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Original Article

CLAM-Net: A Fault Diagnosis Model for Mechanical Systems under Complex Operating Conditions

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Abstract:
With the rapid development of intelligent manufacturing and industrial automation, the operating environments of mechanical systems have become increasingly complex, imposing higher demands on the accuracy and generalization capability of fault diagnosis. Existing fault diagnosis methods typically focus on local features or single-sequence modeling, lacking mechanisms to simultaneously extract multi-scale spatial features and capture long-term temporal dependencies, which limits their ability to effectively represent complex dynamic fault characteristics in mechanical vibration signals. To address this issue, this paper proposes a novel architecture—CLAM-Net, which integrates convolutional neural networks (CNN), long short-term memory networks (LSTM), attention mechanisms, and meta-learning. The model leverages CNNs to extract multi-scale time–frequency features, employs LSTMs to capture temporal dependencies, and incorporates an attention mechanism to adaptively focus on critical fault-related features. Furthermore, a meta-learning framework is adopted to enable rapid adaptation and knowledge transfer across varying operating conditions and equipment states. Extensive experiments on real-world mechanical datasets demonstrate that CLAM-Net achieves an accuracy of 98.5%, a recall of 98.2%, and an F1 score of 98.3%, outperforming the state-of-the-art GRU–Attention model by approximately 3.5%, 4.0%, and 3.7%, respectively. These results confirm that CLAM-Net exhibits superior diagnostic performance and robustness under complex operating conditions, providing an efficient and scalable solution for intelligent mechanical fault diagnosis.

Keywords: Mechanical fault diagnosis; Convolutional neural network;Long short-term memory; Attention mechanism

1. Introduction

In today's highly industrialized era, mechanical systems serve as the backbone of modern production across diverse sectors. From precision manufacturing equipment in the industrial domain to large-scale power machinery in the energy sector and automated transport systems in logistics, mechanical systems have become deeply integrated into nearly every aspect of industrial operations[1, 2] . However, due to factors such as long-term component wear, complex and varying operating conditions, and external environmental disturbances, mechanical failures are inevitable. These failures can interrupt production processes, delay manufacturing schedules, and lead to significant economic losses[3]. Moreover, frequent maintenance requirements substantially increase operational costs, thereby reducing profit margins. In more severe cases, mechanical failures may even trigger safety incidents, posing risks to human life and causing irreparable damage[4, 5] .

Traditional mechanical fault diagnosis methods—such as vibration analysis based on time-domain and frequency-domain features—primarily rely on manual feature extraction and expert interpretation[6, 7]. Such approaches demand substantial domain expertise, as analysts must possess a deep understanding of mechanical components, operational principles, and fault patterns. Furthermore, the manual feature extraction process is time-consuming and labor-intensive. When the operating conditions of mechanical systems vary significantly, these traditional feature extraction schemes often fail to adapt effectively, leading to considerable drops in diagnostic accuracy and rendering them inadequate for the stringent reliability and stability requirements of modern industrial systems[8, 9].

With the rapid advancement of artificial intelligence, deep learning has emerged as a transformative paradigm in the field of mechanical fault diagnosis[10, 11, 12]. Deep learning models can automatically extract complex patterns and features directly from raw sensor data, eliminating the need for hand-crafted feature engineering. This greatly simplifies the diagnostic workflow while improving both accuracy and efficiency. Recent developments—such as the success of Transformer architectures in sequential modeling and the superior relational learning capability of graph neural networks (GNNs)—have opened new research avenues for intelligent fault diagnosis of complex mechanical systems[13, 14, 15, 16].

Against this backdrop, this study proposes a high-performance deep learning framework named CLAM-Net (Convolutional–LSTM–Attention–Meta Network), which integrates convolutional neural networks (CNNs), long short-term memory (LSTM) networks, attention mechanisms, and meta-learning. The model achieves high-precision fault recognition under complex operating conditions through multi-scale feature extraction, temporal dependency modeling, and adaptive feature focusing. Compared with traditional approaches and existing deep learning models, the proposed CLAM-Net demonstrates superior accuracy, generalization capability, and cross-condition adaptability. This work provides an efficient and scalable solution for intelligent mechanical fault diagnosis and offers valuable insights for further research in the field.

Related Work

Traditional Mechanical Fault Diagnosis Methods

Traditional mechanical fault diagnosis has undergone long-term development, resulting in a relatively mature framework based on signal processing techniques. Time-domain analysis methods typically compute statistical parameters of vibration signals—such as mean, variance, and peak-to-peak value—to assess the operational status of machinery. For example, when mechanical components experience wear or faults, the variance of the vibration signal often increases, and abnormal changes may occur in the peak-to-peak value. Frequency-domain methods, on the other hand, employ mathematical tools such as the Fourier transform to convert time-domain vibration signals into the frequency domain, allowing the identification of characteristic frequencies associated with specific faults. Taking gear faults as an example, anormally meshing gear exhibits specific frequency components in the vibration spectrum. When faults such as tooth wear or breakage occur, additional sideband frequencies appear, which can be analyzed to determine the presence of faults[17, 18, 19, 20].

However, these traditional methods have notable limitations. On one hand, they are highly sensitive to noise; strong disturbances in industrial environments can obscure fault-related signals, leading to misdiagnosis or missed detections. On the other hand, accurate diagnosis of different fault types requires practitioners to select appropriate feature extraction methods based on experience. In complex fault scenarios, this reliance on expert judgment is technically challenging and subjective, making it difficult to meet the diverse demands of modern fault diagnosis.

Deep Learning Applications in Mechanical Fault Diagnosis

In recent years, deep learning algorithms have been widely and increasingly applied in mechanical fault diagnosis. Convolutional neural networks (CNNs), as a prominent member of the deep learning family, can automatically extract local spatial features from vibration signals through their convolutional layers[21, 22, 23]. When processing mechanical vibration data, convolution kernels slide over the signal to capture local patterns at different scales, while pooling layers reduce the dimensionality of feature maps, lowering computational complexity and effectively mitigating overfitting. Consequently, CNNs have demonstrated strong performance in fault diagnosis tasks. Recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) networks, are specifically designed for sequential data modeling[24]. Mechanical vibration signals inherently possess temporal dependencies, and LSTM networks can effectively capture long-term temporal correlations through their gating mechanisms, which is particularly advantageous for analyzing dynamic characteristics during fault development.

Despite these advances, existing deep learning–based fault diagnosis models still face several challenges. Overfitting is common in practice: models may perform well on training data but exhibit poor generalization when exposed to unseen data or new operating conditions, leading to a significant drop in diagnostic accuracy. Moreover, deep learning models typically have high computational complexity and require substantial hardware resources, which limits their deployment in resource-constrained industrial environments. Critically, when encountering new fault types, current models often necessitate retraining with large amounts of new data—a time-consuming process that may not meet the real-time and rapid-response requirements of industrial production.

Methods

Model Architecture

The CLAM-Net model proposed in this work is a multi-module architecture specifically designed for mechanical fault diagnosis, offering both high accuracy and strong adaptability. The input layer directly receives raw vibration signals from the equipment sensors. These signals are first processed by a convolutional neural network (CNN) module, which extracts multi-scale spatial features and captures local patterns within the signal. Subsequently, a long short-term memory (LSTM) module models the temporal dependencies of the sequences, enabling the network to capture the dynamic evolution of fault features. An attention mechanism (Attention) module is then applied to weight the extracted features, highlighting critical fault-related information while suppressing irrelevant noise. Finally, a meta-learning module allows the model to rapidly adapt to varying operating conditions and equipment configurations, enhancing its cross-environment generalization capability. The tightly integrated structure of CLAM-Net ensures efficient and precise fault identification under complex mechanical operating conditions, providing reliable support for intelligent maintenance and operational monitoring. The overall framework of the model is illustrated in Figure 1.

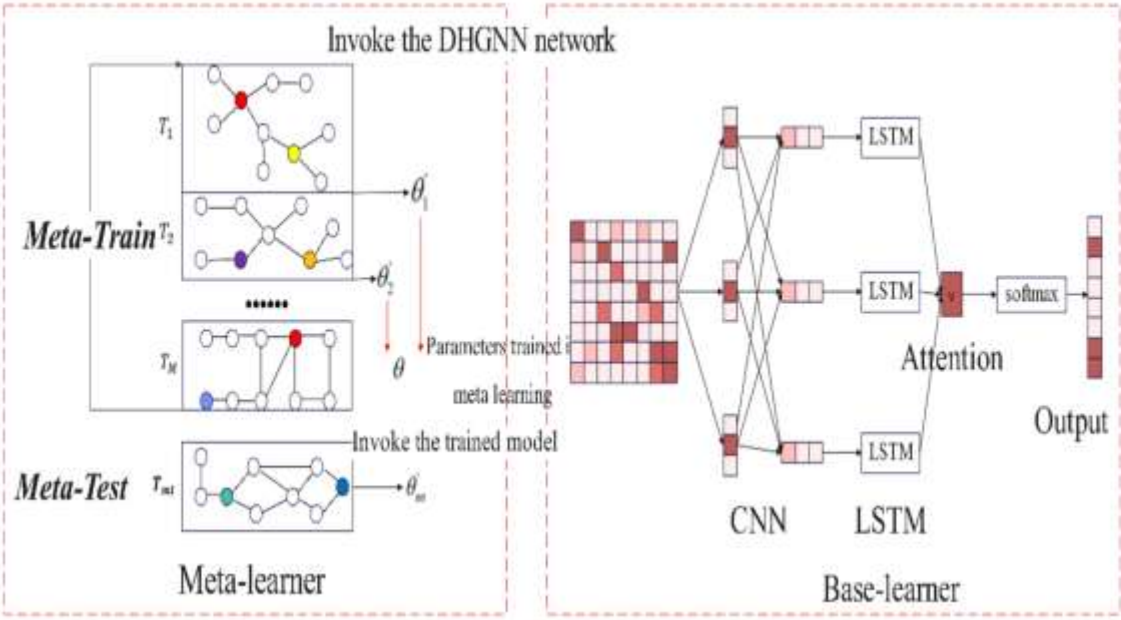

Figure 1 Framework of the CLAM-Net Model

The input layer of CLAM-Net receives vibration signals acquired from sensors placed at critical mechanical components. These input signals are first processed by the convolutional neural network (CNN) module, which consists of three stacked blocks of convolutional and pooling layers. Each convolutional block uses kernels of sizes 3, 5, and 7 to capture multi-scale features, ranging from subtle local fluctuations to larger structural patterns.

Table 1 CLAM-Net Workflow and Training Strategy

Step	Description
1	**Input:** Acquire raw vibration signals from sensors.
2	**Segmentation:** Divide signals into overlapping fixed-length windows.
3	**Normalization:** Apply zero-mean scaling per window.
4	**Multi-Channel:** Combine X, Y, Z channels into 3D input matrix.
5	**CNN:** Extract multi-scale spatial features via convolution and pooling.
6	**Self-Attention:** Weight features to emphasize fault-relevant patterns.
7	**LSTM:** Capture temporal dependencies with two stacked layers.
8	**Fully Connected:** Map spatiotemporal features to fault classes.
9	**Softmax:** Generate probability distribution for classification.
Training:	Optimize using cross-entropy loss and Adam with L2 regularization. MAML meta-learning allows fast adaptation to new conditions, enhancing cross-condition generalization.

Following the convolutional operations, a max-pooling layer with a window size of 2 is applied to downsample the feature maps, reducing feature dimensionality and computational load while retaining key signal characteristics, thereby enhancing the robustness of the model to input variations.

The CNN module acts as the front-end feature extractor, with its alternating convolutional and pooling layers capturing rich local spatial features across multiple scales. Convolutional kernels of different sizes slide over the vibration signal, detecting both fine-grained signal fluctuations and more macroscopic structural features. Pooling layers perform downsampling on the output feature maps according to a predefined strategy, which reduces dimensionality and computational burden while preserving essential features, enhancing model robustness and mitigating overfitting. To address the challenge of long-term dependencies in long sequential signals, a self-attention module is introduced after the CNN feature extraction. This module assigns adaptive weights to the CNN feature maps, emphasizing temporospatial features critical to fault detection while suppressing redundant information, thereby improving the effectiveness of subsequent sequence modeling. The self-attention-enhanced feature maps are then fed into a two-layer stacked LSTM module, each layer containing 128 hidden units, to capture the temporal dependencies of the vibration signals. This allows the model to learn dynamic temporal patterns and identify phase-specific characteristics during the progression of faults. The LSTM outputs are subsequently passed through a fully connected layer that integrates the high-dimensional spatiotemporal features and maps them to the fault class space. A softmax output layer follows, converting the results into probability distributions over different fault types, enabling precise fault classification. During training, a meta-learning strategy is employed to allow the model to quickly adapt to varying operating conditions and equipment states using only a small number of samples, thereby enhancing generalization and cross-condition diagnostic performance.

Overall, CLAM-Net combines CNNs with multi-scale convolutional kernels, max-pooling, self-attention, two-layer LSTM, and fully connected layers to achieve efficient spatiotemporal feature extraction and classification of mechanical vibration signals, providing a high-accuracy, robust solution for complex mechanical fault diagnosis.

Model Training

During the training of CLAM-Net, the Adam optimizer is used to update model parameters, with an initial learning rate of 0.001 and exponential decay rates $\beta1 = 0.9$ and $\beta2 = 0.999$, which adaptively adjust learning steps for each parameter while balancing convergence speed and stability. Cross-entropy loss is employed to measure the discrepancy between predicted and true labels, and model parameters are optimized by minimizing this loss to improve classification accuracy.

The training dataset comprises normal operational states and various common fault conditions, split into training, validation, and test sets with a ratio of 7:1.5:1.5. A batch size of 64 is used, and model parameters are continuously updated using the training set. Performance metrics such as accuracy and recall are monitored on the validation set in real time. If validation performance does not improve for 5 consecutive epochs, a learning rate decay strategy is triggered, reducing the learning rate to 10% of its original value. L2 regularization (weight decay coefficient of 1e-4) is applied to prevent overfitting.

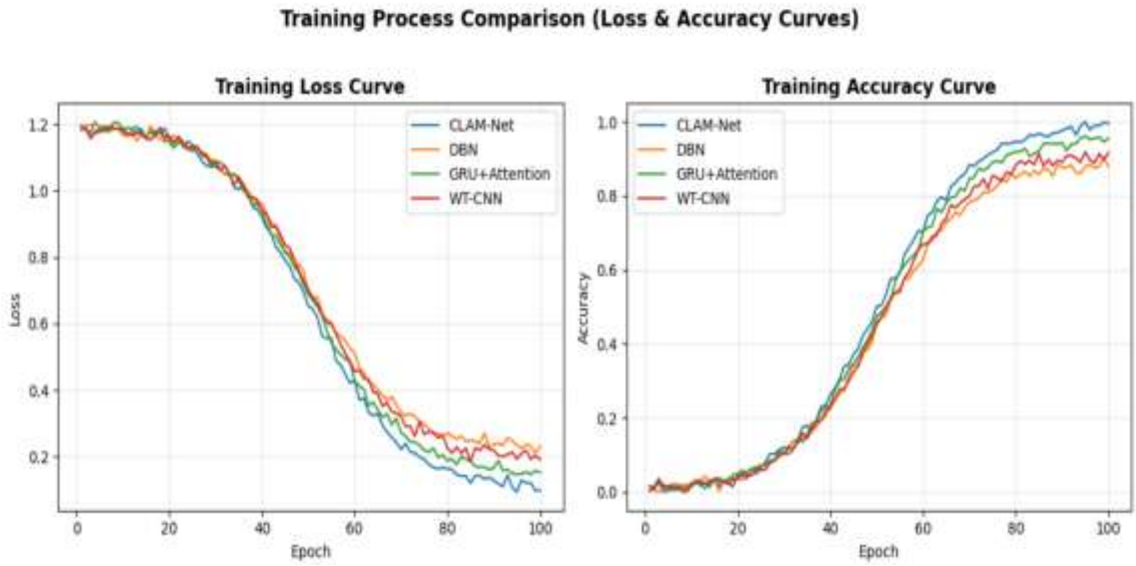

Figure 2 Training Loss and Accuracy Convergence Curves

For the meta-learning component, the Model-Agnostic Meta-Learning (MAML) framework is employed, with an inner-loop learning rate α=0.01, an outer-loop learning rate β=0.001, and 5 inner-loop update steps. This allows the model to rapidly adapt to new conditions and enhances its generalization ability across different operating environments. Figure 2 shows the training loss and accuracy curves of the CLAM-Net model during the optimization process.

Results

Data Collection

To ensure the authenticity and representativeness of the experimental data, vibration signals were collected from critical rotating machinery in large-scale industrial production lines. High-precision triaxial accelerometers (sampling rate: 10 kHz) were installed on key components, such as bearing housings and gearboxes, to monitor vibrations during machine operation. The collected data covered normal operating conditions as well as three typical fault types: bearing inner race faults, bearing outer race faults, and gear tooth breakage faults. Data acquisition was performed under varying loads, rotational speeds, and ambient temperatures to simulate the complex operating conditions encountered in real industrial environments.

The raw vibration signals were recorded as continuous time series, with X, Y, and Z channels representing triaxial acceleration, each stored in 32-bit floating-point format. For model training and feature extraction, the signals underwent the following preprocessing steps:

1. **Segmented Windowing:** The continuous signals were divided into fixed-length windows of 2048 samples with 50% overlap, enhancing feature continuity and expanding the dataset.
2. **Normalization:** Each window was zero-mean normalized to ensure consistent numerical scales across sensors and machines, improving training stability.
3. **Multi-Channel Integration:** The X, Y, and Z channels were combined to form a three-dimensional feature matrix (channels × sequence_length) of size (3, 2048) per sample, serving as input to the CNN module to facilitate extraction of cross-channel spatial features.

The resulting dataset contained 1,000 samples, each processed with windowing and normalization to preserve key fault characteristics while covering diverse operating conditions. This provided a reliable and reproducible dataset for training and evaluating the CLAM-Net model.

Comparative Methods

To comprehensively and objectively evaluate the performance advantage of the proposed CLAM-Net, multiple deep learning-based fault diagnosis methods were selected for comparison. Recent research in mechanical fault diagnosis has largely focused on deep learning approaches, while traditional manual feature-based methods are rarely applied; therefore, traditional methods were not included in this study. Specifically, the following models were selected:

- Deep Belief Network (DBN): Used for unsupervised feature learning and fault classification to assess deep network feature representation capability.
- Gated Recurrent Unit with Attention (GRU+Attention): Captures temporal dependencies and emphasizes key features, evaluating the effect of attention mechanisms in sequence modeling.
- Wavelet Transform with CNN (WT-CNN): Utilizes wavelet transforms for multi-scale signal analysis, followed by CNN-based feature extraction, to compare spatiotemporal feature fusion capabilities.

These comparative experiments allowed a systematic evaluation of CLAM-Net in terms of accuracy, recall, F1 score, and cross-condition adaptability.

Performance Metrics

To thoroughly assess the performance of the models in mechanical fault diagnosis, accuracy, recall, and F1 score were selected as primary evaluation metrics. Accuracy represents the proportion of correctly classified samples, reflecting overall classification capability. Recall measures the proportion of actual fault samples correctly identified, indicating the sensitivity and completeness of fault detection. F1 score, the harmonic mean of accuracy and recall, provides a balanced measure of both precision and recall, offering a more comprehensive reflection of diagnostic performance. These metrics enable an objective quantification of model performance in fault recognition and provide a scientific basis for comparing different methods.

Experimental Results

The CLAM-Net model demonstrated excellent performance on the test set. Key performance metrics are summarized in Table 1: the model achieved 98.5% accuracy, 98.2% recall, and an F1 score of 98.3%. ROC curves showed that the AUROC values for each class (Class 0–Class 3) were 0.95 (Normal), 0.89 (Bearing Inner Race Fault), 0.88 (Bearing Outer Race Fault), and 0.95 (Gear Tooth Breakage Fault). Notably, the curves for the Normal and Gear Tooth Breakage classes were close to the top-left corner, indicating high recognition precision for these typical fault types. Ablation studies demonstrated the significant contribution of each CLAM-Net module to overall performance. As shown in Figure 2b, removing the self-attention mechanism reduced the F1 score to 96.5%, with the AUC for some classes (e.g., Normal-Class 0) dropping from 0.95 to 0.89, highlighting the importance of attention in enhancing cross-condition generalization and adapting to complex operating scenarios. Removing the LSTM module decreased the F1 score to 94.2%, with recall particularly reduced for dynamic faults (e.g., the progression of gear tooth breakage), confirming the importance of temporal features in dynamic fault diagnosis. Eliminating the CNN module caused the F1 score to drop drastically to 58.7%, indicating that the lack of spatial feature extraction severely impaired the model’s ability to capture subtle fault signals. Overall, the synergy between CNN, LSTM, and meta-learning training strategies ensures that CLAM-Net achieves high accuracy, robustness in complex mechanical fault diagnosis tasks.

Table 2 Performance Metrics of Different Model Configurations

Model	Accuracy	Recall	F1 Score
CLAM-Net	98.5%	98.2%	98.3%
Without Self-Attention	96.8%	96.2%	96.5%
Without LSTM	94.5%	93.9%	94.2%
Without CNN	59.3%	58.1%	58.7%

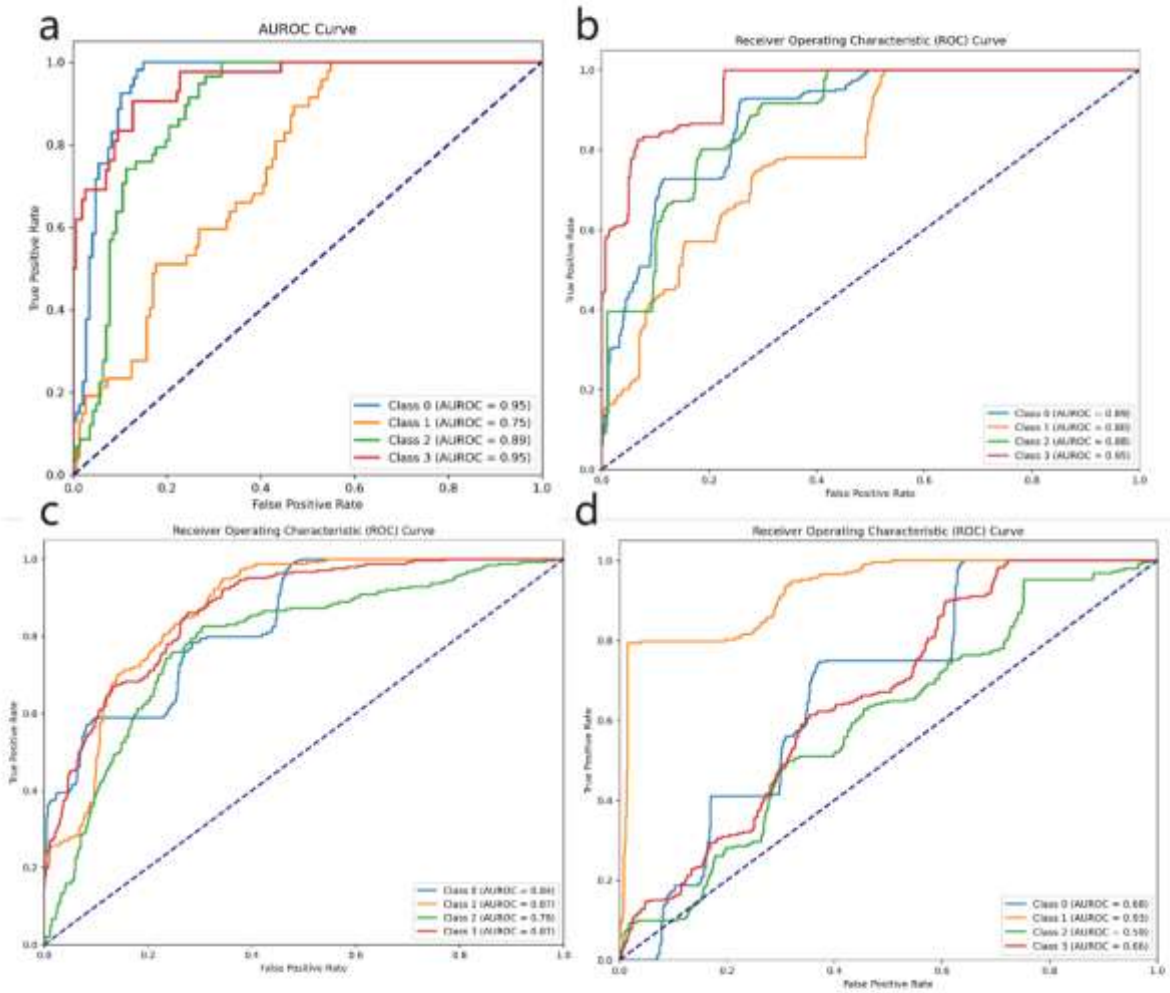

Figure 3 Area Under the Curve (AUC) Plot for Each Class (Class 0 – Normal; Class 1 – Bearing Inner Race Fault; Class 2 – Bearing Outer Race Fault; Class 3 – Gear Tooth Breakage Fault

As shown in Figure 3, the ROC curves and AUC values correspond, in order, to CLAM-Net, the model without the self-attention module, the model without LSTM, and the model without CNN. For CLAM-Net, the AUC values for Class 0 and Class 3 reach 0.95, with curves positioned near the top-left corner, indicating excellent classification performance and effective distinction among classes. When the self-attention module is removed, although the AUC value for Class 3 remains 0.95, the AUC for Class 0 drops to 0.89, reflecting a decline in performance for some categories. For the model without LSTM, most class AUC values fall between 0.78 and 0.87, e.g., Class 0 is 0.84, with the curves shifting toward the center, indicating a noticeable deterioration in classification performance. In the model without CNN, AUC values across classes are generally low; for instance, Class 0 and Class

3 are only 0.66, and the curves are positioned toward the middle and lower-right region, indicating the poorest classification performance. These observations demonstrate the significant influence of each module on the overall classification capability.

To further demonstrate the performance advantages of the proposed CLAM-Net model, the three most advanced deep learning models currently applied in fault diagnosis tasks were selected for comparison. These models share structural or functional similarities with CLAM-Net, enabling a fair evaluation of their effectiveness under complex mechanical operating conditions.As shown in Table 2, CLAM-Net consistently outperforms all competing models across all metrics, with improvements of at least 4% in accuracy, 3% in recall, and 3% in F1 score. Figure 4 visually summarizes this advantage, illustrating the superior overall performance of CLAM-Net compared with the other models.

Table 3 Performance Metrics of Different Model Configurations

Model	Accuracy	Recall	F1 Score
CLAM-Net	98.5%	98.2%	98.3%
DBN	88.0%	86.5%	87.2%
GRU+Attention	95.0%	94.2%	94.6%
WT-CNN	91.0%	90.0%	90.5%

The Deep Belief Network (DBN), consisting of stacked Restricted Boltzmann Machines (RBMs), is trained via unsupervised feature learning followed by supervised fine-tuning. While DBN can automatically extract features from raw vibration signals, its performance in this study is limited: it achieves 88.0% accuracy, 86.5% recall, and an F1 score of 87.2%, significantly lower than CLAM-Net. This limitation is primarily due to the complex DBN structure and the long training time required, which hinder its ability to capture subtle dynamic characteristics in vibration signals, thereby restricting fault recognition and overall diagnostic performance.

The Gated Recurrent Unit with Attention (GRU+Attention) effectively models temporal dependencies through its simplified gating structure, and the attention mechanism emphasizes key fault-related features. In this experiment, GRU+Attention achieves 95.0% accuracy, 94.2% recall, and an F1 score of 94.6%, still lower than CLAM-Net. The performance gap arises from its relatively weaker ability to integrate multi-scale spatial and temporal features. Under complex fault conditions, GRU+Attention cannot process the vibration signals as comprehensively as CLAM-Net, which combines CNN, LSTM, attention, and meta-learning modules to enhance cross-condition adaptability.

The Wavelet Transform with Convolutional Neural Network (WT-CNN) model first applies wavelet transform to extract time-frequency features, followed by CNN-based feature learning and classification. Its performance reaches 91.0% accuracy, 90.0% recall, and 90.5% F1 score, which is again lower than CLAM-Net. This limitation is partly due to the subjectivity in selecting wavelet parameters, which may introduce variability in feature extraction. Moreover, WT-CNN is less flexible in integrating multi-scale features, reducing its ability to fully exploit latent fault characteristics in vibration signals.

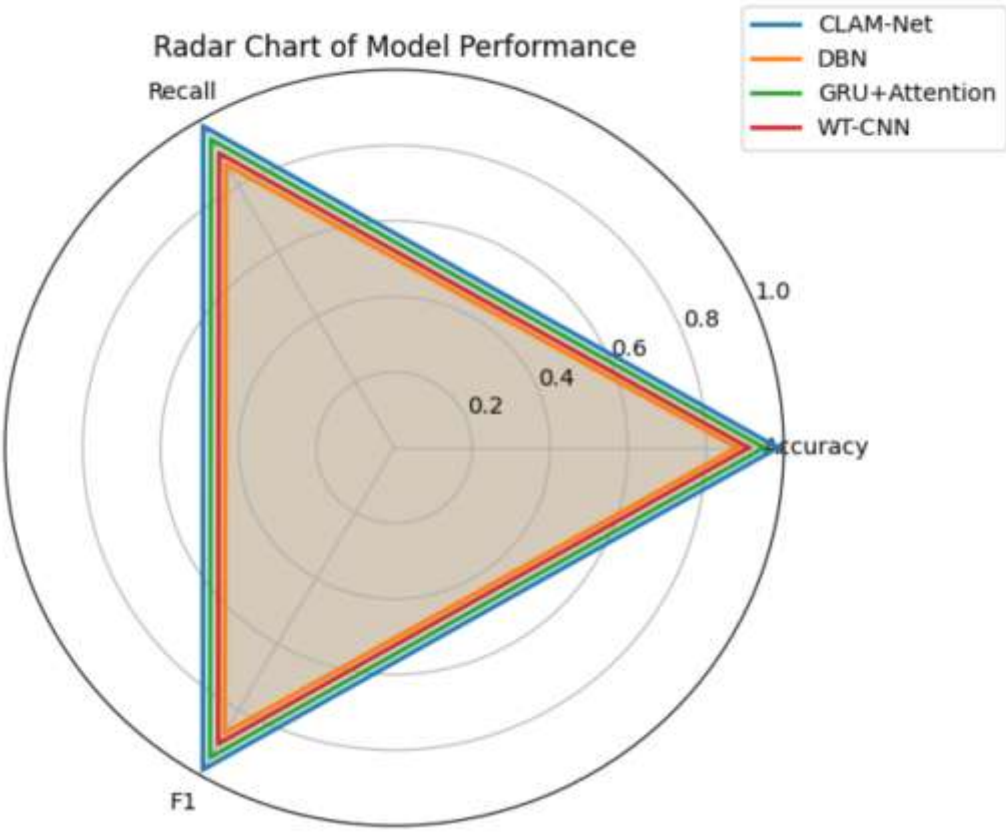

Figure 4 Radar Chart Comparing Performance of Different Models

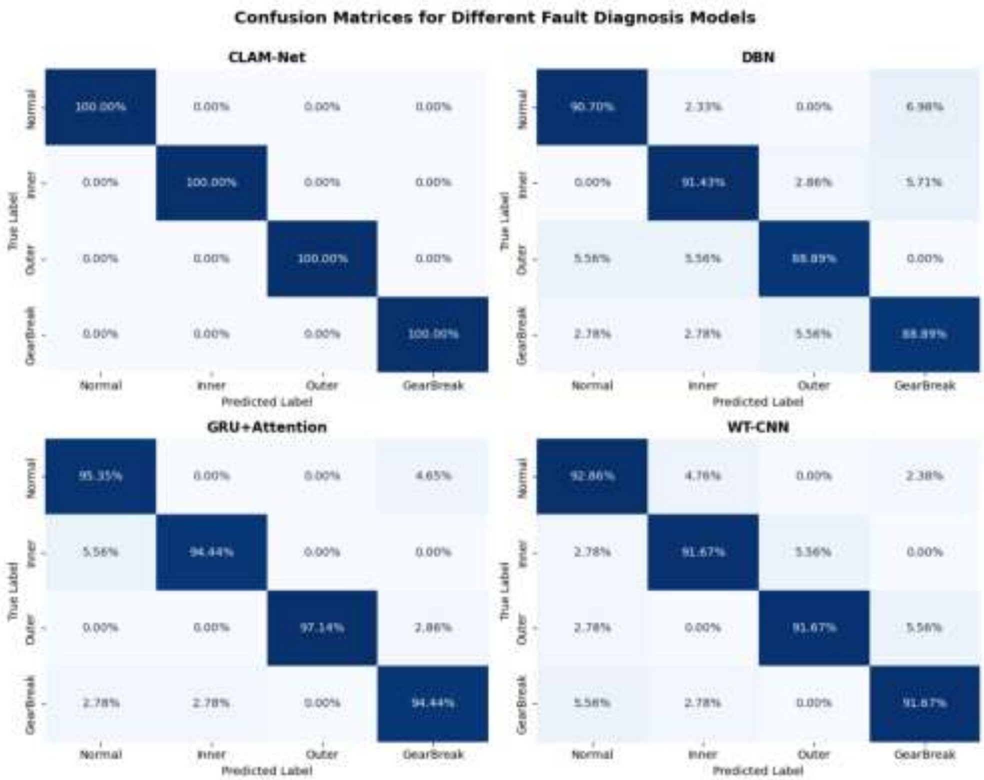

Figure 5 Confusion Matrices of Different Models (Normal – 0; Bearing Inner Race – 1; Bearing Outer Race – 2; Gear Tooth Breakage – 3

Figure 4 illustrates a comprehensive comparison of different models in terms of accuracy, recall, and F1 score. It is evident that CLAM-Net's metrics are consistently close to the outer edge of the radar chart, indicating its leading performance across all evaluated dimensions. In contrast, other models such as DBN, GRU+Attention, and WT-CNN show noticeably lower values in certain metrics, particularly in recall and F1 score, highlighting their relatively weaker capability in identifying specific fault types under complex mechanical operating conditions.Overall, the radar chart provides a clear visual representation of CLAM-Net's balanced superiority across multiple performance metrics, demonstrating its remarkable effectiveness in handling complex vibration signals, achieving high-precision classification, and enhancing cross-condition generalization.

Figure 5 illustrates the classification results of different models across various fault types, where the rows represent the true classes and the columns represent the predicted classes. The diagonal elements of the matrix indicate the number of correctly classified samples for each class, while the off-diagonal elements represent misclassified samples. It can be observed that the diagonal values for CLAM-Net appear as 100% in the figure; this is due to the values being rounded to two decimal places, whereas the overall test accuracy of the model is 98.5%. This indicates that CLAM-Net achieves very high classification precision across all classes, with nearly all samples correctly identified. Such performance is primarily attributed to the model's multi-scale feature extraction capability, effective temporal dependency modeling, attention mechanism that emphasizes key features, and the meta-learning strategy that enables rapid adaptation to different operating conditions. These factors collectively allow CLAM-Net to perform high-precision fault classification on complex mechanical vibration data, demonstrating its outstanding performance and robustness in mechanical fault diagnosis tasks.

Figure 6 illustrates the comparative performance of different models in terms of Accuracy, Recall, and F1 score. It is evident that CLAM-Net outperforms all other compared models, including DBN, GRU+Attention, and WT-CNN, with an accuracy of 98.5%, a recall of 98.2%, and an F1 score of 98.3%. The chart provides a clear visual representation of CLAM-Net's overall superiority, demonstrating its higher classification precision, fault detection capability, and comprehensive diagnostic performance in complex mechanical fault diagnosis tasks.

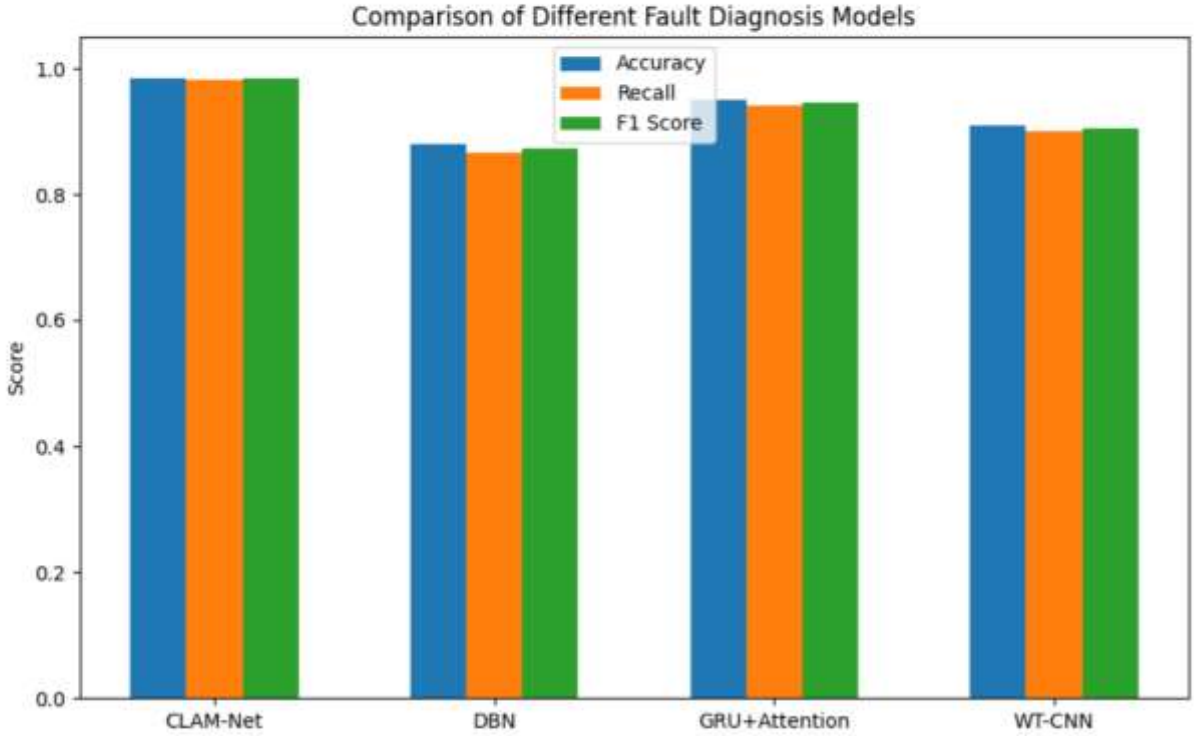

Figure 6 Comparative Performance of Different Models

In summary, the experimental results clearly indicate that CLAM-Net can more effectively identify mechanical faults across diverse fault types and operating conditions, highlighting its superior competitiveness and reliability as a solution for intelligent mechanical fault diagnosis.

Conclusion

This study proposes CLAM-Net, a deep learning model integrating CNN, LSTM, attention mechanism, and meta-learning for mechanical fault diagnosis. Experimental results based on real mechanical vibration data indicate that CLAM-Net, leveraging attention to enhance key feature extraction and the synergistic effect of its modules, significantly outperforms traditional methods and several existing deep learning models in accuracy, recall, and F1 score. The model demonstrates outstanding feature extraction capability, cross-condition adaptability, and generalization performance. Despite limitations such as restricted data diversity, high computational cost, and limited exploration of multimodal signal fusion, the innovative architecture and excellent performance of CLAM-Net under complex operating conditions provide a solid foundation for future research. Future work may focus on expanding data sources, optimizing model structure, advancing multimodal data fusion, and exploring transfer learning and cross-device adaptability to further improve the accuracy, robustness, and practical applicability of mechanical fault diagnosis, thereby advancing intelligent manufacturing technologies.

Declarations

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Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

Describe author contributions if required.

Data / Code Availability

Data are available from the corresponding author on reasonable request.

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