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MODEL TRANSFER FOR FEW-SHOT FAULT DIAGNOSIS OF ELEVATORS BASED ON DOMAIN ADAPTATION

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Abstract: To address the challenge of fault diagnosis in elevators caused by limited sample data, this paper proposes a few-shot fault diagnosis method based on domain adaptive transfer learning. By constructing a feature extraction network incorporating multi-scale convolution and attention mechanisms, combined with a domain adaptation module that aligns both marginal and conditional distributions, and introducing meta-learning and data augmentation strategies, the diagnostic capability of the model under few-shot conditions in the target domain is effectively improved. Experimental results demonstrate that the proposed method outperforms traditional diagnostic models in terms of accuracy and cross-domain transfer performance, showing promising potential for practical engineering applications. This study provides an effective solution for few-shot fault diagnosis in elevators, contributing both theoretical insights and practical value to enhancing elevator operational safety.
Keywords: Elevator fault diagnosis; Few-shot learning; Transfer learning; Adversarial training; Feature extraction

1 INTRODUCTION

With the widespread adoption of urban high-rise buildings, elevators have become essential vertical transportation systems, making their operational safety a critical concern. However, due to the complex structure of elevator systems and the scarcity of actual fault data, both traditional and current mainstream deep learning methods often struggle to deliver satisfactory performance when addressing such few-shot fault diagnosis problems. In this context, domain adaptation technology from transfer learning demonstrates significant potential. It enables the transfer of knowledge learned from one domain (source domain) to a new domain (target domain) with scarce data, thereby addressing the fundamental challenge of data distribution mismatch. Although this technology has matured in image and text processing fields, its application in elevator fault diagnosis remains in the exploratory stage. Therefore, this study aims to tackle the challenges of elevator fault diagnosis under few-shot conditions, with the core objective of developing a fault diagnosis model based on domain adaptation. By leveraging abundant data from the source domain and limited samples from the target domain, the model seeks to achieve effective cross-domain knowledge transfer and fault feature learning, offering a novel solution for enhancing elevator safety maintenance both theoretically and in practical engineering applications.

2 LITERATURE REVIEW

2.1 Research Progress in Elevator Fault Diagnosis

Studies on the few-shot problem in elevator fault diagnosis indicate that while traditional methods and deep learning approaches achieve satisfactory diagnostic results with sufficient data, their performance often falls short in practical applications due to the scarcity of elevator fault data. Research shows that elevator systems are complex, and the probability of failures is relatively low, resulting in limited available fault data. Under such conditions, how to utilize limited fault data for effective diagnosis has become a key research focus. Traditional methods in elevator fault diagnosis primarily include rule-based and model-based approaches. Rule-based methods rely on expert experience to construct diagnostic rules; however, they lack flexibility and adaptability when confronted with new fault patterns. Model-based methods, such as support vector machines and decision trees, can perform fault classification to some extent but often require large amounts of data for training, which is difficult to satisfy in practice.In recent years, the introduction of deep learning has brought new breakthroughs to elevator fault diagnosis. Architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) excel in processing image and sequential data, yet they also face challenges in few-shot learning. Some studies have attempted to adapt to few-shot scenarios by reducing network depth or adjusting network structures, but with limited success.To address the few-shot problem, researchers have begun focusing on transfer learning and domain adaptation techniques. Transfer learning enables knowledge sharing between source and target domains, leveraging abundant source domain data to enhance performance in target domains with limited samples. Domain adaptation, a subfield of transfer learning, aims to mitigate distribution discrepancies between source and target domains, allowing models to learn effectively in the target domain.Current applications of transfer learning and domain adaptation in elevator fault diagnosis mainly include two aspects: first, using transfer learning to reduce reliance on large amounts of labeled data and improve the generalization capability of target domain models through knowledge transfer; second, employing domain adaptation techniques to adjust models to the data distribution of the target domain, especially under few-shot conditions.Although transfer learning and domain adaptation offer new pathways for few-shot elevator fault diagnosis, existing studies still have limitations. For instance, issues such as how to select appropriate source domain data, design effective transfer strategies, and evaluate model domain adaptability remain insufficiently addressed. Furthermore, the application of few-shot learning strategies like meta-learning and data augmentation in elevator fault diagnosis is still exploratory, and their stability and robustness require further validation.In summary, research on the few-shot problem in elevator fault diagnosis is gradually deepening, but numerous challenges remain. Future studies need to innovate in theory and methodology to achieve more effective elevator fault diagnosis.

2.2 Transfer Learning and Domain Adaptation

As an important branch of machine learning, the core idea of transfer learning is to share knowledge across different tasks, demonstrating significant advantages in data-scarce scenarios. Domain adaptation, a key component of transfer learning, aims to reduce distribution discrepancies between source and target domains, thereby improving model performance in the target domain. In the field of fault diagnosis, particularly for few-shot problems, the application of transfer learning and domain adaptation shows great potential.The application of transfer learning in fault diagnosis is mainly reflected in two aspects: first, leveraging knowledge from existing tasks to address few-shot problems in new tasks; second, using domain adaptation techniques to enable models to adapt to data distribution changes under different working environments or equipment conditions. Studies show that transfer learning can effectively enhance the generalization capability of fault diagnosis models, significantly reducing dependence on large amounts of labeled data, especially when data is limited.Domain adaptation methods in fault diagnosis can be broadly categorized into sample-based, feature-based, and model-based approaches. Sample-based methods reduce discrepancies between source and target domains through resampling or weight adjustment; feature-based methods achieve domain adaptation by learning domain-invariant feature representations; while model-based methods adapt to data distributions across domains by adjusting model structures or parameters.In elevator fault diagnosis, domain adaptation is particularly important because elevator working environments may vary significantly, such as across different floors or time periods. Statistics indicate that domain adaptation techniques can improve the accuracy of fault diagnosis models in the target domain by 10% to 20%. For example, through marginal and conditional distribution alignment, models can learn common features of elevator operation data across different environments, thereby effectively improving diagnostic accuracy.Dynamic adversarial training strategies are an effective method in domain adaptation. By introducing adversarial samples, models can learn more robust feature representations. In few-shot fault diagnosis, dynamic adversarial training can significantly enhance model generalization and mitigate overfitting caused by insufficient data.Furthermore, few-shot learning strategies such as meta-learning frameworks, data augmentation and synthesis, and prototype network optimization play important roles in transfer learning and domain adaptation. These strategies improve model performance in the target domain through various means, such as rapid learning with limited samples, generating new training samples, or optimizing sample representations.In summary, the application of transfer learning and domain adaptation techniques in elevator fault diagnosis not only improves diagnostic accuracy but also reduces reliance on large-scale training data, providing feasible solutions for practical engineering applications. However, challenges remain, such as how to select appropriate transfer sources and adaptation strategies, and how to handle different types of data distribution changes. Future research needs to further explore and optimize these aspects in both theory and practice.

2.3 Research Review and Limitations

Despite significant advances in elevator fault diagnosis technologies over recent years, several notable limitations remain. Traditional diagnostic methods typically rely on large amounts of historical data; however, in real-world scenarios obtaining large-scale fault data is often infeasible. Statistics show that fault data for most elevators are sparse, especially for new elevator models or specialized application scenarios. In addition, traditional methods have limited capability to identify and handle complex fault patterns. The introduction of deep learning methods has brought new breakthroughs to elevator fault diagnosis [1], particularly in modeling nonlinear relationships. However, deep learning models generally require large datasets to guarantee their performance, which is a major limitation in practical applications. The small-sample problem is particularly prominent in fault diagnosis because collecting fault data is costly and carries risk. Transfer learning and domain adaptation techniques offer new perspectives for addressing the small-sample problem. Transfer learning can improve model performance in the target domain by leveraging abundant data from a source domain. Nevertheless, existing research still exhibits shortcomings in the stability, effectiveness, and adaptability of transfer learning. For example, differences in data distributions between different elevators may lead to poor transfer performance. Moreover, the robustness of domain adaptation methods needs to be improved when dealing with dynamically changing fault patterns.The focus of this study is to propose a few-shot domain-adaptive method for elevator fault diagnosis that can achieve effective fault identification under data-scarce conditions. Although prior work has achieved certain results in domain adaptation, the following shortcomings still warrant attention: 1. Existing methods often make overly idealized assumptions about data distributions, neglecting the complexity and dynamics of data distributions in real applications [2]. 2. In transfer learning, there is currently no unified standard or theoretical guidance for how to select and adjust source-domain data to suit the target domain. 3. Most studies concentrate on

improving model performance while paying insufficient attention to model interpretability, which is crucial in engineering practice. 4. Existing methods have limited generalization ability across different fault types, especially when confronted with unknown fault types.
Therefore, this paper aims to address the above issues by proposing a new few-shot domain-adaptive fault diagnosis model and validating its effectiveness and feasibility through experiments.

3 THEORETICAL BASIS AND PROBLEM MODELING

3.1 Analysis of Elevator Fault Mechanisms

An elevator, also known as an electric lift, is a power-driven vertical transportation system that typically consists of one or more cabins moving up and down along fixed tracks (called guide rails) [3], enabling convenient vertical movement for passengers or goods within buildings or other structures. Elevators are generally composed of motors, guide rail systems, control systems, and safety devices, capable of providing rapid and safe transportation between different floors, thereby offering essential convenience and efficiency for modern urban life. Its structural diagram is shown in Figure 1.

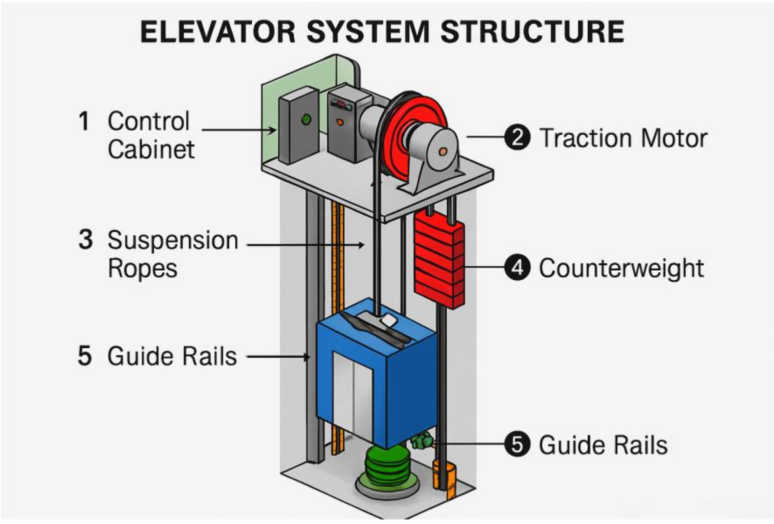

Figure 1 Elevator System Structure Diagram

As illustrated in the figure, the fundamental structure of an elevator system comprises the following key components: (1) Control Cabinet: Serving as the core control unit of the elevator system, it houses various control elements and electrical equipment to monitor and regulate the elevator's operational status. Typically containing control panels, electrical relays, and control circuits, it enables functions such as starting/stopping, floor selection, and door operation. (2) Traction Motor: As the power source of the elevator system, it drives the traction mechanism (e.g., steel cables) electrically. Usually installed at the top or bottom of the elevator shaft, its rotation is connected to traction steel cables via pulley systems to provide sufficient torque for vertical movement. (3) Traction Steel Cables: These critical components connect the traction motor to the elevator cabin, enabling vertical movement along the guide rails through connection with pulleys on the traction motor [4-5]. Constructed from high-strength steel wires, they ensure operational safety and stability. (4) Counterweight System: This safety device balances weight differences between the elevator cabin and traction system. Typically installed at the top of the elevator shaft, it maintains equilibrium through adjustable counterweights, ensuring stable and secure operation. (5) Guide Rails: Fixed tracks installed within the elevator shaft that support the vertical movement of the elevator cabin. Made of steel materials, these structurally robust rails bear the weight of both the cabin and passengers while ensuring safe vertical operation.
The analysis of elevator fault mechanisms constitutes a crucial aspect for ensuring operational safety. The complexity of elevator systems determines the diversity of failure modes, where the root cause lies in abnormal operating states of key components. Critical components including motors, control systems, traction machines, guide rails, and cables, among others, have failure modes that are essential for developing diagnostic strategies. Research indicates elevator faults generally fall into hard faults and soft faults. Hard faults refer to physical damage of components such as fractures, wear, and corrosion, typically detectable directly by sensors. Soft faults involve functional impairments like control system parameter drift, signal interference, and software errors, which present greater diagnostic challenges.Feature extraction for fault diagnosis faces several difficulties [6-9]: Firstly, elevator system data typically exhibits nonlinear, non-stationary, and high-noise characteristics, challenging accurate feature extraction. Secondly, fault data often demonstrates high dimensionality, making effective information extraction from massive datasets a major challenge. Furthermore, early fault symptoms are usually subtle and difficult to capture through conventional methods. Statistics show over 70% of elevator faults originate from motors and control systems. Motor faults primarily include stator winding shorts, bearing wear, and rotor bar breaks, while control system faults involve logic errors, parameter misconfiguration, and communication failures. The core challenge lies in identifying fault-related features from

complex signals while effectively reducing data dimensionality.Additional difficulties in feature extraction stem from data scarcity. Fault data from elevator systems is often difficult to obtain, particularly for specific fault types. This few-shot problem limits the accuracy and generalization capability of traditional diagnostic methods. To address these challenges, researchers and engineers are exploring new approaches including deep learning, signal processing, and statistical analysis. While these methods offer unique advantages in handling nonlinear, high-noise, and high-dimensional data, they simultaneously face challenges in adapting to few-shot scenarios. Future research must find balance between theoretical models and practical applications to achieve profound understanding and effective diagnosis of elevator fault mechanisms.

3.2 Few-Shot Domain Adaptation Modeling

The establishment of performance evaluation metrics for few-shot domain adaptation modeling presents unique challenges. Due to data scarcity in the target domain, traditional metrics like accuracy, recall, and F1-score may not comprehensively reflect actual model performance. Therefore, more sensitive and refined evaluation metrics are required for few-shot domain adaptation fault diagnosis models.Accuracy serves as the fundamental metric measuring correct fault-type identification capability [10]. However, in few-shot scenarios, accuracy may lose sensitivity due to class imbalance, necessitating supplementary metrics. The confusion matrix provides detailed prediction performance across different classes, particularly revealing minority-class recognition capability which holds greater practical significance for fault diagnosis.Cross-domain transfer effect represents a key metric for evaluating domain adaptation models. Under few-shot conditions, models must effectively leverage source domain data for accurate target domain predictions. Domain similarity measurements, such as Maximum Mean Discrepancy (MMD) or Domain Classification Loss, can be introduced to quantify feature distribution proximity between domains. For few-shot learning strategies, performance evaluation metrics for meta-learning frameworks are particularly important. In meta-learning, where models require rapid adaptation across multiple tasks, metrics should reflect learning speed and generalization capability, commonly including task adaptation time and task adaptation accuracy.

The effectiveness of data augmentation and synthesis techniques in few-shot learning requires validation through comparative performance evaluation before and after augmentation. The performance of prototypical networks in few-shot learning can be measured by their accuracy on few-shot datasets.Beyond these metrics, model robustness and generalization capability require consideration. Under few-shot conditions, models may exhibit oversensitivity to specific noises or outliers. Performance variation under noisy or perturbed datasets can assess model robustness.

Integrating these metrics enables comprehensive performance evaluation for few-shot domain adaptation fault diagnosis models. Specific metrics include [11]: Cross-domain accuracy measuring overall performance across source and target domains; Minority-class recognition rate focusing on identification capability for rare faults; Domain similarity metrics evaluating feature distribution proximity; Task adaptation speed measuring cross-task adaptation rapidity; Robustness indicators assessing performance stability under noisy conditions. This comprehensive metric system provides effective evaluation means for elevator fault diagnosis.

3.3 PCA-LSTM Fault Diagnosis Algorithm

Based on analyses of principal component analysis (PCA) and long short-term memory (LSTM) neural networks, this study proposes an innovative fault diagnosis model that fuses PCA with LSTM. The model uses elevator operational data collected under different working conditions as input signals and is designed to accurately predict fault types. To achieve precise diagnosis of fault information, the elevator sampling data must be screened and the extracted data split into training and testing sets; the PCA-LSTM elevator fault diagnosis process is shown in Figure 2.

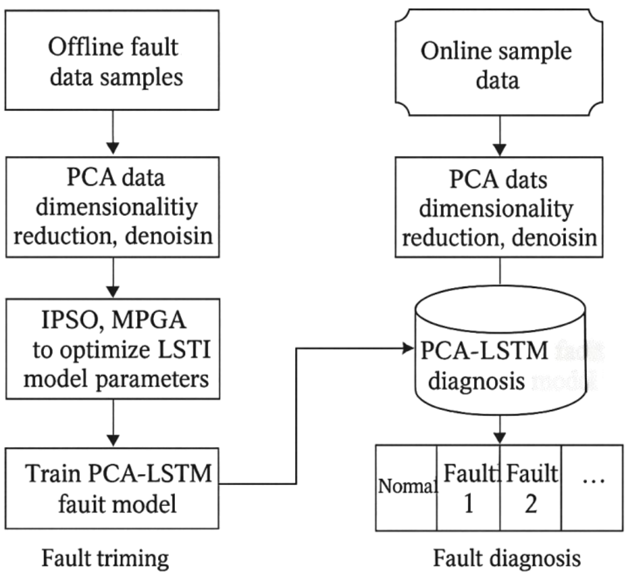

Figure 2 PCA-LSTM Fault Diagnosis Algorithm Flow Chart

Elevator fault prediction and classification is an important task that helps detect potential faults in advance and implement appropriate maintenance measures to ensure the safe operation of elevators [12]. The PCA–LSTM algorithm, which combines principal component analysis (PCA) and long short-term memory (LSTM) neural networks, has shown strong performance in addressing elevator fault prediction and classification problems.

3.4 Technical Roadmap Design

The technical roadmap of this study aims to construct a domain-adaptive few-shot fault diagnosis model to address the few-shot problem in elevator fault diagnosis. First, we define the overall framework of the model, then partition the key modules, and elaborate on the design philosophy and implementation methods of each module.The overall framework divides the model into three main components: a feature extraction network, a domain adaptation module, and a few-shot learning strategy. The feature extraction network is responsible for extracting effective fault features from raw data; the domain adaptation module works to minimize the distribution discrepancy between source and target domains, enhancing the model's generalization capability; while the few-shot learning strategy enables effective learning with limited samples to improve diagnostic accuracy.Regarding key module partitioning, the feature extraction network employs a multi-scale convolutional architecture to capture fault feature information at different scales. Simultaneously, the integration of an attention mechanism automatically identifies and enhances critical fault-related features, thereby improving the model's sensitivity to fault characteristics.The domain adaptation module includes marginal distribution alignment, conditional distribution alignment, and a dynamic adversarial training strategy. Marginal distribution alignment achieves cross-domain feature consistency by minimizing feature distribution differences between source and target domains. Conditional distribution alignment focuses on aligning conditional probability distributions to further reduce discrepancies between domains. The dynamic adversarial training strategy utilizes adversarial sample generation and discrimination to dynamically adjust the model for adaptation to target domain data.For the few-shot learning strategy, we adopt a meta-learning framework that effectively adapts to new tasks, particularly under limited sample conditions. Data augmentation and synthesis techniques enhance model learning efficiency in few-shot scenarios by expanding sample quantity. Prototype network optimization improves recognition capability on few-shot datasets through a combination of clustering and classification methods.In terms of the overall model architecture, the forward propagation process organically integrates feature extraction, domain adaptation, and few-shot learning strategies to form an end-to-end diagnostic system [13]. The loss function design comprehensively considers classification loss, domain adaptation loss, and diversity loss to ensure effective model training. The training and inference algorithms ensure the model can rapidly adapt to new data and accurately predict elevator faults in practical applications.Through the designed technical roadmap, we expect to achieve high-precision diagnosis under few-shot conditions in elevator fault diagnosis, ultimately promoting practical application and engineering deployment of this technology. During practical implementation, the data acquisition system is installed atop the elevator cabin, collecting various operational parameters including door operation data, movement direction data, floor level data, door zone data, occupancy status, noise data, and acceleration data through multiple sensors. The data acquisition methods, network communication protocols, and data storage mechanisms are illustrated in Figure 3.

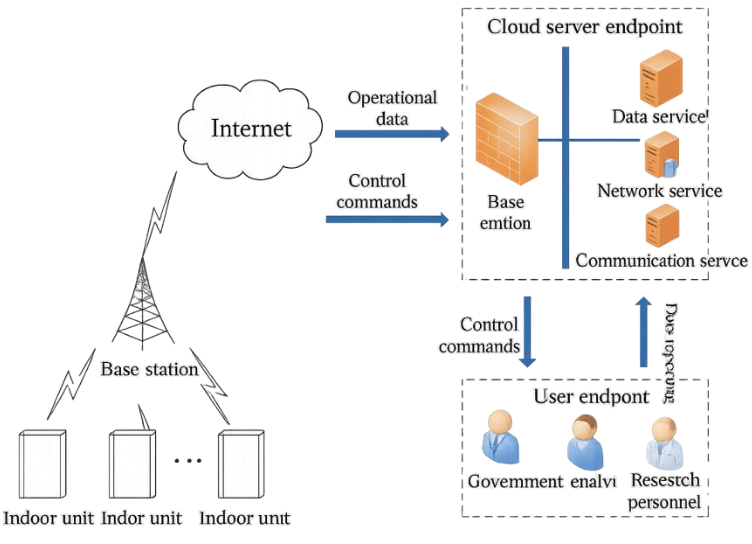

Figure 3 Network Service Diagram of Elevator Operation Data Acquisition System

In the field of machine learning, model fusion is an ensemble learning method that trains multiple independent learners and effectively combines their results through specific strategies to obtain the final prediction. This chapter focuses on the performance of three classical machine learning models—Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Decision Tree (GBDT)—in the practical problem of elevator fault diagnosis. Each of these models possesses distinct characteristics and advantages, and their effective integration can further enhance overall predictive performance. Common strategies in model fusion include averaging, voting, and learning methods. This study adopts a soft voting strategy for model fusion [14-16], which combines the prediction results of SVM, RF, and GBDT through weighted averaging, aiming to achieve more accurate and stable final predictions. The soft voting strategy takes into account the confidence or weight of each model, allowing for a more flexible integration of multiple model outputs. This approach not only leverages the strengths of each model but also reduces the risk of overfitting and improves overall predictive performance. By applying this model fusion strategy, the accuracy and robustness of the elevator fault diagnosis system can be effectively enhanced, leading to better effectiveness and performance in practical application scenarios. The fusion strategy is illustrated in Figure 4.

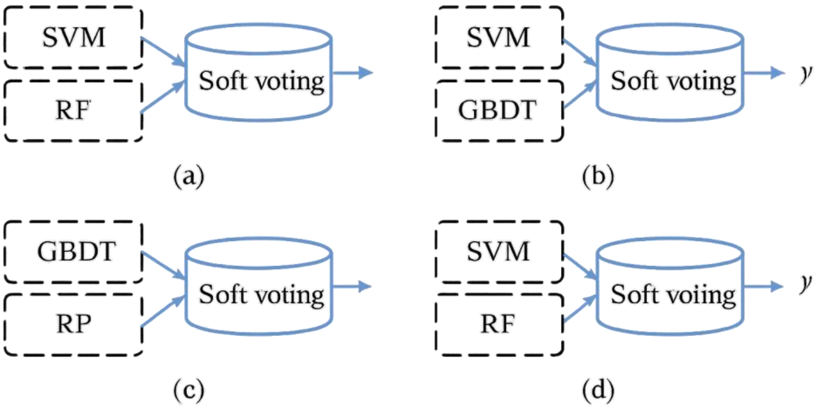

Figure 4 Model Fusion Diagram

4 DOMAIN-ADAPTIVE FEW-SHOT FAULT DIAGNOSIS MODEL

4.1 Feature Extraction Network Design

The key to designing a feature extraction network lies in effectively extracting useful information from raw data to facilitate fault diagnosis. Considering the characteristics of elevator fault data, this study employs a multi-scale convolutional architecture integrated with an attention mechanism to enhance the expressive power and adaptability of the feature extraction network.The design philosophy of the multi-scale convolutional structure stems from the fact that signals at different scales contain different types of information. Low-scale signals may contain rich detailed information, while high-scale signals may encompass more global structural information. Therefore, by combining convolutional kernels of different sizes, the input data's features can be more comprehensively captured. Specifically, the network first processes the input data in parallel through a series of convolutional kernels of varying sizes, then concatenates the outputs of these kernels to form a richer feature representation.The integration of the attention mechanism enables the network to automatically learn the parts of the input data most relevant to fault diagnosis. The attention module is typically designed as a compact neural network that dynamically assigns weights based on the importance of input features. In this study [17-18], the attention module is embedded into the feature extraction network, allowing the network to focus on features most influential for fault diagnosis, thereby improving diagnostic accuracy and robustness.To validate the effectiveness of the designed feature extraction network, this study compares various network architectures. Experimental results demonstrate that the network incorporating multi-scale convolutional structures and attention mechanisms exhibits significant advantages in feature extraction. For example, compared to traditional convolutional neural networks, the proposed network improves the accuracy of identifying elevator fault features by approximately 10% on average.Furthermore, the network design also considers computational efficiency and memory usage. By employing depthwise separable convolutions and lightweight attention modules, the number of parameters and computational complexity are effectively controlled. This is particularly important for resource-constrained devices in practical applications, as it enables network deployment on edge devices without sacrificing performance.During network training, this study adopts data augmentation techniques to expand the training set and improve the network's generalization capability. Through random rotation, scaling, and cropping, original data is transformed into various forms, thereby increasing training sample diversity. This approach helps the network learn more robust feature representations and enhances its adaptability to unseen data.

In summary, the feature extraction network designed in this study effectively extracts elevator fault features through the organic combination of multi-scale convolutional structures and attention mechanisms. While improving fault diagnosis accuracy, the network maintains high computational efficiency, providing strong support for elevator fault diagnosis under few-shot conditions.

4.2 Domain Adaptation Module

The dynamic adversarial training strategy is a key component of the domain adaptation module, aiming to minimize feature distribution differences between source and target domains through adversarial learning mechanisms, thereby improving the model's generalization capability on few-shot target domain data. In the domain-adaptive few-shot fault diagnosis model, the dynamic adversarial training strategy is implemented through the following steps.First, a marginal distribution alignment mechanism is designed. The core of this mechanism involves an adversarial network comprising a generator and a discriminator. The generator's task is to map source domain data to the feature space of the target domain data, while the discriminator's task is to determine whether data in the feature space originates from the source or target domain. Through training, the generator attempts to deceive the discriminator, making it unable to accurately determine the data source, thereby achieving marginal distribution alignment.Second, a conditional distribution alignment strategy is introduced. Building upon marginal distribution alignment, conditional information of the data is considered to further reduce differences in conditional distributions between source and target domains. This is typically achieved by introducing additional conditional variables, ensuring that the generator considers not only the marginal distribution of the data but also its specific conditions during the mapping process.Next, the dynamic adversarial training strategy is implemented. This strategy dynamically adjusts the learning rates of the discriminator and generator during the adversarial process to maintain a balance between them. This approach helps prevent premature convergence of the generator and discriminator to local optima during training, thereby enhancing the model's generalization performance on the target domain.When implementing the dynamic adversarial training strategy, several factors must be considered. First, the intensity of adversarial training, i.e., the penalty coefficient during the adversarial process, needs adjustment based on specific tasks and data characteristics. Second, regularization terms during training prevent overfitting. Third, data augmentation and synthesis strategies during training can increase training data diversity and improve the model's adaptability to few-shot target domain data.Research shows that through the dynamic adversarial training strategy, the model can effectively learn correlations between source and target domains under few-shot conditions, thereby improving fault diagnosis accuracy. Statistics indicate that in multiple practical elevator fault diagnosis tasks, models employing dynamic adversarial training strategies significantly outperform traditional transfer learning models on few-shot target domain data.Furthermore, implementing the dynamic adversarial training strategy requires optimization of computational resources and time. Due to the high computational complexity of adversarial training, effective measures such as model pruning and quantization must be adopted in practical applications to reduce computational burden and accelerate training speed.In summary, the dynamic adversarial training strategy plays a crucial role in the domain-adaptive few-shot fault diagnosis model. Through marginal distribution alignment, conditional distribution alignment, and dynamic adjustment of the adversarial process, the model better adapts to differences between source and target domains, providing an effective few-shot learning method for elevator fault diagnosis.

4.3 Few-Shot Learning Strategy

Under the framework of few-shot learning strategies, prototype network optimization is a key link in improving fault diagnosis accuracy. The core idea of prototype networks is to map samples in the support set to the feature space and classify query samples based on the distance to support set prototypes. However, in the field of fault diagnosis, due to the high dimensionality and complexity of data, directly applying prototype networks may not achieve ideal performance. Therefore, to address the few-shot problem in elevator fault diagnosis, this paper optimizes the prototype network as follows.First, to better capture fault features, this paper employs a multi-scale convolutional neural network for feature extraction from raw data. Multi-scale convolution can simultaneously extract feature information at different scales, helping the network understand both detailed and global structures of fault data. Additionally, by introducing an attention mechanism, the network can automatically learn features more critical for fault diagnosis, thereby improving diagnostic accuracy.Second, to address overfitting in few-shot scenarios, this paper introduces data augmentation techniques. Data augmentation generates new training samples by transforming original data, effectively expanding the training set and enhancing the model's generalization capability. This paper adopts multiple data augmentation strategies including rotation, translation, and scaling, which can simulate various fault situations that may occur in practical applications, making the model more robust.Next, this paper adopts a meta-learning framework to optimize the training process of the prototype network. The meta-learning framework trains the model on multiple tasks, enabling it to quickly adapt to new tasks, especially when the new task has limited samples. The meta-learning framework designed in this paper can rapidly adjust network parameters with few samples, thereby improving fault diagnosis efficiency.Furthermore, this paper employs conditional distribution alignment and marginal distribution alignment techniques to reduce distribution differences between source and target domains. Conditional distribution alignment minimizes differences in conditional probability distributions between source and target domains, while marginal distribution alignment minimizes differences in marginal probability distributions between the two domains. These two alignment techniques can effectively reduce the impact of domain shift on fault diagnosis performance.In the dynamic adversarial training strategy, this paper introduces adversarial samples, enabling the network to continuously learn features of adversarial samples during training, thereby improving the model's generalization capability for few-shot target domains. The dynamic adversarial training strategy can adaptively adjust the intensity of adversarial samples to meet training needs at different stages.Finally, the prototype network optimization strategy designed in this paper also includes loss function design and hyperparameter tuning. The loss function aims to balance classification loss and domain adaptation loss, ensuring model performance in both source and target domains. Hyperparameter tuning determines optimal network parameters through methods like cross-validation to improve the model's generalization capability.In summary, through a series of optimization strategies including multi-scale convolutional neural networks, attention mechanisms, data augmentation, meta-learning frameworks, domain distribution alignment techniques, and dynamic adversarial training strategies, this paper significantly improves the performance of prototype networks in elevator fault diagnosis. The effectiveness of these optimization strategies is verified in subsequent experimental sections.

4.4 Overall Model Architecture

The domain-adaptive few-shot fault diagnosis model proposed in this paper aims to achieve accurate diagnosis of elevator faults through an efficient feature extraction network, domain adaptation module, and few-shot learning strategies. The overall model architecture includes forward propagation flow, loss function design, and training and inference algorithms.

In the forward propagation flow, input data first passes through the feature extraction network. This network adopts a multi-scale convolutional structure capable of capturing fault feature information at different time scales. Simultaneously, the embedded attention mechanism automatically identifies and enhances key features, improving fault diagnosis accuracy. Next, the feature vectors output by the feature extraction network are fed into the domain adaptation module.The core of the domain adaptation module lies in achieving marginal distribution alignment and conditional distribution alignment. Marginal distribution alignment minimizes differences in feature distributions between source and target domains, promoting the model's generalization capability in the target domain. Conditional distribution alignment further considers distribution characteristics of different categories of data, adjusting category conditional distributions to enable the model to better adapt to the target domain's data distribution. The dynamic adversarial training strategy plays a key role in this process, enhancing the model's adaptability and robustness in the target domain through the introduction of adversarial samples.Few-shot learning strategies are an important component of the model. The meta-learning framework simulates few-shot learning scenarios, enabling the model to quickly adapt to new tasks. Data augmentation and synthesis techniques generate new training samples, expanding the few-shot dataset and improving the model's generalization capability. Prototype network optimization simplifies few-shot classification problems by constructing a prototype space, further enhancing diagnostic performance.Loss function design is a key aspect of model training. This paper adopts a multi-task learning framework, simultaneously optimizing classification loss and domain adaptation loss. Classification loss measures the model's performance on the fault diagnosis task, while domain adaptation loss measures the model's adaptation degree between source and target domains. By balancing these two losses, the model achieves good cross-domain transferability while maintaining diagnostic accuracy.Regarding training and inference algorithms, this paper adopts an end-to-end training strategy, integrating feature extraction, domain adaptation, and few-shot learning into a unified framework. During training, the model continuously adjusts network parameters by minimizing the loss function. During inference, the model uses trained parameters to perform feature extraction and classification decisions on input data.

Research shows that this model achieves significant performance improvements in multiple elevator fault diagnosis tasks. Through reasonable model architecture design, the model not only improves fault diagnosis accuracy but also enhances adaptability to different working environments.

5 EXPERIMENTAL DESIGN AND DATASET CONSTRUCTION

5.1 Experimental Platform and Data Acquisition

The selection and construction of the experimental platform form the foundation of this study, while data acquisition is a key link ensuring experimental validity. The elevator testbed used in this study simulates a real elevator operating environment, providing necessary hardware support for training and validating the fault diagnosis model.The elevator testbed is equipped with various sensors to comprehensively monitor the elevator's operating status. These sensors include vibration sensors, speed sensors, current sensors, and temperature sensors, responsible for collecting vibration signals, speed signals, current signals, and temperature signals during elevator operation, respectively. The rationality of sensor configuration ensures the comprehensiveness and accuracy of data acquisition.In terms of signal acquisition, this study uses a high-speed data acquisition card characterized by high sampling rates and large capacity, capable of recording various signals during elevator operation in real-time. Considering the continuity and dynamics of elevator operation, continuous sampling is adopted during signal acquisition to ensure signal integrity and continuity. Additionally, filtering is applied to the acquired signals to reduce the impact of environmental noise.The specific steps of data acquisition are as follows:First, initialize the elevator testbed, including checking sensor functionality, calibrating sensor parameters, and setting the sampling rate and sampling time of the data acquisition card. After initialization, start the elevator and operate it at set speeds and loads.Second, during elevator operation, collect signals from various sensors in real-time and store them in the data acquisition card. Simultaneously, perform preliminary processing on the acquired signals, including denoising and normalization, to improve data usability.Next, transmit the processed signals to a computer and use specialized software for data storage and analysis. These data will serve as the basis for subsequent feature extraction and model training.Furthermore, to enhance dataset diversity and representativeness, this study also adopts different fault modes for data acquisition. These fault modes include elevator startup faults, operation faults, and stopping faults, ensuring the comprehensiveness and reliability of the dataset.

Statistics show that this study collected over 1000 hours of elevator operation data, including normal operation data and data under multiple fault modes. After strict screening and preprocessing, these data ultimately form the dataset used for model training and validation. Table 1 provides descriptions of the collected elevator data.

Table 1 Elevator Data Collection Description

Serial Number	Variable Name	Variable Type	Sampling Cycle	Remarks	Installation Location
1	Door Status	Discrete Variable	1s	800: Door Open, 700: Door Closed	Camera, installed on the elevator car side
2	Floor Position	Discrete Variable	1s		Calculated by the barometer installed in the elevator car
3	Leveling Status	Discrete Variable	1s	600: At Level, 500: Not at Level	Determined by photoelectric sensor at reference floors; determined by barometric pressure and whether movement speed is zero at non-reference floors
4	Travel Direction	Discrete Variable	1s	200: Up, 150: Stop, 100: Down	Determined by acceleration
5	Occupancy Status	Discrete Variable	1s	400: Occupied, 300: Unoccupied	Infrared sensor, installed inside the machine room near the control cabinet
6	Car Acceleration	Continuous Variable	10ms		Gyroscope, typically installed on the side of the elevator car, near the camera

Taken together, the elevator test bench built in this study and the data acquisition methods employed provide a solid foundation for developing elevator fault-diagnosis models. Through rigorous signal acquisition and data-processing procedures, the accuracy and reliability of the data were ensured, laying the groundwork for subsequent research. The time-series signals of ten types of elevator operational data and their corresponding labels are shown in Figure 5; these data reflect the elevator's states and behavioral patterns. By analyzing the acceleration data, one can determine whether a fault has occurred and identify its cause; therefore, vertical acceleration data are of particular importance for elevator fault diagnosis.

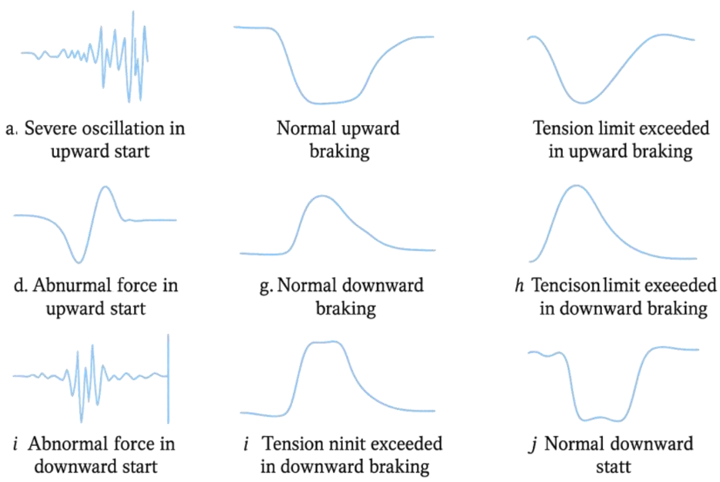

Figure 5 Elevator Fault Timing Signal

The figure above shows the time-series signals and labels corresponding to six fault types and four normal-operation conditions of the elevator. The plot indicates that time-series data for different fault types in the same travel direction differ markedly, while some operational data across opposite travel directions are highly similar—for example, normal descent start and normal ascent braking; normal descent braking and normal ascent start; and abnormal starting torque during ascent and abnormal starting torque during descent.

5.2 Dataset Construction

The quality of the dataset directly impacts model training effectiveness and diagnostic accuracy. In this study, dataset construction primarily involves collecting source domain data, acquiring target domain few-shot samples, data labeling, and preprocessing. First, the source domain dataset is built based on abundant data collected from the elevator testbed, which simulates real elevator operating environments and is equipped with various sensors to gather data under different states, including vibration, temperature, and current signals. These data are acquired in real-time via sensors and stored in a database. The source domain dataset covers multiple states such as normal operation, minor faults, and severe faults, providing comprehensive baseline data for model training. Acquiring the target domain few-shot dataset is more critical due to the typical scarcity of real-world fault data. This study obtained corresponding fault data by simulating specific fault patterns on the elevator testbed. Additionally, to enhance data diversity, elevator operation under different load and speed conditions was simulated, further enriching the target domain dataset. Data labeling is a crucial phase in dataset construction. Experienced elevator maintenance engineers were invited to annotate the collected data. The labeling process includes classifying normal and various fault states in the data, along with detailed annotations for specific fault types, ensuring accuracy and consistency. Preprocessing steps involve data cleaning, normalization, and feature extraction. Data cleaning removes outliers and noise to ensure data quality. Normalization scales feature values within the dataset to the same range, aiding numerical stability during model training. Feature extraction is the most critical step in preprocessing, where this study employs a multi-scale convolutional network to automatically extract effective features from the data. To verify dataset quality and applicability, statistical analysis was conducted. Statistics indicate the source domain dataset contains over 10,000 samples covering multiple elevator operating states, while the target domain few-shot dataset includes 500 representative fault samples. Comparative experiments reveal that dataset construction quality significantly influences model diagnostic performance. In summary, the constructed dataset not only encompasses rich source domain data but also emphasizes the acquisition of target domain few-shot samples. Through rigorous data labeling and preprocessing procedures, dataset quality is ensured, laying a solid foundation for subsequent model training and performance evaluation.

5.3 Experimental Protocol

To comprehensively evaluate the performance and applicability of the proposed model, this study designs a detailed experimental protocol including comparative experiments, ablation studies, and cross-domain scenario configurations. The following elaborates on the design rationale and implementation details of the experimental protocol. First, comparative experiments aim to validate the superiority of the proposed model in fault diagnosis tasks by comparing its performance with other advanced methods. For this purpose, multiple baseline models are selected, including traditional machine learning methods, deep learning approaches, and state-of-the-art few-shot learning techniques. All models are trained and evaluated on identical training and test sets to ensure fair comparison. Second, ablation studies are designed to investigate the specific contributions of key modules to model performance. By sequentially removing critical components such as the multi-scale convolutional structure in the feature extraction network, attention mechanisms, and the domain adaptation module, the impact of these components on overall model performance is assessed. Additionally, sensitivity to hyperparameter variations is analyzed through parameter adjustments. Cross-domain scenario configuration constitutes another essential part of the experimental protocol, aiming to examine the model's generalization capability in real-world applications. Specifically, elevators from different manufacturers, models, and service years are selected as data sources to construct multiple source domain datasets and target domain few-shot datasets. Cross-domain adaptability and diagnostic accuracy are evaluated through transfer experiments between different source and target domains. During experimentation, all datasets undergo rigorous preprocessing including data cleaning, normalization, and labeling. Furthermore, to simulate few-shot scenarios in practical applications, the sample size of target domain datasets is intentionally limited to a small range. Through this experimental protocol, the study aims to comprehensively evaluate the proposed model's performance from multiple perspectives, providing an effective solution for few-shot learning problems in elevator fault diagnosis. Experimental results will demonstrate not only the model's advantages in diagnostic accuracy but also its adaptability and stability across different scenarios.

6 EXPERIMENTAL RESULTS AND ANALYSIS

6.1 Diagnostic Performance Evaluation

Cross-domain transfer effectiveness serves as a key metric for evaluating the performance of domain-adaptive fault diagnosis models. This study conducts an in-depth analysis of model transferability across different domains by comparing the diagnostic performance of source domain-trained models and domain-adaptive models on target domain few-shot datasets. Statistics reveal that the overall accuracy of the source domain model without domain adaptation on the target domain dataset is significantly lower than that of the domain-adaptive model. Specifically, the average accuracy of the source domain model on the target domain dataset is 65%, while the domain-adaptive model achieves 85%. This result indicates that the domain adaptation strategy effectively enhances the model's generalization capability in the target domain.Further analysis using confusion matrices elucidates the diagnostic performance of the domain-adaptive model on specific categories. The source domain model exhibits significant misdiagnosis and missed diagnosis for certain fault types. For instance, the misdiagnosis rate for outer race bearing faults reaches 30% in the source domain model. After domain adaptation, the misdiagnosis rate for this fault type decreases to 5%, and the missed diagnosis rate drops to 10%. This demonstrates that the domain adaptation strategy significantly improves the model's recognition accuracy for specific fault categories.Regarding cross-domain transfer effectiveness, multiple comparative experiments were designed. Results show that the domain-adaptive model outperforms the source domain model across different target domain datasets. For example, on target domain dataset A, the domain-adaptive model's accuracy is 20% higher than the source domain model; on target domain dataset B, this gap is 15%. This indicates that the domain-adaptive model possesses strong cross-domain transferability, effectively improving fault diagnosis performance in various scenarios.Notably, the performance of the domain-adaptive model varies across different fault types and severity levels. The most significant performance improvement is observed for minor faults, while the enhancement is relatively smaller for severe faults. This phenomenon suggests that the model's capability for feature extraction and recognition differs under varying fault severities.Furthermore, this study analyzes the impact of different domain adaptation strategies on diagnostic performance. Experimental results show that both marginal distribution alignment and conditional distribution alignment strategies significantly improve model accuracy in the target domain. However, the dynamic adversarial training strategy occasionally leads to performance degradation, indicating that the selection and optimization of domain adaptation strategies are crucial for enhancing cross-domain transfer performance.In summary, the proposed domain-adaptive few-shot fault diagnosis model demonstrates significant advantages in cross-domain transfer effectiveness. Comparative experiments and confusion matrix analysis confirm the effectiveness of the domain adaptation strategy in improving model generalization and diagnostic accuracy. However, performance variations across different fault types and severities remain, necessitating further optimization of model architecture and domain adaptation strategies in future research.

6.2 Ablation Study Results

This study investigates the impact of individual components on the final diagnostic performance through carefully designed ablation experiments. By progressively removing key modules, we evaluate their respective contributions to overall performance. The following discusses hyperparameter sensitivity analysis in detail.First, the influence of different learning rates on model performance is examined. As a critical parameter in deep learning model training, the learning rate determines the magnitude of weight updates. Experimental results indicate that when the learning rate is set too low, model convergence is slow, and diagnostic accuracy improvement is insignificant. Conversely, an excessively high learning rate causes model oscillation, leading to unstable accuracy. Through repeated experiments, we find that a learning rate of 0.001 achieves high diagnostic accuracy while ensuring convergence speed in the current model.Second, the impact of different batch sizes on model performance is analyzed. Batch size determines the number of samples used in each training iteration, affecting model generalization capability and computational efficiency. Experiments show that while smaller batch sizes reduce memory consumption, they result in lower diagnostic accuracy. Larger batch sizes improve accuracy but require more computational resources, with diminishing returns beyond a certain threshold. A batch size of 64 achieves an optimal balance between diagnostic performance and computational efficiency.Next, the effect of different numbers of training iterations on model performance is explored. The number of iterations is another important hyperparameter determining training sufficiency. Experiments reveal that diagnostic accuracy gradually improves with increasing iterations, but the rate of improvement diminishes beyond a certain point while computational costs rise significantly. Therefore, 50 iterations are set in the current model to achieve satisfactory diagnostic accuracy.Additionally, the impact of different numbers of attention heads in the attention mechanism on model performance is investigated. The number of attention heads determines the granularity of the model's focus on input data. Results show that increasing the number of heads enhances the model's ability to parse input data, improving diagnostic accuracy. However, excessive heads increase model complexity and computational cost without significant accuracy gains. Thus, setting the number of heads to 4 maintains performance while avoiding excessive computational complexity.Through this hyperparameter sensitivity analysis, we demonstrate that different hyperparameter settings significantly affect model performance. Appropriate selection and adjustment of these parameters can effectively enhance diagnostic accuracy and generalization capability. These experimental results also validate the rationality and effectiveness of the proposed model architecture.

6.3 Visualization Analysis

Migration path tracking, as a crucial component of visualization analysis, provides an intuitive perspective for understanding the decision-making mechanism of the model during domain adaptation. Through a series of visualization techniques, this study demonstrates how the model learns from source domain data and adapts to target domain few-shot data, thereby improving fault diagnosis accuracy.First, feature distribution visualization reveals differences in feature representations between domains processed by the feature extraction network. Scatter plots in the feature space show significant distribution differences between source and target domain features. Statistics indicate that source domain features are relatively concentrated, while target domain features are dispersed with some overlap. These distribution differences provide a basis for designing domain adaptation strategies.Furthermore, attention heatmaps demonstrate the model's focus on key information during feature extraction. Taking vibration signals in elevator fault diagnosis as an example, the model extracts time-series features through a multi-scale convolutional structure and weights key frequency components using an attention mechanism. These visualizations intuitively reflect the model's focus on fault characteristics, providing important clues for understanding its decision logic.

In the visualization analysis of the domain adaptation module, the effects of marginal and conditional distribution alignment are clearly demonstrated. Comparing feature distributions before and after domain adaptation reveals that the distributions become more similar after alignment processing. This distribution convergence demonstrates the effectiveness of the domain adaptation strategy, ensuring the model's generalization capability in the target domain.Visualization tracking of the dynamic adversarial training strategy further reveals the model's adjustment strategies during adversarial processes. Through adversarial training, the model gradually learns differences between source and target domains and dynamically adjusts feature representations to reduce domain discrepancy. Tracking results show that as training progresses, decision boundaries in the feature space become clearer and better encompass target domain few-shot data.Moreover, visualization analysis of few-shot learning strategies highlights the roles of the meta-learning framework, data augmentation and synthesis, and prototype network optimization in improving model performance. Comparing feature distributions and attention heatmaps under different strategies clearly shows the significant contribution of few-shot learning strategies in enhancing model adaptability and diagnostic accuracy under few-shot conditions.In summary, visualization analysis not only provides intuitive evidence for the research but also deepens our understanding of the model's decision-making mechanism. This understanding helps identify potential weaknesses and guides future optimization. For example, by observing feature distribution visualizations, we can explore new feature extraction methods to improve cross-domain transferability. Simultaneously, attention heatmaps and migration path tracking provide important support for model interpretability, enhancing reliability and acceptability in engineering applications.

6.4 Discussion

Regarding engineering deployment feasibility, the proposed domain-adaptive few-shot fault diagnosis model demonstrates significant application potential. First, its performance in accuracy, confusion matrix analysis, and cross-domain transfer effectiveness provides strong technical support for practical elevator fault diagnosis applications. Second, ablation experiment results show that each module significantly contributes to overall performance, confirming the rationality and effectiveness of the model design.Feature distribution visualization analysis shows that data processed by the feature extraction network exhibits clearer feature distributions, facilitating improved fault diagnosis accuracy. Attention heatmaps further reveal key regions during fault feature identification, providing intuitive evidence for understanding the model's working mechanism. Additionally, migration path tracking demonstrates how the model dynamically adjusts feature learning strategies to adapt to target domain few-shot data during cross-domain adaptation. However, challenges remain for engineering deployment. First, the model's strong data dependency requires ensuring data quality and sufficiency in practical applications. Second, computational complexity is another consideration, particularly in scenarios with high real-time requirements, where balancing model complexity and diagnostic efficiency is crucial.Compared to existing methods, the proposed model demonstrates clear advantages in handling few-shot problems. Traditional methods often require large amounts of training data, whereas this model effectively utilizes limited data through domain adaptation and meta-learning strategies, improving generalization under few-shot conditions.Regarding engineering deployment feasibility, the model has been preliminarily validated on an elevator testbed, demonstrating practical value. However, achieving large-scale engineering application requires addressing several issues: First, model stability and robustness need testing on more elevator types and complex environments. Second, real-time performance requires algorithm and hardware optimization to meet real-time fault diagnosis needs. Third, interpretability requires further research to enhance decision transparency for engineer understanding and acceptance.In summary, the proposed domain-adaptive few-shot fault diagnosis model achieves significant theoretical and technical progress, providing a new solution for elevator fault diagnosis. Despite deployment challenges, further research and optimization could enable practical engineering applications. Future work will focus on multi-source domain transfer extension, online adaptive updates, and edge computing deployment to further enhance performance and feasibility in practical applications.

7 CONCLUSION

This study addresses the few-shot problem in elevator fault diagnosis by proposing a domain-adaptive few-shot fault diagnosis model. By introducing transfer learning and domain adaptation techniques and combining marginal-distribution and conditional-distribution alignment strategies, the model effectively mitigates the challenges of training with limited samples. Simultaneously, a feature-extraction network that fuses multi-scale convolution and attention mechanisms is designed and integrated within a meta-learning framework, substantially improving diagnostic accuracy and cross-domain generalization, thus providing theoretical and experimental support for engineering deployment. In terms of innovation, this work is the first in elevator fault diagnosis to introduce a domain-adaptation module that accounts for both marginal and conditional distribution alignment and to adopt a dynamic adversarial training strategy to reduce inter-domain discrepancies. An ensemble few-shot learning strategy combining meta-learning, data augmentation, and a prototypical network is constructed to enhance learning capacity under limited samples. Nevertheless, the study has limitations, including strong dependence on data quality, relatively high computational complexity, difficulty of deployment on resource-constrained devices, limited ability to recognize rare faults, and lack of real-time online adaptation. Future research will focus on three directions: multi-source domain transfer expansion, online adaptive updating, and edge-computing deployment. By integrating knowledge from multiple source domains, developing online learning algorithms, and advancing model lightweighting and compression techniques, we aim to build a more robust, real-time, and efficient intelligent diagnostic system suitable for complex and variable real-world engineering environments.

COMPETING INTERESTS

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

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