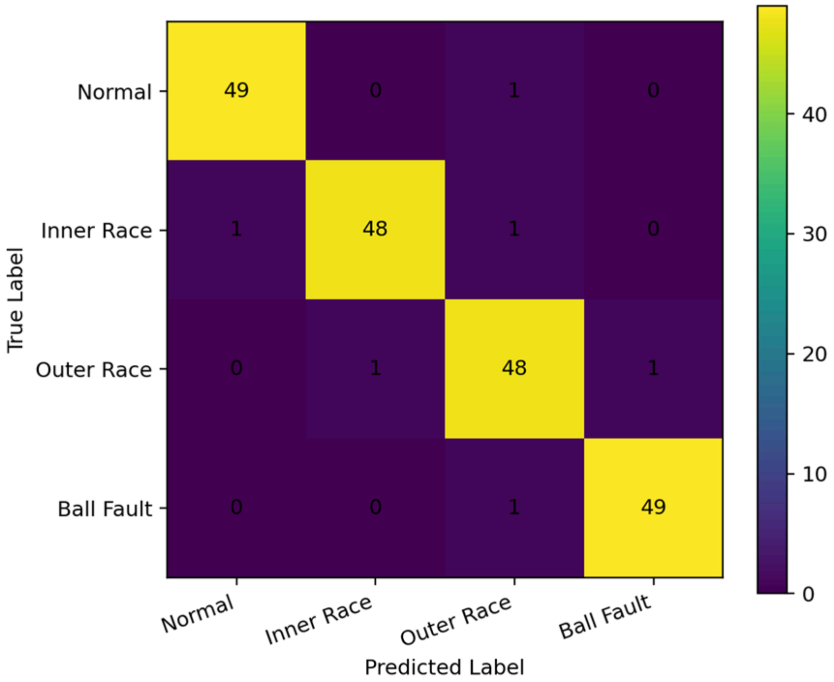

Figure 2. Confusion Matrix

### Remaining Useful Life Prediction Results

To evaluate the capability of the proposed method in modeling degradation trends, Fig. 3 compares the true RUL curve with the prediction curves produced by different methods. It can be observed that the simple feature concatenation method is able to follow the overall life evolution trend, but still shows noticeable deviation in local stages, especially in the middle and late degradation periods where the prediction error becomes more pronounced. In contrast, the prediction curve of the proposed method is much closer to the true curve, showing better consistency in overall trend tracking and local fitting performance throughout the entire degradation process.

This result indicates that the proposed shared health representation can not only integrate degradation-related information from different sensors, but also improve the model's ability to characterize the continuity of life evolution. In particular, during the later degradation stage, where the machinery condition changes more dramatically, the proposed method can still stably track the real life evolution trend, demonstrating a stronger perception of key degradation features. Combined with the quantitative results reported in Table 2, it can be concluded that the proposed method achieves satisfactory accuracy and stability in the RUL prediction task.

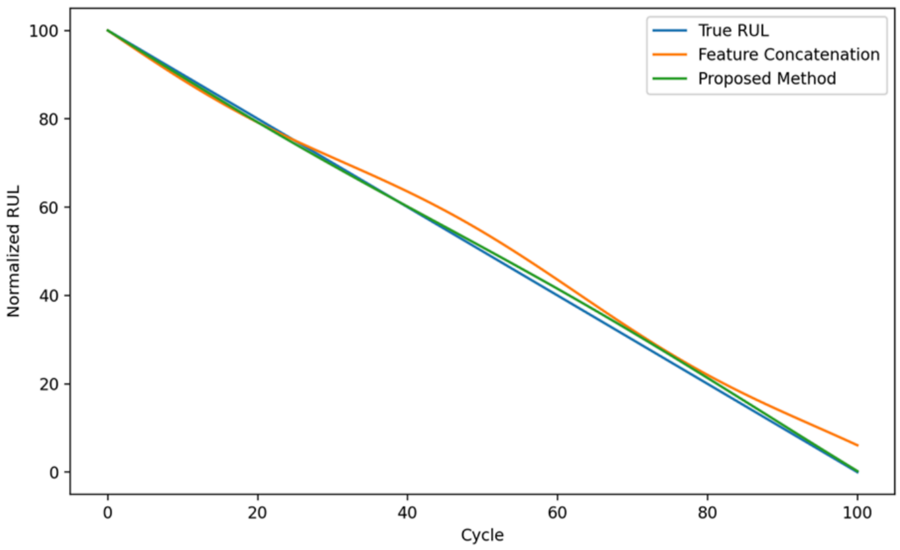

Figure 3. RUL curves

### Ablation Study

To verify the contribution of each component in the proposed framework, three groups of ablation experiments were conducted by removing the multisensor input, the adaptive fusion module, and the joint learning mechanism, respectively, and comparing the resulting variants with the full model. Table 3 reports the results of different ablation variants on both the fault diagnosis and RUL prediction tasks.

Table 3. Ablation study results

| Variant | Accuracy (%) | RMSE |
|---|---|---|
| w/o Multisensor | 95.9 | 13.21 |
| w/o Adaptive Fusion | 96.8 | 11.84 |
| w/o Joint Learning | 97.1 | 10.92 |
| Full Model | 98.4 | 9.86 |

As shown in Table 3, removing the multisensor input leads to a noticeable performance drop in both tasks, confirming that single-source information is insufficient for comprehensive machinery health characterization. When the adaptive fusion module is removed, the model can still benefit from multisensor information, but its performance is clearly inferior to that of the full model due to the lack of dynamic importance modeling across sensor channels. Moreover, removing the joint learning mechanism also degrades both Accuracy and RMSE, indicating that fault diagnosis and RUL prediction indeed share informative state representations, and that joint optimization is beneficial for improving overall performance.

Therefore, the ablation study further verifies the effectiveness of the three core design components of the proposed framework: multisensor input provides richer operating information, the adaptive fusion module strengthens key health-related features, and the joint learning strategy enhances both the discriminative and continuous properties of the shared health representation.

**Robustness Analysis**

Considering that monitoring signals in practical industrial scenarios are often affected by environmental noise and operating disturbances, robustness experiments under different signal-to-noise ratio (SNR) conditions were further conducted to evaluate the performance variation of the model in noisy environments. Table 4 and Fig. 4 show the diagnostic Accuracy of different methods under different noise levels.

Table 4. Robustness performance under different noise levels

| SNR (dB) | Feature Concatenation | Attention Fusion | Proposed Method |
|---|---|---|---|
| 0 | 88.1 | 90.8 | 92.7 |
| 5 | 90.7 | 93.1 | 95.0 |
| 10 | 93.4 | 95.1 | 96.6 |
| 15 | 94.6 | 96.3 | 97.6 |
| 20 | 95.6 | 97.3 | 98.4 |

From Table 4 and Fig. 4, it can be observed that the diagnostic performance of all methods decreases as the SNR becomes lower. However, the proposed method consistently achieves the best performance across all noise levels, and its degradation trend is relatively milder than those of the comparison methods. Particularly under low-SNR conditions, the proposed method still maintains a clear advantage over the simple feature concatenation strategy, indicating that the adaptive fusion mechanism can more effectively suppress the interference of noisy channels and redundant information, thereby enhancing the extraction of key health-related features.

These results further demonstrate that the proposed shared health representation not only achieves high accuracy under ideal conditions, but also exhibits strong stability and generalization capability in complex scenarios with noise disturbances. This is of practical significance for the real-world application of rotating machinery health monitoring.

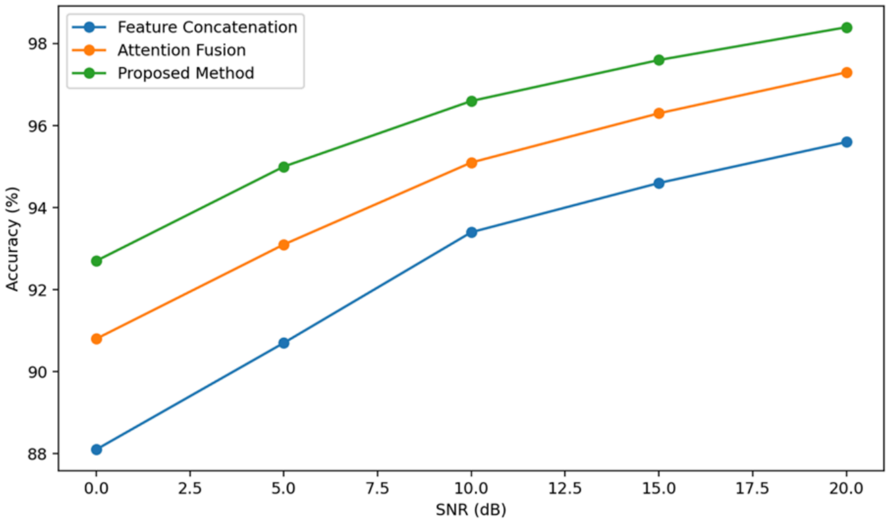

Figure 4. Robustness Analysis

## DISCUSSION

The experimental results in Section 4 show that the proposed method consistently outperforms single-sensor methods and simple fusion methods in both fault diagnosis and remaining useful life (RUL) prediction, indicating the clear advantage of multisensor data fusion for machinery health modeling. As shown in Table 1, although the single-vibration model and the single-acoustic-emission model are both capable of capturing part of the fault-related information, their overall diagnostic performance is notably inferior to that of multi-sensor models. This suggests that different sensors respond to machinery health conditions in different ways, and a single signal source is insufficient to comprehensively cover all the information associated with complex fault patterns. In contrast, multisensor fusion can integrate information from different physical origins in the feature space, enabling the model to achieve stronger discrimination when dealing with similar fault types or weak fault signatures. This is further supported by the confusion matrix in Fig. 3, where only a small number of samples are misclassified. Even between similar fault categories, the proposed method maintains a high recognition rate, indicating that the fused shared health representation indeed enhances the model’s ability to capture fine-grained fault differences.

A further comparison among Feature Concatenation, Attention Fusion, and the proposed method reveals that the observed performance improvement does not simply come from increasing the number of sensors, but more importantly from how the multisource information is fused. In Table 1, Feature Concatenation already shows a clear improvement over the single-sensor methods, confirming the complementary value of multisource information itself. However, its performance is still inferior to that of Attention Fusion and the proposed method, which indicates that straightforward feature stacking is insufficient to fully exploit the importance differences and intrinsic relationships among sensors. Attention Fusion further improves both the diagnosis and RUL prediction results, suggesting that dynamic weighting can effectively emphasize more informative sensor features. Nevertheless, a performance gap still remains between Attention Fusion and the proposed method, which implies that attention-based weighting alone is not enough to fully support dual-task health modeling. The advantage of the proposed method lies in the fact that it not only employs adaptive fusion, but also connects state recognition and degradation modeling through a shared health representation. As a result, the learned features are both discriminative for fault category identification and continuous for degradation trend characterization.

From the RUL prediction results, Table 2 and Fig. 2 jointly demonstrate the effectiveness of the proposed method in degradation trend modeling. Compared with the single-sensor approaches, the multisensor fusion methods achieve substantially lower MAE and RMSE values, indicating that a single sensor is more easily affected by local noise, transient fluctuations, or instability in individual degradation-sensitive features. This effect becomes more apparent in the middle and late degradation stages, where machinery condition changes more rapidly and the information provided by a single channel is often less stable. In such cases, multisensor information can provide complementary observations of degradation from different perspectives, which is beneficial for improving the consistency between the predicted life curve and the true life curve. Figure 2 also shows that although Feature Concatenation can roughly follow the overall downward trend, noticeable deviations still exist in local stages, whereas the proposed method remains closer to the true curve throughout the degradation process. This indicates that the shared health representation is more effective in preserving the continuous information associated with life evolution, thereby improving the model’s fitting capability for nonlinear degradation processes.

The ablation study further clarifies the functional role of each component in the proposed framework. As reported in Table 3, removing the multisensor input causes the most obvious degradation in both Accuracy and RMSE, indicating that multisource monitoring information is the foundation of performance improvement. When the adaptive fusion module is removed, the model performance also drops significantly, suggesting that multisensor input itself does not automatically lead to a better representation; the benefit of fusion can only be fully realized when the model is able to distinguish the contribution of different sensors under different health conditions. By comparison, removing the joint learning mechanism also deteriorates the results, although the reduction is relatively smaller than that caused by removing multisensor input or adaptive fusion. This indicates that the construction of the shared health representation depends not only on sufficient multisource information and an effective fusion strategy, but also on the collaborative constraint imposed by the fault diagnosis and RUL prediction tasks. In other words, multisensor input and adaptive fusion determine whether the information is sufficiently exploited, while joint learning further determines whether the learned representation is unified and effective across tasks.

The robustness analysis further suggests that the performance improvement of the proposed method is not limited to ideal conditions, but also extends to noisy environments. As shown in Fig. 4, the proposed method consistently achieves the highest diagnostic accuracy under all signal-to-noise ratio (SNR) conditions, and particularly under low-SNR settings, it exhibits a smaller performance drop than Feature Concatenation and Attention Fusion. This indicates that when the monitoring signals are heavily contaminated by noise, simple concatenation methods are more likely to directly propagate noisy information into the fused representation, whereas the proposed method can alleviate the interference of low-quality channels through adaptive weighting to some extent, thereby preserving stronger feature extraction capability. In other words, the advantage of the proposed framework is reflected not only in its higher average performance, but also in its improved adaptability to complex monitoring environments, which is especially important for practical engineering applications.

In addition, the consistent improvement observed in both fault diagnosis and RUL prediction suggests that the shared health representation learned by the proposed framework has good cross-task stability. If a representation only improves classification performance but fails to enhance life prediction, it would imply that the representation mainly emphasizes discrete decision boundaries while lacking the ability to characterize continuous degradation patterns. Conversely, if it only improves RUL prediction but offers limited benefit for diagnosis, it would indicate a stronger focus on trend fitting but insufficient discriminative power. In the present study, the proposed method achieves stable improvement in both tasks, which suggests that the learned representation simultaneously preserves discriminative and continuous properties to a certain extent. This is, in fact, one of the key distinctions between the proposed framework and conventional single-task modeling approaches: instead of designing two completely separate representations for diagnosis and prediction, the proposed framework attempts to construct an intermediate representation that can uniformly describe the machinery health state. The experimental results indicate that this idea is effective.

Overall, the experimental findings in Section 4 suggest that the performance gain of the proposed method can be explained by a relatively clear mechanism: multisensor input provides a more complete description of machinery conditions, the adaptive fusion mechanism improves the efficiency of multisource feature utilization, and the joint learning framework enhances the task consistency of the shared health representation. The combined effect of these three aspects enables the proposed method to achieve superior performance in fault identification accuracy, life prediction error, and robustness under noisy environments. These results not only validate the rationality of the method design, but also demonstrate that combining multisensor fusion with dual-task health modeling is an effective way to improve intelligent health monitoring performance for rotating machinery.

## CONCLUSION

To address the limitations of incomplete condition information in single-sensor monitoring, the separation between fault diagnosis and remaining useful life (RUL) prediction, and the insufficient utilization of multisource data in rotating machinery health monitoring, this paper proposed a multisensor data fusion method for fault diagnosis and RUL prediction of rotating machinery. The proposed method takes multisource monitoring signals as input, learns sensor-specific local condition features through dedicated feature extraction modules, and further constructs a shared health representation by means of an adaptive fusion mechanism. Based on this representation, fault diagnosis and RUL prediction are integrated into a unified dual-task learning framework, enabling collaborative optimization of current fault-state recognition and future degradation trend modeling.

Experimental results demonstrated that the proposed method outperformed single-sensor models, simple feature concatenation methods, and representative deep learning baselines in terms of diagnostic accuracy, RUL prediction error, and robustness under noisy environments. These findings indicate that multisensor information fusion can provide a more comprehensive description of machinery health conditions, while the shared health representation can simultaneously preserve fault discriminability and degradation continuity, thereby offering a unified and effective feature basis for both diagnosis and life prediction. In addition, the ablation study further confirmed the necessity and effectiveness of multisensor input, the adaptive fusion strategy, and the dual-task joint learning mechanism within the overall framework.

Overall, this study demonstrates that combining multisensor fusion with joint modeling of fault diagnosis and RUL prediction is an effective way to improve intelligent health monitoring performance for rotating machinery. The proposed framework provides a feasible path toward unified machinery health state representation and offers methodological support for predictive maintenance and intelligent operation of rotating machinery. Nevertheless, the current method still depends to some extent on data synchronization quality and sample completeness, and there remains room for improvement in cross-condition transferability, robustness to missing sensors, and model interpretability. Future work will focus on robust fusion under complex industrial scenarios, cross-domain generalization, and mechanism-constrained modeling so as to further enhance the engineering applicability and practical deployment capability of the proposed approach.

*Author Contributions*

Conceptualization – Tianxing Yang; methodology – Tianxing Yang; formal analysis – Tianxing Yang; investigation – Tianxing Yang; resources – Tianxing Yang; writing-original draft preparation – Tianxing Yang; writing-review and editing – Tianxing Yang; visualization – Tianxing Yang; supervision – Tianxing Yang. All authors have read and agreed to the published version of the manuscript.

*Conflicts of Interest*

The author declares no conflict of interest.

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## REFERENCES

[1] Song X, Liu J, Chen C, et al. Advanced Methods in Rotating Machines. MDPI. 2022; 15(15):5414. doi: 10.3390/en15155414

[2] Zhang Q, Su N, Qin B, et al. Fault diagnosis for rotating machinery based on dimensionless indices: Current status, development, technologies, and future directions. Electronics. 2024; 13(24):4931. doi: 10.3390/electronics13244931

[3] Prasad KN, Narayanan G. Electromagnetic bearings with power electronic control for high-speed rotating machines: Review, analysis, and design example. IEEE Transactions on Industry Applications. 2021; 57(5):4946-4957. doi: 10.1109/TIA.2021.3093013

[4] Kumar N, Satapathy RK. Bearings in aerospace, application, distress, and life: a review. Journal of Failure Analysis and Prevention. 2023; 23(3):915-947. doi: 10.1007/s11668-023-01658-z

[5] Liu X, Zhang Z, Li Z, et al. Advancements in bearing health monitoring and remaining useful life prediction: techniques, challenges, and future directions. Measurement Science and Technology. 2025; 36(3):32003. doi: 10.1088/1361-6501/adafc8

[6] Gebraeel N, Lei Y, Li N, et al. Prognostics and remaining useful life prediction of machinery: advances, opportunities and challenges. Journal of Dynamics, Monitoring and Diagnostics. 2023: 1-12. doi: 10.37965/jdmd.2023.148

[7] Kannan V, Zhang T, Li H. A review of the intelligent condition monitoring of rolling element bearings. Machines. 2024; 12(7):484. doi: 10.3390/machines12070484

[8] Hamani K, Kuchar M, Kubatko M, et al. Advancements in Induction Motor Fault Diagnosis and Condition Monitoring: A Comprehensive Review. Sensors (Basel, Switzerland). 2025; 25(19):5942. doi: 10.3390/s25195942

[9] Gawde S, Patil S, Kumar S, et al. A scoping review on multi-fault diagnosis of industrial rotating machines using multi-sensor data fusion. Artificial Intelligence Review. 2023; 56(5):4711-4764. doi: 10.1007/s10462-022-10243-z

[10] Lin T, Ren Z, Zhu L, et al. A systematic review of multi-sensor information fusion for equipment fault diagnosis. IEEE Transactions on Instrumentation and Measurement. 2025. doi: 10.1109/tim.2025.3529577

[11] Saeed A, A. Khan M, Akram U, et al. Deep learning based approaches for intelligent industrial machinery health management and fault diagnosis in resource-constrained environments. Scientific Reports. 2025; 15(1):1114. doi: 10.1038/s41598-024-79151-2

[12] Han P, Liu Z, He X, et al. Multi-condition fault diagnosis of dynamic systems: A survey, insights, and prospects. IEEE Transactions on Automation Science and Engineering. 2025. doi: 10.1109/TASE.2025.3571516

[13] Xia M, Li T, Xu L, et al. Fault diagnosis for rotating machinery using multiple sensors and convolutional neural networks. IEEE/ASME transactions on mechatronics. 2017; 23(1):101-110. doi: 10.1109/TMECH.2017.2728371

[14] Chen G, Liu Z, Yu G, et al. A new view of multisensor data fusion: research on generalized fusion. Mathematical Problems in Engineering. 2021; 2021(1):5471242. doi: 10.1155/2021/5471242

[15] De Farias CM, Pirmez L, Fortino G, et al. A multi-sensor data fusion technique using data correlations among multiple applications. Future generation computer systems. 2019; 92:109-118. doi: 10.1016/j.future.2018.09.034