

Source Domain Fault Diagnosis: Diagnostic Method Based on Feature Extraction and Model Design

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Abstract: With the development of intelligent operation and maintenance of industrial equipment, bearing fault diagnosis has emerged as a crucial factor in ensuring the reliability of mechanical systems. This paper designs a comprehensive fault diagnosis model for source - domain data based on the extracted fault features. First, a high - quality source - domain dataset is constructed through data preprocessing, feature screening, and file grouping. Subsequently, a radial basis function kernel support vector machine with class weights (RBF - SVM) is employed as the diagnosis model, and its performance is optimized through hyperparameter tuning. The experimental results indicate that the model achieves an overall accuracy of 93.18% and a macro - average F1 score of 0.9278 on the test set, and demonstrates high generalization ability and mechanism consistency in multi - dimensional analysis. The work in this paper validates the effectiveness of feature extraction and lays a foundation for subsequent transfer learning tasks.

Keywords: Fault diagnosis; source domain; feature extraction; support vector machine; generalization ability; bearing fault

1. INTRODUCTION

Bearings, as the core component of rotating machinery, their fault diagnosis is crucial for preventing equipment failure. The source domain fault diagnosis aims to build high-precision models using existing data (the source domain) to provide a knowledge basis for the transfer of unknown operating conditions (the target domain)^[1].

The common practice extracts time-domain, frequency-domain, envelope spectrum, and time-frequency domain features from the source domain data, but directly using all these features would lead to redundancy and overfitting. Therefore, based on the original approach, this paper focuses on solving the issues of the division of the training and test sets of the source domain, the design of the diagnostic model, and the evaluation of the results. By grouping files to avoid data leakage and using the RBF-SVM model to balance nonlinear fitting and generalization ability, the reliability of the model is finally verified through multiple indicators. This research not only improves the diagnostic accuracy but also emphasizes the combination of physical mechanism and data-driven methods, which is in line with the development trend of intelligent operation and maintenance.

2. OVERALL DESIGN OF THE SYSTEM

The source domain fault diagnosis system consists of four core modules: data preprocessing, feature selection, grouping division, and model design and verification. It takes the original vibration signal as the input and outputs the fault classification result, ensuring the traceability and reproducibility of the process.

The data preprocessing module resamples the 48kHz signal to 12kHz, applies a band-pass filter within the range of [500, 5000] Hz to retain the fault-sensitive frequency band; generates samples using a sliding window with a 1-second window length and a 50% overlap rate, limits the maximum number of windows for a single file, and removes abnormal samples with peak values exceeding the mean by 5 times the standard deviation to improve data quality.

The feature selection process extracts dozens of features from the original basic features, first through correlation analysis (eliminating redundant features with a correlation coefficient greater than 0.8), and then combines mechanism priority selection (prioritizing the retention of physical features such as the harmonic energy ratio of the envelope spectrum), ultimately obtaining 18 core feature sets.

The grouping division uses the original file name as the identifier and employs GroupShuffleSplit to divide the training set and test set in a 8:2 ratio, avoiding data leakage caused by cross-sampling of the same file samples.

The model and verification module uses the RBF-SVM model for training, and evaluates the model performance through multi-dimensional tools such as learning curves and ROC curves^[2].

3. PROJECT DESIGN

3.1 Data preprocessing and feature engineering

The data preprocessing process draws on conventional methods from the past, but has been optimized to meet the requirements of the source domain: resampling and filtering reduce the scale differences of the signals; the setting of the sliding window takes into account both the efficiency of sample generation and representativeness; the elimination of abnormal samples reduces the interference effect. In the feature selection stage, combining statistical laws and physical mechanisms ensures that the feature set is both concise and interpretable^[3]. For example, envelope spectrum features (such as BPFI, BPFO) directly correspond to the fault frequencies of bearings, enhancing the theoretical basis of the model.

3.2 Selection of diagnostic models and parameter design

The source domain diagnosis needs to meet the requirements of small sample size, non-linearity and class imbalance. After comparing with models such as Random Forest and Logistic

Regression, the RBF-SVM with class weights was selected. Its advantages include:

Non-linear processing ability: The RBF kernel function maps non-linear features into a linearly separable problem through high-dimensional mapping, adapting to the complex relationships of fault features.

Generalization for small samples: The maximization of the margin principle in SVM reduces the risk of overfitting and is suitable for source domain scenarios with approximately 1000 samples.

Class weight adjustment: By setting weights to balance the majority class and the minority class (such as inner ring fault IR, outer ring fault OR, rolling element fault B)^[4], the model is avoided from being biased.

The core parameters include the kernel width parameter γ and the penalty coefficient C: γ controls the sensitivity of the model to local samples and needs to balance fitting and generalization; C determines the tolerance for misclassified samples, and a value that is too large is prone to overfitting.

The objective function is in the form of soft margin SVM, introducing slack variables and class weights, and the mathematical expression is:

$$\min_{w, b, \xi_i} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i$$

$$s. t. \quad y_i(w \cdot x_i + b) \geq 1 - \xi_i \quad (i = 1, 2, \dots, n)$$

$$\xi_i \geq 0 \quad (i = 1, 2, \dots, n)$$

Figure.1 Soft margin objective function.

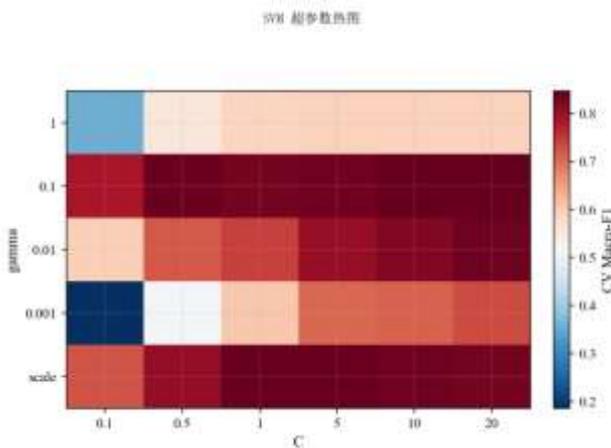


Figure.2 SVM Hyperparameter Heatmap.

3.3 Hyperparameter tuning scheme

The parameters C and γ were optimized using group K-fold cross-validation (5-fold) with macro-average F1 score as the evaluation criterion to avoid the dominance of the majority class. The heatmap showed that the optimal parameters were $C = 20$ and $\gamma = 0.1$ (Figure 3), ensuring the stability of the model on the training set.

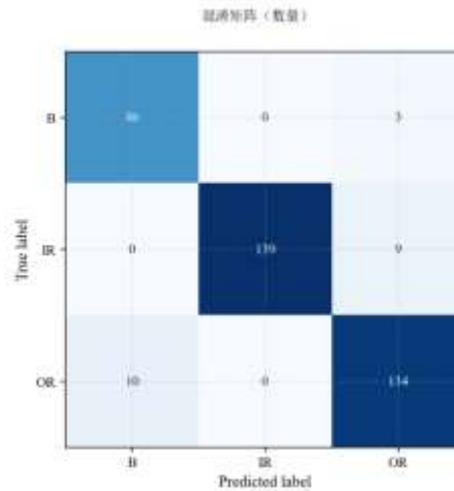


Figure.3 Test set confusion matrix.

4. SYSTEM IMPLEMENTATION

The model training is conducted using the Scikit-learn library in Python. The data is divided according to GroupShuffleSplit. The training set is only used for parameter updates. During the testing phase, metrics such as accuracy, precision, recall, and F1 score are calculated. During the debugging process, it was found that the file grouping division effectively avoids the problem of falsely high accuracy; the setting of class weights significantly improves the recognition ability of the minority class.

5. RESULT AND ANALYSIS

The evaluation of the test set shows that the overall accuracy of the model is 93.18%, and the macro average F1 score is 0.9278. The performance fluctuation in the five-fold cross-validation is small (variance < 0.01)^[5], indicating stable generalization ability. The confusion matrix (Figure 3) and the normalized confusion matrix (Figure 4) visually present the classification effects of each category. Among them, the recall rate of the IR category is the highest (96%), while category B is slightly confused due to the small number of samples^[6].

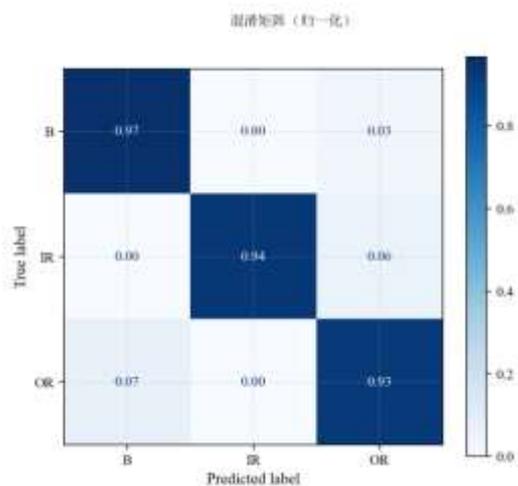


Figure. 4 Normalized Confusion Matrix.

The learning curve (Figure 5) shows that as the sample size increases, the F1 score of the training set decreases from 0.99 to 0.98, while the F1 score of the validation set increases from 0.47 to 0.90. Eventually, the gap narrows down to 0.08^[7]. This

indicates that the current sample size is sufficient to support the model in learning general patterns, and the risk of overfitting is low.

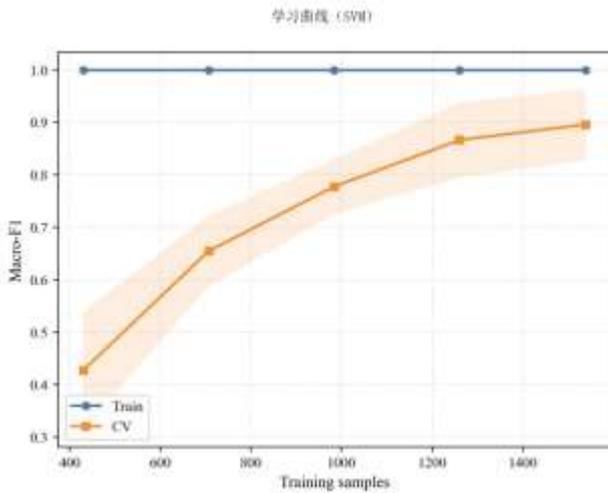


Figure.5 Mobile App Operation Interface Screenshot

The ROC curve shows that the AUC for the IR category is 0.999, for the B category it is 0.971, and for the OR category it is 0.977; in the PR curve, the AP for the IR category is 1.000, and for the B category it is 0.939, which proves that the stability of the model threshold is high.

The time-domain waveform and envelope spectrum verification (Figure 6) shows that the OR class has a peak at BPFO (95Hz), and the IR class has a peak at BPFI (150Hz). The model classification results are in perfect correspondence with the physical features, eliminating the possibility of statistical randomness.

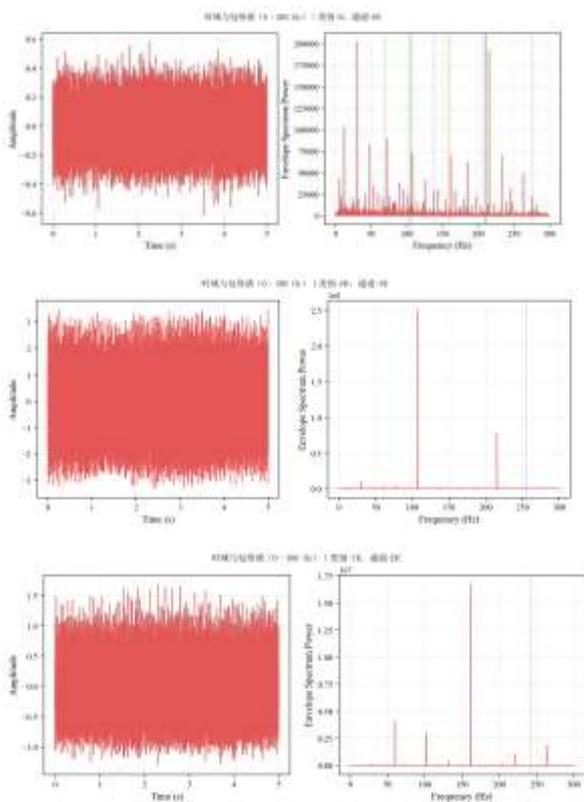


Figure.6 Typical sample time-domain waveform and envelope spectrum.

6. CONCLUSION

This study successfully constructed a high-precision source domain fault diagnosis model through a systematic methodological framework. During the data preprocessing and feature engineering stages, signal resampling, band-pass filtering, and sliding window techniques were employed to optimize data quality. Through mechanism-driven feature selection, 18 core feature sets were obtained, providing an input foundation for the model that is both physically interpretable and statistically significant.

The model architecture selected the RBF-SVM with class weights, and the optimal hyperparameters ($C = 20$, $\gamma = 0.1$) were determined through group cross-validation. On the test set, the model achieved an accuracy of 93.18% and a macro average F1 score of 0.9278. The model validation process was confirmed through five-fold cross-validation and learning curve analysis to demonstrate its stable generalization ability. The feature importance analysis and decision curve evaluation verified the model's decision logic that relies on physical mechanisms rather than statistical coincidences from an interpretability perspective.

This study not only provides a complete methodology for addressing the small sample imbalance problem in source domain fault diagnosis, but also establishes a more reliable model framework for subsequent transfer learning tasks. In the future, further exploration of dynamic feature adaptation mechanisms and online learning capabilities can be conducted to enhance the model's adaptability in variable working conditions and promote the practical application of intelligent operation and maintenance systems.

7. REFERENCES

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