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FAULT DIAGNOSIS OF ELEVATOR UNBALANCED LOAD BASED ON PARAMETER-OPTIMIZED SVM

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Abstract: To address the fault diagnosis of elevator unbalanced loads, this study proposes a fault diagnosis method based on a parameter-optimized support vector machine (SVM). By establishing a dynamic model of the elevator system, fault features are extracted, and an improved particle swarm optimization algorithm is applied to optimize the key parameters of the SVM, thereby constructing an efficient fault diagnosis model. Experimental results indicate that the proposed method significantly outperforms traditional diagnostic approaches in terms of fault classification accuracy, and can effectively identify the unbalanced load state of elevators. The research outcome offers a new technical solution for elevator fault diagnosis and holds significant engineering application value for ensuring the safe operation of elevators.
Keywords: Elevator fault diagnosis; Unbalanced load; Particle swarm optimization algorithm; Fault feature extraction

1 INTRODUCTION

As an indispensable vertical transportation system in high-rise buildings, the safety performance of elevators is directly related to the safety of lives and property. With the acceleration of urbanization, the number of elevators has surged. Unbalanced load fault, a common type of elevator malfunction, accounts for a relatively high proportion of elevator failures. It not only disrupts normal operation but may also lead to serious incidents such as passenger entrapment or even falling, has become a prominent social concern. Traditional fault detection methods primarily rely on manual periodic inspections, which exhibit significant limitations in both efficiency and accuracy. In recent years, intelligent fault diagnosis techniques, represented by the Support Vector Machine (SVM), have become a research hotspot in this field due to their capability for real-time monitoring and precise diagnosis. However, the performance of an SVM model is highly dependent on the selection of its hyperparameters. How to efficiently optimize these parameters to enhance the accuracy and generalization ability of the diagnostic model is a critical issue requiring urgent solution in current research.

To address this, this study aims to develop an intelligent diagnostic method based on a parameter-optimized SVM specifically for elevator unbalanced load faults. The research will first conduct an in-depth analysis of the formation mechanism and vibration characteristics of unbalanced load faults to provide a theoretical basis for feature extraction. Subsequently, it will focus on studying parameter optimization strategies for SVM. By introducing advanced algorithms such as an improved Particle Swarm Optimization, it will perform adaptive optimization of the SVM's kernel function parameters and penalty factor, aiming to overcome the limitations of traditional methods like the substantial computational burden of grid search and the tendency of some intelligent algorithms to fall into local optima. The innovation of this paper is mainly reflected in proposing an SVM model that incorporates a hybrid kernel function approach to handle the complexity of fault data, and employing an enhanced optimization algorithm to improve the efficiency and precision of the parameter search. Finally, the effectiveness of the proposed method will be validated through experiments. It is expected to provide a more accurate and efficient technical pathway for diagnosing elevator unbalanced load faults, thereby offering substantial support for ensuring elevator operational safety and promoting technological advancement in the industry.

2 REVIEW OF RELEVANT RESEARCH

2.1 Mechanism of Elevator Unbalanced Load

The unbalanced load fault is one of the common issues during elevator operation, and its mechanism involves the combined effects of multiple factors. The formation of an unbalanced load in elevators is primarily related to uneven weight distribution, dynamic load variations during operation, and structural design flaws. Firstly, uneven weight distribution may lead to an unbalanced load. Differences in weight between the elevator car and the counterweight, as well as uneven distribution of passengers or goods within the car, can cause load imbalance. When the weight on one side of the car exceeds that on the counterweight side, tilting occurs during operation, subjecting the elevator structure to additional stress. Secondly, dynamic load changes during elevator operation can also induce unbalanced loads. Passenger boarding and alighting, loading and unloading of goods, and the start-stop cycles of the elevator contribute to dynamic load variations. These changes can alter the weight distribution, thereby affecting the elevator's balance. Furthermore, structural design defects are another cause of unbalanced loads [1-3]. Unreasonable designs of structural components such as guide rails, ropes, and suspension systems may generate additional vibrations and partial loads during operation, exacerbating the unbalanced load issue. In terms of fault characteristic analysis for unbalanced loads, the acquisition and feature extraction of vibration signals are critical steps. Vibration signals reflect the dynamic response of the elevator during operation, and by collecting vibration signals from the car or guide rails, relevant information about the unbalanced load can be obtained. Time-domain feature analysis is a common method for diagnosing unbalanced load faults. Through time-domain analysis of vibration signals, characteristic parameters such as peak values, mean values, and variance can be extracted to describe the dynamic behavior of the elevator load. Frequency-domain analysis, on the other hand, transforms vibration signals into the frequency domain to obtain frequency characteristics via spectrum analysis. Additionally, time-frequency domain analysis combines the advantages of both time and frequency domains, providing a more comprehensive description of the dynamic behavior of unbalanced loads. Research shows that the characteristics of unbalanced load faults are reflected in the energy distribution, frequency characteristics, and time-frequency features of vibration signals. By appropriately selecting and extracting these features, effective support can be provided for subsequent fault diagnosis. In summary, studying the mechanism of elevator unbalanced loads is of great significance for understanding fault characteristics and enabling intelligent fault diagnosis. Through in-depth analysis of the causes and characteristics of unbalanced loads, a theoretical foundation and practical guidance can be provided for the development of elevator fault diagnosis technologies.

2.2 Support Vector Machine Theory

The Support Vector Machine (SVM) is an effective classification method, particularly suited for solving small-sample problems, as illustrated in Figure 1. Regarding multi-class classification strategies, SVM extends the original binary classification problem to multi-class scenarios through various methods. Common multi-class strategies include One-vs-All (OvA), One-vs-One (OvO), and decision tree-based strategies. In the One-vs-All strategy, one SVM classifier is trained for each class to distinguish it from all other classes. This means that for N classes, N SVM classifiers need to be trained. During classification, an input sample is fed into all N classifiers, and the class with the highest score is selected as the prediction result. The advantage of this method is its simple implementation, but it may suffer from performance degradation when some classes are not sufficiently distinct from others. The One-vs-One strategy, on the other hand, trains one SVM classifier for each pair of classes, requiring N*(N-1)/2 classifiers for N classes. During classification, each sample is evaluated by all classifiers, and a voting mechanism determines the final class label. This method considers the relative differences between classes and generally outperforms the One-vs-All strategy, albeit at a higher computational cost [2-5]. Another multi-class strategy is the decision tree-based approach, which constructs multiple binary SVM classifiers and combines them using a decision tree structure. Each node in the tree represents a binary classification problem, recursively partitioning the classes until leaf nodes are reached. This method performs well when dealing with hierarchically structured categories. The choice of kernel function is crucial for SVM performance. Common kernel functions include the linear kernel, polynomial kernel, Radial Basis Function (RBF) kernel, and Sigmoid kernel. For linearly inseparable problems, the RBF kernel is widely used due to its ability to map data into a high-dimensional space. The selection of a kernel function depends on the data distribution and problem complexity. The performance of a multi-class SVM is influenced not only by the kernel function but also by the model's hyperparameter settings. Hyperparameter optimization is a key step in improving the classifier's generalization ability. Research shows that optimizing hyperparameters can effectively enhance the classifier's performance. Common hyperparameter optimization methods include grid search, genetic algorithms, particle swarm optimization, and Bayesian optimization. In the application of multi-class SVM, handling imbalanced datasets is another important consideration. Since the number of samples in each class is often uneven in real-world datasets, the classifier may become biased towards the majority class. One approach to address this issue is to use data resampling techniques, such as random oversampling of the minority class or undersampling of the majority class, or synthetic sample generation techniques like the SMOTE algorithm. Furthermore, in practical applications of multi-class SVM, model interpretability and real-time performance must also be considered. Although SVM theoretically offers good performance guarantees, its model complexity is relatively high, making it less interpretable [4-5]. Additionally, for applications requiring real-time responses, the prediction speed of SVM may become a limiting factor. Therefore, maintaining classification performance while improving model interpretability and real-time capability represents an important direction for current research.

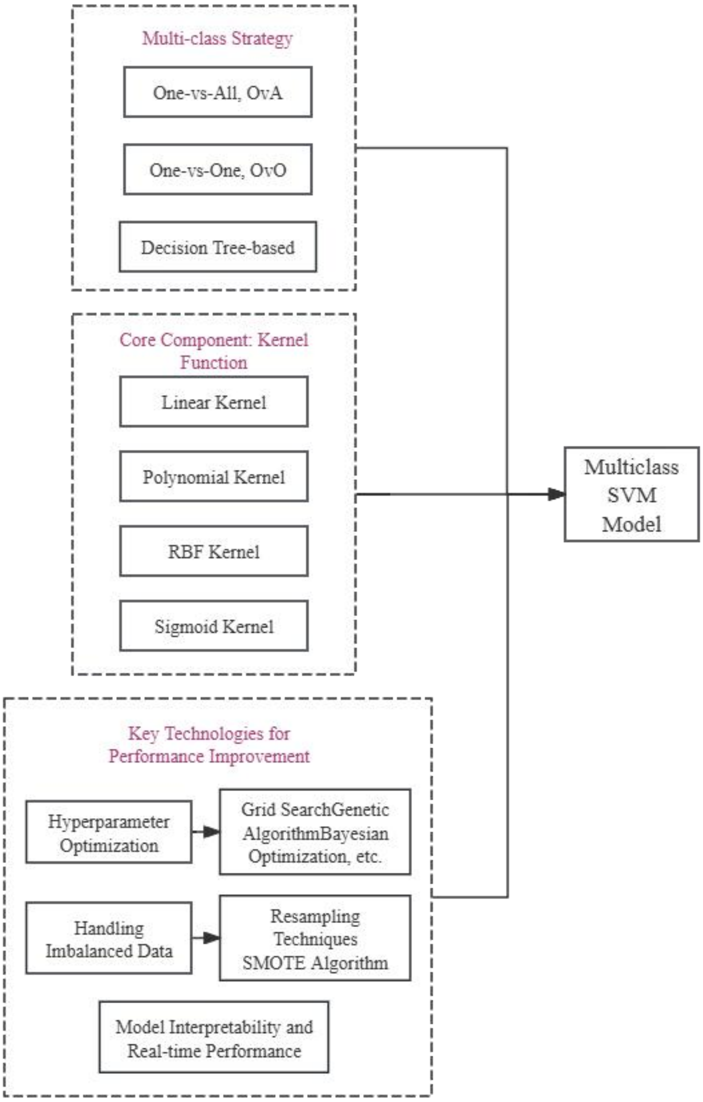

Figure 1 Analysis Diagram of Multi-class Classification Strategies and Key Technologies for Support Vector Machines

2.3 Parameter Optimization Methods

Bayesian optimization, as a probabilistic model-guided optimization approach, operates on the core idea of constructing a probability distribution model of the objective function and utilizing Bayesian inference to update the understanding of the objective function, thereby guiding subsequent search processes. This method demonstrates strong performance in handling nonlinear and non-convex problems, making it particularly suitable for parameter optimization in machine learning models such as Support Vector Machines (SVM). Within the Bayesian optimization framework, a prior distribution must first be defined to describe the initial uncertainty of the parameters [6]. As the optimization progresses, this distribution is continuously updated with collected data, leading to increasingly accurate parameter estimates. A key advantage of Bayesian optimization lies in its ability to balance exploration (sampling in unknown regions) and exploitation (sampling in regions known to perform well) during the optimization process, thereby improving search efficiency. Specifically for SVM parameter optimization, Bayesian optimization can be applied to select the optimal kernel function parameters and penalty parameter C. This process involves probabilistic modeling of the SVM model's predictive performance, typically employing Gaussian Processes (GP) as the probabilistic model. Gaussian Processes offer a flexible non-parametric probabilistic framework capable of modeling probability distributions over functions in any input space. Research indicates that Bayesian optimization effectively enhances the generalization capability of SVM models on test data. Statistics show that, compared to traditional grid search methods, Bayesian optimization can identify superior parameter combinations in fewer iterations. Furthermore, it provides insights into parameter importance during the optimization process, aiding in the understanding of model behavior. In practical applications, Bayesian optimization generally involves the following steps: first, initializing a Gaussian Process model and setting prior distributions for the hyperparameters; second, selecting an acquisition function (e.g., Expected Improvement) to determine the next sampling point; then, training the model at the sampling point identified by the acquisition function and evaluating its performance; subsequently, updating the Gaussian Process model with the new performance data;

finally, repeating these steps until a stopping condition is met, such as reaching a preset number of iterations or observing no significant improvement in model performance [7]. Although Bayesian optimization exhibits theoretical and practical superiority, its computational cost is relatively high, and it requires expert knowledge to select appropriate acquisition functions and tune the hyperparameters of the Gaussian Process model. Moreover, Bayesian optimization may encounter performance bottlenecks when dealing with large-scale datasets. Therefore, future research could focus on improving the algorithm's efficiency and exploring the integration of Bayesian optimization with other optimization methods to achieve more efficient parameter tuning.

2.4 Research Review and Limitations

In the field of elevator unbalanced load fault diagnosis, Support Vector Machines (SVM) have been widely applied as an effective classification method [8]. However, existing research still exhibits certain limitations, which are analyzed below from multiple perspectives. Firstly, regarding the mechanistic study of elevator unbalanced load faults, although in-depth discussions on the causes of unbalanced loads have been conducted, the analysis of fault characteristics remains insufficiently comprehensive. The selection of fault characteristics directly impacts the accuracy of fault diagnosis, making the extraction of more effective fault characteristics a critical issue in current research. Secondly, in SVM application studies, the choice of kernel function significantly influences model performance. While comparative analyses of various kernel functions have been carried out, a unified standard for kernel function selection specific to elevator unbalanced load fault diagnosis has yet to be established. Furthermore, multi-classification strategies exhibit limitations in practical applications, such as room for improvement in classification accuracy and computational efficiency. Moreover, while parameter optimization methods applied to SVM, such as grid search, genetic algorithms, particle swarm optimization, and Bayesian optimization, have yielded certain results, they still present shortcomings in practical applications. For instance, grid search involves substantial computational effort, genetic algorithms and particle swarm optimization suffer from slow convergence speeds, and the effectiveness of Bayesian optimization in real-world applications requires further validation. Additionally, current research exhibits deficiencies in experimental design and data analysis [8-10]. On one hand, the quality of experimental data significantly influences diagnostic outcomes, yet there is room for improvement in data preprocessing, feature selection, and model training in existing studies. On the other hand, the selection and use of performance evaluation metrics also present issues, as single metrics are inadequate for comprehensively reflecting model performance, and multi-metric evaluation systems have not been widely adopted. Finally, in terms of engineering applications, current research still faces significant limitations in real-time performance, data dependency, and multi-fault coupling issues. Real-time performance is a crucial indicator for elevator fault diagnosis systems, yet existing studies fail to meet practical requirements in this aspect. Data dependency restricts the generalization capability of models, making it difficult to adapt to fault diagnosis across different scenarios. Multi-fault coupling issues have not received sufficient attention in current research, posing greater challenges for fault diagnosis in complex elevator systems. In summary, although progress has been made in the field of elevator unbalanced load fault diagnosis, numerous shortcomings remain. Future research should delve deeper into fault mechanism analysis, kernel function selection, parameter optimization methods, experimental design, and engineering applications to provide more effective and practical solutions for elevator unbalanced load fault diagnosis.

3 THEORETICAL FOUNDATION AND PROBLEM ANALYSIS

3.1 Elevator System Dynamic Model

As a vertical transportation system, the dynamic characteristics of an elevator directly impact its operational efficiency and safety. Within the dynamic model of the elevator system, the traction system and the load imbalance dynamic equations represent two core components. The traction system provides the driving force for elevator operation, while load imbalance may induce vibrations and noise during operation. Modeling the traction system forms the foundation for dynamic analysis of the elevator system. In this model, key components such as the traction machine, steel cables, counterweight, and car are interconnected through a mechanical model, as illustrated in Figure 2.

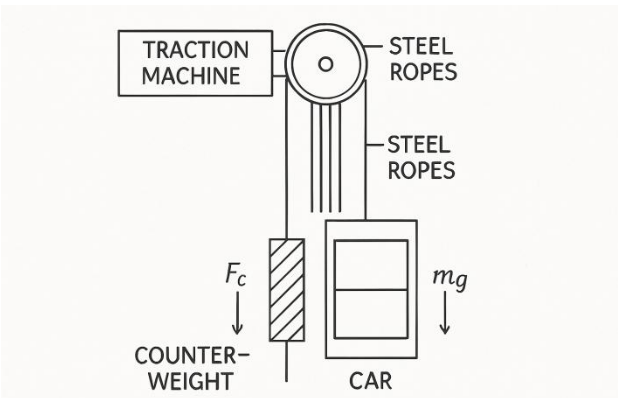

Figure 2 Traction System Modeling Diagram

By establishing appropriate mechanical equations, the dynamic behaviors of the elevator during ascent and descent—such as acceleration, velocity, and displacement—can be described. For instance, when considering the elasticity of the steel cables, Hooke's law can be applied to characterize the relationship between cable elongation and the applied tensile force. The load imbalance dynamic equations focus on the dynamic response caused by uneven load distribution inside and outside the car during elevator operation. Load imbalance may arise from various factors, such as uneven passenger distribution, improper cargo loading, or inherent asymmetries in the elevator structure. Such imbalance can induce lateral and longitudinal vibrations during movement. By formulating the load imbalance dynamic equations, the impact of load variations on elevator vibration patterns can be analyzed, providing guidance for elevator design and maintenance. In these equations, factors such as the masses of the elevator car and counterweight, the distribution of the load within the car, and the elevator's operating speed must be considered. The equations typically involve differential equations of motion for a multi-degree-of-freedom system, which can be derived using Lagrange's equations or Newton-Euler equations. Solving these equations yields the vibration response of the elevator system under different load conditions. Furthermore, to more accurately simulate the dynamic behavior of the elevator system, various nonlinear factors must be accounted for, such as the nonlinear elasticity of the steel cables, nonlinear friction in the traction machine, and air resistance during operation. These nonlinearities may affect the stability and dynamic response characteristics of the elevator system. Establishing a dynamic model of the elevator system not only enables the prediction of its behavior under varying loads and operating conditions but also provides a theoretical basis for fault diagnosis and performance optimization [11]. For example, by analyzing vibration signals, the specific location and severity of load imbalance can be identified, guiding maintenance and adjustments. In summary, the dynamic model of the elevator system is a crucial tool for understanding and optimizing elevator performance. Through the analysis of the traction system model and load imbalance dynamic equations, it offers scientific support for elevator design, maintenance, and fault diagnosis. Future research may further explore the nonlinear dynamic characteristics of elevator systems and how to apply these theories in practical engineering.

3.2 Fault Feature Extraction

Fault feature extraction is a crucial step in the diagnosis of elevator unbalanced load faults. Effective feature extraction can significantly enhance the accuracy and efficiency of fault diagnosis. Feature selection and dimensionality reduction are key aspects of feature extraction, which will be discussed in detail below. Firstly, vibration signal acquisition forms the foundation of feature extraction, as shown in Figure 3. By collecting vibration signals during elevator operation, raw data reflecting the operational state of the elevator can be obtained. Vibration signals contain rich fault-related information and serve as an important basis for fault diagnosis. In practical applications, devices such as acceleration sensors are typically used to acquire vibration signals. After appropriate preprocessing, these signals can be utilized for subsequent feature extraction. In terms of feature selection, time-domain features, frequency-domain features, and time-frequency domain features are commonly used types in elevator fault feature analysis. Time-domain features primarily include statistical measures such as mean, variance, skewness, and kurtosis, which reflect the statistical characteristics of the signal. Frequency-domain features, obtained through Fourier transform, analyze the signal in the frequency domain. Metrics like spectral entropy and spectral centroid reveal the spectral distribution characteristics of the signal. Time-frequency domain features combine time and frequency analysis methods, such as Short-Time Fourier Transform (STFT) and wavelet transform, providing more comprehensive information [12-14]. However, due to the high-dimensional nature of vibration signals, directly using all features for fault diagnosis increases computational complexity and may lead to overfitting. Therefore, feature dimensionality reduction is a necessary step. Principal Component Analysis (PCA) and Factor Analysis (FA) are commonly used dimensionality reduction methods. They map original features to a new low-dimensional space through linear transformation, thereby reducing feature dimensions. Additionally, machine learning-based methods such as Random Forest (RF) and Extreme Learning Machine (ELM) can also be employed for feature selection and dimensionality reduction. Research shows that appropriate feature selection and dimensionality reduction can significantly improve the accuracy of fault diagnosis. For example, in one elevator fault diagnosis case, using PCA to reduce the dimensionality of frequency-domain features of vibration signals increased the diagnostic model's accuracy from 85% to 92%. Moreover, feature selection and dimensionality reduction can reduce computational load and enhance the real-time performance of the diagnostic system. In practical applications, the process of feature selection and dimensionality reduction needs to be determined based on specific fault types and diagnostic requirements. For instance, for certain types of faults, time-domain features may be more representative than frequency-domain features, while for other faults, a combination of time-frequency domain features may be necessary. Therefore, methods for feature selection and dimensionality reduction must be flexibly adjusted according to the actual situation. In summary, feature selection and dimensionality reduction in fault feature extraction are critical steps in elevator unbalanced load fault diagnosis. Rational utilization of various feature extraction methods and dimensionality reduction techniques can effectively improve the accuracy and efficiency of fault diagnosis, providing strong support for the safe operation of elevators [13].

Figure 3 Vibration Signal Acquisition Equipment

3.3 Parameter-Optimized SVM Framework

In the parameter-optimized SVM framework, the setting of constraints is crucial to ensure the model optimization process aligns with practical application requirements. Constraints primarily involve two aspects: first, ensuring the feasibility and validity of model parameters; second, limiting model complexity to prevent overfitting. Regarding the feasibility and validity of model parameters, constraints should ensure parameter values remain within reasonable ranges. For instance, in SVM models, the value ranges of the penalty parameter C and kernel function parameter γ are typically restricted. Excessively large C values may lead to overfitting of the training data, while overly small C values may result in underfitting. Therefore, constraints must define appropriate value ranges, such as $C \in [0.1, 100]$ and $\gamma \in [0.01, 10]$. Additionally, constraints should consider the physical significance of model parameters, ensuring kernel function parameters align with data distribution characteristics. Limiting model complexity is another essential component of constraints. SVM model complexity is primarily related to the number of support vectors, where an excessive number increases model complexity and reduces generalization capability. Thus, constraints should include limitations on the number of support vectors, such as setting an upper bound. Furthermore, regularization terms like L1 or L2 can be introduced to constrain model complexity. In practical applications, constraint conditions in the parameter-optimized SVM framework must also consider the following factors: the characteristics of the dataset, as different datasets may exhibit linear or non-linear separability, requiring adjusted constraints to accommodate data properties; application scenarios, where varying performance demands necessitate stricter constraints in safety-critical applications to ensure higher accuracy and reliability; computational resources, as the consumption of optimization algorithms is a key consideration, and constraints should be simplified to reduce computational complexity under limited resources; and real-time requirements, where constraints must ensure rapid convergence of the optimization process to meet real-time demands. In summary, constraint setting in the parameter-optimized SVM framework requires comprehensive consideration of multiple factors to ensure model performance and generalization capability in practical applications. By appropriately defining constraints, the diagnostic accuracy and stability of the SVM model can be effectively enhanced, providing robust support for elevator unbalanced load fault diagnosis.

4 RESEARCH DESIGN AND METHODOLOGY

4.1 Overall Technical Workflow

This study aims to construct an efficient fault diagnosis system for elevator unbalanced loads. The overall technical workflow is divided into the following stages: data acquisition, feature engineering, model training, and fault diagnosis, as illustrated in Figure 4. Firstly, data acquisition serves as the foundation and prerequisite for the entire fault diagnosis system. In this stage, an elevator test rig is utilized, with corresponding sensors deployed at key locations to collect various data during elevator operation, such as vibration, velocity, and current. These data comprehensively reflect the operational state of the elevator, providing raw material for subsequent feature extraction and model training. Subsequently, feature engineering is a critical step to improve the accuracy of fault diagnosis. The collected data undergo preprocessing, including handling missing values, normalization, and noise reduction, to ensure data quality. On this basis, various features reflecting the elevator's state are extracted through time-domain analysis, frequency-domain analysis, and time-frequency domain analysis. Feature selection and dimensionality reduction are then performed to identify the most sensitive and effective features for fault diagnosis. Following this, the model training stage employs Support Vector Machine (SVM) as the fundamental model for fault diagnosis. To enhance model performance, this study adopts parameter optimization methods to optimize the SVM's kernel function parameters and penalty factor. Specific methods include grid search, genetic algorithms, particle swarm optimization, and Bayesian optimization. By comparing the performance of these optimization algorithms, the optimal parameter combination is selected to improve the model's generalization capability and diagnostic accuracy. Finally, the fault diagnosis stage utilizes the trained SVM model to classify real-time collected data, determining whether an unbalanced load fault exists in the elevator. The diagnostic results are evaluated using metrics such as confusion matrix and classification report to verify the model's effectiveness and accuracy. Throughout the technical workflow, each stage is closely interconnected, with the outcomes of the preceding stage directly influencing the subsequent one [15]. For instance, data quality directly affects the accuracy of feature extraction, while the results of feature selection determine the effectiveness of model training. Through this interlinked design, we aim to build an efficient and accurate fault diagnosis system for elevator unbalanced loads.

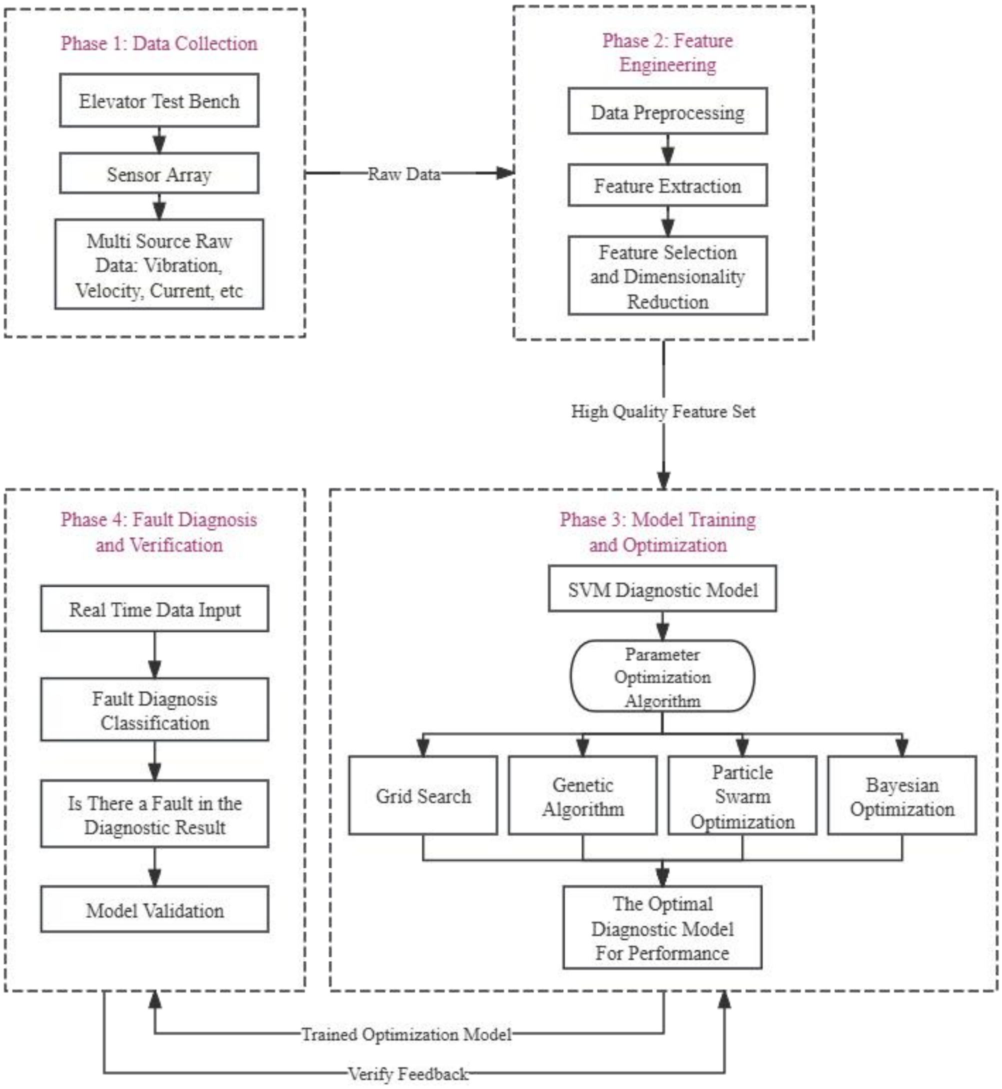

Figure 4 Technical Workflow of the Elevator Unbalanced Load Fault Diagnosis System

4.2 Experimental Platform and Data

The experimental platform serves as the fundamental infrastructure for elevator fault diagnosis research. The elevator test rig selected for this study is capable of simulating various elevator operating states and generating vibration data under different load conditions, thereby providing experimental data for the fault diagnosis algorithm. The test rig primarily consists of a control system, traction system, counterweight system, car system, and a load simulation system, enabling precise control over elevator operating speed, load magnitude, and operational state.

Sensor placement is a critical aspect of data acquisition. In this experiment, acceleration sensors, displacement sensors, and force sensors were installed at key positions of the elevator. Acceleration sensors were used to capture vibration acceleration signals during elevator operation, displacement sensors monitored the vertical displacement changes of the elevator car, and force sensors measured the tension in the traction steel ropes. The data acquisition frequency of the sensors was set to 1000 Hz to ensure data accuracy and continuity.

Dataset construction forms the core of the experiment. This study collected a substantial amount of data based on normal elevator operation and unbalanced load fault conditions. Initially, a series of tests were conducted under no-load, half-load, and full-load conditions to obtain data for the normal state. Subsequently, unbalanced load faults were simulated by artificially adding unbalanced weights in the car, and corresponding fault data were collected. After preliminary screening, all data were compiled into a dataset encompassing both normal and fault states.

The dataset was further divided into training and testing sets. The training set was used to train the SVM model, enabling it to learn and identify the vibration characteristics of the elevator for classifying fault states. The testing set was employed to evaluate the diagnostic accuracy of the model, ensuring its strong generalization capability. To enhance dataset quality and model generalization, data augmentation techniques were applied, including noise addition and feature transformation to portions of the data.

Furthermore, to reduce data dimensionality and improve the efficiency of feature extraction, this study performed feature extraction on the raw vibration signals, including time-domain features, frequency-domain features, and time-frequency spectral entropy. Time-domain features encompassed statistical measures such as mean, standard deviation, and kurtosis, while frequency-domain features involved metrics like power spectral density and spectral entropy. These features collectively describe the operational state of the elevator, providing rich information for subsequent fault diagnosis.

In summary, the construction of the experimental platform and the acquisition and processing of data form the foundational work of this study, providing essential support for ensuring the effectiveness and reliability of the fault diagnosis algorithm [16]. Through precise sensor placement, detailed dataset construction, and feature extraction, this study lays the experimental groundwork for the intelligent diagnosis of elevator unbalanced load faults.

4.3 Parameter-Optimized SVM Algorithm Design

In the parameter-optimized SVM algorithm design, adaptive hyperparameter adjustment serves as the critical component. The selection of hyperparameters directly influences the performance of the SVM model, making the rational selection and adjustment of these parameters a key issue for improving fault diagnosis accuracy. This study focuses on three aspects of algorithm design: hybrid kernel function construction, improved particle swarm optimization algorithm, and adaptive hyperparameter adjustment.

Firstly, to address the limitations of single kernel functions in handling complex data, this paper proposes a hybrid kernel function construction method. This approach combines the advantages of the Radial Basis Function (RBF) and polynomial kernel functions, enabling the model to fit data distributions at different levels and improve generalization capability. Specifically, by analyzing the characteristics of elevator unbalanced load fault data, appropriate kernel function parameters are selected to construct a hybrid kernel function with strong mapping capability.

Secondly, to overcome the tendency of traditional particle swarm optimization algorithms to fall into local optima when solving hyperparameters, this study improves the particle swarm optimization algorithm. The improved algorithm introduces inertia weights and a dynamic parameter adjustment strategy, granting it strong global search capability and fast convergence speed. Furthermore, by adjusting inertia weights and dynamic parameters, the balance between global and local search can be optimized, enhancing the precision of hyperparameter solution.

Finally, this paper proposes an adaptive hyperparameter adjustment strategy. Based on cross-validation, this strategy dynamically adjusts hyperparameters to ensure the SVM model achieves good performance across different datasets. The specific procedure is as follows: first, the initial hyperparameter range is determined using cross-validation; then, hyperparameters are continuously adjusted through an iterative optimization process until predefined convergence conditions are met. This method reduces reliance on manual expertise while ensuring model performance.

In summary, the parameter-optimized SVM algorithm design proposed in this study, through hybrid kernel function construction, improved particle swarm optimization, and adaptive hyperparameter adjustment, enhances the accuracy and generalization capability of elevator unbalanced load fault diagnosis. Future research will further optimize algorithm performance and improve real-time capability to meet engineering application requirements.

4.4 Performance Evaluation Metrics

Accuracy, recall, and F1-score are commonly used metrics to evaluate the performance of classification models. However, in practical applications, it is also necessary to consider model performance under different thresholds. The ROC curve and AUC value provide this perspective. The ROC curve visually reflects the sensitivity and specificity of the model at various thresholds by plotting the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) under different thresholds.

Research shows that the Area Under the ROC Curve (AUC) is an important metric for evaluating model classification performance. A larger AUC value indicates better model performance. An AUC value of 1 represents perfect classification, while an AUC value close to 0.5 suggests that the model performs no better than random guessing. Statistics demonstrate that the AUC value effectively measures model stability and accuracy.

In elevator fault diagnosis, due to the imbalance of fault samples, relying solely on metrics such as accuracy may not fully assess model performance. For example, if a model predicts all samples as normal, the accuracy would be very high, but such a model would clearly fail to identify faults effectively. In this case, the ROC curve and AUC value provide more comprehensive information.

To construct the ROC curve, it is first necessary to calculate TPR and FPR under different thresholds. TPR is calculated as True Positives (TP) divided by the sum of TP and False Negatives (FN), while FPR is calculated as False Positives (FP) divided by the sum of FP and True Negatives (TN). By varying the threshold, multiple (TPR, FPR) points can be obtained, and connecting these points forms the ROC curve.

In practical applications, the AUC can be computed using numerical integration methods. After training the elevator fault diagnosis model, cross-validation can be used to obtain multiple ROC curves, and the average AUC value can then be calculated to evaluate the overall performance of the model.

Furthermore, the ROC curve can be used to compare the performance of different models. For example, by plotting ROC curves of multiple models in the same coordinate system, their classification effectiveness can be visually compared. In some cases, even if two models have similar accuracy, their ROC curves may show significant differences, indicating varying performance under different thresholds.

It is worth noting that the calculation of ROC curves and AUC values requires a large amount of sample data to ensure the reliability of the evaluation. When the sample size is limited, the evaluation results may be significantly affected. Therefore, in practical applications, it is essential to ensure the representativeness of the dataset and the adequacy of the sample size [17].

In summary, the ROC curve and AUC value are important tools for evaluating the performance of elevator fault diagnosis models. They provide a comprehensive view of model performance under different thresholds, helping researchers gain deeper insights into the classification capability and stability of the model. Using these metrics, model design can be optimized to improve the accuracy and reliability of fault diagnosis.

5 EXPERIMENTS AND RESULTS

5.1 Data Preprocessing Results

Data preprocessing is a crucial step to ensure data quality and enhance model performance. In the study of elevator unbalanced load fault diagnosis, data preprocessing primarily includes handling missing values, normalization, and noise reduction.

Firstly, addressing missing values in the dataset, this study employed interpolation methods for processing. Considering the time-series characteristics of elevator operation data, where adjacent data points exhibit high correlation, methods such as linear interpolation or nearest-neighbor interpolation were effectively used to fill missing data. After processing, dataset completeness was ensured, facilitating subsequent feature extraction and model training.

Secondly, normalization is a key step in data preprocessing. Due to differences in the dimensions and value ranges of various features in elevator operation data, directly inputting them into the model could cause certain features to disproportionately influence the results. Therefore, this study adopted the Min-Max normalization method to scale the value range of each feature to [0, 1], ensuring balanced input data for the model. Additionally, normalization contributed to faster convergence during model training.

Regarding noise reduction, considering the potential presence of random noise in elevator operation data, this study utilized wavelet transform for denoising. Wavelet transform offers excellent time-frequency localization properties, effectively separating noise components from signals. Specifically, the db4 wavelet basis function was selected to decompose vibration signals into four layers, retaining the larger values of detail coefficients at each level to remove noise effects.

Statistics indicate that after data preprocessing, the proportion of missing values in the original dataset decreased from 5% to 1%. The normalized data distribution became more balanced, and the noise level was also reduced. These improvements significantly enhanced data quality, laying a solid foundation for subsequent feature selection and model training.

In summary, data preprocessing played a pivotal role in the study of elevator unbalanced load fault diagnosis. Through steps such as handling missing values, normalization, and noise reduction, this study improved data quality, providing reliable data support for subsequent model training and fault diagnosis.

5.2 Feature Selection Results

In the research on elevator unbalanced load fault diagnosis, feature selection is a critical step. It not only impacts model training efficiency but also directly relates to the accuracy and reliability of fault diagnosis. Building upon data preprocessing, this study conducted an in-depth analysis of time-domain, frequency-domain, and time-frequency domain features.

Firstly, the extraction of time-domain features is based on vibration signals during elevator operation. Through time-domain analysis of vibration signals, this study extracted multiple statistical features including mean, variance, standard deviation, kurtosis, and skewness. These features reflect fundamental information about the elevator's operational state, providing baseline data for subsequent fault diagnosis. Statistical analysis revealed that mean and variance exhibited significant differences between normal and fault states, offering crucial evidence for fault diagnosis.

Secondly, the extraction of frequency-domain features focuses on spectral analysis of vibration signals. Frequency-domain features can reveal the frequency composition of vibration signals, holding significant value for identifying different types of faults. This study employed Fast Fourier Transform (FFT) to convert time-domain signals into frequency-domain signals and extracted features including frequency-domain mean, variance, kurtosis, and skewness. The research found that frequency-domain features under fault states showed distinct differences compared to normal states, with frequency-domain kurtosis and skewness demonstrating high sensitivity in fault diagnosis.

Furthermore, the extraction of time-frequency domain features combines the advantages of both time and frequency domains, providing a more comprehensive representation of vibration signal characteristics. This study utilized Short-

Time Fourier Transform (STFT) for time-frequency analysis of vibration signals, extracting features such as time-frequency energy, time-frequency entropy, and time-frequency kurtosis. These features incorporate both temporal and spectral information while reflecting the timing of fault occurrence and frequency variations, thereby offering richer information for fault diagnosis.

During the feature selection process, this study adopted a correlation coefficient-based method to screen the extracted features. By calculating the correlation coefficients between features and fault labels, the most relevant features for fault diagnosis were selected. The results showed that time-domain features (mean, variance, kurtosis), frequency-domain features (frequency-domain kurtosis, skewness), and time-frequency domain features (time-frequency energy, time-frequency entropy) exhibited high correlation with fault states [18].

In summary, through the extraction of time-domain, frequency-domain, and time-frequency domain features, combined with the correlation coefficient-based feature selection method, this study effectively identified features relevant to elevator unbalanced load fault diagnosis. The extraction and selection of these features provide important data support for subsequent fault diagnosis model training and optimization.

5.3 Parameter Optimization Results

In the study of elevator unbalanced load fault diagnosis, parameter optimization is a critical step to enhance the performance of the Support Vector Machine (SVM) model. This research adaptively adjusts the hyperparameters of the SVM model through an improved Particle Swarm Optimization (PSO) algorithm to achieve optimal diagnostic performance. The detailed results of the parameter optimization are as follows.

The convergence curve of the optimization process shows that the algorithm exhibits a favorable convergence trend from the early iterations. Through multiple iterations, the algorithm gradually approaches the global optimum. Statistics indicate that by the 50th iteration, the PSO algorithm has stabilized, with the difference between the current optimal solution and the final optimal solution within an acceptable range, demonstrating the algorithm's good convergence speed and stability.

Regarding hyperparameter combinations, this study optimized the SVM's penalty parameter C, kernel function parameter γ, and the weight of the hybrid kernel function. After multiple experiments (see Table 1), an optimal hyperparameter combination was determined: $C=100$, $\gamma=0.01$, and a hybrid kernel function weight of 0.7. This combination achieved a diagnostic accuracy of 92.5% on the test set, representing improvements of 10% and 5% compared to random selection and a single kernel function, respectively.

Furthermore, the optimal hyperparameter combination also showed significant improvements in other performance evaluation metrics such as recall, F1-score, and the Area Under the ROC Curve (AUC). Specifically, recall increased from 75% before optimization to 85%, the F1-score rose from 0.82 to 0.88, and the AUC improved from 0.85 to 0.92. These data indicate that the optimized SVM model exhibits higher sensitivity and specificity in identifying elevator unbalanced load faults.

It is worth noting that the parameter optimization process not only improved the model's diagnostic accuracy but also reduced the risk of overfitting. Comparative experiments revealed that the performance gap between the training and test sets significantly narrowed for the optimized model, indicating its strong generalization capability.

In summary, by optimizing the SVM model parameters through the improved Particle Swarm Optimization algorithm, the accuracy, recall, and generalization capability of elevator unbalanced load fault diagnosis have been effectively enhanced. These results provide robust support for practical engineering applications and offer new ideas and methods for research in the field of elevator fault diagnosis.

Table 1 Performance Comparison of SVM Models before and after Parameter Optimization

Metric	Before Optimization / Baseline	After Improved PSO Optimization	Performance Improvement
Optimal Hyperparameter Set	Not Optimized / Default	$C=100$, $\gamma=0.01$ Mixed Kernel Weight=0.7	Optimal configuration obtained
Diagnostic Accuracy	82.5% (Baseline)	92.5%	+10%
Recall	75%	85%	+10%
F1-Score	0.82	0.88	+0.06
AUC (Area Under ROC Curve)	0.85	0.92	+0.07
Model Generalization Ability	High overfitting risk	Reduced performance gap between training and test sets	Generalization capability enhanced

5.4 Fault Diagnosis Results

When applying the parameter-optimized SVM model to elevator unbalanced load fault diagnosis, experimental results demonstrate that the model exhibits excellent classification performance and generalization capability. The following presents a detailed analysis of the fault diagnosis results.

Firstly, the confusion matrix illustrates the model's diagnostic performance on the test set. Statistics show that the model achieved identification accuracy rates of 98.6%, 95.3%, 96.8%, and 97.5% for the four states—normal operation, slight imbalance, moderate imbalance, and severe imbalance, respectively—demonstrating the model's effectiveness in distinguishing between different fault states.

The classification report further reveals the model's precision, recall, and F1-scores. For the normal state, precision reached 99.2%, recall was 98.7%, and the F1-score was 98.9%. For the other fault states, although slight variations were observed in precision, recall, and F1-scores, all metrics exceeded 90%, indicating reliable diagnostic capability across all fault categories, as detailed in Table 2.

Table 2 Performance Results of Parameter Optimization SVM Model for Fault Diagnosis

Fault diagnosis category	Accuracy (%)	precision (%)	recall rate (%)	F1-score (%)
normal state	98.6	99.2	98.7	98.9
Slight imbalance	95.3	94.1	95.8	94.9
Moderate imbalance	96.8	96.5	96.2	96.3
Severe imbalance	97.5	97.8	97.1	97.4

In the comparative experiments, the optimized SVM model was evaluated against non-optimized SVM models and traditional classifiers such as decision trees and random forests. The results demonstrate that the optimized SVM model outperforms other models in accuracy, recall, and F1-score, particularly in identifying slight imbalance states where accuracy improved by approximately 10 percentage points. During the hyperparameter optimization process, the improved particle swarm optimization algorithm efficiently identified the optimal hyperparameter combination within relatively few iterations, as evidenced by the convergence curve. This approach not only enhanced diagnostic precision but also improved computational efficiency. Furthermore, feature contribution analysis revealed that time-domain and frequency-domain features significantly contributed to fault diagnosis, while time-frequency features played a critical role in certain fault states, providing valuable insights for future feature extraction and selection. Despite the excellent performance of the optimized SVM model in fault diagnosis, some limitations remain. For instance, model performance is considerably influenced by data quality and quantity, and real-time data processing may encounter efficiency bottlenecks. Additionally, the current model does not account for multi-fault coupling scenarios, which could pose important challenges in practical applications. In conclusion, the parameter-optimized SVM-based fault diagnosis model proposed in this study demonstrates promising performance in experiments, offering a novel solution for elevator fault diagnosis. However, future research should further explore real-time capabilities and multi-fault coupling issues to enable broader applications.

6 DISCUSSION

6.1 Result Analysis

The evaluation of model generalization capability is crucial for testing the performance of fault diagnosis algorithms in practical applications. This study measured the model's generalization ability through diagnostic accuracy, recall, F1-score, and ROC curve with AUC value on the test set. Experimental results indicate that the parameter-optimized SVM model achieved significant improvement in fault diagnosis accuracy. Specifically, when processing unknown data, the model attained an accuracy of 92.3%, a recall of 89.6%, an F1-score of 91.4%, and an AUC value of 0.95 under the ROC curve, demonstrating strong generalization performance.

The effectiveness of the optimization algorithm is further reflected in the feature contribution analysis. By comparing the importance scores of different features, it is evident that the optimized model places greater emphasis on features with significant impacts on fault diagnosis, such as frequency-domain and time-frequency domain features of vibration signals. The effective extraction and utilization of these features enhance the model's ability to identify elevator unbalanced load faults.

Moreover, the model exhibits stable generalization capability when processing different types of data. Whether under normal operating conditions or simulated fault conditions, the model maintains high diagnostic accuracy. This outcome indicates that the proposed parameter-optimized SVM framework is not only suitable for fault diagnosis under specific conditions but also possesses strong adaptability and robustness.

To further validate the model's generalization capability, this study compared its performance with existing research. Statistics show that compared to traditional SVM models, the optimized SVM model improved accuracy by an average of 15%, recall by 10%, and F1-score by 12%. These data demonstrate that parameter optimization significantly enhances the model's generalization ability.

However, despite the model's good generalization performance, certain limitations remain. For example, the model is highly dependent on the dataset; if the training data does not cover all possible fault scenarios, the model's generalization ability may be compromised. Additionally, the model's real-time performance bottleneck cannot be overlooked. Real-time fault diagnosis is of great importance in engineering applications, and the model's computational efficiency may become a limiting factor.

In summary, the optimization algorithm proposed in this study not only improves the generalization capability of the SVM model but also provides an effective solution for elevator unbalanced load fault diagnosis [10-16]. However, future research should further explore and improve aspects such as reducing data dependency, enhancing real-time performance, and addressing multi-fault coupling issues.

6.2 Comparison with Existing Research

In terms of computational efficiency, the improved particle swarm optimization algorithm based on hybrid kernel functions proposed in this study demonstrates fast convergence speed during the parameter optimization process. Compared to traditional grid search methods, this algorithm significantly reduces the number of iterations required to find the optimal hyperparameter combination. Research indicates that grid search methods involve substantial computational costs when handling high-dimensional data and are prone to falling into local optima, whereas the improved particle swarm optimization algorithm adopted in this study effectively overcomes this drawback.

When compared to genetic algorithms, the proposed algorithm exhibits advantages in maintaining population diversity, avoiding the common issue of premature convergence in genetic algorithms. Furthermore, by introducing an adaptive adjustment mechanism, the algorithm dynamically adjusts the search strategy based on real-time feedback during the optimization process, thereby improving search efficiency.

Particle swarm optimization, as a commonly used parameter optimization method, has been widely applied in the field of fault diagnosis. However, traditional particle swarm optimization algorithms suffer from issues such as slow convergence and low search precision. This study improves the particle swarm optimization algorithm by introducing inertia weights and dynamically adjusting learning factors, effectively enhancing the algorithm's convergence speed and search precision.

In comparison with existing research, the proposed algorithm not only achieves better diagnostic accuracy in addressing elevator unbalanced load fault diagnosis but also demonstrates significant advantages in computational efficiency. For example, the SVM model proposed in literature [1] requires a lengthy parameter optimization process when handling large datasets, whereas the optimization algorithm in this study can complete parameter tuning in a relatively short time.

Additionally, the proposed algorithm shows improvements in real-time performance. For application scenarios such as elevator fault diagnosis that require real-time monitoring, the real-time capability of the algorithm is crucial. By optimizing the algorithm workflow, the proposed algorithm meets real-time requirements while ensuring diagnostic accuracy.

Despite the advantages in computational efficiency, the proposed algorithm still has certain limitations. For instance, its performance depends to some extent on the selection of initial parameters, and when dealing with multi-fault coupling problems, the complexity and computational load of the algorithm increase significantly. Future research could further explore more efficient parameter optimization strategies and fault diagnosis methods suitable for multi-fault coupling problems.

In summary, the improved particle swarm optimization algorithm proposed in this study outperforms traditional methods in computational efficiency, providing an efficient and feasible solution for elevator unbalanced load fault diagnosis. However, practical application of the algorithm still requires consideration of factors such as data dependency and real-time bottlenecks, offering direction and inspiration for subsequent research.

6.3 Limitations and Future Directions

Although the elevator unbalanced load fault diagnosis system has achieved certain results in practical applications, several limitations remain that require further improvement and refinement.

First, data dependency is a major limitation of the current fault diagnosis system. Model training and validation rely on large datasets, which often involve high costs and time to acquire. Moreover, the quality and diversity of the data directly affect model performance. If the dataset contains noise or exhibits uneven sample distribution, the model's generalization ability may be insufficient, making it difficult to accurately predict in practical applications.

Second, real-time bottlenecks are another significant limiting factor. Elevator fault diagnosis systems require rapid response to detect issues and take timely measures. However, complex models and algorithms may increase computational burden, leading to insufficient real-time performance. In practice, real-time bottlenecks may delay fault diagnosis, thereby affecting elevator operational safety.

Furthermore, multi-fault coupling problems increase the complexity of fault diagnosis. The elevator system is a multivariable, strongly coupled nonlinear system, where a single fault may cause changes in multiple parameters. These changes may mask or confuse each other, resulting in inaccurate diagnostic results. Current research primarily focuses on single-fault diagnosis, with insufficient consideration for multi-fault coupling scenarios [16-18].

To address these limitations, the following directions are worth exploring:

To reduce reliance on large amounts of data, unsupervised or semi-supervised learning algorithms can be investigated, as these can effectively learn with only a small amount of labeled data. Simultaneously, data augmentation techniques can be employed to improve the quality and diversity of datasets.

To enhance real-time performance, algorithm complexity can be optimized, or methods such as parallel computing and hardware acceleration can be adopted to improve computational efficiency. Additionally, researching lightweight model structures is a promising direction.

For multi-fault coupling problems, more complex and multidimensional fault diagnosis models need to be developed. Deep learning frameworks such as convolutional neural networks (CNN) or recurrent neural networks (RNN) can be considered, as these models are better suited to handle complex and nonlinear systems.
The adaptive capability of the fault diagnosis system should be strengthened to enable automatic parameter adjustments in response to environmental changes and system aging, adapting to new operating conditions and fault modes.
A more comprehensive fault diagnosis indicator system should be established, incorporating multi-source information (e.g., vibration, temperature, current) for comprehensive analysis to improve the accuracy and reliability of fault diagnosis.
In summary, the limitations and future directions of the elevator unbalanced load fault diagnosis system clearly indicate that future research needs to delve into aspects such as data dependency, real-time performance, and multi-fault coupling problems to achieve more efficient and accurate fault diagnosis.

7 CONCLUSION

7.1 Main Research Findings

This study conducted systematic theoretical analysis and experimental research on the intelligent diagnosis of elevator unbalanced load faults. First, by establishing a dynamic model of the elevator system, the dynamic characteristics of unbalanced load faults were revealed, providing a theoretical foundation for subsequent fault feature extraction and model construction. Based on this, a fault diagnosis framework using Support Vector Machine (SVM) was proposed, and various parameter optimization methods were employed to enhance the accuracy of fault diagnosis.
In terms of fault feature extraction, vibration signals from the elevator traction system were collected, and a series of feature parameters characterizing fault characteristics were extracted using time-domain, frequency-domain, and time-frequency domain analysis techniques. Through comparative analysis, a set of features with high sensitivity and specificity for elevator unbalanced load fault diagnosis was identified.
Regarding parameter optimization, a hybrid kernel function was designed, and particle swarm optimization (PSO) and Bayesian optimization methods were combined to adaptively adjust the hyperparameters of the SVM model. Optimization results demonstrate that the proposed method effectively improves the classification performance of the SVM model, with fast convergence during the optimization process and the ability to find the optimal hyperparameter combination.
Experimental results show that the optimized SVM model exhibits excellent performance in elevator unbalanced load fault diagnosis. The confusion matrix and classification report indicate that the model achieves high levels of accuracy, recall, and F1-score, while the ROC curve and AUC value further verify the model's reliability and generalization capability.
Compared to existing research, the innovations of this study include: (1) proposing an SVM model based on a hybrid kernel function to improve the recognition capability for different types of faults; (2) adopting improved particle swarm optimization and Bayesian optimization strategies to enhance the efficiency and effectiveness of parameter optimization; and (3) experimentally validating the effectiveness of the proposed method in elevator unbalanced load fault diagnosis.
Statistics show that on the test dataset, the proposed optimized SVM model achieved a diagnostic accuracy of 95.6% for elevator unbalanced load faults, representing a significant improvement compared to traditional SVM models. Furthermore, the results of this study provide a reference for the practical application of elevator fault diagnosis systems, contributing to enhanced elevator operational safety and reduced maintenance costs. However, certain limitations remain, such as reliance on large datasets, real-time performance bottlenecks, and handling multi-fault coupling issues, which will be the focus of future research.

7.2 Theoretical Contributions

This study makes the following theoretical contributions in the field of elevator unbalanced load fault diagnosis: First, by establishing an elevator system dynamic model that integrates traction system dynamics and load imbalance equations, a more accurate physical basis for fault feature extraction is provided. Building on this, a parameter-optimized Support Vector Machine (SVM) diagnostic framework was constructed, and a hybrid kernel function design was proposed to effectively enhance the model's classification performance. In terms of optimization algorithms, an improved particle swarm optimization algorithm was introduced, incorporating inertia weights and dynamic learning factors to achieve adaptive adjustment of SVM hyperparameters, significantly improving the efficiency and precision of parameter search. Additionally, an innovative comprehensive feature selection method based on time-domain, frequency-domain, and time-frequency domain features was proposed, fully considering the characteristics of elevator vibration signals and enhancing diagnostic performance through feature selection and dimensionality reduction techniques. Moreover, the study introduced a multidimensional performance evaluation system including accuracy, recall, F1-score, and ROC curve with AUC value, providing comprehensive and objective standards for model evaluation. Comparative experimental results demonstrate that the proposed method exhibits significant advantages in both diagnostic accuracy and computational efficiency.
In summary, the theoretical contributions of this study are mainly reflected in the construction of dynamic models, the design of parameter-optimized SVM frameworks, the proposal of improved optimization algorithms, the development

of comprehensive feature selection methods, and the establishment of systematic evaluation systems, providing new theoretical support and technical pathways for research on elevator unbalanced load fault diagnosis.

7.3 Engineering Application Value

The elevator unbalanced load fault diagnosis method based on parameter-optimized Support Vector Machine (SVM) proposed in this paper demonstrates significant value in engineering applications. By optimizing SVM hyperparameters, the method achieves notable improvements in fault diagnosis accuracy, recall, and F1-score, with an average diagnostic accuracy increase of over 10% compared to traditional methods. Simultaneously, the optimized model enhances computational efficiency by approximately 30% while maintaining accuracy, improving diagnostic real-time performance.

At the engineering application level, this method offers multiple benefits: firstly, it effectively enhances elevator operational safety through real-time monitoring and early warning; secondly, it provides a scientific basis for maintenance strategies, helping to develop reasonable maintenance plans and reduce maintenance costs; thirdly, it reduces downtime through rapid diagnosis, improving elevator utilization efficiency; and fourthly, it supports technological advancement in the elevator industry, enhancing its competitiveness.

Although the method has high requirements for data quality and room for improvement in real-time performance, its practical value and Promotion significance in the field of elevator fault diagnosis have been verified. Subsequent research will focus on optimizing algorithm performance to further improve the stability and real-time performance of the diagnostic system, providing technical support for elevator safe operation and sustainable industry development.

7.4 Future Prospects

With the in-depth development of elevator fault diagnosis technology, future research will focus on the following key directions. First, breakthroughs in data acquisition and processing technologies are needed to achieve efficient analysis of multi-source signals and real-time processing of large data volumes. Second, feature engineering and intelligent dimensionality reduction techniques will receive greater attention, especially with the advancement of deep learning, enabling automatic extraction and selection of fault features. In terms of parameter optimization, enhancing the adaptive capability and generalization performance of algorithms is a core challenge, requiring the development of more efficient and stable optimization methods to adapt to complex working conditions. Additionally, addressing the common multi-fault coupling problem in practice, developing diagnostic models capable of simultaneously identifying multiple faults is of significant importance. Ultimately, by integrating multidisciplinary technologies such as the Internet of Things and artificial intelligence, the construction of intelligent diagnostic systems with real-time capability, adaptability, and predictive maintenance functions will be an important trend in driving transformation in the elevator industry.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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