An Interpretable Lightweight CNN Framework for Fault Diagnosis in Centrifugal Pumps Using Time-Frequency Scalograms

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Abstract. Early and accurate detection of faults in centrifugal pumps is essential for ensuring system reliability, minimizing unplanned shutdowns, and reducing maintenance costs. This study introduces a reliable diagnostic framework that utilizes vibration signals and time–frequency analysis to identify critical faults under real operating conditions. Raw vibration signals are first pre-processed through mean removal and transformed into log-scaled Continuous Wavelet Transform (CWT) scalograms, effectively capturing the localized time-frequency patterns associated with pump anomalies. These enhanced scalograms are then passed through a lightweight frequency-aware convolutional neural network (LF-CNN) specifically designed with depth-wise separable convolutions and squeeze-and-excitation (SE) blocks to emphasize relevant frequency features while maintaining computational efficiency. Frequency-guided convolution layers further improve fault localization by focusing on discriminative spectral zones. A fully connected classification layer maps the extracted features into four health states. To ensure the transparency and reliability of the fault diagnosis process, frequency attribution maps and Grad-CAM visualizations are incorporated, highlighting the frequency bands that contribute most to each classification outcome. Various experiments on a centrifugal pump dataset confirm the proposed method's ability to deliver 99.60% classification accuracy across all fault categories. These results demonstrate that the proposed method offers a lightweight, interpretable, and highly accurate solution for condition monitoring and fault diagnosis in centrifugal pumping systems.

Keywords: centrifugal pump fault diagnosis, vibration signal analysis, continuous wavelet transform, lightweight convolutional neural network, explainable fault classification.

1 Introduction

Centrifugal pumps (CPs) are essential components across numerous industrial sectors, including power generation, petrochemical processing, water treatment, and manufacturing systems [1]. These pumps play an integral role in fluid transfer, with industry estimates suggesting that nearly 20% of global energy consumption by pumps is attributed to CPs [2]. Despite their structural simplicity and operational robustness, CPs remain vulnerable to mechanical degradation over time, particularly under variable loading and environmental conditions. Faults related to impellers and mechanical seals are among the most frequently observed, often leading to performance degradation, leakage, downtime, or even catastrophic failure [3, 4].

Mechanical seal faults, such as scratches or internal holes, are commonly caused by dry run conditions, debris entrapment, or improper alignment, while impeller damage may result from erosion, imbalance, or cavitation [5]. Early diagnosis of such faults is essential to maintain reliability and prevent prolonged shutdowns. Vibration analysis has emerged as a non-invasive and effective means of identifying such defects, as mechanical faults directly influence the vibrational characteristics of the pump system. However, vibration signals generated during faulty operation are highly non-stationary and exhibit complex transient behaviors, making them difficult to interpret using conventional time-domain or frequency-domain methods alone. Traditional signal processing approaches, such as the Fourier Transform and Short-Time Fourier Transform, offer limited resolution or suffer from fixed-window constraints, which reduce their effectiveness in representing localized frequency variations over time [6, 7].

To overcome these limitations, time-frequency transformations such as CWT have been widely adopted [8]. The CWT allows for a detailed analysis of signal frequency content as it evolves over time, producing two-dimensional scalograms that capture transient fault characteristics with improved clarity. These scalograms offer a rich visual representation of frequency energy distributions, particularly useful in detecting subtle or overlapping faults [9]. However, interpreting these representations and extracting meaningful features still poses a challenge, especially in real-time applications. Recent advances in data-driven models, particularly convolutional neural networks (CNNs), have made it possible to automate feature extraction from CWT scalograms. These networks are capable of learning discriminative patterns directly from input images, eliminating the need for handcrafted features [10]. However, conventional CNNs often involve heavy architecture with millions of parameters, making them unsuitable for deployment in resource-constrained environments such as edge devices or embedded diagnostic systems. Furthermore, traditional CNNs do not explicitly account for the frequency-domain relevance of features, which is useful in the context of mechanical fault detection, where specific frequency bands carry diagnostic significance.

To address these challenges, this study proposes a lightweight and interpretable framework for centrifugal pump fault diagnosis using time-frequency scalograms. The core architecture integrates a depth-wise separable convolutional network with Squeeze-and-Excitation (SE) blocks, which are designed to reconfigure feature responses based on channel-wise importance. These attention mechanisms enhance the model's sensitivity to fault-relevant frequency bands, thereby improving diagnostic accuracy without increasing computational complexity. To ensure scalability, the model maintains a compact structure with a parameter count suitable for real-time implementation. The main contributions of this study are as follows.

1. A time-frequency representation pipeline using CWT and logarithmic scaling to enhance the separability of transient fault signatures in centrifugal pump vibration signals.

2. An LF-CNN architecture that integrates depth-wise separable convolutions and SE blocks to provide high classification performance with low parameter complexity.
3. An explainable diagnosis system that uses frequency attribution and Grad-CAM++ visualization to show the model's decision-making process.
4. Comprehensive validation on a real-world centrifugal pump dataset, achieving high diagnostic accuracy with visual interpretability.

The remainder of the paper is organized as follows: Section 2 describes the proposed methodology, Section 3 outlines the technical background, Section 4 presents the experimental setup, Section 5 presents the results and discussion, including classification metrics, confusion matrix, t-SNE visualization, and explainability analysis. Finally, Section 6 concludes the paper with a summary and future directions.

2 Proposed Methodology

This section outlines a proposed interpretable framework for centrifugal pump fault diagnosis using vibration signals, log CWT scalograms, an LF-CNN, and explainability with Grad-CAM. The method comprises three key stages: signal preprocessing, model architecture, training, and interpretability analysis as illustrated in Fig. 1.

Step 1: The process begins with the acquisition of raw vibration signals from centrifugal pump experiments under four operating conditions: Normal, Impeller Fault, Mechanical Seal Hole, and Mechanical Seal Scratch. To remove baseline noise, mean subtraction is applied. The denoised signals are then transformed into log-scaled CWT scalograms, which preserve useful time-frequency patterns of the non-stationary vibration data. These scalograms are resized and pixel-normalized to 128×128 to match the model input dimensions.

Step 2: The normalized scalograms are fed into a custom-designed lightweight CNN optimized for real-time industrial deployment. The model begins with depth-wise separable convolutions to reduce computational load while retaining representational power. Squeeze-and-Excitation blocks are integrated to apply channel-wise attention, highlighting the most informative frequency bands. Frequency-Guided Convolution Layers further enhance the model's focus on frequency-domain fault characteristics. A final fully connected layer, followed by a SoftMax classifier, outputs the predicted fault category. The model is trained end-to-end using categorical cross-entropy loss and the Adam optimizer. It achieves high classification performance with a parameter count of less than 1.2M, offering both efficiency and accuracy.

Step 3: To ensure interpretability, the model incorporates an explainability module based on Grad-CAM++. This technique generates class-discriminative heatmaps that highlight the regions of the input CWT scalograms contributing most to the model's predictions. By visualizing these time-frequency regions, the method provides valuable insight into how the model identifies fault-related patterns, such as localized bursts or shifts in frequency components. These visual explanations help verify that the model is focusing on relevant physical features associated with each fault type, thereby enhancing trust and reliability in real-world industrial applications.

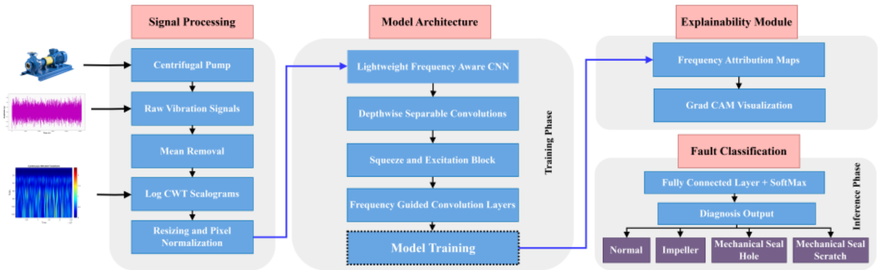


Fig. 1. Block diagram illustrating the proposed method.

3 Technical Background

3.1 Vibration Signal

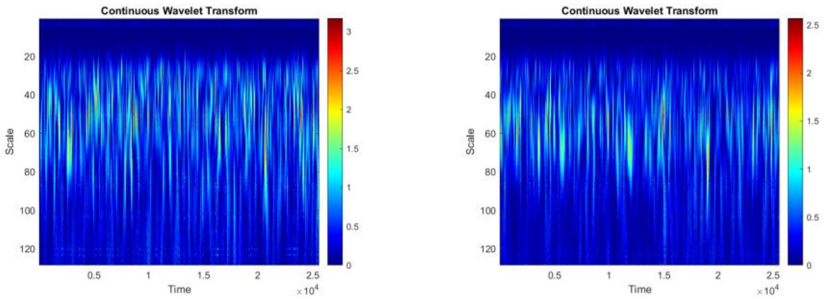
Vibration signals are a primary diagnostic tool in assessing the health of centrifugal pumps, as they directly reflect the mechanical behavior of internal components under different operating conditions. Mechanical faults generate distinct vibration patterns, often characterized by increased amplitude, irregular waveforms, or repetitive impact signatures. These signals are sensitive to variations in load, speed, and system imbalance, making them effective indicators of early-stage faults. By capturing and analyzing vibration responses from different sensor positions on the pump, fault-related anomalies can be distinguished from normal operational behavior. Thus, vibration-based monitoring serves as a reliable and non-invasive technique for identifying and tracking the progression of mechanical faults in industrial pump systems.

3.2 Time-Frequency Analysis

Fault diagnosis in CPs causes a significant challenge due to the non-stationary nature of the vibration signals generated during various fault conditions. These signals exhibit transient patterns and time-varying frequency content, particularly when faults such as impeller damage or mechanical seal defects occur. Traditional signal analysis techniques, while effective for stationary signals, fall short in capturing localized, short-duration fault signatures. To overcome this limitation, time-frequency analysis is essential, as it allows for the simultaneous observation of both temporal and spectral information within the vibration signal. In this work, CWT is employed to convert raw vibration signals into two-dimensional log-scaled scalograms, which provide a detailed visualization, as depicted in Fig. 2, of how frequency components evolve over time [11]. The CWT of a signal $x(t)$ is mathematically defined as in Eq. 1:

$$W_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt \tag{1}$$

where a is the scale parameter, b is the time-shift parameter, and $\psi^*(\cdot)$ denotes the complex conjugate of the mother wavelet function. By varying a and b, the CWT captures both high-frequency short-duration events and low-frequency long-duration components. The resulting time-frequency representation effectively preserves useful fault-related features in the vibration signals. This ensures accurate and interpretable identification of fault types in centrifugal pump systems.



(a) **(b)**

Fig. 2. Log CWT scalograms: **(a)** Mechanical Seal Scratch; **(b)** Mechanical Seal Hole.

3.3 Lightweight Frequency-Aware CNN

To achieve accurate yet computationally efficient fault classification in centrifugal pumps, a custom lightweight CNN is employed in this study. The model is designed with a low parameter count and optimized architecture. Instead of using traditional, heavy CNN architectures, the proposed model incorporates depth-wise separable convolutions, which significantly reduce the number of trainable parameters and computational complexity without compromising the model's ability to learn discriminative features [12]. To further enhance model performance, Squeeze-and-Excitation blocks are integrated into the architecture. These attention modules adaptively refine channel-wise feature responses, allowing the network to emphasize more informative frequency components within the CWT scalograms. This is particularly effective in fault diagnosis scenarios, where certain frequency bands are more relevant for identifying specific fault types. The SE block recalibrates the feature map channels by learning attention weights through global context embedding and gating as shown in Fig. 3. Given an input feature map $U \in \mathbb{R}^{H\times W\times C}$ where H, W, and C denote height, width, and number of channels, the recalibration is computed as in Eq. 2.

$$\mathrm{F}_{\mathrm{SE}}(U_C) = \sigma\big(W_2 \cdot \sigma(W_1 \cdot z)\big) \cdot U_C \tag{2}$$

CNN processes this 2D input through a series of lightweight convolutional blocks, followed by a global average pooling layer and a fully connected softmax layer to output the predicted classes.

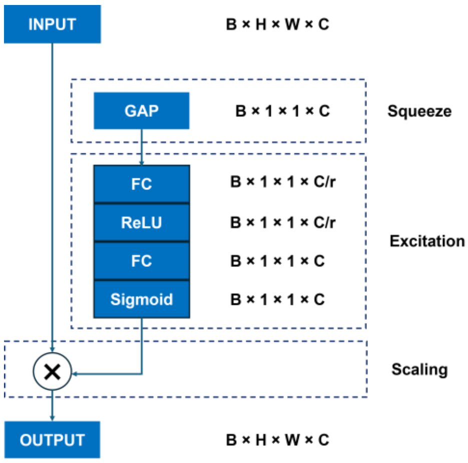


Fig. 3. Diagram of SE block architecture used in the proposed frequency-aware CNN.

3.4 Interpretability Using Grad-CAM++

In fault-critical industrial environments, it is not sufficient for a model to achieve high accuracy alone; its decision-making process must also be interpretable. This is especially true in centrifugal pump health monitoring, where predictive decisions directly influence maintenance actions, cost, and operational safety. Therefore, explainability plays an important role in verifying and validating the predictions of machine learning models used in such scenarios. While the lightweight frequency-aware CNN proposed in this study effectively classifies AE-based fault patterns from time-frequency scalograms, its deep structure introduces challenges typical of black-box models, namely, the lack of transparency in how predictions are made. Engineers and operators often require insights into why a particular fault is detected to validate its relevance and reliability in real-world settings. To address this, this method integrates Grad-CAM++ as a post-hoc visualization method. Grad-CAM++ computes the gradients of the output class with respect to the final convolutional layers in the network and generates heatmaps of activation [13]. When applied to the CWT scalograms, these heatmaps reveal the specific time-frequency regions that the model relies on to make its classification decisions. This allows domain experts to visually inspect whether the model is focusing on meaningful features, such as frequency spikes or localized transients commonly associated with faults like impeller erosion or seal damage. The use of Grad-CAM++ enhances trust in the proposed model by enabling intuitive and human-interpretable explanations. It not only helps ensure that the model is not attending to irrelevant artifacts or noise but also provides an essential tool for debugging, validation, and industrial adoption of deep learning-based fault diagnosis systems.

4 Experimental Setup

The experimental study was conducted using a PMT-4008 CP, a widely adopted industrial pump model. The pump was driven by a 5.5 kW electric motor and integrated into a controlled environment comprising a dedicated control panel with ON/OFF functionality, speed and flow rate controllers, a temperature controller, water supply regulation, pressure gauges, and display interfaces. The setup also included transparent steel pipelines, a main tank, and a buffer tank to facilitate continuous water recirculation in a closed-loop configuration as can be seen in Fig. 4. After establishing the mechanical and electrical setup, the pump was operated under both normal and fault-induced conditions to simulate realistic industrial environments. To capture vibration signals, four piezoelectric accelerometers were strategically mounted at different points on the pump structure. Two sensors were affixed to the main pump casing, while the remaining two were installed near the impeller and the mechanical seal assembly. Each sensor was assigned to a dedicated acquisition channel to ensure independent and interference-free signal collection. The analog vibration signals were digitized using a National Instruments 9234 data acquisition system. Data was recorded continuously for 300 seconds at a high sampling rate of 25.6 kHz, ensuring the resolution required for detailed time-frequency analysis. A total of 1247 signal samples were collected, each comprising 25,600 data points, representing various operating conditions of the pump. These included normal operation, mechanical seal hole fault, mechanical seal scratch fault, and impeller fault conditions.

Mechanical seal faults were simulated by intentionally damaging the rotating component of the seal while keeping the stationary component intact. For the hole fault, a defect with a diameter and depth of 2.8 mm was introduced into one of the 38 mm diameter rotating seals. This modification aimed to mimic erosion or localized wear caused by particulate contamination or pressure instability. In the case of the scratch fault, a surface abrasion measuring 2.5 mm in diameter, 10 mm in length, and 2.8 mm in depth was manually applied to the rotating face of the seal. Both of these fault types were selected based on real-world failure modes often encountered in mechanical seals due to over-compression, loss of lubrication, or the intrusion of abrasive materials. For impeller fault simulation, crevice corrosion was emulated by artificially removing material from the impeller surface. Three cast iron impellers, each with a diameter of 161 mm, were used during the experimentation. Two were kept in pristine condition, while the third was modified by creating a defect measuring 2.5 mm in diameter, 18 mm in length, and 2.8 mm in depth. This emulated damage typically occurs over time due to chemical wear and material fatigue under operational stress. The vibration signals obtained under these fault conditions exhibited transient anomalies that were distinguishable from those recorded during normal pump operation. Each of the induced fault conditions was validated by measuring the signal-to-noise ratio (SNR) relative to a healthy baseline. The recorded SNRs were -69.10 dB for the mechanical seal hole, -62.07 dB for the mechanical seal scratch, and -63.78 dB for the impeller fault. These measurements confirmed the presence of subtle yet significant variations in the acquired signals, which served as input for further time-frequency analysis and deep learning-based classification. This experimental setup provided a comprehensive and high-quality dataset for the proposed CP fault diagnosis.

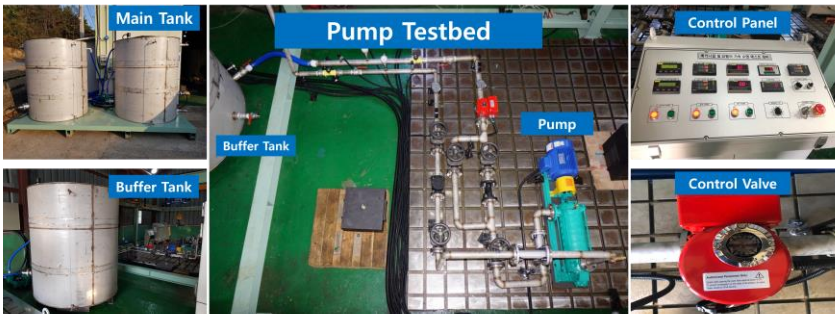


Fig. 4. Laboratory setup for CP vibration data collection.

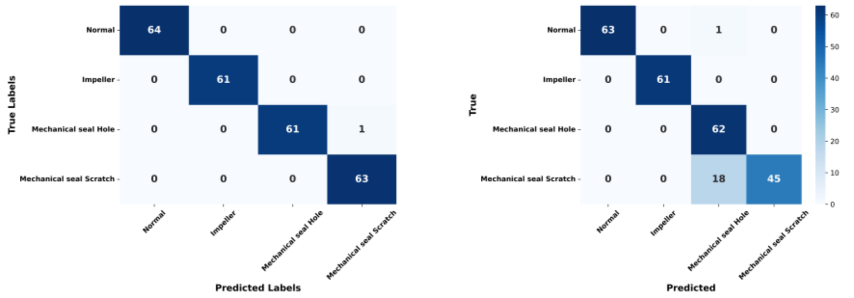
5 Performance Evaluation and Comparison

The effectiveness of the proposed lightweight fault diagnosis framework for CPs was rigorously evaluated using vibration signals converted into CWT scalograms, after appropriate preprocessing steps including mean removal and pixel normalization. The dataset consisted of 1247 scalogram samples, each belonging to one of four classes: Normal, Impeller Fault, Mechanical Seal Hole, and Mechanical Seal Scratch. The classification model was designed using a custom lightweight CNN embedded with SE blocks for frequency attention and trained end-to-end on scalograms. This section discusses the performance of the model in terms of accuracy, precision, recall, F1-score, and interpretability.

A comparative analysis of classification performance, as in Table 1, demonstrates that the proposed model achieves superior accuracy, precision, recall, and F1-score when compared to traditional CNN [14], highlighting its effectiveness in fault diagnosis tasks. To visually validate the model's classification behavior, a confusion matrix is plotted in Fig. 5. All predicted samples fell on the diagonal, with zero misclassifications across the four classes. This further affirms that the model is highly capable of distinguishing even subtle variations in fault-related vibration patterns.

Table 1. Comparison of classification performance.

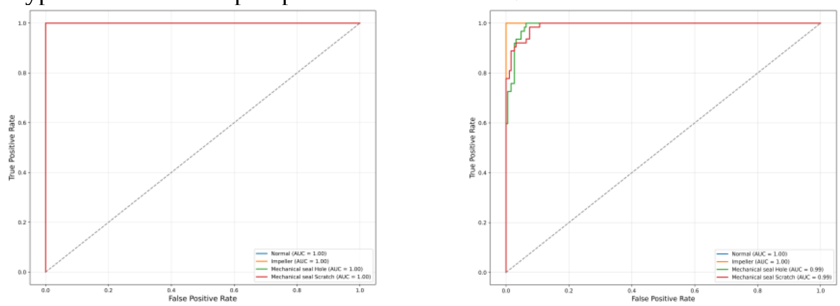
Models	Accuracy	Precision	Recall	F-1 Score
Proposed Model	99.60	99	99	99
Traditional CNN	92	94	92	93



(a) **(b)**

Fig 5. Confusion matrix results: **(a)** Proposed method; **(b)** Traditional CNN.

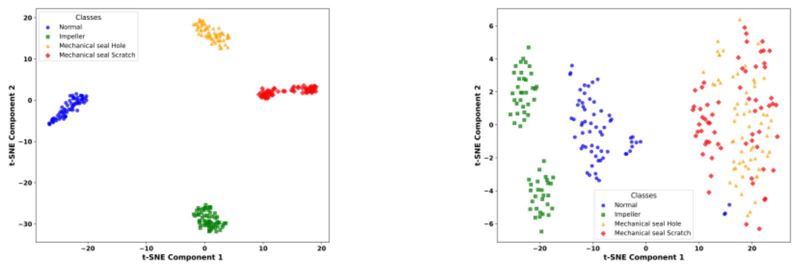
In addition to classification accuracy, the Receiver Operating Characteristic (ROC) curves were generated for each class as in Fig. 6. Each ROC curve demonstrates a perfect AUC value of 1.00, indicating that the model can reliably differentiate between the fault types with no overlap in prediction boundaries.



(a) **(b)**

Fig 6. ROC curve: **(a)** Proposed method; **(b)** Traditional CNN.

To gain deeper insight into the latent feature space learned by the model, t-SNE plots are displayed as in Fig. 7. The visualizations show that the feature representations form well-separated and dense clusters, with minimal intra-class variance and maximum inter-class separation. This not only reflects the model's generalization ability but also confirms that the frequency-guided layers are successfully capturing unique class-specific patterns from the vibration-based scalograms.



(a) **(b)**

Fig 7. t-SNE plots: **(a)** Proposed method; **(b)** Traditional CNN.

To improve the transparency of the model's internal decision-making, Grad-CAM++ was applied to the CWT scalograms. The resulting visualizations in Fig. 8 reveal the most influential time-frequency regions used by the model for each fault class. For instance, the mechanical seal scratch class highlighted high-frequency transient areas, while impeller faults activated slightly different patterns with distinct modulation zones. This interpretability ensures that the model focuses on physically meaningful signal components rather than background noise or irrelevant features.

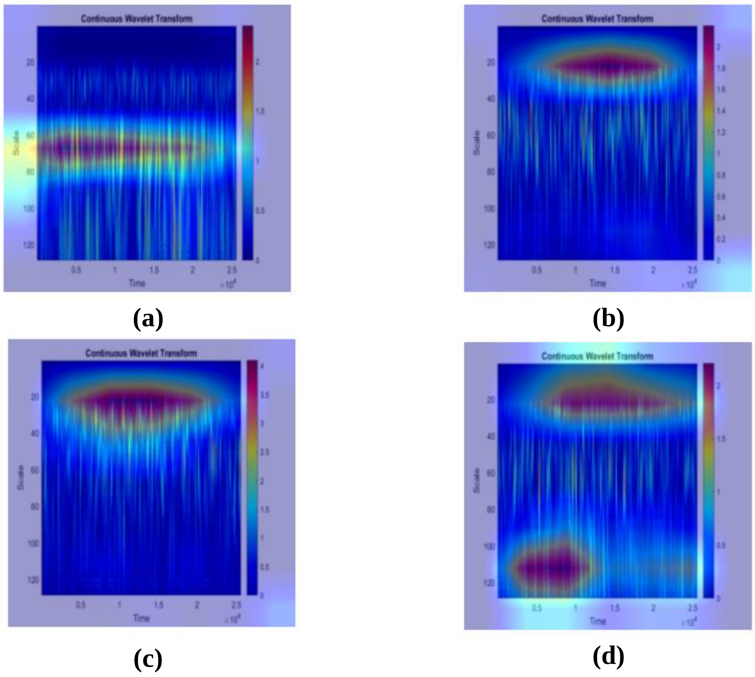


Fig 8. Grad-CAM++ visualization over CWT scalograms: **(a)** Impeller; **(b)** Mechanical Seal Hole; **(c)** Mechanical Seal Scratch; and **(d)** Normal.

The proposed method demonstrates that combining log-scaled CWT scalograms with a lightweight frequency-aware CNN can lead to highly accurate and interpretable fault diagnosis in centrifugal pumps. Unlike traditional methods that rely heavily on handcrafted features, this approach automates both feature extraction and classification with minimal computational overhead. The use of SE blocks and frequency-guided layers ensures that the model remains sensitive to subtle variations in vibration signals, while the Grad-CAM++ visualization module enhances transparency and trust. The complete alignment between high performance and interpretability marks a significant advancement in centrifugal pump diagnostics. Furthermore, the model's ability to generalize well across all classes makes it a strong candidate for real-time monitoring systems in industrial settings.

6 Conclusion

This study proposed a lightweight and interpretable framework for fault diagnosis in centrifugal pumps using vibration signals and time-frequency analysis. Raw signals were transformed into log CWT scalograms, capturing essential fault-related patterns. A compact CNN model with depth-wise separable convolutions and Squeeze-and-Excitation blocks was designed to extract frequency-aware features effectively. The model achieved 99.60% classification accuracy across four conditions: Normal, Impeller Fault, Mechanical Seal Hole, and Mechanical Seal Scratch. To enhance trust in the model's decisions, explainability techniques were integrated using Frequency Attribution Scores and Grad-CAM++ visualizations, which highlighted the important frequency regions influencing predictions. These insights are valuable for maintenance teams and support transparent decision-making. The proposed method is efficient, accurate, and suitable for real-time industrial monitoring. Future work may include expanding the approach to other machinery types and integrating multiple sensors signals to improve robustness and deployment on edge devices.

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