Resnet with CBAM-SE for Bolt Fault Diagnosis in Simulated Noisy Industrial Environments

Peng Jiang [1], Qing Meng [2], Luying Zhang [3, *], Qiancheng Sun [4]

[1] Sanya Offshore Oil and Gas Research Institute Northeast Petroleum University Sanya 122518, China

[2] Mechanical Science and Engineering Northeast Petroleum University Daqing 163318, China

[3] College of petroleum Engineering Northeast Petroleum University Daqing 163318, China

[4] Mechanical Science and Engineering Northeast Petroleum University

* Corresponding Author Email: zhangluying@nepu.edu.cn

Abstract. This paper explores the use of a deep learning approach combining a ResNet50 model and CBAM-SE (Convolutional Block Attention Module with Squeeze-and-Excitation) for bolt fault diagnosis in a noisy industrial environment. The aim of the study is to improve the model's immunity to different noise conditions, covering fluid noise, impact noise, periodic noise and mixed noise. Experimental results show that the ResNet50+CBAM-SE model outperforms the conventional ResNet50 and CNN models in all noise cases, especially when dealing with complex noise disturbances.The addition of the CBAM-SE module enables the model to better focus on key features, thus improving its robustness and classification performance. This study demonstrates the potential of deep learning models with attention mechanisms for fault diagnosis, especially in industrial settings.

Keywords: ResNet50, bolts, acoustic emission, noise immunity, CBAM.

1. Introduction

High-strength bolts are widely used in petrochemical equipment for connecting critical components such as reactors, pipelines, pump bodies and fans, which are subject to complex vibration and dynamic loads [1]. During long-term operation, bolts may loosen, slip, or even fracture, which in turn leads to structural failure [2]. Therefore, experimental research on bolts under vibration conditions can effectively identify and diagnose their potential damage and thus ensure the safety and reliability of the equipment.

To address this issue, recent studies have gradually focused on the physical characterization and condition monitoring of bolt assemblies to improve the accuracy and reliability of loosening detection.Shaheen, Shaheen, M.A.,Foster,A. S., Cunningham, L.S.,&Afshan,S. [3] investigated the performance of bolt assemblies in structural steel connections at elevated temperatures, evaluated the strength reduction factors specified in the European and U.S. standards, and found that they were often too conservative for the high temperature range and recommended that they be updated. The study also discussed the effects of fire on the microstructure of steel bolts and proposed a new equation based on experimental results. The study also discusses the effect of fire on the microstructure of steel bolts and proposes a new equation for the discount factor based on experimental results. Li, D., Nie, J. H., Wang, H., & Ren, W. X. [4] investigated lifecycle condition monitoring of high strength bolted joints, proposing a physically guided deep learning framework that combines supervised and unsupervised learning to diagnose multiple damage mechanisms and identify different loading phases using acoustic emission (AE) data. They successfully identified four loading stages such as static friction, slip, confinement and failure and their overlapping damage mechanisms by means of convolutional neural network (CNN) and Gaussian mixture model (GMM). Ramasso, E., Verdin, B., & Chevallier, G. [5] proposed the ORION-AE dataset, which collects raw data from five different fastening conditions by means of three different acoustic emission transducers and laser vibrometer streams for challenging ultrasonic data interpretation methods and signal processing techniques. They created this dataset as a benchmark to support the comparison of data-driven methods in material characterization and structural health monitoring. Qin, X., Peng, C., Zhao, G., Ju, Z., Lv, S., Jiang, M., ... & Jia, L. [6] investigated the full lifecycle monitoring of bolt loosening, proposing an improved vibro-acoustic modulation (VAM) method capable of providing earlier warnings at the stage of thread loosening. It was found that the nonlinear effect of bolt loosening was related to the applied torque, and a monitoring method based on the nonlinear and linear transfer energy indices was proposed, which helps to improve the reliability of the VAM technique in the early loosening monitoring of bolts.

Existing research methods mainly focus on the analysis of bolt signal characteristics, which are usually carried out under a single noise type or a specific working condition. However, these methods generally suffer from noise sensitivity and are susceptible to noise interference, which affects diagnostic accuracy and reliability. To cope with the complex noise interference and feature extraction challenges in industrial environments, this study innovatively constructs the ResNet50+CBAM-SE deep learning framework. The model achieves performance enhancement through a dual-module synergetic architecture: the Convolutional Block Attention Module (CBAM) adopts a spatial-channel dual-path attention mechanism, which dynamically enhances the weight distribution of key features; and the Squeeze-and-Excitation (SE) module realizes the adaptive calibration of the feature response through the global modeling of the feature channels. The overall methodology flowchart is shown in Fig. 1. These two modules form a complementary mechanism - CBAM performs feature selection in the pixel dimension to effectively suppress high-frequency noise interference; SE implements feature enhancement in the channel dimension to ensure the salient expression of diagnostically relevant features. The complementary mechanism of the two makes the model more robust in complex noise scenarios, breaking through the performance bottleneck of traditional methods in such environments.

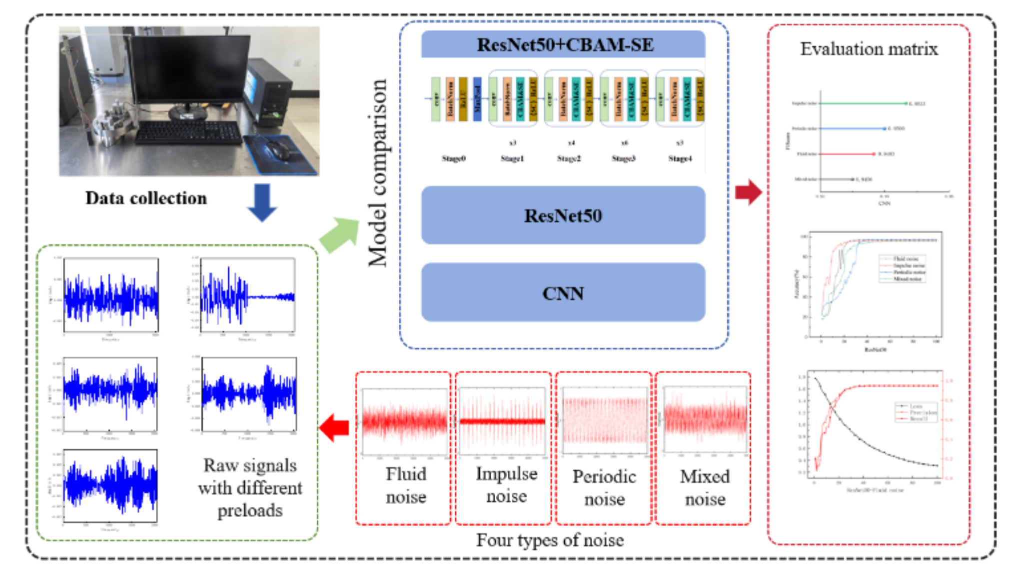


Fig. 1. Flowchart.

2. Experimental setup and data acquisition

The test stand consists of a torque wrench, a frame, a flange, M10 bolts, and an FF180 eccentric vibration motor, as shown in Table 1, in which the frame transmits the vibration force and provides the loading state through bolting, as shown in Fig. 2. The test stand has the following features: the distance between the transducer and the bolt can be changed, the measurement angle between the transducer and the bolt can be adjusted, and the bolt is easy to replace. During operation, the test stand maintains overall stability, operates with low noise and slight vibration, and meets the expected design requirements.

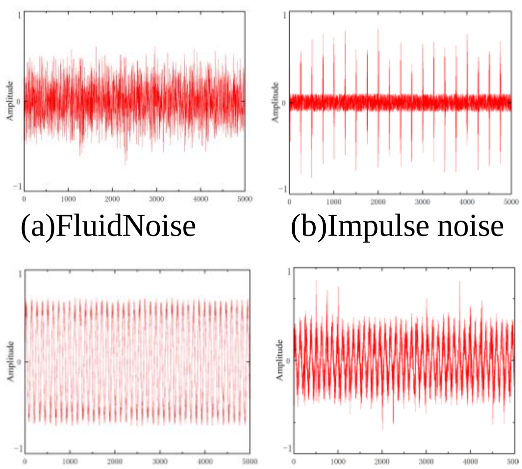
Fig. 2. Experimental setup.

Table 1. Key parameters of the FF180 motor

Parameters	(Be) worth
Operating voltage	3v-12v
Number of revolutions per minute	3000-12000RPM
Amps	100-300mA
Overall dimensions	15mmx20mm

In order to study the acoustic emission characteristics of bolts under different preload conditions, five preload conditions were set up: 0 Nm, 20 Nm, 35 Nm, 49 Nm and 60 Nm, of which 49 Nm is the recommended standard preload for M10 bolts of grade 8.8, as determined according to GB/T 3098.1-2010. Under each preload condition, four bolts were tested. In the experiment, the bolt flanges were fixed to the support block, and the acoustic emission signals under each condition were monitored and recorded in real time using an acoustic emission sensor by applying a constant vibration load. To ensure the reliability of the results, all tests were repeated several times.

In the experiments, four types of noise conditions were simulated, including periodic noise, shock noise, fluid noise, and combinations of these noise types. These noise conditions were designed to simulate disturbances that are common in realistic industrial environments, such as motor and fan noise in factory environments (periodic noise), transient noise caused by loose bolts or collisions (impact noise), and disturbances from hydraulic systems or airflow (fluid noise),as shown in fig.3. For the comparison of noise training models, the ResNet50 + CBAM-SE model, the ResNet50 model, and the CNN model were used. By training the models under these complex noise conditions, this study verifies the superior noise immunity and robustness of the ResNet50 + CBAM-SE model under noise disturbances.



(a)FluidNoise (b)Impulse noise

(c)Periodic noise (d)Mixed noise

Fig. 3 Amplitude-frequency diagram of analog noise signals

3. Proposed Methodology

This section describes ResNet-50 deep residual network in detail.

3.1. Improvement of ResNet-50 Deep Residual Network

Gradient vanishing and network degradation are common problems in deep learning training, and ResNet-50 effectively solves these problems through residual learning and jump connection, which significantly improves the training effect and performance of deep networks. In this paper, we combine the vibration features in acoustic emission signals and the improved ResNet-50 model for recognizing bolt loosening. To further enhance the model's adaptability to vibration modes and noise robustness, CBAM and SE modules are introduced in this paper, as shown in Fig. 5.The CBAM module adaptively highlights key features and suppresses noise by learning channel and spatial attentional weights, while the SE module enhances the network's attention to important frequency features through channel weighting to improve the accuracy of recognition and classification. The combination of the two allows ResNet-50 to exhibit enhanced robustness and generalization capabilities in complex signal processing tasks.

The improved ResNet-50 model consists of five phases, as shown in Fig. 4: an initial convolution and pooling phase for rapid reduction of the spatial size of the feature map, followed by four main phases containing multiple residual blocks for deep feature extraction via convolution, batch normalization, CBAM and SE modules, hopping connections, and ReLU activation. The combination of these blocks effectively enhances the learning of critical signals and noise suppression, allowing each stage to efficiently process complex signal features.

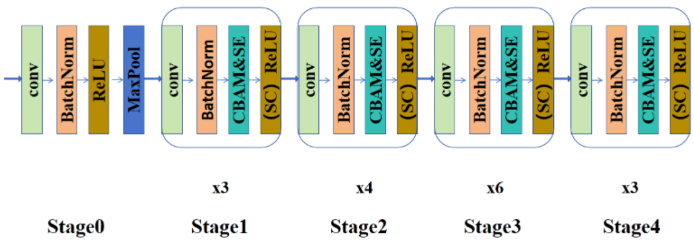


Fig. 4. Improved resnet-50 deep residual network graphs.

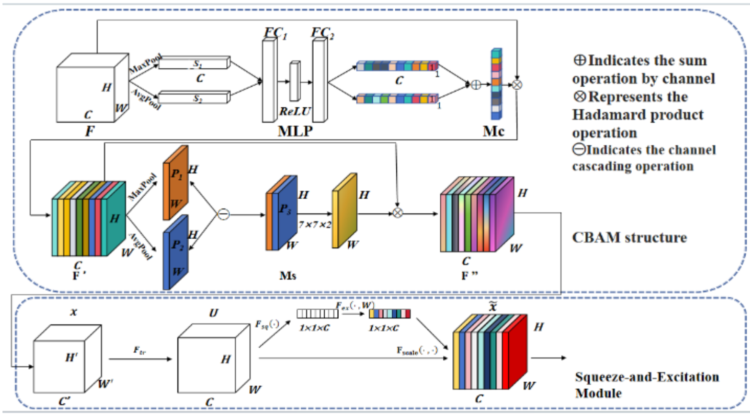


Fig. 5. Structure of CBAM module and SE module. Units

3.2. F1 score

Accuracy is defined as the ratio of correctly predicted samples to the total number of samples and is given by the formula:

$$Auucracy = \frac{CorrectPredictions}{TotalPredictions}$$

Where "Correct Predictions" refers to the samples where the predicted label matches the true label.

The loss value is the difference between the predicted category and the true category, given by the following formula:

$$Loss = -\frac{1}{N}\sum_{N}^{i=1}(y_i log(\hat{y_i}) + (1 - y_i)log(1 - \hat{y_i}))$$

Where: y_i is the true label. $\hat{y_i}$ is the predicted probability.

Precision is calculated as the ratio of correctly predicted positive samples to the total predicted positive samples and is expressed as:

$$Precision = \frac{TP}{TP + FP}$$

Recall is the ratio of correctly predicted positive samples to the actual positive samples and is given by:

$$Recall = \frac{TP}{TP + FN}$$

The F1 score, representing the harmonic means of precision and recall, provides a comprehensive measure of the model's ability to correctly identify positive samples and is calculated as:

$$F1 = 2 \cdot \frac{Preceison \cdot Recall}{Precision + Recall}$$

TP (True Positive): The number of samples that are predicted as positive and are actually positive.

FP (False Positive): The number of samples that are predicted as positive but are actually negative.

TN (True Negative): The number of samples that are predicted as negative and are actually negative.

FN (False Negative): The number of samples that are predicted as negative but are actually positive.

3.3. Training

The training process was performed in a laboratory environment as detailed in

Table 2. Experimental environment Specifically, 150 model iterations were performed using a batch size of 16 and an initial learning rate of 0.001, with each cycle consisting of 2400 batches. The training parameters are shown in

Table 3. Training parameters.

Table 2. Experimental environment

Hardware environment		Software environment	
Memory	16.0 GB	System	Windows 11
CPU	AMD Ryzen 9 5000 U (3.2 GHz)	Environment	Pytorch-gpu 1.13

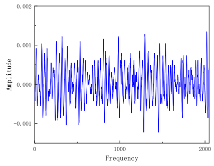
Table 3. Training parameters

Related parameter	Value	Meaning
Batch size	16	Number of pictures per training
Learning rate	0.001	Initial learning rate
Epoch	150	Training iteration times
CUDA	Enable	Comp

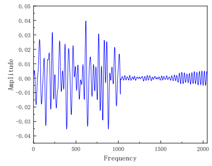
4. Experimental results and analysis

4.1. Bolt Acoustic Emission Signal and Analog Noise Signal

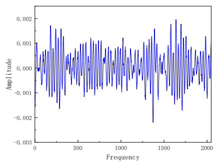
In this study, the acoustic emission signals and analog noise signals of bolts under different preload forces were analyzed to explore the differences in their characteristics,as shown in Fig. 6. The different signal types reflect the different working conditions and environmental disturbances that may be encountered by the bolts in the working process, and these differences provide reliable data support for loosening detection. By comparing the signal waveforms, it is found that the acoustic emission signals of bolts under different preloads show different vibration patterns and frequency responses, which provides a data basis for the subsequent analysis of the classification accuracy and adaptability of the ResNet-50+CBAM-SE model under different damage types.



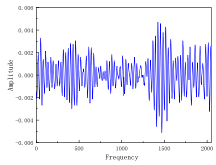
(a)00Nm



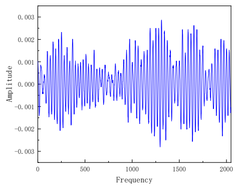
(b)20Nm



(c)35Nm



(d)49Nm

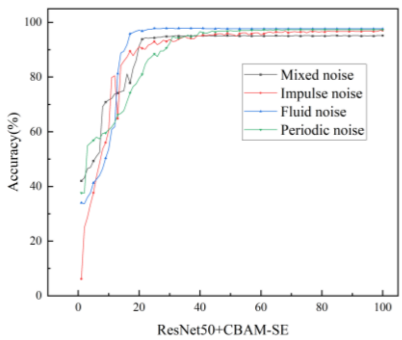


(e)60Nm

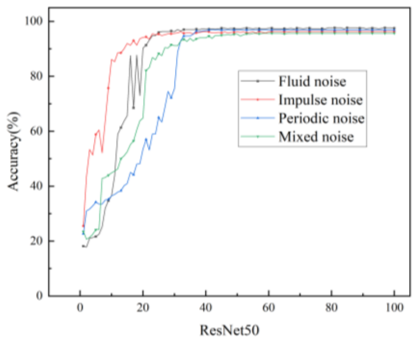
Fig.6 Amplitude-frequency diagram of the acoustic emission signals

4.2. Comparative performance analysis of different deep learning models

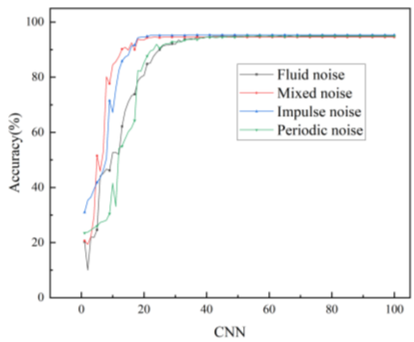
By analyzing the accuracy performance of the three models under different noise types,as shown in Fig.7,the results show that ResNet50+CBAM-SE exhibits significant advantages under all noise conditions. Specifically, under fluid noise, the accuracy of ResNet50+CBAM-SE is 97.7%, which is higher than the 97.5% of ResNet50 and 94.83% of CNN; under impulse noise, the accuracy of ResNet50+CBAM-SE is 97.1%, which is also higher than the 96.33% of ResNet50 and 94.5% of CNN; Under periodic noise, the accuracy of ResNet50+CBAM-SE is 97.4%, which is also ahead of ResNet50's 96.83% and CNN's 95.33%;under mixed noise, the accuracy of ResNet50+CBAM-SE is 95.7%, which is also higher than ResNet50's 95.2% and CNN's 94.5%. In summary, the ResNet50+CBAM-SE model demonstrates significant advantages in terms of noise adaptation and classification accuracy, especially when facing complex noises (e.g., fluid and impulse noises), the accuracy is significantly ahead.



(a)ResNet50+CBAM-SE



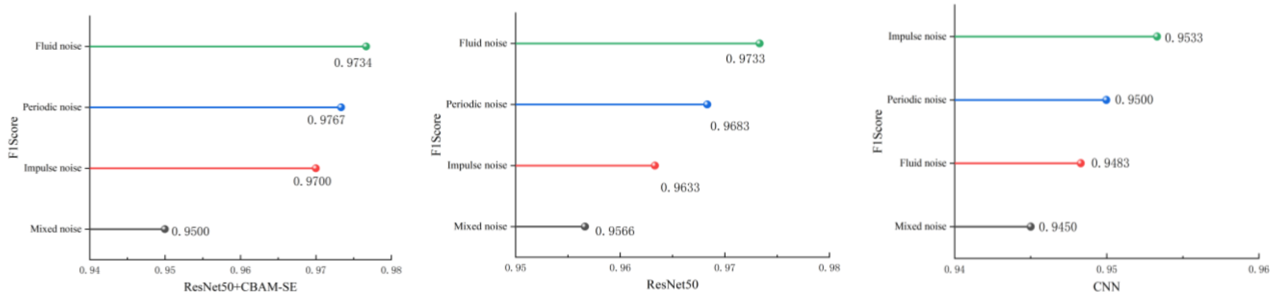
(b)ResNet50



(c)CNN

Fig. 7 Accuracy of the three models under different noise types

By analyzing the F1 Score performance of the three models under different noise types, as shown in Fig.8, the results show that ResNet50+CBAM-SE exhibits significant advantages under all noise conditions. Specifically, under fluid noise, the F1 Score of ResNet50+CBAM-SE is 0.9734, which is higher than that of ResNet50's 0.9733 and CNN's 0.9483; under impulse noise, the F1 Score of ResNet50+CBAM-SE is 0.9700, which is also higher than that of ResNet50's 0.9633 and CNN's 0.9533; under periodic noise, ResNet50+CBAM-SE's F1 Score is 0.9767, ahead of ResNet50's 0.9683 and CNN's 0.9500; under mixed noise, ResNet50+CBAM-SE's F1 Score is 0.9500, which is relatively low but still higher than 0.9566 of ResNet50 and 0.9450 of CNN.In summary, the ResNet50+CBAM-SE model demonstrates significant advantages in noise adaptation and classification accuracy, and the F1 Score performs significantly better, especially in fluid noise and periodic noise conditions.



(a)ResNet50+CBAM-SE (b) ResNet50 (c)CNN

Fig. 8 F1 Score for three models with different noise types

5. Discussion

This study shows that the ResNet50+CBAM-SE model outperforms the traditional ResNet50 and CNN models under different noise conditions. By introducing the CBAM-SE module, the model is able to better focus on key features, which improves the adaptability to complex noise (e.g., fluid noise, impact noise). In all noise environments, ResNet50+CBAM-SE outperforms in terms of accuracy and F1 scores, and the performance improvement is especially noticeable in fluid noise and periodic noise.

Although the performance of ResNet50+CBAM-SE slightly decreases in mixed noise environments, it still outperforms the other two models. The possible reason for this is that the complexity of the mixed noise has an impact on the model judgment. In the future, the robustness of the model under mixed noise can be further optimized or combined with other noise suppression techniques to further improve performance.

In summary, the CBAM-SE module enhances the robustness of the ResNet50 model in industrial fault diagnosis, especially in noisy environments, demonstrating the potential of deep learning models for application in complex environments.

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