

Identification of Electrical Abnormal Signals Based on Deep Learning Methods

Ziyang Wang
China Jiliang University
258 Xueyuan St, Hangzhou, Zhejiang 310018, P R China

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Abstract

In the field of abnormal event detection, optical fiber vibration data is increasingly being applied. However, existing detection methods have shortcomings, necessitating new technologies to enhance performance. This study uses optical fiber vibration data for electrical signal classification. Fiber optic sensor signals are collected under conditions such as calmness, shaking, and pressing. Through time-domain and frequency-domain feature extraction, combined with recursive feature elimination to screen key features, models such as support vector machines (SVM), linear discriminant analysis (LDA), long short-term memory networks (LSTM), gated recurrent units (GRU), and convolutional neural networks (CNN) are constructed. Experiments show that the CNN model has better classification accuracy.

Keywords: optical fiber vibration data; electrical signal classification; deep learning; feature extraction.

1. Introduction

With the continuous development of technology, optical fiber vibration data has been widely applied in the field of anomaly detection. Fiber optic sensors, with their high sensitivity and strong anti-electromagnetic interference capabilities, can collect rich vibration data in real-time, providing powerful means for monitoring abnormal events (Luo et al., 2023). Currently, common detection methods are mostly based on traditional signal processing techniques, identifying anomalies through time-domain or frequency-domain analysis of optical fiber vibration data. However, these methods often face many challenges (Lin et al., 2024). On one hand, vibration signals in real environments are complex and diverse, with severe noise interference, making it difficult for traditional methods to accurately extract effective features, resulting in low detection accuracy. On the other hand, traditional detection methods are usually designed for specific types of abnormal events, with poor generalization ability and difficulty in adapting to detection needs in different scenarios (Wang et al., 2024). Therefore, this study aims to explore new methods using machine learning and deep learning models to classify optic fiber vibration electrical signals, in order to improve anomaly detection performance, which has important practical significance.

Theoretically, the application of machine learning and deep learning models for classifying optical fiber vibration electrical signals provides new ideas and methods for research in the field of anomaly detection. Traditional signal processing methods have limitations in handling complex data, while machine learning and deep learning models possess powerful feature learning and pattern recognition capabilities. They can automatically extract effective features from large amounts of data and build complex classification models, thereby supporting the further development of anomaly detection theory. In practical applications, accurate signal classification can significantly improve the accuracy of anomaly detection, timely identify potential security risks, and ensure the safe and stable operation of various systems. For example, in power systems, real-time monitoring of power equipment operation status can be achieved through accurate classification of optical fiber vibration electrical signals, enabling early detection of equipment failures and prevention of power outages. Meanwhile, this classification method also helps improve detection efficiency, reduce the cost of manual intervention, and provide more efficient and reliable solutions for practical applications of anomaly detection (Lin et al., 2024; Wang et al., 2024; Adrian et al., 2023; Chen and Zhang, 2018).

In the field of anomaly detection, optical fiber vibration data has shown significant application value. In previous studies, some scholars used optical fiber vibration data to detect specific types of anomalies (Adrian et al., 2023). For example, by extracting time-domain and frequency-domain features of optical fiber vibration signals and combining them with traditional threshold judgment methods, preliminary detection of intrusion events was achieved. However, such methods have poor adaptability to complex and variable anomaly scenarios, prone to false positives and false negatives. In terms of signal classification, some studies have attempted to use simple machine learning algorithms to classify optical fiber vibration signals. For instance, Support Vector Machine (SVM) was used to distinguish different types of optical fiber vibration signals, but the classification accuracy was limited, making it difficult to meet practical application requirements (Qi et al., 2024). Overall, existing research has achieved certain results in utilising optical fiber vibration data, but there is still room for improvement in the accuracy of anomaly detection and the granularity of signal classification.

Machine learning algorithms are widely applied in signal classification. Support Vector Machine (SVM) effectively separates signals of different classes by finding the optimal hyperplane. It has certain advantages in small-sample and nonlinear signal classification problems, but its processing efficiency is relatively low for large-scale datasets (Yang et al., 2012). Linear Discriminant Analysis (LDA) projects high-dimensional signal data into low-dimensional space through dimensionality reduction, making signals of the same class gather as closely as possible while keeping signals of different classes apart as much as possible. It is suitable for signal classification tasks with redundant features, but it has strict assumptions about data distribution (Wang et al., 2025). In deep learning models, Long Short-Term Memory (LSTM) networks can handle long-term dependencies in sequential data and perform well in tasks such as speech recognition and time series signal classification. However, LSTM models have complex structures and require training time (Ribeiro et al., 2012). Gated Recurrent Unit (GRU), as a

simplified version of LSTM, maintains good classification performance while reducing model parameters and computational complexity, making it suitable in resource-constrained scenarios (Salem 2022). However, GRU's ability to handle complex sequential signals is slightly inferior to LSTM (Wang et al., 2025). Convolutional Neural Networks (CNN) automatically extract local features of signals through convolutional and pooling layers, achieving significant results in image and speech signal classification. CNN has unique advantages for signal classification tasks with local correlations, but may suffer from information loss when processing long sequential signals.

Current research on optical fiber vibration electrical signal classification is mostly limited to the application of single models, and the feature extraction methods are relatively traditional. This study selects multiple models for combination, such as combining CNN with LSTM, to fully utilize the advantages of CNN in extracting local features and LSTM in processing sequence data, with the aim of improving classification accuracy and generalization ability (Ribeiro 2002; Salem 2022). In terms of feature extraction, recursive feature elimination is combined with traditional time-domain and frequency-domain feature extraction methods to achieve effective screening of key features, reduce dimensions, improve model training efficiency, and provide new ideas and methods for optical fiber vibration electrical signal classification.

2. Method

2.1 Data Acquisition

The data for this project comes from experiments. The electrical signals from the same fiber optic sensor are recorded under three conditions: calm, shaking, and pressing. The sampling frequency of the signals is 18,680,000 Hz, and the duration of each sample is 0.01 seconds, containing 186,800 data points. Each sample includes 100 cycles. The samples for each condition are stored in three separate folders. Therefore, any sample data in this project can be viewed as a sequence with 186,800 data points. Since it is a vibration signal read by the sensor, we hypothesize that it may exhibit periodicity.

To obtain representative electrical signal data of optical fiber vibration, this study conducted data collection under different conditions. Under quiet conditions, the fiber optic sensor was placed on a stable experimental platform to ensure no external interference from the surroundings, such as vibration or wind, in order to collect electrical signals from the fiber optic sensor in its natural state. This process aimed to obtain baseline signal data for reference in subsequent abnormal signal recognition. Under shaking conditions, regular or irregular shaking movements were applied to the experimental platform through mechanical devices to simulate vibration situations that might occur in actual scenarios due to object shaking or vehicle movement, thereby collecting electrical signal responses from the fiber optic sensor in this dynamic environment. Under pressure conditions, specific tools were used to apply varying degrees of pressure to the fiber optic sensor to simulate the impact of external forces on optical fiber vibration, and thus obtain corresponding electrical signals (Luo et al., 2023; Chang et al., 2023).

2.2 Feature extraction

Feature extraction is a crucial step in signal classification. This study conducts feature extraction from both time-domain and frequency-domain aspects. In the time domain, statistical features such as mean, variance, peak value, and zero-crossing count are calculated to describe the signal's shape and variation trend. For example, the mean reflects the average level of the signal, variance represents the dispersion degree, and the peak value indicates the maximum signal intensity. These time-domain features can intuitively demonstrate the signal's basic characteristics in the time dimension (Wang et al., 2024).

Fourier transform is utilized to convert time-domain signals into frequency-domain signals, thereby extracting spectral characteristics such as frequency components and power spectral density. Spectral analysis helps reveal hidden frequency information in signals. Electrical signals generated under different vibration conditions often exhibit distinct frequency distribution characteristics. For example, signals collected under shaking conditions may show prominent peaks within specific frequency ranges, while the signal spectrum under pressing conditions may present different patterns (Xun et al., 2025).

However, the numerous features extracted from both time and frequency domains may contain redundant and irrelevant features. This not only increases the computational complexity of the model but also may degrade its classification performance. Therefore, this study selects the Recursive Feature Elimination (RFE) method for key feature selection. RFE gradually eliminates unimportant features by repeatedly constructing models and evaluating feature importance, ultimately filter out the most critical features that contribute the most to classification results. This method can effectively achieve dimensionality reduction, reduce model training time, and simultaneously improve model training efficiency and classification accuracy.

2.3 Model Building

Support Vector Machine (SVM) is a binary classification model based on statistical learning theory. Its principle is to find an optimal hyperplane that maximises the separation of data from different classes in feature space. In this study, the SVM model structure transforms nonlinear problems in low-dimensional space into linearly separable problems in high-dimensional space through kernel function mapping of collected optical fiber vibration electrical signal data. By selecting appropriate kernel functions (such as Radial Basis Function) and adjusting relevant parameters such as penalty coefficient C and kernel function parameter γ , it is expected that SVM can accurately classify electrical signals and effectively distinguish signals generated under different vibration conditions (Ribeiro et al., 2002).

Linear Discriminant Analysis (LDA) is a classical dimensionality reduction and classification method. Its principle is to find a linear projection direction that minimizes the within-class scatter while maximizing the between-class scatter. In terms of dimensionality reduction, LDA can map high-dimensional optical fiber vibration electrical signal data to a low-dimensional

space while preserving the most discriminative information in the data. For signal classification, LDA can effectively distinguish different types of signals through simple linear classification of the projected data. Its advantages lie in its low computational complexity and good classification performance when the data distribution satisfies certain assumptions (Lin et al., 2024).

Long Short-Term Memory (LSTM) network is a special type of recurrent neural network designed for processing sequence data. Its network structure consists of memory cells, input gates, forget gates, and output gates. The working principle involves storing long-term information in memory cells, controlling the input of new information through input gates, determining the discarding of old information by forget gates, and managing information output through output gates. LSTM effectively addresses the gradient vanishing and gradient exploding problems that traditional recurrent neural networks encounter when dealing with long sequence data. For sequence data classification tasks like fibre optic vibration electrical signals, LSTM can fully utilize the time-series information of signals and capture long-term dependencies within them, thus demonstrating high applicability and advantages. It is expected to accurately classify signals under different vibration conditions (Ribeiro et al., 2002).

Gated Recurrent Unit (GRU) is a simplified variant of LSTM with a more concise structure. It removes the memory cell and only retains the update gate and reset gate. The update gate controls the degree of information update, while the reset gate determines the degree of forgetting historical information. GRU has the advantage of fewer parameters and faster model training speed, while still maintaining good performance to a certain extent. In this study, GRU is applied to signal classification, expected to efficiently classify optical fiber vibration electrical signals under different vibration conditions and achieve a good balance between complexity and performance (Lin et al., 2024).

Convolutional Neural Networks (CNNs) have shown excellent performance in fields such as image processing and signal classification (Ribeiro and Alquezar, 2002). The convolutional layers perform convolution operations on input signals using convolution kernels to extract local features of the signals. The convolution kernels slide over the signals, computing weighted sums of local regions with the kernels, thus generating feature maps. The pooling layers then downsample the feature maps, reducing data volume while preserving important features. In the classification of optical fiber vibration electrical signals, CNNs can automatically extract local features of signals, such as waveform patterns within specific frequency ranges, achieving efficient classification. Through multiple layers of convolution and pooling operations, CNNs can gradually extract more abstract and discriminative features, enabling accurate classification of signals under different vibration conditions (Ribeiro and Alquezar, 2002).

Figure 1 shows the schematic workflow for this study. As to block diagrams with different models please refer to relevant references. Finally, the performance parameters are compared to get the best results.

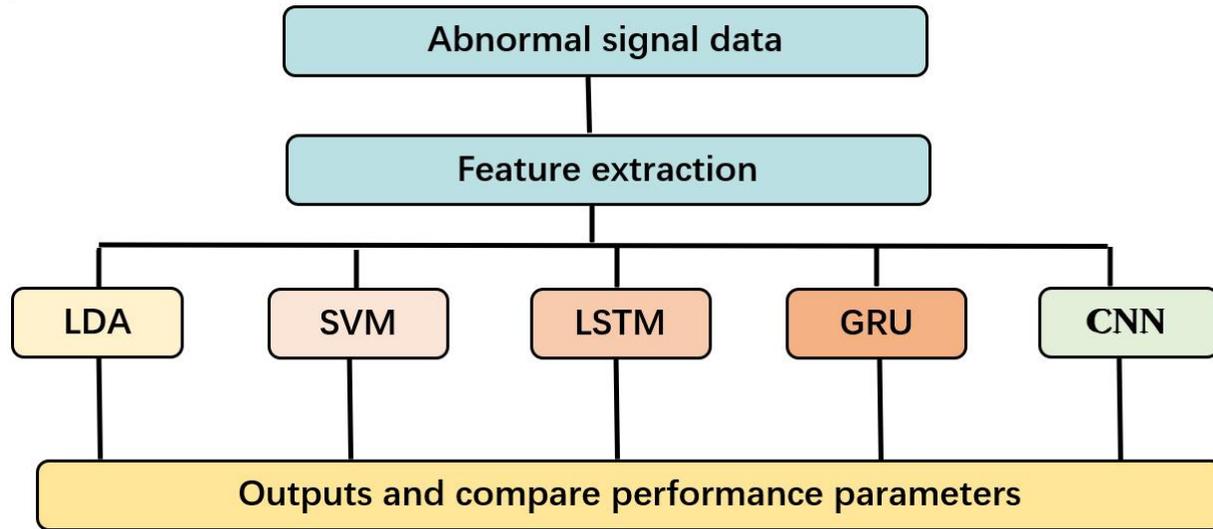


Figure 1 Schematic workflow diagram for this study

3. Results and Discussion

3.1 Comparison of Model Classification Accuracy

In this study, we obtained the accuracy data of each model in classifying optic fiber vibration electrical signals through experiments (Figure 2). The experiments showed that the accuracy rate of Linear Discriminant Analysis (LDA) was 65.84%. LDA aims to project data into the optimal discriminant vector space through dimensionality reduction to achieve classification. However, for data with potentially complex feature distributions like optic fiber vibration electrical signals, the linear assumption of LDA may limit its classification performance. Support Vector Machine (SVM), as a classical machine learning algorithm, achieved an accuracy rate of 66.61% for electrical signal classification. SVM achieves classification by finding the optimal hyperplane and has certain advantages in handling small sample and nonlinear data. However, when facing complex optic fiber vibration electrical signal data, its accuracy performance is relatively limited.

The accuracy rate of Long Short-Term Memory (LSTM) network is 71.28%. As a commonly used model in deep learning for processing sequence data, LSTM effectively captures long-term dependencies in sequences by introducing memory units and gating mechanisms. This makes it advantageous for processing time-series data like optical fiber vibration electrical signals. The accuracy rate of Gated Recurrent Unit (GRU) is 77.00%. As a variant of LSTM, GRU has fewer parameters and a more concise model structure, which allows it to handle sequence data classification tasks relatively well. However, compared to LSTM, its accuracy rate is slightly lower in this experiment, possibly due to its simplified structure resulting in slightly reduced capability in handling complex sequence features.

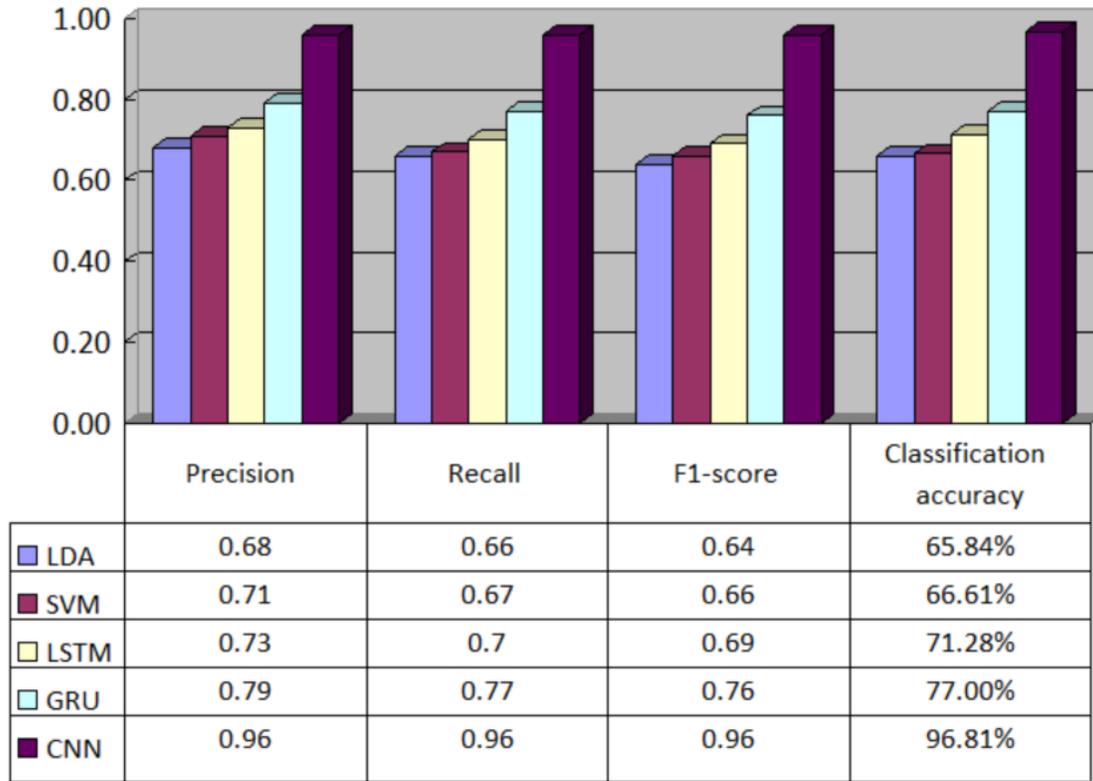


Figure 2 Comparison of performance parameters with different models

Convolutional Neural Network (CNN) demonstrated significant advantages in this experiment, achieving an accuracy rate of 96.81%. Its precision, recognition rate, and F1 score were all superior to other methods (Table 1). Through convolutional and pooling layers, CNN can automatically extract local features of signals. For data like optical fiber vibration electrical signals that exhibit local feature patterns, CNN can effectively learn key feature patterns, thus achieving high-precision classification. After comprehensive comparison of various models, CNN clearly outperformed other models in classification accuracy, Fully demonstrate its powerful capabilities in optical fiber vibration electrical signal classifications (Wang et al., 2024; Salem, 2022).

To prevent overfitting, we use validation loss curve with stable and lower than the training loss, showing no signs of overfing. The gap between training and validation results is only 2-3%, which is within the normal range (Figure 3).

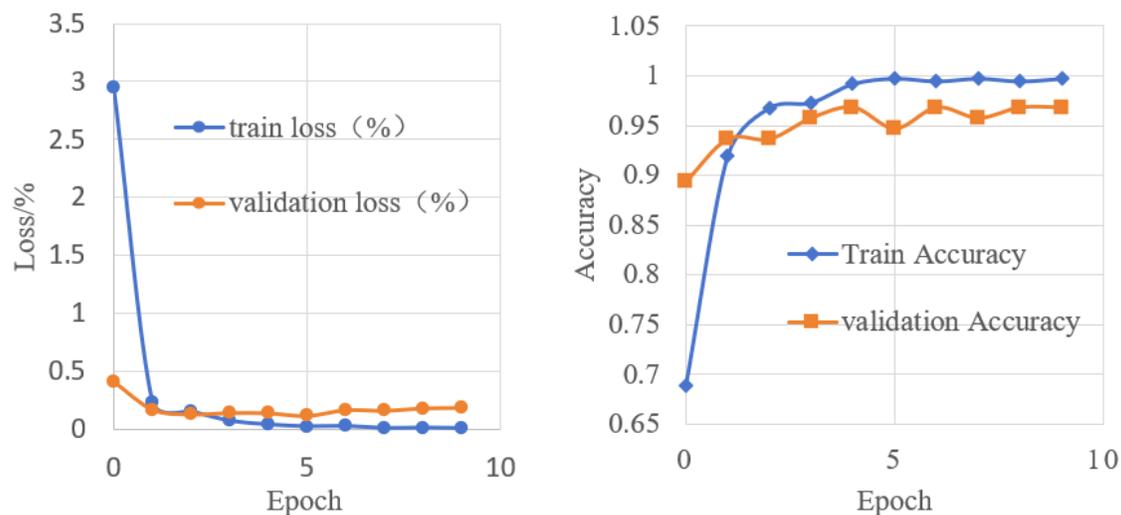


Figure 3 Loss and accuracy Curves of the CNN model

3.2 Model Generalization Analysis

Generalization ability is a crucial indicator to measure the performance stability of models on different datasets. In this study, there are differences in the generalization performance of various models across different datasets. The CNN model demonstrates the best generalization ability across all datasets. This is mainly attributed to the translation invariance of CNN's convolutional operations, which can capture local patterns in data. Regardless of how the data changes, as long as the local feature patterns exist, CNN can effectively recognize them. Moreover, through multi-layer convolution and pooling operations, CNN gradually extracts features from local to global, enabling the model to have a deeper understanding of the overall data features, thus maintaining good classification performance on different datasets.

In contrast, other models have certain limitations in generalization ability. Although SVM performs well on small-scale data, its generalization ability is weak for large-scale and complex datasets. This is because SVM mainly relies on finding the optimal hyperplane for classification, and when the data distribution changes, the original hyperplane may no longer be applicable. Due to its linear assumption, LDA cannot effectively capture the true structure of the data when facing complex nonlinearly distributed datasets, resulting in limited generalization ability. While LSTM and GRU have certain advantages in processing sequential data, they are sensitive to sequence length and feature distribution. When the sequence length or feature distribution of the dataset changes, the model performance may fluctuate significantly, thereby affecting generalization ability (Adrian et al., 2023; Chang et al., 2023; Xun et al., 2025; Mentari et al., 2025; He et al., 2023).

3.3 Practical Application Challenges and Solutions

In practical applications, electrical signal classification models based on fiber optic vibration data face numerous challenges. First is the difficulty in data acquisition. In real-world scenarios, the environment where fiber optic sensors are deployed is complex and diverse, making it challenging to obtain high-quality vibration data. For example, environmental noise may interfere with the fiber optic vibration signals, resulting in degraded data quality. Moreover, electrical signal characteristics can vary significantly across different scenarios, requiring large amounts of representative data for model training. However, the cost of data collection and annotation is relatively high.

Model training complexity is also a significant challenge. Deep learning models such as LSTM, GRU, and CNN typically require substantial computational resources and time for training. Especially for large-scale optical fiber vibration data, the model training process can be very time-consuming and demanding on hardware equipment (Majdi et al., 2022; Wang et al., 2024; Liu et al., 2016).

To address the difficulty of data acquisition, data collection methods can be optimized. For example, more advanced fiber optic sensor technology can be adopted to improve the sensor's anti-interference ability against environmental noise, ensuring the collection of purer vibration data. Meanwhile, unsupervised or semi-supervised learning methods can be utilized to preprocess large amounts of unlabeled data, mining potential information to assist in the training of supervised learning models, thereby reducing the dependence on large amounts of labeled data.

To address the complexity of model training, we can consider improving the model architecture. For example, drawing from the optimization ideas of deep learning under different pruning strategies, we can prune the model to reduce the number of parameters and lower computational complexity, while maintaining model performance as much as possible. Additionally, distributed computing technology can be utilized to distribute model training tasks across multiple computing nodes for parallel processing, thereby reducing training time (Wang et al., 2024; Xun et al., 2025; Mentari et al., 2025; He et al., 2023).

4. Conclusion

This study utilizes optical fiber vibration data for electrical signal classification, aiming to enhance the performance of anomaly detection. During the experiment, electrical signals from fiber optic sensors were collected under different conditions (quiet, shaking, and pressing). By applying time-domain and frequency-domain feature extraction principles and methods, combined with recursive feature elimination for key feature selection, multiple models including SVM, LDA, LSTM, GRU, and CNN, were successfully constructed for signal classification.

Through comparative analysis of classification results from various models, the CNN model demonstrates significant advantages in classification accuracy and generalization ability. Compared to other models, the CNN model can more effectively extract local signal features, achieving efficient electrical signal classification with high accuracy rates of 96.81%. Moreover, it shows good generalization ability across different datasets, providing more reliable technical support for anomaly detection. These results verify the applicability and effectiveness of the CNN model in classifying fiber optic vibration electrical signals (Majdi et al., 2022), providing support for the identification of actual fiber optic cable states. Future research should further optimize model structures, expand dataset sizes, and explore more advanced feature extraction and optimization methods to enhance model performance.

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