American International Journal of Scientific & Technical Research

Official Website: https://aijstr.com

An intelligent fault diagnosis method for industrial equipment based on the improved CNN-LSTM hybrid model

Aaron T. Hill, Steven K. Bell

A B S T R A C T

With the comprehensive promotion of intelligent manufacturing and Industrial Internet of Things (IIoT) technology, industrial production equipment is developing toward high-speed, automated, precise and long-term continuous operation (Zhang et al., 2023). Mechanical transmission equipment, motor equipment and hydraulic equipment in intelligent factories are prone to wear, looseness, abrasion and fatigue failure after long-term operation, which seriously affects production safety and operational stability of industrial systems (Liu & Wang, 2024). Traditional industrial equipment fault diagnosis methods mainly rely on manual inspection and simple signal threshold judgment, which have prominent defects such as low diagnosis efficiency, strong subjectivity, difficulty in identifying early weak faults, and poor anti-interference ability under complex industrial noise environment (Chen et al., 2022). In order to solve the problems of low accuracy, weak feature extraction ability and poor real-time performance of existing industrial equipment fault diagnosis technologies, this paper proposes an intelligent fault diagnosis method for industrial equipment based on improved CNN-LSTM hybrid model. Aiming at the characteristics of industrial equipment vibration signals with strong noise, complex feature distribution and obvious temporal degradation rules, the convolutional neural network (CNN) is used to extract spatial local feature information of equipment operating signals, and the long short-term memory (LSTM) network is introduced to mine time-series correlation features of equipment operation state changes. On this basis, an adaptive attention mechanism is embedded into the hybrid model to optimize the weight distribution of effective fault features, suppress redundant noise features, and solve the problem of weak early fault feature extraction and feature flooding under complex industrial interference. A large number of comparison experiments based on industrial equipment actual operation datasets and simulation data verify that the improved CNN-LSTM hybrid model can effectively extract multi-dimensional fault features of industrial equipment, realize accurate identification and classification of early weak faults and typical severe faults. Compared with traditional machine learning models and single deep learning models, the proposed method has higher diagnosis accuracy, stronger noise robustness and better generalization performance. The intelligent fault diagnosis technical scheme can be widely applied to fault monitoring, early warning and health management of mechanical equipment, electrical equipment and automated production lines in intelligent factories, which provides an effective technical guarantee for intelligent operation and maintenance and safe production of industrial systems.

Keywords: *industrial equipment; fault diagnosis; CNN-LSTM hybrid model; deep learning; attention mechanism; feature extraction; intelligent operation and maintenance*

1. Introduction

In the era of Industry 4.0, intelligent manufacturing and digital industrial transformation have become the core development trend of the global manufacturing industry (Smith et al., 2022). Industrial mechanical and electrical equipment is the core execution unit of factory production. Long-term continuous load operation, frequent start-stop impact and complex industrial environmental interference will inevitably lead to performance degradation and structural failure of equipment components (Jones & Taylor, 2023). Common industrial equipment faults include bearing wear, gear damage, motor rotor imbalance, mechanical looseness and hydraulic system blockage. Early minor faults will gradually evolve into serious equipment failures without timely diagnosis and maintenance, resulting in production line shutdown, economic losses and even industrial safety accidents (Zhao et al., 2023).

* *Corresponding author : Aaron T. Hill*

Therefore, accurate, real-time and intelligent fault diagnosis of industrial equipment is of great significance to ensure the stable operation of intelligent factories, reduce maintenance costs and improve production efficiency.

Traditional industrial equipment fault diagnosis mainly adopts manual regular inspection, vibration signal analysis, spectrum analysis and other technical means (Li et al., 2022). Manual inspection relies on engineer experience, with strong subjectivity, low efficiency and high missed detection rate, which cannot meet the real-time monitoring requirements of automated production lines. The traditional signal analysis method can only judge faults based on artificial feature extraction and threshold comparison, which is difficult to identify early weak fault features submerged in industrial noise, and has poor adaptability to complex variable working conditions (Wang & Zhang, 2023). With the rapid development of industrial big data and artificial intelligence technology, deep learning-based intelligent fault diagnosis methods have gradually become the mainstream research direction in the field of industrial equipment health management (Gupta et al., 2024).

At present, single deep learning models such as CNN and LSTM have been applied to equipment fault diagnosis. CNN has excellent spatial feature extraction ability and can effectively extract local feature information of equipment vibration signals, but it cannot capture the long-term time-series correlation of equipment operation state (Kim et al., 2022). LSTM network can mine time-series change rules of sequential data, but it has insufficient ability of local fine-grained feature extraction and is easily affected by complex industrial noise (Park et al., 2023). In addition, most existing hybrid models have fixed feature weight distribution, which cannot adaptively enhance effective fault features and suppress interference features, resulting in limited diagnosis accuracy of early weak faults (Liu et al., 2024).

Aiming at the above technical deficiencies, this paper constructs an improved CNN-LSTM hybrid intelligent fault diagnosis model embedded with an attention mechanism. The model gives full play to the advantages of CNN spatial feature extraction and LSTM time-series feature mining, and realizes adaptive optimization of feature weight through the attention mechanism, which significantly improves the accuracy and anti-noise ability of industrial equipment fault diagnosis. The research results can provide technical reference for intelligent fault early warning and health management of industrial automation equipment.

2. Related Work

2.1 Research Status of Industrial Equipment Fault Diagnosis

Industrial equipment fault diagnosis technology is an important part of industrial intelligent operation and maintenance system, which is mainly divided into traditional manual diagnosis, signal analysis diagnosis and intelligent diagnosis (Yang et al., 2022). Traditional diagnosis methods rely on artificial experience and simple signal comparison, which have low intelligence and poor diagnosis stability. Signal analysis technologies such as Fourier transform and wavelet analysis can realize preliminary fault feature analysis, but they require artificial feature selection and extraction, which have high professional dependence and are difficult to adapt to complex industrial working conditions (Hernandez et al., 2023).

In recent years, with the development of industrial Internet monitoring technology, equipment operation data presents massive and high-dimensional characteristics, which promotes the rapid development of intelligent fault diagnosis technology based on machine learning and deep learning (Brown et al., 2023). Intelligent diagnosis methods can automatically mine fault feature rules from massive monitoring data, realize end-to-end fault identification and classification, and effectively avoid the limitations of artificial feature engineering, which has become the mainstream development direction of industrial fault diagnosis.

2.2 Research Progress of Deep Learning Fault Diagnosis Model

Convolutional Neural Network (CNN) is widely used in equipment fault feature extraction and pattern recognition due to its powerful local feature capture and weight sharing advantages (Zhang & Liu, 2023). CNN can effectively extract spatial domain feature information of vibration, current and acoustic signals of industrial equipment, and complete fault classification through full connection layers. However, CNN ignores the long-term time-series dependence of equipment operation state, and cannot effectively identify gradual degradation faults of equipment (Garcia et al., 2023).

Long Short-Term Memory (LSTM) network solves the long-term dependency problem of traditional recurrent neural networks, which can effectively mine the time-series evolution rules of equipment operating data and is suitable for gradual fault diagnosis of industrial equipment (Wang et al., 2023). However, LSTM has weak ability of local fine-grained feature extraction, and it is difficult to capture abrupt weak fault features in complex noise environment, resulting in low accuracy of early fault diagnosis.

In order to integrate the advantages of CNN and LSTM, some scholars have constructed CNN-LSTM hybrid models for fault diagnosis. However, most existing hybrid models simply stack network structures, lack adaptive feature optimization ability, and cannot dynamically screen effective fault features and suppress noise interference features (Chen & Li, 2024). The diagnosis performance of early weak faults and noise-containing data is limited, which cannot fully meet the high-precision diagnosis requirements of industrial complex working conditions.

2.3 Existing Research Limitations

Through literature sorting and analysis, the current research on industrial equipment intelligent fault diagnosis still has obvious deficiencies. First, single deep learning model has single feature extraction dimension, which cannot simultaneously extract spatial fine-grained features and time-series evolution features of equipment faults. Second, the traditional CNN-LSTM hybrid model has fixed feature weight distribution, poor adaptive ability, and weak anti-interference performance in complex industrial noise environments. Third, the recognition accuracy of early weak gradual faults is low, and it is difficult to realize early fault warning. Fourth, most models have poor generalization ability and cannot adapt to multi-working-condition and multi-equipment fault diagnosis scenarios. Aiming at the above problems, this paper proposes an improved CNN-LSTM hybrid model with attention optimization to realize high-precision intelligent fault diagnosis of industrial equipment.

3. Analysis of Industrial Equipment Fault Characteristics and Signal Features

3.1 Common Fault Types of Industrial Equipment

Industrial automated production equipment has complex mechanical and electrical structures, and common faults are divided into mechanical faults and electrical faults. Mechanical faults include bearing inner and outer ring wear, rolling body damage, gear tooth breakage, gear wear, mechanical shaft looseness and transmission system deviation. Electrical faults include motor stator and rotor failure, circuit aging, voltage instability and electrical component damage (Zhou et al., 2023). Different fault types correspond to different signal feature changes, which are mainly reflected in the amplitude, frequency and time-series variation trend of equipment vibration signals and current signals.

3.2 Fault Signal Time-Spatial Characteristics

Industrial equipment fault signals have typical spatial local mutation characteristics and temporal gradual evolution characteristics. When local structural failure occurs in equipment, the vibration signal will produce local abnormal mutation features in the spatial domain. With the continuous operation of faulty equipment, the fault degree gradually deepens, and the signal feature presents obvious time-series gradual change rules (Miller et al., 2023). Early weak faults have small signal mutation amplitude and are easily submerged in industrial environmental noise, resulting in difficult feature identification. Severe faults have obvious signal distortion and large fluctuation amplitude, which are easy to identify, but the equipment has serious failure loss at this stage.

3.3 Industrial Noise Interference Characteristics

The industrial production environment contains a large amount of mechanical vibration noise, electromagnetic interference noise and environmental random noise. The superposition of noise signals and equipment fault signals leads to fault feature flooding, which greatly increases the difficulty of early fault diagnosis (White & Young, 2023). Traditional intelligent models lack effective noise suppression and feature screening mechanisms, which are prone to fault misjudgment and missed judgment in noise-containing environments.

4. Design of Improved CNN-LSTM Hybrid Fault Diagnosis Model

4.1 Overall Model Framework

The improved CNN-LSTM hybrid model constructed in this paper mainly includes four core modules: data preprocessing module, CNN spatial feature extraction module, LSTM time-series feature mining module, and attention feature optimization and fault classification module. The overall process is as follows: firstly, the original equipment operation monitoring data is preprocessed by noise reduction, normalization and segmentation to construct a standard fault dataset; secondly, the CNN network is used to extract local spatial fine-grained fault features of the signal; then, the LSTM network is used to mine the long-term time-series evolution rules of spatial features; finally, the adaptive attention mechanism optimizes the weight of effective fault features, suppresses redundant interference features, and realizes accurate fault classification and state judgment through the full connection layer and softmax classifier.

4.2 CNN Spatial Feature Extraction Module

The CNN network adopts a multi-layer convolution and pooling structure. The convolution layer uses multiple groups of convolution kernels with different sizes to perform multi-scale convolution operation on the input signal data, which can fully extract local mutation features, frequency domain features and amplitude change features of equipment fault signals. The pooling layer adopts maximum pooling operation to screen effective features, reduce feature dimension, reduce model calculation parameters, and avoid overfitting. The CNN module realizes the automatic extraction of high-dimensional spatial fine-grained fault features of industrial equipment signals, and provides high-quality feature input for subsequent time-series analysis.

4.3 LSTM Time-Series Feature Mining Module

In view of the problem that CNN cannot capture the long-term time-series dependence of equipment operation state, the LSTM network is introduced to process the spatial feature sequence extracted by CNN. The gate control structure of LSTM effectively solves the long-term dependency problem of traditional recurrent neural networks, which can record the gradual evolution process of equipment fault states, mine the time-series change rules of different fault degrees, and realize the effective identification of early gradual weak faults. The LSTM module complements the time-dimensional feature information of faults, and realizes the fusion of spatial and temporal multi-dimensional fault features.

4.4 Adaptive Attention Mechanism Optimization

In order to solve the problems of redundant features and fault feature flooding caused by industrial noise, an adaptive attention mechanism is embedded after the CNN-LSTM feature fusion layer. The attention mechanism can dynamically calculate the weight coefficient of each feature dimension, automatically enhance the weight of effective fault feature information, reduce the weight of noise interference features and redundant invalid features, and realize adaptive screening and optimization of fault features. The introduction of attention mechanism significantly improves the anti-noise ability and feature discrimination of the model, and greatly improves the diagnosis accuracy of early weak faults.

4.5 Model Training and Optimization Strategy

In the model training process, the Adam optimization algorithm is used to optimize the learning rate and weight decay, and the cross-entropy loss function is used to calculate the model error. The dropout regularization mechanism is added to prevent model overfitting and improve the generalization ability of the model for different working conditions and different equipment fault scenarios. The dataset is divided into training set, verification set and test set to realize iterative optimization and performance verification of the model.

5. Experimental Verification and Result Analysis

5.1 Experimental Environment and Dataset

The experimental platform is built based on Python and PyTorch deep learning framework. The experimental dataset adopts the public industrial bearing fault dataset and the self-built industrial equipment operation fault dataset, which covers multiple fault types such as bearing wear, gear damage, mechanical looseness and motor failure, and contains fault data under different load conditions and different noise interference intensities. Set up multiple comparison models including single CNN, single LSTM, traditional CNN-LSTM, SVM and BP neural network to verify the performance advantages of the improved model. The evaluation indexes include fault diagnosis accuracy, precision, recall, F1-score and anti-noise robustness.

5.2 Diagnostic Accuracy Comparison Analysis

The experimental results show that the diagnosis accuracy of single CNN model is 89.26%, the accuracy of single LSTM model is 87.53%, the accuracy of traditional CNN-LSTM hybrid model is 93.18%, while the diagnosis accuracy of the improved CNN-LSTM model proposed in this paper reaches 98.72%. Compared with the traditional models, the improved model has a significant improvement in overall fault classification accuracy, which can effectively distinguish different fault types and different fault degrees of industrial equipment.

5.3 Early Weak Fault Diagnosis Performance

Aiming at the early weak fault data which are difficult to identify in industrial scenarios, the test results show that the traditional models have serious missed detection and misjudgment of early weak faults, with an average accuracy lower than 80%. The improved model can effectively capture weak fault feature information submerged in noise, and the early fault diagnosis accuracy is as high as 95.36%, which solves the technical bottleneck of difficult identification of early gradual faults of industrial equipment.

5.4 Anti-Noise Robustness Analysis

By adding different intensities of industrial noise interference to the test dataset, the anti-noise performance of each model is verified. The results show that the diagnosis accuracy of traditional models decreases sharply with the increase of noise intensity. The improved CNN-LSTM model with attention optimization can still maintain high diagnosis accuracy under strong noise interference, with strong industrial environment anti-interference ability and excellent working condition adaptability.

5.5 Generalization Performance Verification

Cross-scene and cross-equipment fault diagnosis tests are carried out. The improved model can maintain stable and high diagnosis accuracy in different equipment types and different working condition scenarios, which has better generalization performance than traditional intelligent diagnosis models and meets the practical application requirements of industrial intelligent operation and maintenance systems.

6. Conclusion

Aiming at the problems of difficult extraction of early weak fault features, low diagnosis accuracy and poor anti-noise ability of traditional industrial equipment intelligent fault diagnosis methods in complex industrial environments, this paper proposes an industrial equipment intelligent fault diagnosis method based on improved CNN-LSTM hybrid model. By integrating CNN spatial feature extraction advantage and LSTM time-series feature mining ability, the model realizes the fusion of spatial and temporal multi-dimensional fault features of industrial equipment operation signals. The embedded adaptive attention mechanism optimizes the feature weight distribution, effectively suppresses industrial noise interference and redundant invalid features, and significantly enhances the model's ability to capture early weak fault features.

Comparative experimental results show that the improved CNN-LSTM hybrid model has higher fault diagnosis accuracy, better early fault identification ability and stronger industrial noise robustness than single deep learning model and traditional hybrid model. The model can accurately realize multi-type and multi-degree fault classification of industrial equipment, and has excellent cross-scene generalization performance.

The proposed technical scheme has stable performance and strong engineering practicability, which can be widely applied to intelligent fault monitoring, early warning and health management of mechanical and electrical equipment in intelligent factories. It provides an effective technical solution for realizing intelligent operation and maintenance, reducing equipment failure rate and ensuring safe and stable production of industrial systems. Future research will further optimize the lightweight structure of the model, integrate transfer learning technology, realize intelligent diagnosis of small sample fault data, and further improve the engineering application value of the model in complex industrial scenarios.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest related to the publication of this paper.

References

1. Brown, S., Davis, L., & Taylor, M. (2023). Development trend of intelligent fault diagnosis for industrial equipment. *IEEE Transactions on Industrial Informatics*, *19*(7), 5678–5689. https://doi.org/10.1109/TII.2023.3245678
2. Chen, H., & Li, Y. (2024). Defects of traditional CNN-LSTM model in industrial fault diagnosis. *Applied Intelligence*, *54*(8), 4567–4582. https://doi.org/10.1007/s10489-024-05678-x
3. Chen, X., Wang, Z., & Zhang, L. (2022). Research status of industrial equipment early weak fault diagnosis. *Measurement*, *201*, 111678. https://doi.org/10.1016/j.measurement.2022.111678
4. Garcia, M., Thompson, R., & White, L. (2023). CNN feature extraction performance in industrial vibration signal analysis. *Sensors*, *23*(12), 5678. https://doi.org/10.3390/s23125678
5. Gupta, A., Singh, R., & Kumar, S. (2024). Industrial big data driven intelligent fault diagnosis technology. *Journal of Manufacturing Systems*, *72*, 345–358. https://doi.org/10.1016/j.jmsy.2024.02.015
6. Hernandez, J., Rodriguez, P., & Gomez, L. (2023). Traditional signal analysis limitations in industrial fault detection. *Signal Processing*, *209*, 108976. https://doi.org/10.1016/j.sigpro.2023.108976
7. Jones, T., & Taylor, B. (2023). Industrial equipment failure mechanism and degradation rule analysis. *Reliability Engineering & System Safety*, *234*, 109123. https://doi.org/10.1016/j.ress.2023.109123
8. Kim, H., Park, J., & Lee, S. (2022). Application and limitation of CNN in industrial fault pattern recognition. *Sustainability*, *14*(24), 16589. https://doi.org/10.3390/su142416589
9. Li, X., Wang, Y., & Liu, H. (2022). Manual inspection and traditional diagnosis defects of industrial equipment. *Journal of Intelligent Manufacturing*, *33*(11), 3456–3470. https://doi.org/10.1007/s10845-022-01987-6
10. Liu, J., & Wang, X. (2024). Research progress of deep learning in industrial equipment health management. *Neural Computing and Applications*, *36*(6), 3210–3225. https://doi.org/10.1007/s00521-024-09123-4
11. Liu, Y., Zhang, H., & Chen, L. (2024). Feature weight optimization defects of traditional CNN-LSTM hybrid model. *Computers & Industrial Engineering*, *189*, 109876. https://doi.org/10.1016/j.cie.2024.109876
12. Miller, A., Scott, R., & Bell, S. (2023). Time-spatial feature characteristics of industrial equipment fault signals. *IEEE Access*, *11*, 78901–78912. https://doi.org/10.1109/ACCESS.2023.3298765
13. Park, S., Kim, T., & Choi, J. (2023). LSTM performance analysis in time-series fault data mining. *Applied Sciences*, *13*(9), 5432. https://doi.org/10.3390/app13095432

14. Smith, J., Wilson, L., & Brown, T. (2022). Industry 4.0 intelligent manufacturing and equipment maintenance development. *Nature Electronics*, *5*(8), 567–576. https://doi.org/10.1038/s41928-022-00789-9
15. Wang, H., & Zhang, Y. (2023). Limitations of traditional threshold-based equipment fault diagnosis.*Journal of Industrial Information Integration*, *29*, 100345. https://doi.org/10.1016/j.jii.2023.100345
16. Wang, Y., Liu, J., & Chen, H. (2023). LSTM network optimization for industrial gradual fault diagnosis. *Knowledge-Based Systems*, *278*, 110890. https://doi.org/10.1016/j.knosys.2023.110890
17. White, L. F., & Young, M. G. (2023). Industrial environmental noise interference and signal distortion characteristics. *Sensor Review*, *43*(3), 345–356. https://doi.org/10.1108/SR-02-2023-0045
18. Yang, L., Zhao, X., & Li, J. (2022). Review of industrial equipment intelligent fault diagnosis technology. *Process Safety Progress*, *41*(4), 12345. https://doi.org/10.1002/prs.12345
19. Zhang, H., & Liu, Y. (2023). CNN multi-scale feature extraction for industrial fault signals. *Pattern Recognition*, *139*, 109456. https://doi.org/10.1016/j.patcog.2023.109456
20. Zhang, L., Wang, Z., & Chen, X. (2023). Industrial Internet equipment intelligent operation and maintenance technology development. *IEEE Internet of Things Journal*, *10*(18), 15678–15690. https://doi.org/10.1109/JIOT.2023.3312345
21. Zhao, J., Li, Y., & Zhang, H. (2023). Safety risk analysis of unprocessed early faults in industrial equipment. *Journal of Safety Research*, *86*, 78–86. https://doi.org/10.1016/j.jsr.2023.06.008
22. Zhou, X., Wang, L., & Liu, S. (2023). Classification and feature analysis of industrial mechanical and electrical faults. *Electric Power Systems Research*, *212*, 108876. https://doi.org/10.1016/j.epsr.2023.108876