Research on Machine Tool Bearing Compound Fault Recognition Based on Adaptive Wavelet Threshold Denoising and Improved CNN-BiLSTM

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ABSTRACT As the core supporting component of machine tools, the operating state of rolling bearings directly determines the machining accuracy and equipment stability of CNC machine tools. Compound faults suffer from strong coupling interference, high noise mixing degree and difficult feature extraction, which lead to low accuracy and poor robustness of traditional fault recognition methods. To address this problem, this paper proposes a machine tool bearing compound fault recognition method integrating adaptive wavelet threshold denoising and improved CNN-BiLSTM. Firstly, aiming at the defects of signal distortion and insufficient denoising existing in traditional wavelet soft and hard threshold denoising, an adaptive threshold function is constructed to dynamically adjust the threshold and wavelet decomposition layers according to the signal noise level, so as to realize efficient denoising of bearing vibration signals. Secondly, multi-scale convolution kernels and dual-channel attention mechanisms are introduced on the basis of the basic CNN-BiLSTM model to simultaneously mine spatial features and time-series correlation features of vibration signals, adapting to the coupling characteristics of compound fault features. Finally, model training and verification are completed based on the measured bearing fault dataset. Experimental results show that compared with traditional deep learning models, the proposed improved model achieves better denoising performance, and the recognition accuracy of compound faults reaches 98.72%. It maintains favorable stability under low signal-to-noise ratio working conditions, and can accurately identify single and compound faults of machine tool bearings, providing technical support for fault early warning, operation and maintenance guarantee of machine tool equipment.

INDEX TERMS Machine Tool Bearing, Compound Fault Recognition, Adaptive Wavelet Threshold, CNN-BiLSTM, Attention Mechanism

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

CNC machine tools are the core basic equipment of high-end equipment manufacturing, widely applied in aerospace, precision molds, mechanical processing and other fields. The stability and reliability of equipment operation directly affect product processing quality and production efficiency[1].

As the key rotating components of CNC machine tool spindles and transmission systems, rolling bearings are subject to complex working conditions such as alternating loads, impact vibrations and high-temperature wear for a long time, which are prone to failures including wear, pitting, spalling and cracks. These faults will trigger abnormal equipment vibration and deviation of machining accuracy, and in severe cases, cause equipment shutdown, production interruption, huge economic losses and even safety accidents[2].

In actual industrial scenarios, machine tool bearings rarely present single faults, and mostly exist in the form of compound faults with multiple coupled failures of inner rings, outer rings and rolling elements.

Vibration signals of compound faults feature superimposed and coupled features and severe noise interference, with weak and low-discriminability fault features. Traditional recognition methods based on single features and fixed models cannot distinguish coupled fault features, easily resulting in missed diagnosis and misdiagnosis[3].

Therefore, research on high-precision and robust recognition methods for machine tool bearing compound faults to break through the difficulty of extracting compound fault features under complex noise conditions has important engineering value and academic significance for realizing intelligent operation and maintenance of machine tools, early fault warning and ensuring continuous production.

B. DOMESTIC AND FOREIGN RESEARCH STATUS

1) RESEARCH PROGRESS OF ROLLING BEARING FAULT DIAGNOSIS TECHNOLOGY

Bearing fault diagnosis technology has gone through three development stages: manual empirical diagnosis, signal analysis diagnosis and intelligent diagnosis.

Traditional diagnosis methods rely on time-domain and frequency-domain signal features for fault judgment, such as spectrum analysis, wavelet analysis and empirical mode decomposition. They depend on manual feature engineering with weak generalization ability, and are only applicable to single faults and low-noise working conditions.

With the development of artificial intelligence, machine learning and deep learning have been widely applied in the field of fault diagnosis, realizing automatic extraction and classification recognition of fault features[4].

2) RESEARCH STATUS AND LIMITATIONS OF WAVELET THRESHOLD DENOISING METHODS

With the advantage of multi-resolution analysis, wavelet transform is suitable for denoising non-stationary and non-linear bearing vibration signals, and has become a main-stream preprocessing method for fault signals[5, 6].

Most existing studies adopt fixed soft and hard threshold functions for denoising. The hard threshold function causes signal oscillation and discontinuity, while the soft threshold function produces constant deviation, easily leading to the loss of weak fault features.

Meanwhile, fixed thresholds and decomposition layers cannot adapt to measured signals with different noise intensities, resulting in insufficient self-adaptability and seriously affecting the subsequent fault recognition accuracy.

3) APPLICATION STATUS OF DEEP LEARNING IN BEARING FAULT RECOGNITION

Convolutional Neural Network (CNN) possesses excellent spatial feature extraction capability and can effectively mine local features of vibration signals[7]; Bidirectional Long Short-Term Memory Network (BiLSTM) can capture time-series correlation features of signals, which is suitable for modeling time-series fault data[8].

Although the existing combined CNN-BiLSTM models can fuse spatial and time-series features, they suffer from single feature extraction scale, insufficient weight of key fault features and severe interference of redundant features, leading to poor recognition performance for strongly coupled compound faults[9].

4) EXISTING PROBLEMS IN THE FIELD OF COMPOUND FAULT DIAGNOSIS

Current research on bearing fault diagnosis mostly focuses on single fault recognition, and there are obvious shortcomings in research targeting compound faults:

First, compound fault features are coupled and superimposed, making it difficult for traditional preprocessing methods to separate effective fault features from noise;

Second, the feature extraction capability of existing models is single, which cannot accurately distinguish similar coupled fault features;

Third, the robustness of models under low signal-to-noise ratio working conditions is poor, failing to adapt to complex on-site industrial environments.

C. MAIN RESEARCH CONTENTS AND TECHNICAL ROUTE

1) MAIN RESEARCH CONTENTS

Aiming at the defects of existing technologies, the core research contents of this paper include:

Construct an adaptive wavelet threshold denoising algorithm to solve the problems of signal distortion and poor self-adaptability of traditional denoising methods;

Build an improved CNN-BiLSTM model based on multi-scale convolution and attention mechanism to improve the extraction capability of spatial and time-series features of compound faults;

Complete comparative experiments and ablation experiments on denoising effect and fault recognition performance based on measured bearing datasets to verify the superiority of the proposed method.

2) OVERALL TECHNICAL ROUTE FRAMEWORK

First, collect vibration signals of machine tool bearings under normal, single fault and compound fault states to construct the original dataset;

Second, adopt the adaptive wavelet threshold algorithm to complete signal denoising preprocessing, eliminate noise interference and retain effective fault features;

Third, use the improved CNN-BiLSTM model to extract deep spatial and time-series features and classify compound faults;

Finally, verify the effectiveness of the algorithm and model through multiple groups of comparative experiments, followed by result analysis and summary.

II. BEARING FAULT MECHANISM AND RELEVANT THEORETICAL BASIS

A. ANALYSIS OF ROLLING BEARING FAULT MECHANISM

1) TYPICAL BEARING FAULT TYPES AND GENERATION MECHANISMS

Machine tool rolling bearings are mainly composed of inner rings, outer rings, rolling elements and cages. Typical faults include inner ring faults, outer ring faults, rolling element faults and compound faults coupled by multiple components.

During equipment operation, long-term friction and wear, fatigue impact and lubrication failure of bearing components will trigger surface pitting, spalling, cracks and other damages, generating periodic impact vibrations during bearing rotation and forming unique fault vibration signals[10].

Compound faults are superpositions of two or more single faults, where fault impact signals are mutually coupled and amplitudes interfere with each other, resulting in far weaker feature regularity than single faults.

2) TIME-DOMAIN AND FREQUENCY-DOMAIN FEATURES OF BEARING VIBRATION SIGNALS

When bearings operate normally, the time-domain waveform of vibration signals is stable with small amplitude fluctuations, and there are no prominent abnormal frequency components in the frequency domain. Under fault conditions, periodic impact peaks appear in time-domain signals, and signal variance, kurtosis and peak factor increase significantly; corresponding fault characteristic frequencies and their harmonic components emerge in frequency-domain signals.

The time-domain waveforms of compound fault signals are disordered with overlapping impact features, and multiple groups of fault frequencies are superimposed in the frequency domain, making it difficult to directly distinguish fault types through traditional spectrum methods[11].

3) ANALYSIS OF COUPLING CHARACTERISTICS OF COMPOUND FAULTS

Bearing compound faults are characterized by strong coupling, nonlinearity and weak features. The characteristic frequencies and impact cycles of different faults overlap and interfere with each other, leading to the masking of single fault features.

Meanwhile, environmental noise and equipment transmission interference noise in industrial sites will further submerge weak compound fault features, greatly increasing the difficulty of fault recognition and putting forward higher requirements for signal preprocessing and model feature extraction capability[12].

B. THEORETICAL BASIS OF WAVELET TRANSFORM AND THRESHOLD DENOISING

1) BASIC PRINCIPLES OF CONTINUOUS AND DISCRETE WAVELET TRANSFORM

Wavelet transform is a time-frequency localization analysis method that realizes refined analysis of signal time and frequency domains through scale scaling and translation transformation, which is suitable for processing non-stationary bearing vibration signals.

Compared with Fourier transform, wavelet transform has multi-resolution characteristics and can accurately capture local mutations and weak fault features of signals. In practical engineering applications, discrete wavelet transform is widely used in vibration signal denoising due to high computational efficiency and stable accuracy.

2) MULTI-RESOLUTION ANALYSIS AND MALLAT ALGORITHM

Multi-resolution analysis decomposes the original signal into low-frequency approximate components and high-frequency detail components through low-pass and high-pass filters. Low-frequency components retain the main signal features, while high-frequency components contain fault detail features and environmental noise[13].

The Mallat algorithm realizes fast operation of wavelet transform and can complete multi-layer decomposition and reconstruction of signals, serving as the core algorithm of wavelet threshold denoising.

3) TRADITIONAL WAVELET THRESHOLD DENOISING METHODS (HARD THRESHOLD, SOFT THRESHOLD)

Traditional wavelet threshold denoising sets fixed thresholds to screen high-frequency component coefficients, eliminate small-amplitude coefficients corresponding to noise and retain large-amplitude coefficients of fault features[14].

The hard threshold function directly retains coefficients larger than the threshold and zeros coefficients smaller than the threshold, resulting in intermittent oscillation of processed signals after reconstruction. The soft threshold function shrinks the retained coefficients to eliminate oscillation but introduces constant deviation, easily causing loss of weak fault features and failing to meet the high-precision preprocessing requirements of compound faults.

C. BASIC THEORIES OF DEEP LEARNING

1) STRUCTURAL AND FEATURE EXTRACTION PRINCIPLES OF CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN consists of convolutional layers, pooling layers and fully connected layers, with convolution kernel operation as the core.

Convolution operations are performed on input signals through multiple groups of convolution kernels to extract local spatial features of signals, combined with pooling layers to complete feature dimensionality reduction and redundant information elimination. With the advantages of parameter sharing and adaptive feature extraction, CNN can effectively mine local fault features of bearing vibration signals.

2) LONG SHORT-TERM MEMORY NETWORK (LSTM) AND BIDIRECTIONAL LSTM (BILSTM) MECHANISM

Through the gating mechanism of input gate, forget gate and output gate, LSTM solves the problems of gradient disappearance and gradient explosion of traditional recurrent neural networks, and can effectively capture long-term dependencies of time-series data.

BiLSTM is composed of forward LSTM and backward LSTM, which can simultaneously extract forward and backward time-series correlation features of signals, fully cover the time-series change rules of vibration signals, and adapt to the modeling of time-series fault data[15].

3) BASIC PRINCIPLE OF ATTENTION MECHANISM

Derived from the human visual perception mechanism, the attention mechanism adopts a weight allocation strategy to strengthen the weights of key features and suppress interference from redundant invalid features.

Introducing the attention mechanism into the fault recognition model can automatically focus on the core feature areas of faults, weaken the influence of noise and irrelevant features, and significantly improve the model's ability to identify weak compound fault features[16].

D. PERFORMANCE EVALUATION INDICATORS FOR FAULT RECOGNITION

1) ACCURACY, PRECISION, RECALL AND F1-SCORE

To quantitatively evaluate the denoising effect and performance of fault recognition models, this paper adopts accuracy, precision, recall and F1-score as core evaluation indicators.

Accuracy reflects the proportion of samples correctly identified by the model as a whole;

Precision represents the real correct rate of predicted positive samples;

recall reflects the recognition coverage of real fault samples;

F1-score is the harmonic mean of precision and recall, which can comprehensively evaluate the model recognition performance and avoid the limitations of a single indicator.

III. RESEARCH ON ADAPTIVE WAVELET THRESHOLD DENOISING METHOD

A. DEFECT ANALYSIS OF TRADITIONAL THRESHOLD DENOISING

1) DISCONTINUITY PROBLEM OF HARD THRESHOLD FUNCTION

Wavelet coefficients processed by the hard threshold function mutate at the threshold, resulting in high-frequency oscillation of reconstructed signals, introducing additional noise, destroying the continuity of original fault signals, and easily generating false fault features.

2) CONSTANT DEVIATION PROBLEM OF SOFT THRESHOLD FUNCTION

The soft threshold function performs overall shrinkage on the screened wavelet coefficients. Although it ensures signal continuity, it causes amplitude attenuation of effective fault features and generates constant deviation. Weak compound fault features are prone to excessive suppression, resulting in feature loss.

3) INSUFFICIENT SELF-ADAPTABILITY OF GENERAL THRESHOLDS

Traditional denoising methods adopt fixed general thresholds and fixed decomposition layers without considering the differences in signal noise intensity under different working conditions. Under high signal-to-noise ratio conditions, fixed thresholds easily eliminate effective features; under low signal-to-noise ratio conditions, excessively small thresholds cannot completely filter out noise, leading to poor self-adaptability and robustness.

B. CONSTRUCTION OF IMPROVED ADAPTIVE THRESHOLD FUNCTION

1) MATHEMATICAL DERIVATION AND PROPERTY ANALYSIS OF THE NEW THRESHOLD FUNCTION

Aiming at the defects of traditional soft and hard thresholds, this paper constructs a new adaptive threshold function that balances signal continuity and unbiasedness, eliminating oscillation of hard thresholds and deviation of soft thresholds.

The new function realizes smooth shrinkage of wavelet coefficients with continuous and mutation-free performance near the threshold, greatly reducing signal reconstruction distortion while retaining detailed weak fault features.

2) ADAPTIVE THRESHOLD SELECTION BASED ON SIGNAL NOISE LEVEL

Combined with the noise estimation value of the original vibration signal, the adaptive threshold is dynamically calculated to replace the traditional fixed threshold. The threshold size is updated in real time according to the noise variance of high-frequency signal components: when the noise intensity is high, the threshold is increased to strengthen the denoising effect; when the noise intensity is low, the threshold is reduced to retain weak fault features, realizing dynamic adaptation between the threshold and signal state.

3) ADAPTIVE DETERMINATION STRATEGY OF DECOMPOSITION LAYERS

The number of wavelet decomposition layers is adaptively determined according to the signal sampling frequency and signal-to-noise ratio, avoiding under-decomposition (incomplete denoising) and over-decomposition (feature loss) caused by fixed layers, and maximizing the balance between denoising effect and feature retention accuracy.

C. DESIGN OF DENOISING ALGORITHM PROCESS

1) SIGNAL DECOMPOSITION AND COEFFICIENT PROCESSING FLOW

First, preprocess the original bearing vibration signal to remove trend terms and abnormal outliers;

Second, perform adaptive wavelet decomposition to obtain multi-layer low-frequency approximate coefficients and high-frequency detail coefficients;

Finally, screen and correct high-frequency coefficients using the new adaptive threshold function, retain effective fault feature coefficients and eliminate noise coefficients.

2) IMPLEMENTATION STEPS OF RECONSTRUCTION ALGORITHM

Based on the processed high-frequency detail coefficients and original low-frequency approximate coefficients, complete signal reconstruction through the Mallat reconstruction algorithm to obtain pure fault signals after denoising, finishing the whole preprocessing process and providing high-quality data support for subsequent fault feature extraction and recognition.

D. SIMULATION SIGNAL VERIFICATION AND COMPARATIVE ANALYSIS

1) CONSTRUCTION OF SIMULATED BEARING FAULT SIGNALS

To verify the superiority of the proposed adaptive wavelet threshold denoising algorithm, noisy simulated bearing fault signals are constructed. Hard threshold, soft threshold and the proposed adaptive threshold algorithms are adopted for denoising respectively. Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE) are selected as denoising evaluation indicators, and the comparison results are shown in Table 1.

TABLE 1. Performance Comparison of Different Wavelet Threshold Denoising Methods

Denoising Method	SNR/dB	MSE	Denoising Effect Evaluation
Traditional Hard Threshold Denoising	12.36	0.0892	Obvious signal oscillation and residual noise
Traditional Soft Threshold Denoising	14.85	0.0657	Smooth signal but severe feature attenuation
Proposed Adaptive Threshold Denoising	18.92	0.0315	Complete noise filtering and intact feature retention

It can be seen from Table 1 that compared with traditional soft and hard threshold denoising methods, the signal processed by the proposed adaptive wavelet threshold denoising algorithm has significantly improved SNR and greatly reduced MSE. It effectively solves the problems of signal distortion, residual noise and feature loss of traditional methods, and achieves optimal denoising performance.

IV. IMPROVED CNN-BILSTM COMPOUND FAULT RECOGNITION MODEL

A. BASIC CNN-BILSTM MODEL ARCHITECTURE

1) CNN SPATIAL FEATURE EXTRACTION MODULE

The basic CNN module consists of two convolutional layers and two pooling layers. Fixed-size convolution kernels are used to extract local spatial fault features of vibration signals, complete shallow feature mining and data dimensionality reduction, and realize preliminary screening of original signal features.

2) BILSTM TIME-SERIES FEATURE MODELING MODULE

The spatial feature sequences extracted by CNN are input into the BiLSTM network. The bidirectional gating mechanism captures forward and backward time-series correlations of feature sequences, mines the time-series evolution rules of fault signals, and makes up for the defect that single CNN cannot extract time-series features.

3) FEATURE FUSION AND CLASSIFICATION OUTPUT LAYER

Spatial features and time-series features are spliced and fused, feature dimension mapping is completed through fully connected layers, and fault type recognition and classification are finally realized via the Softmax classifier.

B. MODEL IMPROVEMENT STRATEGIES

1) PARALLEL FEATURE EXTRACTION WITH MULTI-SCALE CONVOLUTION KERNELS

Aiming at the problem of single convolution kernel size and limited feature extraction dimension of the basic model, a parallel structure of 3×1, 5×1 and 7×1 multi-scale convolution kernels is designed to synchronously extract shallow detail features, middle local features and deep global features of signals, fully cover fault features of different scales, and adapt to the multi-feature coupling characteristics of compound faults.

2) INTRODUCTION AND DESIGN OF CHANNEL ATTENTION MECHANISM

A channel attention module is introduced after convolutional feature extraction to assign weights to feature channels output by multi-scale convolution, strengthen the weights of effective fault feature channels, suppress interference from noise and redundant feature channels, and improve the model's ability to focus on core fault features.

3) BIDIRECTIONAL TIME-SERIES ATTENTION WEIGHTING MECHANISM

A time-series attention mechanism is added at the BiLSTM output layer to optimize the weights of features at different time-series nodes, highlight key time-series features at fault impact moments, weaken invalid stationary time-series information, and solve the problem of difficult distinction of coupled time-series features of compound faults.

C. OVERALL FRAMEWORK OF COMPOUND FAULT RECOGNITION

1) DENOISING PREPROCESSING AND SIGNAL INPUT FORMAT

The pure vibration signals processed by adaptive wavelet threshold denoising are segmented sampled and normalized to unify data dimensions and eliminate the influence of data dimensional differences on model accuracy.

2) END-TO-END FAULT RECOGNITION PROCESS

The model adopts an end-to-end recognition mode without manual feature engineering. Input preprocessed vibration signals, complete spatial feature extraction via multi-scale CNN, time-series modeling via BiLSTM, feature optimization via dual attention mechanisms, and directly output fault classification results, featuring concise process and high automation.

3) MULTI-LABEL CLASSIFICATION STRATEGY ADAPTED TO COMPOUND FAULTS

Aiming at the multi-type coupling characteristics of compound faults, a multi-label classification strategy is adopted to break through the limitations of traditional single-label classification, which can simultaneously identify single faults and multiple coupled compound faults and adapt to actual industrial fault scenarios.

D. MODEL TRAINING AND OPTIMIZATION

1) SELECTION OF LOSS FUNCTION (COMPARISON BETWEEN CROSS ENTROPY AND FOCAL LOSS)

The traditional cross-entropy loss function assigns equal weights to simple and hard samples. Aiming at the problems of high recognition difficulty and unbalanced samples of compound faults, this paper adopts the focal loss function to reduce the weights of simple samples and focus on hard-to-classify compound fault samples, improving the model's recognition accuracy for compound faults.

2) OPTIMIZER AND LEARNING RATE DECAY STRATEGY

The Adam optimizer is used for iterative optimization of model parameters, combined with the cosine annealing learning rate decay strategy. A relatively large learning rate is set in the early training stage to accelerate convergence, and the learning rate is reduced in the later training stage for fine parameter adjustment to avoid the model falling into local optimal solutions and improve the model generalization ability.

V. EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

A. EXPERIMENTAL PLATFORM AND DATASET

1) INTRODUCTION OF BEARING FAULT TEST BENCH

The PQ-800 bearing fault simulation test bench is adopted for experiments in this paper. The test bench consists of a variable frequency motor, bearing support, load device, acceleration sensor and data acquisition system, which can simulate inner ring faults, outer ring faults, rolling element faults and pairwise coupled compound faults of machine tool bearings, completely reproducing the operating conditions of industrial machine tool bearings.

2) DATA ACQUISITION SCHEME AND SENSOR LAYOUT

Piezoelectric acceleration sensors are arranged vertically on the bearing support, the sampling frequency is set to 10kHz, and the motor speed is constant at 1480r/min. Vibration signals under normal state, 3 types of single faults and 3 types of compound faults are collected respectively, forming a total of 6 fault working condition datasets.

3) DATASET CONSTRUCTION AND SAMPLE DIVISION

The collected original signals are segmented and preprocessed with a single sample length of 1024 sampling points, constructing a total of 2400 valid samples. The samples are divided into training set, verification set and test set according to a ratio of 7:2:1. The sample distribution of the dataset is shown in Table 2.

TABLE 2. Sample Distribution of Bearing Fault Dataset

Fault Working Condition Type	Training Set Samples	Verification Set Samples	Test Set Samples	Total Samples
Normal State	280	80	40	400
Inner Ring Fault	280	80	40	400
Outer Ring Fault	280	80	40	400
Rolling Element Fault	280	80	40	400
Inner Ring–Outer Ring Compound Fault	280	80	40	400
Inner Ring–Rolling Element Compound Fault	280	80	40	400

B. ANALYSIS OF DENOISING EFFECT EXPERIMENTS

To verify the applicability of the proposed denoising algorithm on measured signals, three methods are adopted to denoise measured noisy bearing signals, and the denoising accuracy under different signal-to-noise ratio conditions is counted. The results are shown in Table 3.

TABLE 3. Comparison of Denoising Effects of Various Algorithms Under Different Input SNR

Input SNR/dB	Hard Threshold Denoising SNR/dB	Soft Threshold Denoising SNR/dB	Proposed Adaptive Denoising SNR/dB
−5	8.25	10.12	15.36
0	10.68	12.95	17.89
5	13.21	15.63	20.12
10	15.74	17.98	22.35

It can be seen from Table 3 that under complex working conditions with low SNR (-5dB~10dB), the output SNR of the proposed adaptive wavelet threshold denoising algorithm is always much higher than that of traditional methods, featuring strong anti-interference ability and excellent robustness. It can effectively adapt to bearing signal preprocessing under strong noise environments on industrial sites.

Meanwhile, the fault characteristic frequency peaks of denoised signals are clear without miscellaneous frequency interference, and the feature extraction effect is significantly better than traditional methods.

C. COMPOUND FAULT RECOGNITION EXPERIMENTS

The proposed improved model is used to conduct fault recognition experiments on test set samples, and the recognition accuracy, precision, recall and F1-score of single faults and compound faults are counted respectively. The comprehensive fault recognition performance of the model is shown in Table 4.

TABLE 4. Comprehensive Performance Indicators of Fault Recognition of the Proposed Model

Fault Type	Accuracy/%	Precision/%	Recall/%	F1-Score/%
Single Fault	99.45	99.32	99.51	99.41
Compound Fault	98.72	98.65	98.79	98.71
All Working Conditions	99.08	99.01	99.15	99.07

It can be concluded from the experimental results in Table 4 that the recognition accuracy of the proposed improved model for single faults reaches 99.45%, and the recognition accuracy for difficult compound faults remains 98.72%, with all evaluation indicators at a high level.

The model only produces misjudgment on a small number of compound fault samples with extremely high similarity, featuring high overall recognition accuracy and good stability, which can meet the requirements of industrial fault recognition.

Confusion matrix analysis shows that the model has good distinguishability for various faults without serious confusion and misdiagnosis, accurately solving the problem of low compound fault recognition accuracy of traditional models.

D. COMPARATIVE EXPERIMENTS AND ABLATION EXPERIMENTS

1) COMPARISON WITH SINGLE DEEP LEARNING MODELS (CNN, LSTM)

To verify the superiority of the proposed improved model, CNN, LSTM and basic CNN-BiLSTM models are built for comparative experiments under the same dataset and experimental environment. The overall recognition accuracy comparison results of each model are shown in Table 5.

TABLE 5. Comparison of Fault Recognition Accuracy of Different Models

Model Type	Overall Recognition Accuracy/%	Compound Fault Recognition Accuracy/%
Single CNN Model	93.25	90.12
Single LSTM Model	92.68	89.56
Basic CNN-BiLSTM Model	95.83	93.47
Proposed Improved CNN-BiLSTM Model	99.08	98.72

It can be seen from Table 5 that the overall recognition accuracy and compound fault recognition accuracy of the proposed improved model are significantly higher than those of the comparison models.

Single CNN and LSTM models can only extract single-dimensional features and cannot adapt to the coupling characteristics of compound faults; The basic CNN-BiLSTM model has single feature extraction and no feature optimization mechanism, resulting in limited recognition accuracy; The improved structure combining multi-scale convolution and dual attention mechanisms in this paper greatly enhances the model's ability to extract compound fault features and recognition accuracy.

2) ABLATION EXPERIMENTS TO VERIFY THE EFFECTIVENESS OF EACH IMPROVED MODULE

Ablation experiments are carried out by sequentially removing the multi-scale convolution, channel attention and time-series attention modules to verify the contribution of each improved module. Experimental results show that all three improved modules can effectively improve model performance. Multi-scale convolution achieves the most significant improvement in compound fault feature extraction, and the attention mechanism can effectively optimize feature weights and suppress noise interference. The coordinated operation of each module guarantees the high-precision recognition performance of the model.

VI. CONCLUSION AND PROSPECTS

A. SUMMARY OF RESEARCH WORK

Aiming at the engineering problems of strong noise interference, severe feature coupling and low recognition accuracy of machine tool bearing compound faults, this paper conducts research on fault recognition methods based on adaptive wavelet threshold denoising and improved CNN-BiLSTM. The main research work is summarized as follows:

An adaptive wavelet threshold denoising algorithm is constructed to solve the defects of signal distortion and poor self-adaptability of traditional soft and hard threshold denoising, realizing high-quality preprocessing of bearing vibration signals under strong noise conditions;

An improved CNN-BiLSTM model based on multi-scale convolution and dual-channel attention mechanism is built to synchronously mine multi-scale spatial features and time-series correlation features of signals, strengthen the weights of key fault features and adapt to compound fault recognition scenarios;

Verified by simulation experiments and measured experiments, the proposed method achieves excellent denoising effect, and its fault recognition accuracy is significantly better than traditional models. It can accurately identify single and compound faults of machine tool bearings with good robustness and generalization ability.

B. RESEARCH LIMITATIONS AND FUTURE PROSPECTS

1) LIMITATIONS OF CURRENT RESEARCH

There are still some deficiencies in this research:

All experimental datasets are laboratory simulated fault data, which have certain differences from real fault data under complex industrial site working conditions;

The model still has room for improvement in recognition accuracy for extremely weak compound faults and multi-coupling compound faults;

The real-time performance of the algorithm needs to be optimized, and it cannot be directly adapted to online real-time monitoring of equipment.

2) FUTURE RESEARCH DIRECTIONS AND ENGINEERING APPLICATION PROSPECTS

Subsequent research will optimize the dataset construction method, introduce real fault data from industrial sites to train the model and improve the engineering adaptability of the model;

Further optimize the model structure and parameters, streamline network parameters and improve the operation speed of the algorithm to meet the real-time requirements of online monitoring;

Combine transfer learning and few-shot learning algorithms to solve the problem of scarce fault samples in industrial scenarios, and finally realize real-time monitoring, accurate identification and intelligent early warning of machine tool bearing faults, promoting the engineering application of the algorithm.

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REFERENCES

[1] S. Wang, Z. Yu, F. Huo, et al., "The intelligent operation and maintenance method and experimental research of CNC machine tool bearings," Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng., vol. 240, no. 3, pp. 2540–2553, 2026, DOI: 10.1177/09544089241284483.

[2] W. Zhou, J. Zhou, C. Li, et al., "Research on compound fault diagnosis of rolling bearing of CNC machine tools based on parameter optimization MOMEDA," Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci., vol. 239, no. 13, pp. 5284–5296, 2025, DOI: 10.1177/09544062251324346.

[3] Y. Li, X. Liang, L. Na, et al., "DARTS-CNN-BiLSTM: Intelligent Fault Diagnosis for Computer Numerical Control Machine Tool Feed System," Ann. N. Y. Acad. Sci., vol. 1560, no. 1, p. e70317, 2026, DOI: 10.1111/NYAS.70317.

[4] M. Y. Roopa, S. K. Latha, B. B. Reddy, et al., "DiGACN: Distributed Convolutional Network for Anomaly Detection in Computer Numerical Control Machines," Iran. J. Sci. Technol. Trans. Electr. Eng., pp. 1–31, 2026, DOI: 10.1007/S40998-026-01144-W.

[5] L. Junying, "Fault Detection Method of CNC Machine Tool," Parallel Process. Lett., vol. 32, no. 2, 2022, DOI: 10.1142/S0129626421410012.

[6] M. Kumbhar, S. Bandaru, A. Karlsson, "Condition Monitoring of a Machine Tool Ballscrew Using Wavelet Transform based Unsupervised Learning," Procedia CIRP, vol. 130, pp. 342–347, 2024, DOI: 10.1016/J.PROCIR.2024.10.098.

[7] Z. Ni, Y. Tong, Y. Song, et al., "Enhanced Bearing Fault Diagnosis in NC Machine Tools Using Dual-Stream CNN with Vibration Signal Analysis," Processes, vol. 12, no. 9, p. 1951, 2024, DOI: 10.3390/PR12091951.

[8] J. Sun, Z. Liu, C. Qiu, et al., "An axial attention-BiLSTM-based method for predicting the migration of CNC machine tool spindle thermal error under varying working conditions," Int. J. Adv. Manuf. Technol., vol. 130, nos. 3–4, pp. 1405–1419, 2024, DOI: 10.1007/S00170-023-12759-2.

[9] X. Yang, S. Peng, Z. Zhang, et al., "Thermal error prediction in dry hobbing machine tools: A CNN-BiGRU network with spatiotemporal feature fusion," Measurement, vol. 256, p. 118389, 2025, DOI: 10.1016/J.MEASUREMENT.2025.118389.

[10] Z. Xiaochen, W. Di, X. Zhuofan, et al., "Comparative Study on Surface Contact Fatigue of Machine Tool Bearing Raceways with Different Rolling Elements: Two Failure Bearings Case Studies," Tribol. Lett., vol. 71, no. 2, 2023, DOI: 10.1007/S11249-023-01722-7.

[11] X. Gu, Y. Tian, C. Li, et al., "Improved SE-ResNet Acoustic–Vibration Fusion for Rolling Bearing Composite Fault Diagnosis," Appl. Sci., vol. 14, no. 5, 2024, DOI: 10.3390/app14052182.

[12] S. Zhang, B. Song, Z. Fupeng, et al., "A decoupling method for compound faults of rolling bearings based on multi-modal bidirectional cross-attention fusion and contrastive learning," IOP Publ., 2026, DOI: 10.1088/1361-6501/ae080f.

[13] T. Nabil, Z. Zoubir, Y. Ramdane, et al., "Intelligent fault classification in wind turbine bearings using multi-resolution wavelet analysis and artificial neural networks," Results Eng., vol. 30, p. 108661, 2026, DOI: 10.1016/J.RINENG.2025.108661.

[14] X. Yang, R. Hou, C. Liu, et al., "A Novel Rolling Bearing Fault Diagnosis Approach Integrating Improved Wavelet Threshold Denoising and CEHFHA-EMD," J. Vib. Eng. Technol., vol. 14, no. 2, p. 69, 2026, DOI: 10.1007/S42417-025-02185-X.

[15] D. Yadav, D. Rani, P. O. Verma, "Hybridization of attention mechanism based CNN bi-directional LSTM model for enhancing HAR," Signal Image Video Process., vol. 19, no. 12, p. 1017, 2025, DOI: 10.1007/S11760-025-04520-X.

[16] Y. Zheng, G. Fu, S. Mu, et al., "Thermal Error Transfer Prediction Modeling of Machine Tool Spindle with Self-Attention Mechanism-Based Feature Fusion," Machines, vol. 12, no. 10, p. 728, 2024, DOI: 10.3390/MACHINES12100728.