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A transfer learning method based on MC-1DCNN for elevator guideway fault diagnosis

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Abstract: Elevator guideway vibration fault diagnosis is essential for ensuring elevator safety and stability. However, vibration signals exhibit complex non-stationary characteristics, and abnormal vibration samples are limited. This paper proposes an advanced fault diagnosis method combining Multi-Channel One-Dimensional Convolutional Neural Networks (MC-1DCNN) with transfer learning for elevator guideways. 1D-CNN is employed to extract local temporal correlations in vibration signals, while Empirical Mode Decomposition (EMD) decomposes signals into Intrinsic Mode Functions (IMFs) to provide multi-frequency features as multi-channel inputs. The MC-1DCNN is pre-trained on the Case Western Reserve University (CWRU) bearing fault dataset to learn general mechanical fault features and is then fine-tuned on the elevator guideway dataset by freezing lower convolutional layers and adjusting higher layers. Experimental results demonstrate that the proposed method achieves high classification accuracy and fast convergence in small-sample scenarios. This study validates the effectiveness of transfer learning in elevator fault diagnosis and provides a practical solution for real-world applications.

Keywords: *Elevator Guideway, Empirical Mode Decomposition (EMD), Fault Diagnosis, One-Dimensional Convolutional Neural Network (1D-CNN), Transfer Learning.*

1. Introduction

Elevator guideway is essential for maintaining the safety and stability of elevator operations, particularly in high-rise buildings. Over time, these components are subjected to faults such as Bending, Misalignment and Step [1] often caused by prolonged operation and external environmental factors. These faults can result in abnormal vibrations, compromising the safety and reliability of the elevator system [2]. Early and accurate diagnosis of such faults is essential for timely maintenance and failure prevention.

Commonly used fault diagnosis methods usually depend on manual feature extraction and classical machine learning approaches [3]. While effective in specific scenarios, these approaches are limited in their ability to process the non-stationary and complex nature of vibration signals in real-world applications. Recent advancements in deep learning have introduced effective approaches that automatically extract features from on-site raw data, outperforming traditional methods. However, the effectiveness of deep learning algorithms typically depends on large labeled datasets, which are often unavailable in practical scenarios such as elevator guideway fault diagnosis [4].To overcome these challenges, transfer learning provides an effective approach by utilizing knowledge from relevant source domain to optimize effectiveness in the target domain with insufficient data [5].

In this study, a method (TL-MC-1DCNN) combining Multi-Channel (MC) One-Dimensional Convolutional Neural Networks (1D-CNN) with transfer learning (TL) is constructed for fault diagnosis of elevator guideway. The proposed method based on the advantages of 1D-CNN's processing

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of one-dimensional time series signals [6] and employs Empirical Mode Decomposition (EMD) to preprocess vibration signals into multiple intrinsic mode functions (IMFs) [7] serving as multi-channel inputs for MC-1DCNN. The model is pre-trained on the Case Western Reserve University (CWRU) bearing fault dataset [8] to extract generalized fault features and fine-tuned on the elevator guideway dataset to enhance fault classification accuracy under limited sample conditions.
The contributions of this research include:

The integration of EMD with MC-1DCNN for multi-scale fault feature extraction and classification.

The application of transfer learning to adapt pre-trained models from the CWRU dataset to the elevator guideway dataset.

Experimental validation demonstrating the proposed method's effectiveness in achieving high fault classification accuracy and efficient convergence.

2 Related Work

2.1. Current Status of Elevator Fault Diagnosis

As elevators become increasingly prevalent in modern buildings, their safety and stability have garnered significant attention, making fault diagnosis technologies for elevators a long-standing focus of research. These methods primarily analyze the time-frequency domain of elevator vibration signals to extract fault features [9]. For instance, Qiu, et al. [10] by feature extraction of elevator vibration signals, realized the identification of elevator fault states based on an enhanced Aquila optimizer (IAO) combined with extreme gradient boosting tree (XGBoost) method. Liu, et al. [11] realized elevator traction machine fault diagnosis using an enhanced complementary ensemble empirical mode decomposition method combined with a support vector machine (SVM) algorithm. Song, et al. [12] developed an innovative method for diagnosing faults in elevator control transformers by integrating empirical mode decomposition (EMD), empirical wavelet packet transform, mental evolutionary algorithm (MEA), and back propagation neural network.

Deep learning has become a robust tool for fault diagnosis due to its ability to automatically extract features and recognize patterns from raw data, avoiding the complexity and uncertainty of manual feature extraction, and offering improved scalability and adaptability [13]. For example, Surendran, et al. [14] developed an intelligent industrial fault diagnosis approach utilizing a sailfish algorithm-optimized inception model integrated with a residual network to identify faults in rotating machinery, and Zhou, et al. [15] introduced a deep learning-based fault diagnosis approach leveraging globally optimized GAN to deal with the unbalanced fault data.

Within the domain of elevator fault diagnosis, Chai, et al. [16] detect the anomalies of elevator by utilizes a deep learning algorithm to analyze the current signals from key circuits. Chae, et al. [17] use the autoencoder convert control state data for elevator doors fault diagnosis. Despite these advances, the outcome of deep learning algorithms is still limited by the large amount of available labelled data, which poses a significant challenge for real-world applications, and when dealing with complex unsteady vibration signals, it is difficult to deal with the differences between various fault signals as the complexity of the elevator's operating environment increases [18].

2.2. Transfer Learning in Small-Sample Scenarios

Transfer learning techniques have shown considerable promise in addressing data scarcity by leveraging knowledge from the source domain to benefit the target domain with limited labeled data. For instance, Wu, et al. [19] developed a meta-learning-based few-shot transfer learning approach to address the challenges in rotating machinery intelligent diagnosis under condition transfer and artificial-to-natural transfer scenarios. Dong, et al. [20] realized a fault diagnosis method that combines dynamic modelling and transfer learning to generate diverse simulation data through dynamic modelling, and uses a convolutional neural network with a parameter shifting strategy to tackle the small sample problem in rolling bearing fault diagnosis. Li, et al. [21] proposed a fault diagnosis method for wind turbines with few sample data, combining parameter-based transfer learning and convolutional autoencoder (CAE) to adapt knowledge from comparable wind turbines to the target turbine. The method effectively leverages both target data and universal failure information from other turbines, outperforming traditional and non-transfer methods in classification accuracy.

The above study suggests that transfer learning may have good potential for application in the area of elevator guideway fault diagnosis driven by limited data.

3. Methodology

3.1. Empirical Mode Decomposition (EMD)

Elevator guideway vibration signals often exhibit non-stationary and complex characteristics, influenced by long-term service and operational conditions. To address these challenges, EMD is employed to preprocess the vibration signals and extract multi-scale features [22]. As an adaptive and data-driven method, EMD decomposes a signal into several IMFs, each representing a specific frequency band. The decomposition process iteratively identifies the local extremes of the signal and forms a series of IMFs to extract meaningful features from nonlinear and nonstationary signals.

Given a vibration signal $x(t)$, the EMD process involves [23]:

Detecting all local peaks and valleys in $x(t)$.

Interpolating the maxima and minima separately to form upper and lower envelopes.

Calculating the mean of the envelopes $m(t)$, and subtracting it from $x(t)$ to obtain a candidate IMF: $h(t)=x(t)-m(t)$

Repeating the sifting process until $h(t)$ satisfies the IMF conditions. The resulting IMF represents one component of the signal.

This procedure iterated until the residual signal becomes monotonic, and the results will as show in Figure 1.

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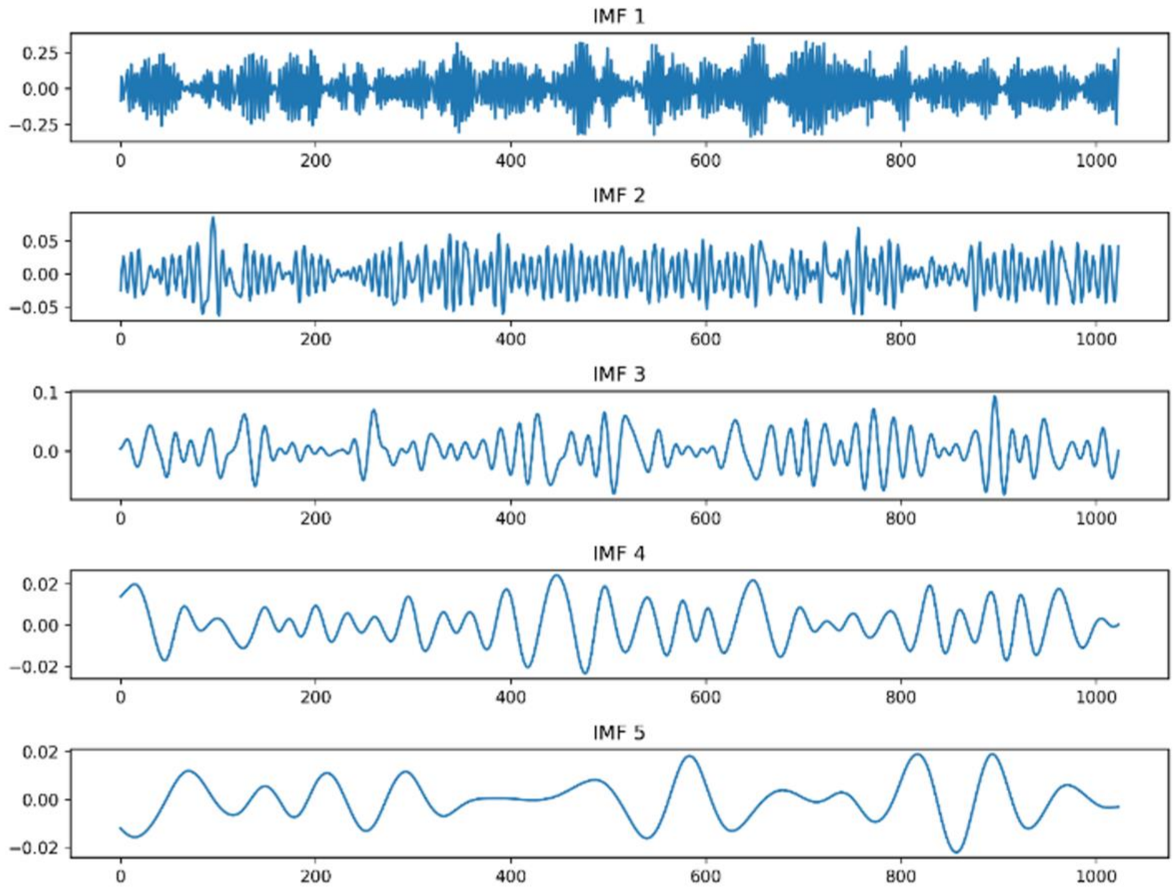

Figure 1.
Schematic of Empirical Mode Decomposition (EMD) Processing Results.

3.2. MC-1DCNN Process

3.2.1. 1D-CNN: A Foundation for Sequential Data Analysis

One-dimensional convolutional neural network (1D-CNN) is particularly effective for processing sequential data, such as vibration signals, since it is capable of capture local temporal dependencies and automatically extract hierarchical features directly from raw inputs [24]. These characteristics make 1D-CNN well-suited for elevator guideway fault diagnosis, where vibration signals often exhibit overlapping fault characteristics and non-linear variations [25]. By leveraging convolutional operations, 1D-CNN can robustly learn fault-related patterns, ensuring reliable performance in noisy environments. The basic structure of 1D-CNN [26] is presented in Figure 2:

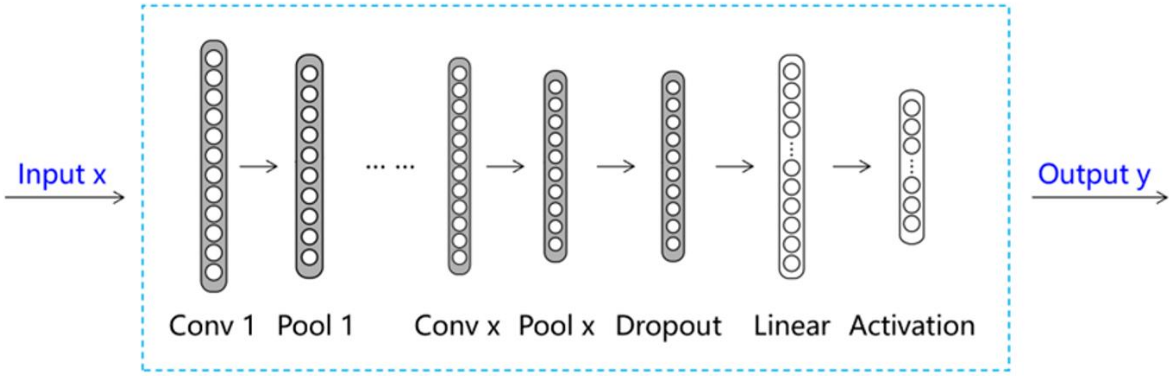

Figure 2.
The Basic Structure of One-Dimensional Convolutional Neural Network (1D-CNN).

3.2.2. Input Layer
Accepts vibration signals data in time-series, with each channel corresponding to an IMF derived from EMD, enabling the model to capture complementary information across different scales.

3.2.3. Convolutional Layers
Employed to extract hierarchical features of input data from each channel, identify patterns within each IMF.

3.2.4. Pooling Layers
Max-pooling is added after each convolutional layer to diminish the dimensionality of the feature maps. This step serves to decrease computational complexity while also helps prevent overfitting by retaining only the most salient features.

3.2.5. Dropout Layer
Incorporated to deactivate a fraction of neurons during training, reducing overfitting and enhances the model's generalization capability, especially when training with limited labeled data.

3.2.6. Fully Connected (Linear) Layer
The features extracted from all channels are flattened and conveyed to a fully connected layer, integrating multi-scale information into a comprehensive representation for classification.

3.2.7. Activation Layer (Classifier)
Outputs probabilities for each fault category, and enables precise classification by leveraging the hierarchical and multi-channel features extracted by the preceding layers.

3.2.8. MC-1DCNN: with Multi-Scale Feature Extraction
In order to effectively process the multi-scale fault-related information embedded in the vibration signals, EMD is adopted as a preprocessing step, in which the vibration signals are decomposed into IMFs, each represents a specific frequency range, and used to retain the key features at different scales. These IMFs are first used as inputs to the 1D-CNN for convolutional operations to capture fault-related features in different frequency bands sequentially, and then the computational results within each channel are summed to obtain the fusion results of each channel. This MC-1DCNN method integrates the multi-frequency feature extraction capability of EMD with the hierarchical learning capability of 1D-CNN to enhance its fault classification capability [27].

The process of MC-1DCNN is illustrated in Figure 3, where convolutional operations are employed to extract hierarchical features from the IMFs.

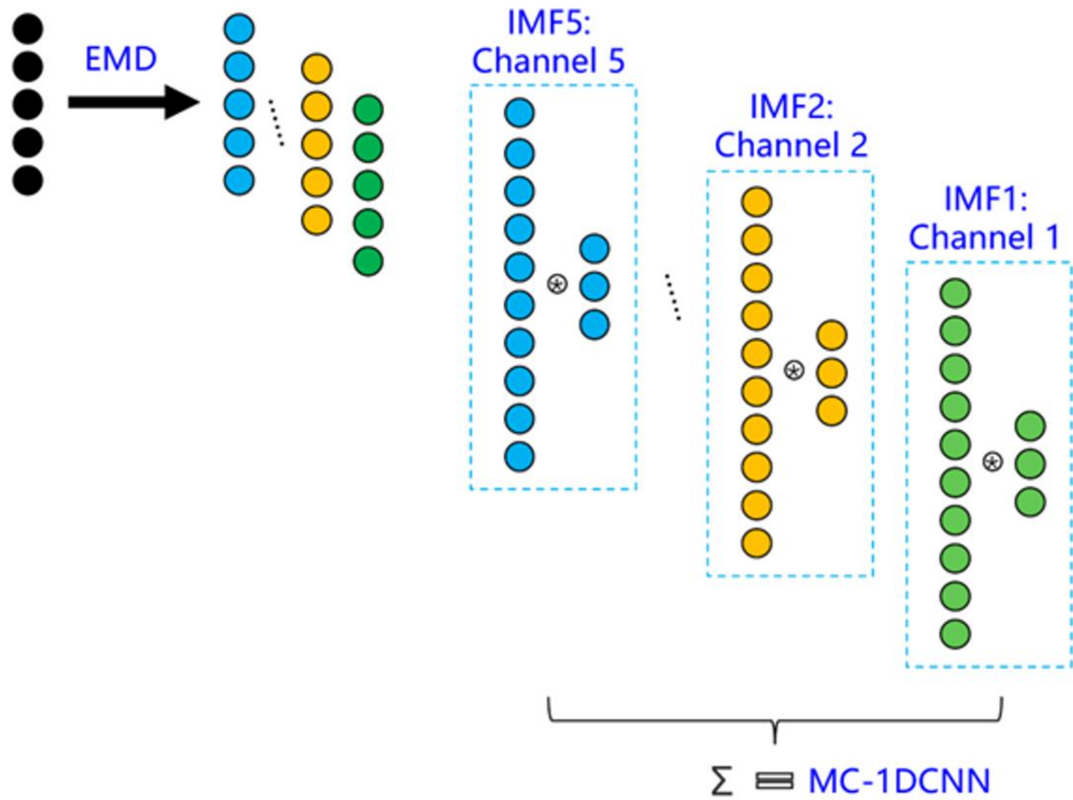

Figure 3.
The MC-1DCNN Process and Convolutional Operations.

3.3. The Proposed TL-MC-1DCNN Framework

The overall framework of the constructed elevator guideway fault diagnosis method (TL-MC-1DCNN) is depicted in Figure 4, which integrates EMD, MC-1DCNN, and TL to tackle the challenges of limited labeled data in elevator guideway fault diagnosis.

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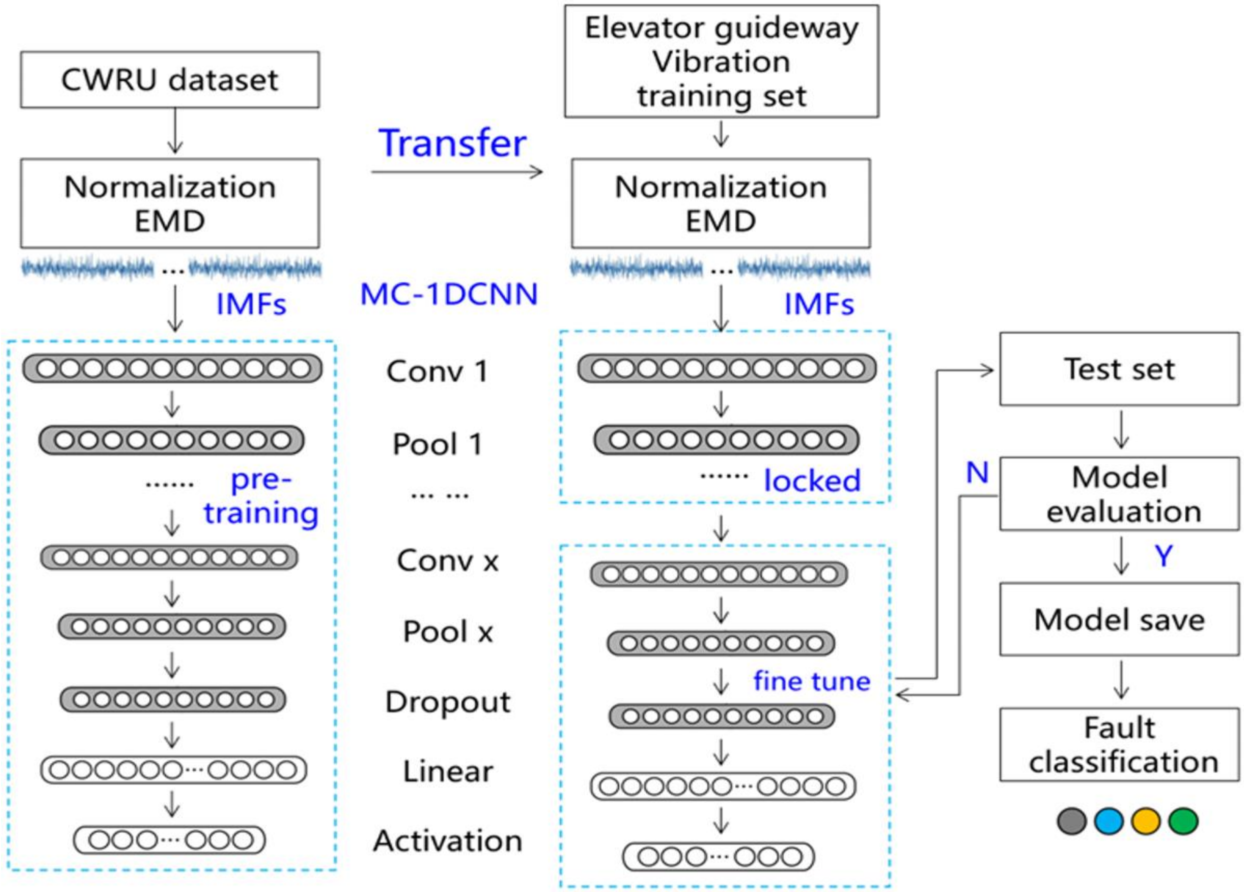

Figure 4.
The Proposed TL-MC-1DCNN Framework

3.4. Data Processing

The dataset includes the Case Western Reserve University (CWRU) bearing fault dataset (source domain) and the elevator guideway vibration dataset (target domain). Both datasets are normalized [28] to a range of [0, 1] to eliminate the influence of amplitude variations, and processed using EMD to decompose the vibration signals into IMFs. The first five IMFs, containing the most relevant fault-related frequency components, were selected as multi-channel inputs for the MC-1DCNN model, enabling the extraction of multi-scale features critical for fault classification.

3.5. Source Domain Pre-Training

After the signal processing step, the MC-1DCNN is pre-trained on the CWRU dataset to learn universal fault features from the sufficient labeled data available in the source domain. This step captures transferable knowledge and establishes a solid foundation for adaptation to the target domain.

3.6. Target Domain Fine-tuning

The pre-trained MC-1DCNN is fine-tuned using the elevator guideway dataset to study its specific characteristics. During fine-tuning, some lower layers of the network, which capture generic features, are frozen, while the upper layers are fine-tuned to learn domain-specific features. This transfer learning approach ensures effective knowledge adaptation while preventing overfitting in the small-sample target domain [29].

3.7. Model Validation

After fine-tuning, the TL-MC-1DCNN is measured on the test set of the elevator guideway dataset. Validation ensures the model achieves stable convergence and satisfactory classification accuracy. Once validated, the model parameters are saved for deployment in real-world fault diagnosis scenarios.

4 Experiments and Results Analysis

4.1. Description of Data Sets

4.1.1. CWRU Dataset

Publicly available, whose bearing model is SKF 6205-2RS (Figure 5). For the pre-training of MC-1DCNN, 2000 samples (including four types: normal, inner race, outer race and ball faults) are randomly selected from the dataset with a sampling frequency of 12 kHz. The raw signals were segmented into 1024-point samples using a sliding window [30] with a 50% overlap, resulting in 1400 samples per category and altogether 5600 samples. The dataset was partitioned into a training set (80%) for pre-training the MC-1DCNN model and a testing set (20%) for evaluating model performance in the source domain [31].

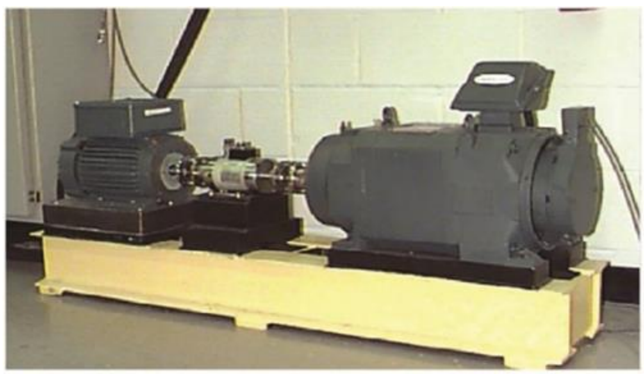

Figure 5.
Test Stand of CWRU Bearing Dataset.

Figure 6.
Sensor Mounted on the Elevator Car.

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4.2. Elevator Guideway Dataset

Vibration signals from the elevator guideway dataset were acquired from a corporation's elevator IoT platform, using a tri-axial acceleration sensor mounted at the top center of the elevator car (Figure 6), recorded at a sampling frequency of 50 Hz. The dataset comprises four fault categories: normal, bending, misalignment, and step faults. After segmentation using the same sliding window method as the CWRU dataset, 300 samples per category were obtained, yielding a total of 1200 samples. The dataset was also partitioned into training and testing subsets with an 8:2 ratio for fine-tuning and evaluation (detailed in Table 1).

Table 1.
Dataset List.

	Data set	Category	Label	Train sample	Test sample
Source domain (pre-train)	CWRU bearing	Normal	0	1120	280
		Ball fault	1	1120	280
		Inner fault	2	1120	280
		Outer fault	3	1120	280
Target domain	Elevator guideway	Normal	0	240	60
		Bending	1	240	60
		Misalignment	2	240	60
		Step	3	240	60

4.3. Experimental Settings and Model Training

The experiments were performed in a computing environment equipped with a 64-bit Windows 11 system, 32 GB RAM, an Intel Core i7-12700K CPU, and an Nvidia GeForce RTX 3080 GPU. Python 3.9 and the PyTorch 1.0 deep learning framework were used for implementation.

Table 2.
Parameters of Basic 1D-CNN.

Network layer	Parameter structure
Input channel * 5	1024×1
Convolutional layer 1	50@64×1
Pooling layer	Max Pooling (3×1)
Convolutional layer 2	100@3×1
Pooling layer	Max Pooling (3×1)
Convolutional layer 3	160@3×1
Pooling layer	Max Pooling (3×1)
Convolutional layer 4	160@3×1
Pooling layer	Max Pooling (3×1)
Dropout layer	0.5
Full connectivity layer	4
Activation layer	Softmax

The constructed TL-MC-1DCNN consists of five input channels corresponding to the first five IMFs decomposed from vibration signals. The basic 1D-CNN (detailed in Table 2) comprises four convolutional layers, each along with max-pooling layers with a window size of 3×1. The convolutional layers progressively extract hierarchical features with filter sizes of 50, 100, and 160. A dropout layer with a rate of 50% is included before the fully connected layer to enhance generalization. Finally, the fully connected layer outputs the probabilities of the four categories through the Softmax activation.

To adapt the pre-trained MC-1DCNN to the small-scale targe dataset of elevator guideway, a transfer learning strategy was applied: The first two convolutional layers were frozen to retain transferable features learned from the source domain (CWRU dataset), and higher convolutional layers and the fully connected layer were fine-tuned to adapt to the specific fault characteristics of the elevator guideway dataset in target domain. Training used the Adam optimizer (initial learning rate: 0.0001, halved every 10 epochs), with 50 epochs (stop to prevent overfitting), a batch size of 32, and the cross-entropy loss function.

To ensure robust evaluation, 5-fold cross-validation [32] was implemented in the training set of the elevator guideway dataset. The results reported in subsequent sections represent the average performance across the five folds, while the independent test set was used to evaluate the final generalization performance.

4.4. Evaluation Metrics

The effectiveness of the TL-MC-1DCNN approach was evaluated by commonly adopted indicators of accuracy and confusion matrix. The definitions are shown in equations (1) and (2) [33]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Confusion\ Matrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \quad (2)$$

Where:
TP (True Positive): The sum of positive samples that are correctly identified as positive.
TN (True Negative): The sum of negative samples that are accurately classified as negative.
FP (False Positive): The sum of negative samples that are mistakenly identified as positive.
FN (False Negative): The sum of positive samples that are incorrectly classified as negative.
Accuracy: Proportion of correctly classified samples across all categories.
Confusion Matrix: Visualization of true vs. predicted labels across fault categories.

4.5. Results and Analysis

When the pre-trained MC-1DCNN is migrated to the elevator dataset, the training process involves 5-fold cross-validation on the training set, where the accuracy and loss curves gradually converge after 20 rounds of training, and the accuracy basically remains stable when the epoch continues to increase (as shown in Figure 7). Subsequently, the classification effect of the test samples is given through the confusion matrix (shown in Figure 8), and the feature distribution of the test samples visualized using the t-SNE algorithm [34] are presented in Figure 9, demonstrating the model's robustness in distinguishing different fault types.

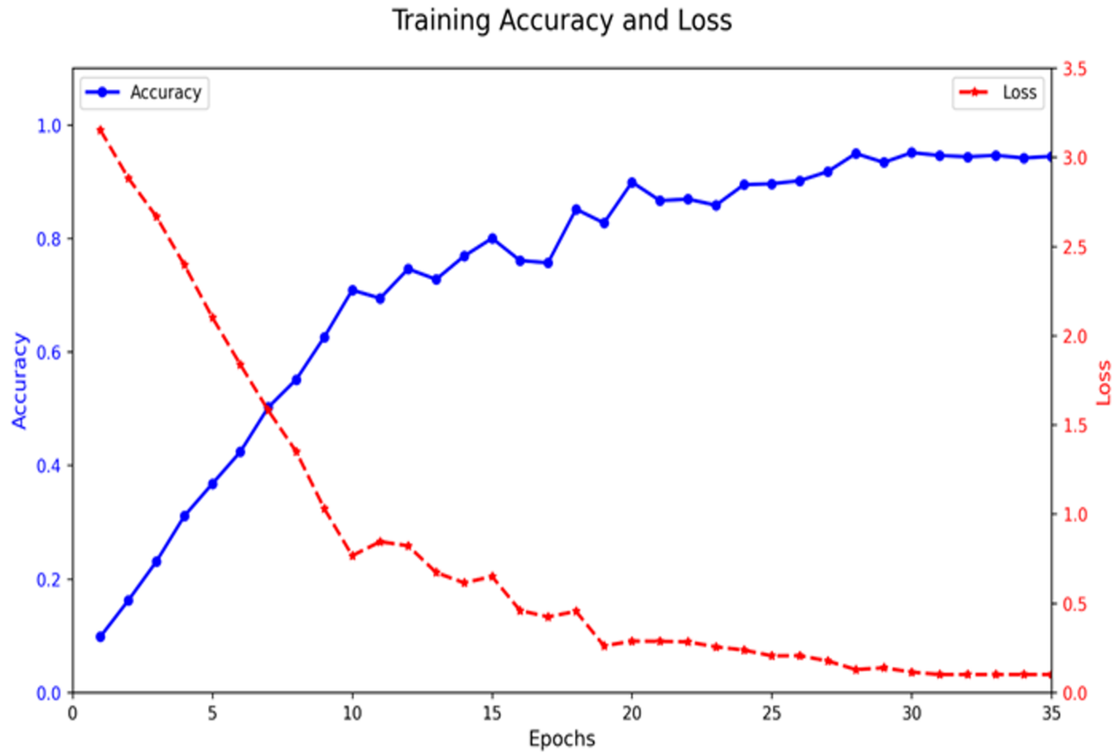

Figure 7.
Iterative Convergence of Accuracy and Loss.

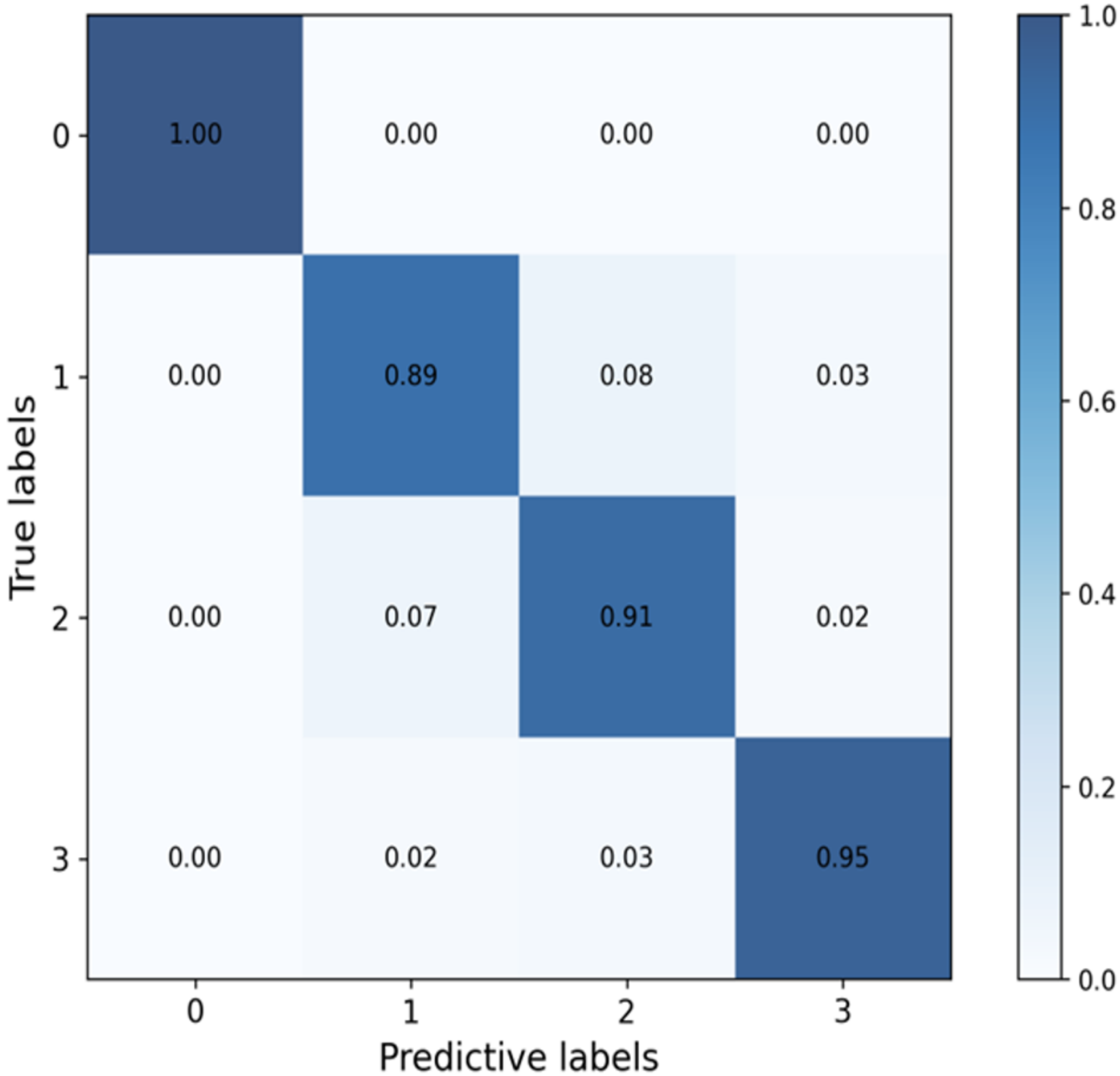

Figure 8.
Confusion Matrix for Classification Results.

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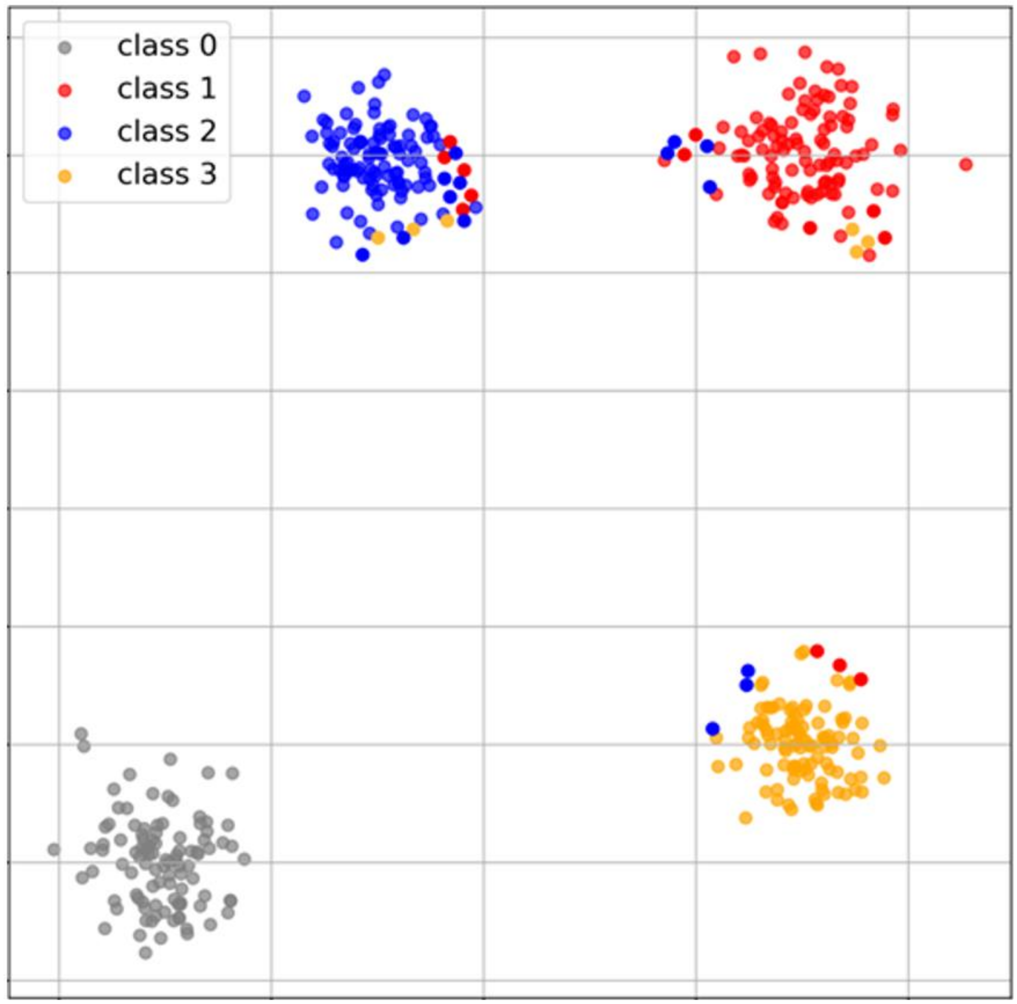

Figure 9.
Visualized Feature Distribution.

The proposed TL-MC-1DCNN model achieves perfect classification for normal samples, indicating its ability to accurately identify healthy elevator guideway conditions. However, for bending faults, 8% and 3% of samples are misclassified as misalignment and step faults, respectively. Similarly, 7% and 2% of misalignment fault samples are misclassified as bending and step faults, and for step faults, 2% and 3% of samples are misclassified as bending and misalignment faults, respectively. The misclassification is likely due to overlapping or shared features among these fault types, especially between bending and misalignment faults, which are more similar than step faults. Despite these minor errors, the overall classification accuracy of the proposed model meets practical requirements, effectively distinguishing abnormal vibration conditions.

4.6. Comparison with Other Models

To evaluate the competitive advantage of the proposed TL-MC-1DCNN, comparative experiments were conducted using two commonly employed deep learning models: MLP and LSTM. Model Configurations:
MLP (Multi-Layer Perceptron):
Input: EMD-extracted IMF features.

Architecture: Three fully connected layers with 128, 64, and 32 neurons, each followed by ReLU activations and a dropout rate of 0.5.
Training: Adam optimizer (lr=0.001), 50 epochs.
LSTM (Long Short-Term Memory):
Input: Raw vibration signals reshaped into time-series sequences.
Architecture: One LSTM layer with 64 units, along with a fully connected layer with 32 neurons.
Training: Adam optimizer (lr=0.001), 50 epochs.

5. Comparison Results

The classification accuracies of the three models, averaged across 5-fold cross-validation on the elevator guideway dataset, are summarized in Table 3. The proposed TL-MC-1DCNN achieves the highest classification accuracy of 94.5%, outperforming MLP (92.7%) and LSTM (93.1%). The advantageous effect of TL-MC-1DCNN is due to its ability to leverage EMD for multi-scale feature extraction and its multi-channel structure, which captures fault-related features across different frequency bands. In contrast, MLP lacks temporal feature extraction, while LSTM, though suitable for sequence learning, struggles with overlapping fault characteristics.

Table 3.
Comparative Results of Model Accuracy.

Model	0 (Normal)	1 (Bending)	2 (Misalignment)	3 (Step)	Average
MLP	100.0	88.2	89.6	93.1	92.7
LSTM	100.0	89.4	88.7	94.3	93.1
TL-MC-1DCNN	100.0	90.7	91.4	95.8	94.5

5.1. Ablation Study

To evaluate the contributions of EMD and transfer learning, ablation experiments were conducted using two simplified configurations:

Without EMD: The raw vibration signals were segmented and directly input into the 1D-CNN for transfer learning.

Without Transfer Learning: The MC-1DCNN model was trained and tested directly on the elevator guideway dataset without pre-training on the CWRU dataset.

Ablation Results:

The classification accuracies across training epochs for the three setups are presented in Figure 10. The constructed method possesses the highest classification accuracy, stabilizing after 20 epochs. In comparison:

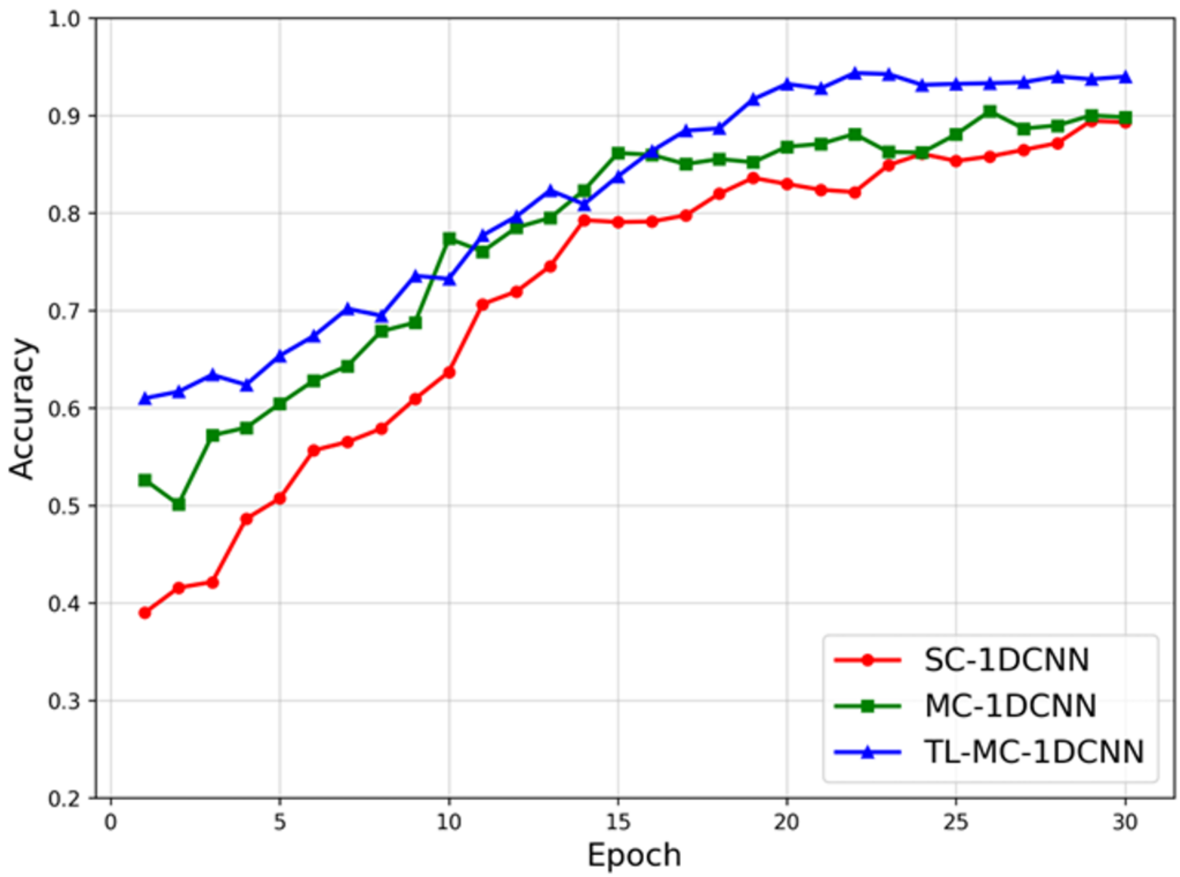

Figure 10.
Results of Ablation Experiments.

The without EMD configuration exhibits slower convergence and lower final accuracy, highlighting the importance of multi-scale feature extraction provided by EMD.

The without transfer learning configuration struggles to converge efficiently, emphasizing the value of pre-training on the source domain for capturing transferable knowledge.

These results validate the necessity of incorporating both EMD and transfer learning into the proposed TL-MC-1DCNN framework, demonstrating their significant impact on improving classification accuracy and convergence speed.

6. Conclusion

In this study, a TL-MC-1DCNN incorporating transfer learning is proposed for fault diagnosis of elevator guideways. The model is pre-trained on the CWRU bearing dataset that also contains four fault types (normal, inner raceway, outer raceway, and ball faults), which provides transferable features relevant to elevator vibration signals. By fine-tuning the pre-trained MC-1DCNN on the elevator guideway dataset, the framework effectively addressed the challenges posed by small-sample scenarios, mitigating overfitting, and exhibits stable convergence. EMD is utilized to decompose the complex vibration signals into multiple IMFs as multi-channel inputs to the MC-1DCNN, which allows the network to perform convolution operations on different frequency bands to capture complementary multi-scale features, greatly improving the model's ability to analyze non-stationary and overlapping fault features, and achieving higher classification accuracy.

Comparative experiments with MLP and LSTM validate the relative superiority of the proposed approach, and ablation studies emphasize the critical contribution of EMD preprocessing and transfer learning to the framework's performance.

6.1. Study Limitation

Although the proposed TL-MC-1DCNN framework performs well in diagnosing elevator guideway faults, it still suffers from several limitations. First, the model relies heavily on the characteristic and diversity of the training data; while transfer learning alleviates the challenge of small sample size, real fault datasets with different operating conditions may affect its generalization to completely new scenarios. Second, the computational complexity of multi-channel convolutional operations and EMD preprocessing may pose challenges for real-time implementation in resource-constrained systems.

6.2. Future Work

Try to enhancing the generalization ability of the proposed framework under variable operating conditions and further reducing its computational complexity to enable real-time fault diagnosis in resource-constrained systems. Additionally, efforts will be directed toward advancing its applicability to few-shot and zero-shot learning scenarios, enabling accurate diagnosis of unseen fault types with minimal or no labeled samples [35].

Transparency:

The authors confirm that the manuscript is an honest, accurate and transparent account of the study that no vital features of the study have been omitted and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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