Interpretable Sensor Importance-Based Multi-Sensor Integration for Condition Monitoring of Rotating Machinery

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Abstract

Accurate condition monitoring of rotating machinery requires integrating multi-sensor data to capture fault-related information distributed across sensing locations. While attention-based deep learning models can assess sensor importance, their lack of transparency limits industrial adoption. This study proposes an interpretable sensor importance-based multi-sensor integration framework combining a CNN-inspired kernel sharing strategy, a Transformer-based feature extraction module for local and global feature extraction, and a channel attention mechanism for dynamic sensor weighting. Attention weights in the Transformer-based feature extraction module were analyzed in the frequency domain to reveal spectral components influencing sensor importance evaluation. Validation on a pump testbed with various speeds conditions shows superior fault diagnosis accuracy, robustness to unseen conditions, and clear alignment between high-weight sensors and known fault frequencies, supporting trustworthy AI-driven condition monitoring in practice.

1. Introduction

Condition monitoring is essential for the predictive maintenance of industrial rotating machinery, ensuring operational reliability, preventing unexpected downtime, and reducing maintenance costs (Lee et al., 2014). Traditional approaches, typically based on single-sensor measurements and expert-driven analysis, have proven effective for well-understood systems under stable operating conditions. However, they often underperform in complex industrial environments, where fault signatures are distributed across multiple sensing modalities and operating states. Single-sensor analysis may fail to capture complementary information from heterogeneous signals, thereby limiting fault diagnosis performance.

The advancement of the industrial Internet of Things (IIoT) has enabled the deployment of diverse sensor networks that collect large-scale, multi-modal datasets, such as vibration, acoustic, temperature, and other process variables (Liu et al., 2018). These data offer richer fault-related information but introduce the challenge of effective integration, particularly when combining signals with varying noise levels, frequency characteristics, and fault sensitivities. Conventional fusion techniques, including simple averaging or fixed expert-defined weights, cannot fully capture the complex, nonlinear dependencies among sensors.

Deep learning-based fusion models have emerged as a promising alternative, leveraging their ability to automatically learn hierarchical feature representations and model cross-modal correlations. Among these, attention mechanisms have shown strong potential for dynamically evaluating sensor importance, allowing models to emphasize the most informative sensors under varying operating conditions (Wu et al., 2023). Despite these advances, most attention-based approaches operate as black boxes, providing little insight into the specific signal characteristics that drive sensor importance estimation, which limits transparency and trust in industrial decision-making (Li et al., 2024).

To address this interpretability gap, this paper proposes an interpretable sensor importance-based multi-sensor integration framework for rotating machinery condition monitoring. The framework employs a unified Transformer-based feature extraction module along with sensor with channel attention to jointly model multi-sensor relationships and adaptively quantify sensor importance. In addition, we introduce a frequency-domain attention weight interpretation method that traces attention flow through network layers and maps it to specific spectral components, thereby linking model decisions to physically meaningful fault indicators. The proposed approach is validated on a pump testbed under multiple rotational speeds and fault conditions, demonstrating superior fault diagnosis accuracy and clear interpretability compared with state-of-the-art fusion methods.

The main contributions of this study are as follows:

1) An interpretable, attention-based multi-sensor integration framework for rotating machinery condition monitoring.

2) A frequency-domain attention weights interpretation method was developed to identify influential spectral information for evaluating sensor importance.

3) Comprehensive experimental validation under various speed conditions.

2. PRELIMINARY BACKGROUNDS

2.1. CNN-inspired Kernel Sharing Strategy

Convolutional Neural Networks (CNNs) have been widely applied across various domains due to their ability to efficiently capture local patterns in image data. Their effectiveness is largely attributed to two key characteristics of image data: stationarity of statistics and locality of dependency, which allow convolution kernels to learn recurring patterns and localized relationships.

These concepts can be extended to multi-sensor condition monitoring data. In this context, kernel operations can be designed to leverage statistical stationarity for capturing recurring fault patterns across sensors, while preserving sensor-specific information by respecting the locality of dependency (Kim et al., 2025).

(1) Stationarity of Statistics

In image analysis, the same convolution kernel is applied across the spatial domain to detect patterns that recur regardless of position. Similarly, in rotating machinery, defect-related periodic components may appear in signals from multiple sensors due to a common fault source. Applying a shared kernel across sensor channels can thus efficiently extract these recurring features.

(2) Locality of Dependency

Locality in image data refers to meaningful information being confined to a limited region. For multi-sensor data, distinctive characteristics are often localized to individual sensor channels. Maintaining this locality can be achieved by applying kernels in a channel-wise (depth-wise) manner, ensuring that each kernel processes only its corresponding sensor channel.

2.2. Attention Rollout

Improving the interpretability of Transformer-based models requires identifying which parts of the input sequence most strongly influence the model's predictions. The attention rollout technique (Abnar and Zuidema, 2020) provides a way to trace the cumulative flow of attention through multiple layers, thereby yielding a global measure of token influence. In this work, the method is adapted to the analysis of time-series data.

Let $A^{(i)}$ denote the average attention weight matrix of the i-th Transformer-based feature extraction module, where the attention weights are averaged over all attention heads.

$$A^{(i)} \in \mathrm{R}^{N_Q \times N_K} \tag{1}$$

Here, where N_Q and N_K are the dimension of query and key tokens in Transformer block, respectively.

Because Transformer block employ residual connections, the identity matrix is added.

$$A_n^{(i)} = \frac{1}{2}(A^{(i)} + \mathrm{I}) \tag{1}$$

The rollout process recursively multiplies the normalized attention matrices across layers to accumulate the influence of each token from the input to a given layer.

$$\widetilde{A}^{(i)} = A_n^{(1)} \cdot A_n^{(2)} \cdot \cdots \cdot A_n^{(i)} \tag{2}$$

The resulting matrix $\widetilde{A}^{(i)}$ aggregates attention contributions from all preceding layers, producing an attention map that reflects the effective contribution of each input segment to the representation at i-th layer.

3. PROPOSED METHOD

The proposed interpretable sensor importance-based multi-sensor integration framework comprises two main components: a sensor-wise shared Transformer-based feature extraction module for feature extraction, and a sensor importance evaluation module with a classification head for fault diagnosis as depicted in . After the fault diagnosis stage, the attention patterns of the Transformer-based feature extraction module are analyzed via an attention rollout procedure to identify the frequency characteristics that most strongly contribute to the evaluated sensor importance. Sensor-wise Shared Transformer-based feature extraction module.

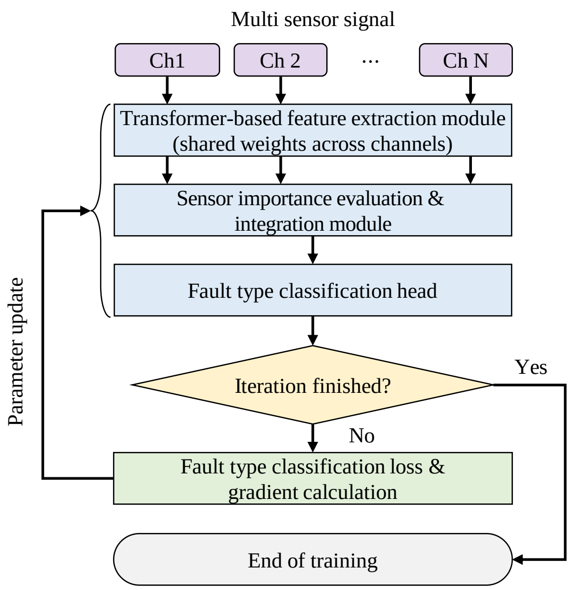


Figure 1. Flowchart of the proposed method

The sensor-wise shared Transformer-based feature extraction module is designed to capture both the periodic fault patterns common across multiple sensors and the unique sensor-specific information crucial for fault diagnosis.

For each sensor channel, the input signal is divided into non-overlapping patches, which are linearly projected to obtain patch embedding. These embedding are then transformed into queries, keys, and values, and processed by a shared Transformer-based feature extraction module. Within the Transformer block, multi-head self-attention (MHSA) captures long-range temporal dependencies. The MHSA output is passed through a position-wise feed-forward network, with each sublayer followed by residual connections and layer normalization to ensure stable training and rich representational capacity.

The feature extraction module is shared across all sensor channels to exploit the statistical stationarity of rotating machinery, where localized defects produce similar periodic patterns in each channel regardless of location. At the same time, to retain sensor-specific responses, the Transformer-based feature extraction module is applied in a depth-wise manner, ensuring that information from different channels is not aggregated during extraction. This preserves distinctive features for each sensor, enabling accurate evaluation of its fault diagnosis contribution.

3.1. Sensor Importance Evaluation with Classification Head

To estimate the importance of each sensor channel for fault diagnosis, a CNN-based channel attention module processes the multi-sensor features as illustrated in **Error! Reference source not found.**. Two stacked one-dimensional convolution layers extract discriminative features that capture contextual patterns within each channel. Temporal average pooling then condenses each feature map into a compact descriptor summarizing its overall activation.

The descriptors are normalized via a softmax function to produce channel attention weights, representing the relative importance of each sensor. These weights are applied to reweight the latent features, which are then fed into a classification module. A fully connected layer maps the features to predefined fault categories, followed by a softmax activation to produce confidence scores for each fault type.

The model is trained using a cross-entropy loss between the predicted confidence scores and the ground-truth labels, guiding both the feature extraction layers and attention weights to emphasize the most informative sensors under varying operating conditions.

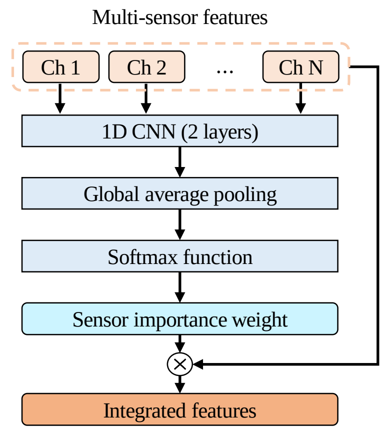


Figure 2. Flowchart of the sensor importance evaluation & integration module

3.2. Self-Attention Weights Interpretation

To enhance interpretability, we apply an extended self-attention interpretation pipeline that links attention patterns to physically meaningful spectral fault characteristics.

First, the attention rollout technique accumulates attention weights across all Transformer layers, tracing the cumulative influence of each input patch. The resulting attention map is interpolated back to the original temporal resolution for alignment with the time-series signals. Finally, the interpolated attention weights are transformed into the frequency domain using the Fast Fourier Transform (FFT), revealing dominant spectral components corresponding to known fault-related frequencies.

This combined time–frequency interpretation highlights both the most influential temporal segments and the key frequency bands that drive the model’s fault diagnosis decisions, improving transparency and aligning the learned importance with domain knowledge.

4. EXPERIMENTAL VALIDATION

The proposed framework was experimentally validated on a pump testbed operating at six distinct rotational frequencies of 20, 22, 24, 26, 28, and 30 Hz. To evaluate the model's capability to generalize to unseen operating conditions, an interpolation training scenario was employed. In this setting, the model was trained only on data from 20 Hz and 30 Hz operating speeds and tested on the intermediate speeds of 22, 24, 26, and 28 Hz, which were excluded from the training set. This configuration represents realistic industrial situations where fault signatures may appear at operating speeds different from those observed during model development.

The fault diagnosis performance of the proposed framework was compared with two state-of-the-art deep learning methods to validate its feature extraction capability. For a fair comparison, recent attention-based fault diagnosis models were selected as baselines. The first baseline, Diagnosisformer, is a Transformer-based approach that exploits spectral representations obtained via the Fast Fourier Transform (Hou et al., 2023). By modeling fault-related dependencies in the frequency domain through the Transformer architecture, it demonstrated improved diagnostic performance on bearing fault datasets. The second baseline, Global Contextual Feature Aggregation Network (GCFAN), is a multi-scale convolutional neural network designed to identify fault patterns under non-stationary conditions (Xu et al., 2023). This model incorporates a global contextual module and a multiscale attention mechanism within the CNN framework to extract both global and local discriminative features, thereby enhancing fault diagnosis robustness under varying operating environments.

In addition to classification accuracy, the proposed method was further evaluated by interpreting the sensor importance derived from the attention weights in the Transformer-based feature extraction module, providing insights into the contribution of each sensor to the fault diagnosis decision.

4.1. Dataset Description

The experiments were conducted using a closed loop pump testbed designed to reproduce various operating speeds encountered in industrial rotating machinery. As shown in Figure 3, the system consists of a water reservoir, a pump driven by an induction motor, and associated piping with adjustable control valves. The pump shaft is supported by rolling element bearings, in which artificial defects were introduced by drilling 3 mm-diameter holes on the inner raceway and the outer raceway to simulate typical bearing spall fault scenarios.

Two accelerometers were mounted directly on the pump to record vibration signals. Accelerometer 1 (Channel 1) was installed near the drive end bearing housing, while Accelerometer 2 (Channel 2) was positioned adjacent to the non-drive end bearing. This placement enabled simultaneous monitoring of vibration responses from different mechanical locations, capturing both localized defect impacts and propagated vibration patterns.

The pump was operated at six discrete rotational frequencies of 20, 22, 24, 26, 28, and 30 Hz. For each operating condition, vibration data were sampled at 20 kHz for a duration of 10 seconds, with a single experimental trial performed for each condition.

4.2. Model training

All models were trained under identical experimental settings to ensure a fair performance comparison. The vibration signals acquired from the pump testbed were lowpass filtered between 4 kHz to highlight the resonance frequency range primarily excited by bearing faults, while attenuating high frequency noise. The filtered signals were subsequently segmented into sequences of 4,000 data points, corresponding to a 0.1 s time window, and normalized before being fed into the models. As a result, 100 samples were obtained for each class at each rotational speed, yielding a total of 1,800 samples across six rotational speed conditions and three fault types.

In the proposed framework, each preprocessed vibration signal samples were further partitioned into 50 non-overlapping segments, which served as discrete input tokens to the Transformer-based feature extraction module. The Adam optimizer was employed with an initial learning rate of 10^{-3}, and an early stopping criterion was applied to the validation loss, terminating training if no performance improvement was observed within 20 consecutive epochs on subset of training dataset. This setup ensured both convergence stability and prevention of overfitting.

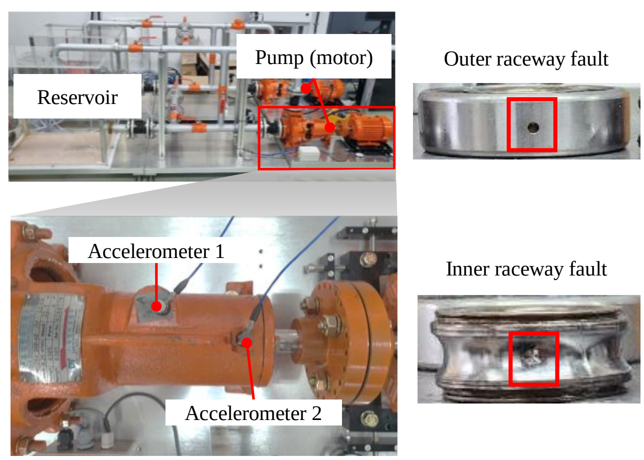
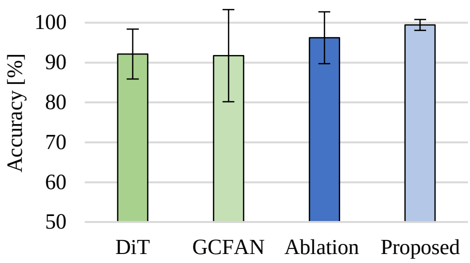


Figure 3. Pump testbed configuration

4.3. Comparative Study

Figure 4 presents the average fault classification accuracy across all test conditions with five-fold cross validation for the comparative models and ablation model with independent feature extraction module on each channel. The proposed method achieved the highest mean accuracy, surpassing both Diagnosisformer and GCFAN. Although these baseline models demonstrated competitive performance, their classification accuracy was more sensitive to variations in operating speed, as evidenced by the wider error bars representing standard deviation.

Furthermore, the ablation study exhibited a 3 percentage-point decrease in fault diagnosis accuracy compared to the proposed method, which is attributed to overfitting in the independently trained feature extraction modules for each channel, resulting in reduced generalization capability. The superior performance of the proposed method is attributed to the sensor-wise shared feature extraction module design preserves sensor-specific fault diagnosis information while efficiently extracting recurring fault patterns common across sensors. By adaptively emphasizing the most informative sensor channels, the framework maintains stable fault diagnosis accuracy. This finding highlights the effectiveness of the shared Transformer-based feature extraction module in enhancing generalizable fault diagnosis performance.



Model	DiT	GCFAN	Ablation	Proposed
Acc. [%]	92.1	91.7	96.2	99.5

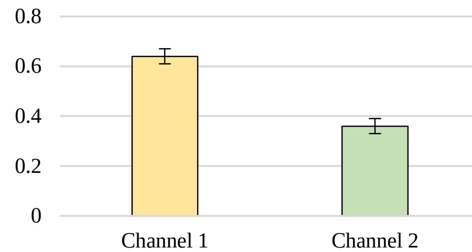
Figure 4. Fault diagnosis performance of existing and proposed methods with ablation study

4.4. Sensor Importance Evaluation Results

Figure 5 presents the sensor importance evaluation results obtained using the proposed framework. Across all test conditions, the model consistently assigned higher importance scores to channel 1 than to channel 2. This finding aligns with the physical setup of the pump testbed, as Accelerometer 1 was installed closer to the drive-end bearing, where fault impacts are more prominent. The elevated weighting indicates that the model effectively learned to prioritize measurements from the sensor capturing stronger fault-related signals, thereby enhancing fault diagnosis accuracy.

In contrast, the lower importance assigned to channel 2 suggests that, although it still contributed meaningful information, its sensitivity to localized fault-induced vibrations was diminished due to its complicated transfer path from the primary fault source. The low standard deviation in sensor importance scores across repeated trials highlights the stability and robustness of the proposed estimation process.

Overall, these results confirm that the method not only achieves strong classification performance but also provides interpretable, physically consistent insights into sensor contributions, supporting informed sensor placement and optimization in practical condition monitoring applications



Channel	Channel 1	Channel 2
Attn. weight	0.64	0.36

Figure 5. Sensor importance evaluation result

4.5. Interpretation on Attention Weights in Transformer-based Feature Extraction Module

The attention weight distributions in the Transformer-based feature extraction module were examined in the frequency domain to interpret how sensor importance is determined. Figure 6 presents the attention weight heat map overlaid on the raw vibration signal, where high-intensity regions correspond to time segments that the model identified as highly relevant for fault diagnosis. These highlighted intervals align with periodic impulse-like patterns commonly associated with bearing defect impacts.

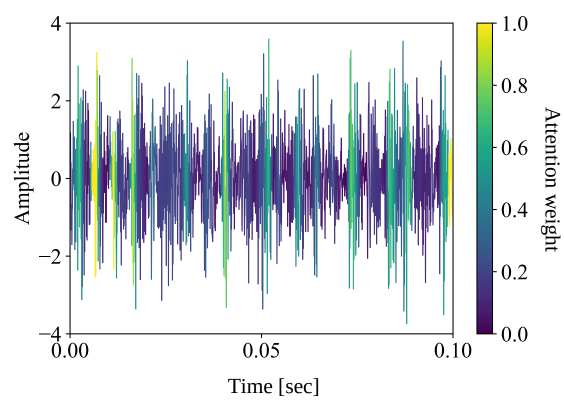


Figure 6. Attention weight heat map on vibration signal

To gain further insight, the interpolated attention weights were transformed into the frequency domain using FFT and compared with analytically derived bearing fault characteristic frequencies, including the ball pass frequency of the inner race (BPFI), ball pass frequency of the outer race (BPFO), and the fundamental train frequency (FTF), as defined in Eqs. (4–6). Here, f_r is the shaft rotational frequency, n is the number of rolling elements, ϕ is the contact angle, and D and d represent the pitch diameter and rolling element diameter of the bearing, respectively.

BPFI:

$$\text{BPFI}=\frac{nf_r}{2}\left(1+\frac{d}{D}cos\phi\right) \tag{4}$$

BPFO:

$$\text{BPFO}=\frac{nf_r}{2}\left(1-\frac{d}{D}cos\phi\right) \tag{5}$$

FTF:

$$\text{FTF}=\frac{f_r}{2}\left(1+\frac{d}{D}cos\phi\right) \tag{6}$$

Under the normal operating condition (Figure 7), no distinct peaks are observed at fault characteristic frequencies. For channel 1, the FFT spectrum of attention weights contain intense 4x harmonics of the rotational frequency, which is induced by the 4-blade impeller rotation, while channel 2 exhibits rotational frequency and its harmonics. This indicates that the Transformer-based feature extraction module adaptively focuses on sensor-specific information relevant to the system's dynamics.

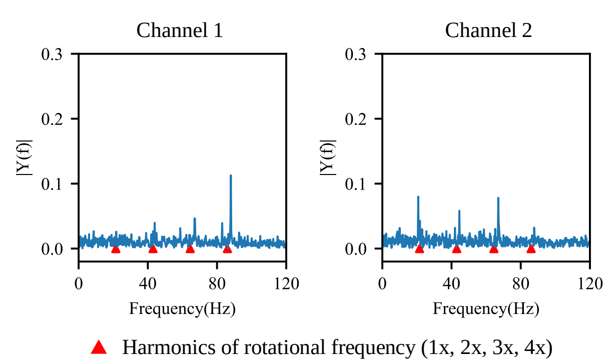


Figure 7. FFT spectrum of attention weight under normal condition

In the inner raceway fault condition (Figure 8), the FFT spectrum shows pronounced peaks at the calculated BPFI (green rhombus), confirming that the model selectively attended to defect-related frequency components. The amplitude at the fault characteristic frequency is higher for channel 1, which also received a higher sensor importance score, demonstrating that sensor importance reflects the intensity of fault-related content in the signal.

For the outer raceway fault condition (Figure 9), distinct peaks appear at the BPFO frequency band (blue triangles), with the FTF located in the low-frequency region below 20 Hz. Although the amplitude at these frequencies is similar for both channels, channel 1 exhibits fewer irrelevant spectral components, suggesting an advantage in fault discrimination.

Overall, these findings confirm that the proposed framework not only delivers accurate fault classification but also offers physically consistent interpretability by linking attention-based sensor importance to established fault characteristic frequencies.

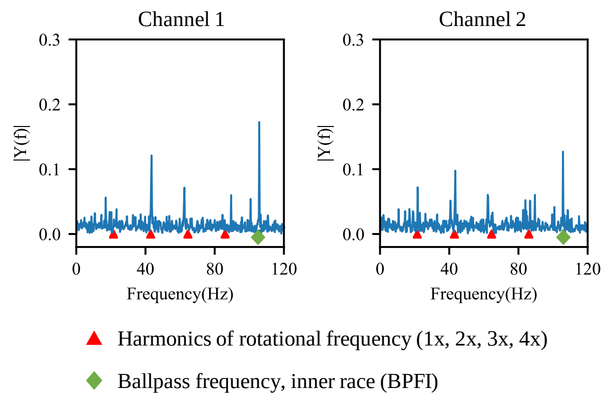


Figure 8. FFT spectrum of attention weight under inner raceway fault condition

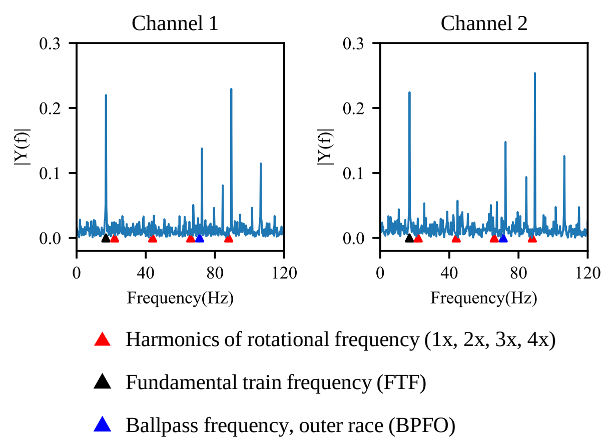


Figure 9. FFT spectrum of attention weight under outer raceway fault condition

5. CONCLUSION

This study proposed an interpretable sensor importance-based multi-sensor integration framework for condition monitoring of rotating machinery. The framework integrates a Sensor-wise Shared Transformer-based feature extraction module with a kernel sharing strategy to simultaneously capture recurring fault patterns and sensor-specific characteristics. In addition, a CNN-based channel attention module was introduced to quantify the relative contribution of each sensor, while an attention interpretation method in the frequency domain was developed to associate attention distributions with fault characteristic frequencies. Experimental validation on a pump testbed under multiple rotational speeds demonstrated that the proposed framework achieved more than a 7 percentage-point improvement in fault diagnosis accuracy compared to existing methods, and a 3 percentage-point improvement over the ablation method. Furthermore, since the proposed framework effectively extracts and integrates fault-related information from multi-sensor data, it can be extended for various health management applications, such as anomaly detection and remaining useful life prediction, by adapting the output layer accordingly.

Although the method achieved strong results in a controlled laboratory environment, its applicability to more complex and dynamic industrial settings remains to be verified. Future work will extend evaluation to diverse machinery types, operating conditions, and compound fault scenarios. Incorporating additional sensing modalities and deploying the framework in real-world industrial monitoring systems will be explored to further enhance fault diagnosis coverage, robustness, and interpretability.

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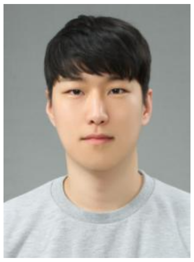
BIOGRAPHIES



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