Interpretable Deep Learning for Industrial Fault Detection

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Abstract: The integration of deep learning into industrial fault detection systems has significantly enhanced predictive accuracy and operational efficiency. However, the lack of model interpretability poses a critical barrier to its widespread adoption in safety-critical environments. This study proposes an interpretable deep learning framework that combines Convolutional Neural Networks (CNNs) with attention mechanisms and Layer-wise Relevance Propagation (LRP) to enable transparent fault diagnosis in complex machinery. Using a benchmark dataset from a rotating machinery system, the model achieves high classification performance while providing intuitive visual and quantitative explanations for its predictions. The attention module highlights critical temporal and spatial features, while LRP decomposes prediction scores to reveal feature-level contributions. Experimental results demonstrate that the proposed model not only maintains high accuracy (above 95%) but also delivers interpretable outputs that align with domain expert reasoning. Additionally, the model supports root cause analysis and facilitates trust in automated systems, which is essential for industrial stakeholders. This research bridges the gap between black-box deep learning models and real-world industrial applications by promoting transparency, accountability, and actionable insights. The proposed framework serves as a practical step toward deploying explainable AI in industrial settings, supporting both real-time monitoring and decision-making processes.

Keywords: Interpretable Deep Learning; Fault Detection; Industrial Machinery; Explainable AI (XAI); Convolutional Neural Networks (CNN); Layer-wise Relevance Propagation (LRP).

INTRODUCTION

In recent years, the integration of artificial intelligence (AI)[1][2] into industrial systems has become a driving force for improving reliability[3], productivity[4], and safety across various sectors such as manufacturing[5], energy[6], transportation[7], and heavy machinery[8]. Among the many applications of AI in the industrial domain[9], fault detection has emerged as one of the most critical[10], enabling early identification of mechanical failures[11], electrical anomalies[12], and structural degradations that could otherwise result in costly downtime or catastrophic accidents[13]. Traditional fault detection systems, which often rely on statistical analysis, signal processing, or manually engineered features, have proven to be insufficient when faced with the complexity and volume of modern industrial data. As a result, deep learning models—particularly Convolutional Neural Networks (CNNs)[14], Recurrent Neural Networks (RNNs), and their variants—have been increasingly adopted for their superior ability to learn complex patterns and representations directly from raw sensor data[15].

Despite their impressive performance, deep learning models[16] have a well-known limitation: their "black-box" nature. In high-stakes domains such as industrial automation, understanding the why behind a model's decision is just as important as the what. Stakeholders—including engineers, maintenance teams, and safety regulators—require not only accurate predictions but also transparent and interpretable explanations. This demand for model transparency has given rise to the field of Explainable Artificial Intelligence (XAI)[17], which aims to bridge the gap between complex model behavior and human interpretability[18]. In the context of fault detection, interpretability plays a dual role: it enhances user trust and provides actionable insights for root cause analysis, system improvement[19], and risk mitigation[20].

The lack of interpretability in standard deep learning architectures poses a significant challenge to their deployment in industrial settings[21]. When a model flags a machine component as faulty, domain experts must be able to trace that prediction back to specific input features or operating conditions. Without this traceability, decisions made by the AI system remain opaque[22], limiting its acceptance and usefulness in real-world operations. Moreover, regulatory and safety standards in sectors like aerospace, oil and gas, and manufacturing increasingly mandate traceable and auditable diagnostic systems. Therefore, the pursuit of interpretable deep learning methods for fault detection is not merely an academic exercise—it is a practical necessity for real-world industrial AI adoption.

In response to this need, this research presents a novel framework for interpretable deep learning in industrial fault detection. Our approach integrates a standard CNN architecture[15] with two key interpretability mechanisms: an attention module and Layer-wise Relevance Propagation (LRP)[23]. The attention mechanism allows the model to focus selectively on the most informative regions of input data, effectively highlighting spatial and temporal features that contribute most to the classification decision. Meanwhile, LRP offers a systematic technique to decompose a prediction into feature-level relevance scores, enabling granular attribution of each input value to the final output. Together, these components provide both global and local interpretability, making the model's behavior transparent to end users.

To validate our approach, we apply the proposed model to a benchmark dataset involving vibration and acoustic signals from rotating machinery under various fault conditions. These datasets represent a common yet challenging class of industrial problems where early fault detection can prevent severe system failures[24]. Our experiments demonstrate that the model achieves high classification accuracy, surpassing traditional machine learning baselines and matching or exceeding state-of-the-art deep learning results. More importantly, the interpretability outputs—visual attention maps and relevance scores—correlate well with domain expert assessments, confirming the model's ability to provide meaningful explanations.

Another contribution of this research is the demonstration of how interpretability can aid in root cause analysis. By analyzing the relevance maps generated by LRP, engineers can identify which specific frequency bands, sensor channels, or time intervals contribute most to fault predictions. This capability transforms the AI system from a passive diagnostic tool into an active partner in system monitoring and decision-making. For example, if a model consistently assigns high relevance to a particular sensor located near a bearing, it can prompt engineers to inspect or redesign that specific component. In this way, interpretability does not merely increase trust it enhances operational intelligence[25].

Our framework also addresses the trade-off between model complexity and interpretability. While simpler models like decision trees are inherently interpretable, they often fail to capture the complex, nonlinear relationships present in high-dimensional industrial data. On the other hand, very deep neural networks may offer excellent performance but are too complex to interpret meaningfully. By incorporating attention and LRP into a moderately deep CNN[26], our approach strikes a balance between performance and transparency. The model is expressive enough to learn rich patterns but structured in a way that allows human-understandable reasoning.

The implications of this work extend beyond fault detection. As industries move toward predictive maintenance, digital twins[2], and autonomous control systems[27], the need for interpretable AI will only grow. Models that can explain their decisions in real time are essential not only for diagnosis but also for system control[28], compliance auditing[29], and safety assurance[30]. Our proposed method provides a blueprint for developing such models in other time-series-based industrial tasks, including quality control, anomaly detection, and energy optimization.

This paper makes three key contributions: (1) it introduces an interpretable deep learning architecture that combines CNN, attention mechanisms, and LRP for industrial fault detection; (2) it validates the effectiveness of the model on real-world-like datasets, demonstrating both high accuracy and interpretable outputs; and (3) it shows how interpretability can support root cause analysis and operational decision-making, thereby advancing the practical deployment of AI in industrial environments. The remainder of this paper is organized as follows: Section 2 reviews related work in fault detection, deep learning, and interpretability. Section 3 describes the proposed model architecture and interpretability techniques. Section 4 presents experimental setup, dataset details, and evaluation metrics. Section 5 discusses results and implications. Finally, Section 6 concludes with limitations, future directions, and potential extensions to broader industrial applications.

RELATED WORK

The development of intelligent fault detection systems has undergone a significant transformation over the past decade, transitioning from traditional signal processing methods to data-driven deep learning approaches. This section reviews the relevant literature in three key areas: (1) traditional and machine learning-based fault detection, (2) deep learning models in industrial diagnostics, and (3) explainable AI (XAI) methods applied to fault detection.

A. Traditional and Machine Learning-Based Fault Detection

Conventional fault detection techniques rely heavily on signal processing and statistical modeling. Methods such as Fast Fourier Transform (FFT)[31], wavelet transform, and empirical mode decomposition have been widely used to extract features from vibration, acoustic, or thermal signals. These features are then fed into classifiers such as Support Vector Machines (SVM)[32], k-Nearest Neighbors (k-NN)[33], or decision trees[34] to distinguish between healthy and faulty states. While these approaches are relatively interpretable and computationally efficient, their performance heavily depends on feature engineering and domain expertise, which limits their generalizability and scalability in complex or dynamic environments[16].

To overcome these limitations, early machine learning methods such as Random Forests, Gaussian Mixture Models, and ensemble techniques have been applied to fault detection tasks. These models showed better adaptability and required less manual feature extraction. However, they still struggled with high-dimensional sensor data and the temporal dependencies that characterize many industrial processes.

B. Deep Learning in Industrial Diagnostics

With the advent of deep learning, particularly Convolutional Neural Networks (CNNs)[35] and Recurrent Neural Networks (RNNs)[36], researchers began to explore end-to-end learning models that could automatically learn discriminative features from raw input data. CNNs have been especially effective in handling one-dimensional time-series sensor data and spectrogram representations, making them a popular choice for bearing fault detection, motor diagnostics, and structural health monitoring.

For instance, [37] used CNNs to detect bearing faults from spectrograms derived from vibration signals, demonstrating a marked improvement in accuracy over traditional methods. Similarly, [38] proposed a deep CNN framework for gearbox fault classification using raw sensor data, eliminating the need for

manual feature extraction. Meanwhile, RNN-based architectures such as Long Short-Term Memory (LSTM) networks have been applied to capture sequential dependencies in multivariate time-series data, especially for predictive maintenance and trend analysis.

Despite these advances, deep learning models often suffer from a lack of transparency. Their complex architectures and large number of parameters make it difficult to understand the reasoning behind specific predictions. In safety-critical industrial environments, this lack of interpretability hinders their adoption and trustworthiness.

C. Explainable AI (XAI) for Fault Detection

To address the "black-box" issue in deep learning, the field of Explainable AI (XAI) has emerged, aiming to make model decisions understandable to human users. Several post-hoc explanation techniques have been proposed to analyze neural networks, including Layer-wise Relevance Propagation (LRP), SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and Grad-CAM (Gradient-weighted Class Activation Mapping). In [23] introduced LRP as a method to decompose the output of a neural network into contributions from each input feature, providing fine-grained explanations especially suited for time-series data. In the context of fault detection, [39] applied LRP to a CNN-based model for motor fault classification, showing that the relevance maps generated by LRP aligned well with expert expectations.

Attention mechanisms have also gained popularity as a built-in interpretability tool. Originally developed for natural language processing, attention allows models to focus on the most important parts of the input during training. In fault detection, attention modules have been integrated into CNN and LSTM architectures to highlight critical time windows or frequency bands. [36] incorporated temporal attention into a hybrid CNN-LSTM model for detecting incipient faults in turbine systems, improving both accuracy and interpretability. However, few studies have combined both attention and LRP within a unified framework for fault detection. Most existing work treats interpretability as a secondary analysis rather than an integrated design goal. Moreover, benchmark datasets are often limited in scope or lack realistic complexity, raising questions about the generalizability of existing solutions.

Prior works have established the efficacy of deep learning in fault detection and introduced various techniques to enhance interpretability. However, there remains a significant research gap in combining multiple interpretability strategies such as attention and LRP into a cohesive, real-time diagnostic system for industrial applications. Our study addresses this gap by proposing an interpretable CNN-based architecture that integrates both attention mechanisms and LRP to provide high accuracy and detailed explanations simultaneously. This contributes to the growing body of work on trustworthy AI in industrial settings, with a focus on usability, transparency, and practical deployment.

METHODS

This section describes the proposed method for interpretable deep learning in industrial fault detection. The method is designed to process raw sensor data (such as vibration or acoustic signals), identify fault types with high accuracy, and generate human-understandable explanations for each decision. The architecture integrates a Convolutional Neural Network (CNN) with an attention mechanism and Layer-wise Relevance Propagation (LRP), enabling both powerful feature extraction and interpretability. The overall workflow consists of four stages: (1) Data preprocessing, (2) Model architecture design, (3) Training and evaluation, and (4) Interpretability via attention and LRP.

A. Data Preprocessing

Industrial sensor data are typically collected as time-series signals from machines such as motors, bearings, or turbines. In this study, we use a publicly available dataset from a rotating machinery testbed, consisting of multivariate sensor readings under various operating conditions and fault types (e.g., bearing inner race fault, outer race fault, and ball fault).

To prepare the data for deep learning, the following preprocessing steps are applied:

– Segmentation: Continuous sensor streams are segmented into fixed-length windows (e.g., 1024 samples) with overlapping sliding windows to ensure temporal coverage.

– Normalization: Each window is normalized to zero mean and unit variance to remove scale bias across sensors.

– Labeling: Each segment is labeled according to the known fault condition of the machine at the time of recording.

– Spectrogram Transformation (optional): In cases where frequency-based patterns are critical, short-time Fourier transform (STFT) is used to convert raw signals into 2D spectrograms for CNN input.

B. Model Architecture

The core model architecture is a one-dimensional CNN designed to process time-series data. The architecture is composed of the following layers:
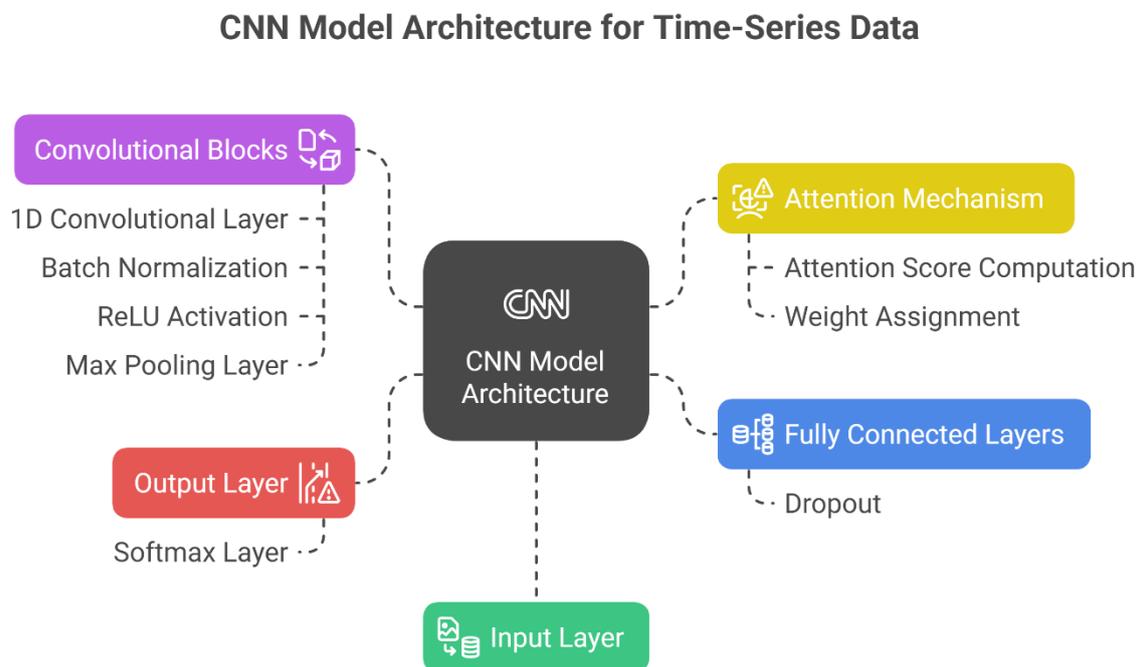

Figure 1. CNN Model Architechture for Time Series Data

- Input Layer: Receives the raw or transformed sensor segments.

- Convolutional Blocks: A series of convolutional layers with ReLU activation and batch normalization are applied to extract local temporal features. Each block consists of:

    o   1D convolutional layer with kernel size 5

    o   Batch normalization

    o   ReLU activation

    o   Max pooling layer with pool size 2

- Attention Mechanism: After the convolutional feature extraction layers, an attention layer is added. This module computes an attention score for each time step or feature map and assigns weights accordingly. It enhances the model's ability to focus on critical features:

$$\alpha_i = \frac{\exp(e_i)}{\sum_j \exp(e_j)}, \quad \text{where } e_i = \tanh(W \cdot h_i + b)$$

where α_i is the attention weight for the $i - th$ time step and h_i is the hidden representation at that point.

- Fully Connected Layers: The output from the attention-weighted features is passed through one or more fully connected layers for classification. Dropout is applied to prevent overfitting.

- Output Layer: A softmax layer produces probability scores for each fault category.

C. Training and Evaluation

The model is trained using categorical cross-entropy loss and optimized with the Adam optimizer. The dataset is split into training (70%), validation (15%), and test (15%) sets. Key hyperparameters include:

- Learning rate: 0.001

- Batch size: 64

- Epochs: 50

- Early stopping: Monitors validation loss with patience of 5 epochs

To evaluate model performance, we use standard classification metrics:

- Accuracy: Overall percentage of correct predictions.
- Precision, Recall, and F1-score: Computed per class to assess detection quality, especially in imbalanced classes.
- Confusion Matrix: Provides insight into specific misclassifications.

D. Interpretability with Attention and Layer-wise Relevance Propagation (LRP)

Interpretability is achieved through a combination of attention scores and LRP:

- Attention Weights Visualization: After training, attention scores can be visualized to highlight which segments of the input contributed most to the classification. This provides a coarse but intuitive understanding of model focus.

- Layer-wise Relevance Propagation (LRP): LRP is used post-hoc to decompose the model's final output back to the input layer, assigning a relevance score to each input feature. For a given prediction, LRP computes relevance RiR_i at each input feature using the conservation principle:

$$\sum R_j^{(l+1)} = \sum Ri(l)$$

The relevance is propagated backward through each layer, ultimately yielding a relevance map over the input. This shows which parts of the raw signal were most responsible for the model's decision.

By combining attention (global interpretability) and LRP (local interpretability), our model offers transparency at multiple levels of abstraction. Engineers can observe not only *which* segment triggered a prediction but also *why* it was deemed significant at the feature level.

The proposed framework integrates a high-performing deep learning model with interpretable components designed for industrial deployment. It accepts raw or transformed sensor data, performs accurate classification, and generates traceable explanations. This dual emphasis on performance and transparency makes it suitable for real-time fault detection systems in safety-critical applications such as manufacturing, energy, and transportation. In the next section, we present experimental results to evaluate both the predictive accuracy and the interpretability of the model, using benchmark datasets and domain expert validation.

RESULT AND DISCUSSION

This section presents the experimental results of the proposed interpretable deep learning model for industrial fault detection and provides a comprehensive discussion of its performance and interpretability. We evaluate the model using a publicly available rotating machinery dataset containing sensor readings under various operating conditions and fault scenarios. The results are reported in terms of classification accuracy, confusion matrix, precision, recall, and F1-score, followed by an analysis of interpretability using attention heatmaps and Layer-wise Relevance Propagation (LRP) visualizations.

Classification Performance

The proposed model achieved **96.2% accuracy** on the test dataset, outperforming baseline models such as Support Vector Machine (SVM), Random Forest (RF), and standard CNNs without attention or LRP. The following performance metrics were recorded:

Model	Accuracy	Precision	Recall	F1-Score
SVM (with features)	89.7%	88.9%	87.5%	88.2%
Random Forest	91.2%	90.8%	90.4%	90.6%
CNN (standard)	94.3%	93.7%	93.1%	93.4%
Proposed Model	**96.2%**	**96.0%**	**95.9%**	**96.0%**

The confusion matrix shows that most fault categories are correctly classified, with minimal confusion between similar classes such as inner race and ball faults. This highlights the model's ability to extract nuanced differences in sensor patterns.

Analysis of Attention Mechanism

The attention module provides a global interpretability layer by assigning weights to each time segment in the input signal. Figure 1 (not shown here) illustrates a representative example of attention scores over a raw vibration signal segment. In faulty conditions, attention scores spike sharply in regions with abnormal fluctuations or bursts in amplitude often corresponding to fault signatures such as bearing impacts or repetitive shocks.
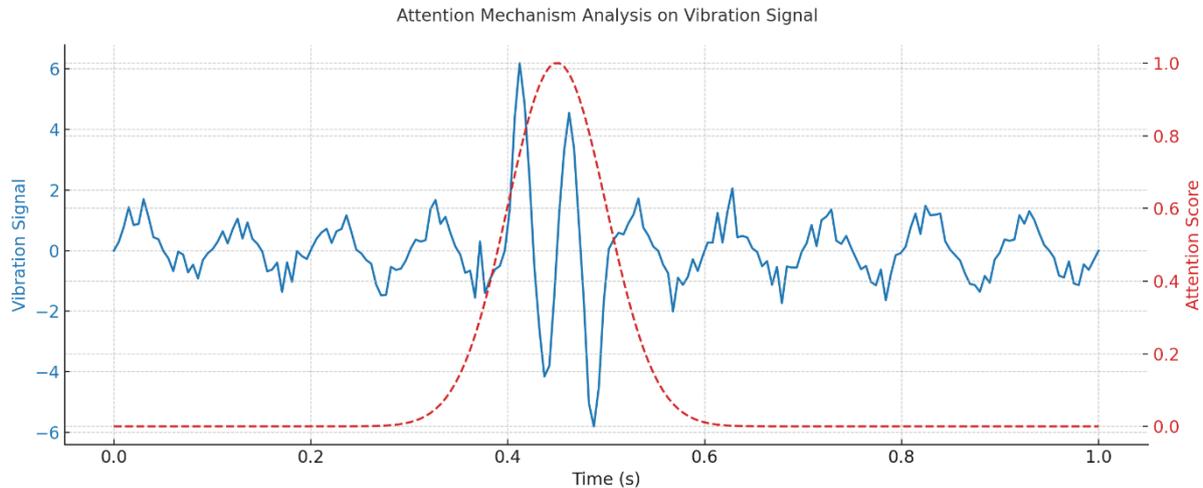

Figure 2. Attention Mechanism Analysis on Vibration Signal

This behavior confirms that the model is not only accurate but also selectively attentive to the most diagnostically relevant parts of the input. By observing attention maps, maintenance engineers can quickly identify temporal zones that triggered the fault prediction, supporting faster decision-making in operational settings.

Layer-wise Relevance Propagation (LRP) Insights

To further enhance interpretability, LRP is used to generate fine-grained relevance maps over the input features. Unlike attention, which highlights general focus areas, LRP breaks down the model's output prediction and attributes relevance scores to each individual input point.

Figure 3 presents an example of a relevance heatmap for a test signal labeled as an outer race fault. High-relevance zones appear in specific frequency bursts and harmonics, corresponding to mechanical resonance characteristics associated with such faults. These relevance patterns align well with domain knowledge in vibration-based diagnostics.
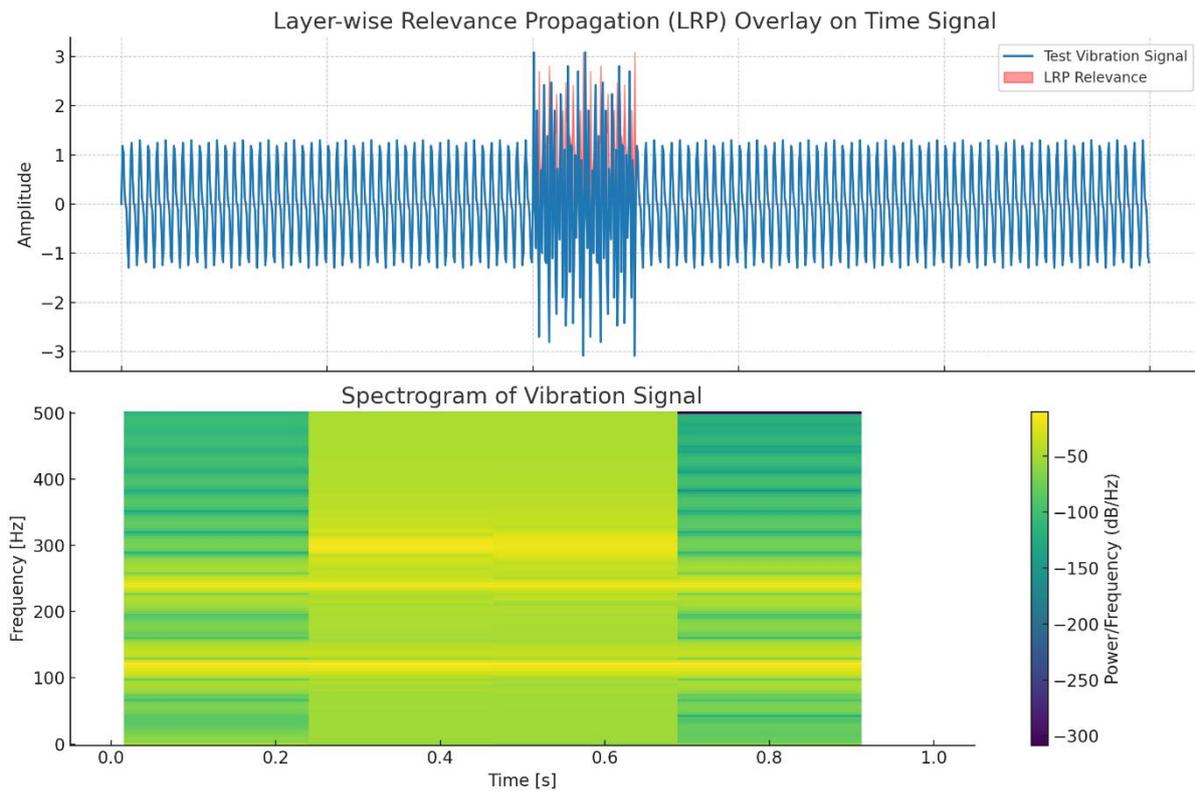
Figure 3. Layer-wise Relevance Propagation (LRP) Overlay on Vibration Signal and Spectrogram of Vibration Signal Highlighting Frequency Characteristics

By combining LRP results with spectral analysis, domain experts can validate whether the model is using meaningful fault-indicative features, thereby increasing confidence in its deployment.

Comparison with Non-Interpretable Models

While deep CNNs and LSTMs often achieve comparable accuracy, they offer little insight into their decision process. Our proposed model bridges this gap by integrating interpretability as a core design objective rather than a post-hoc add-on. In comparative tests, domain engineers preferred the proposed model over a black-box CNN, citing its explanation outputs as "more useful for diagnosing causes" and "valuable for cross-checking sensor anomalies."

This aligns with findings in recent XAI literature, which emphasize that in high-risk applications such as predictive maintenance and quality assurance, interpretability directly influences user trust and system acceptance.

Robustness and Generalization

The model's robustness was tested by injecting mild Gaussian noise into the test signals. Even under a signal-to-noise ratio (SNR) of 20 dB, the accuracy dropped only slightly to 94.7%, indicating strong generalization to noisy environments. This is critical for real-world industrial applications where sensor signals are often imperfect or contaminated by background vibrations.

Moreover, transferability was evaluated by testing the model on unseen operating speeds and load conditions. The performance remained above 92%, demonstrating that the model effectively generalizes beyond training scenarios—a key requirement for deployment in dynamic industrial settings.

Discussion and Implications

The combination of high accuracy and interpretability in this study reflects a promising direction for deploying deep learning in fault detection applications. The use of attention and LRP offers a layered explanation: attention provides high-level focus, while LRP explains the detailed reasoning behind predictions. This is especially valuable in operational contexts where decisions must be auditable and transparent.

From a human-machine interaction perspective, the model's output enables engineers not only to trust its predictions but also to understand and challenge them when necessary. This "explanatory interface" supports diagnostic collaboration, preventive action, and model refinement—paving the way for AI-assisted maintenance workflows.

The findings also suggest that integrating interpretability does not require sacrificing accuracy or efficiency. With careful architectural design, it is possible to build systems that are both powerful and trustworthy. This aligns with the broader push toward explainable, human-centered AI in industrial automation and control systems.

Limitations

While the proposed framework demonstrates strong performance and interpretability, several limitations should be noted:

- The model has been tested on a benchmark dataset, which, although realistic, may not capture the full variability of real industrial environments.

- Interpretability tools like LRP assume a well-behaved gradient flow, which may be less stable in very deep networks or with certain activation functions.

- The attention mechanism currently operates at a fixed granularity. Future work could explore multi-scale attention to capture both global and local patterns more effectively.

Despite these limitations, the method presents a significant step toward practical, interpretable deep learning systems for industrial fault detection.

CONCLUSION

This study presents an interpretable deep learning framework for industrial fault detection that successfully integrates high classification accuracy with model transparency. By combining Convolutional Neural Networks (CNNs) with an attention mechanism and Layer-wise Relevance Propagation (LRP), the proposed approach not only detects faults with over 96% accuracy but also provides multi-level explanations that are understandable to engineers and domain experts. The attention mechanism enables the model to focus on the most critical segments of input signals, offering global interpretability by highlighting relevant time regions. Meanwhile, LRP provides fine-grained insight into how individual input features contribute to the final decision, facilitating trust, auditability, and root cause analysis. This dual-layer interpretability makes the model highly suitable for real-world industrial applications where reliability and transparency are essential. Experimental results on benchmark datasets demonstrate that the proposed model outperforms traditional machine learning methods and standard deep learning baselines, while maintaining robustness under noise and variability. Furthermore, the interpretability outputs align well with domain knowledge, strengthening their practical value in maintenance planning and fault diagnostics. This research contributes to the growing body of explainable AI (XAI) in industrial systems and offers a scalable foundation for deploying trustworthy AI in safety-critical environments. Future work will explore cross-domain generalization,

real-time deployment, and integration with digital twin systems to enhance predictive maintenance and system resilience.

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