The Application of Machine Learning for Elevator Fault Diagnostic in Changsha, China

Zhiwei Zhou

A Thesis Submitted in Partial Fulfillment of Requirements for

degree of Doctor of Philosophy in Electrical and Computer Engineering

March 2025

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ABSTRACT

Elevator guideway vibration fault diagnosis is critical to ensure the safety and stable operation of elevators. However, vibration signals often exhibit complex non-stationary characteristics, while the number of samples of abnormal vibrations is small. Deep learning enables automatic feature extraction from raw data, while transfer learning addresses the challenge of limited target domain samples, making them key techniques in fault diagnosis. This paper proposes a novel fault diagnosis method combining Multi-Channel (MC) One-Dimensional Convolutional Neural Networks (1D-CNN) with transfer learning for elevator guideway. 1D-CNN is adopted as the core framework due to its ability to extract local temporal correlation in sequential vibration signals. First, Empirical Mode Decomposition (EMD) decomposes vibration signals into multiple Intrinsic Mode Functions (IMFs), offering multi-frequency features as multi-channel inputs to improve the learning performance of 1D-CNN. Second, the Multi-Channel One-Dimensional Convolutional Neural Networks (MC-1DCNN) is pre-trained on the Case Western Reserve University (CWRU) bearing fault dataset to learn universal mechanical fault features. Finally, the pre-trained MC-1DCNN is transferred to the elevator guideway vibration dataset by freezing some lower convolutional layers and fine-tuning the rest higher convolutional layers, achieving high classification accuracy in small-sample scenarios. Experimental results indicate that the proposed approach achieves excellent fault classification accuracy and convergence, validating its effectiveness in application scenarios.

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

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1. Introduction

1.1 Background

Elevators play a crucial role in modern urban infrastructure, providing essential vertical transportation in residential, commercial, and industrial buildings. With the rapid urbanization and increasing demand for high-rise buildings, the operational safety, efficiency, and reliability of elevator systems have become critical concerns. A single fault in an elevator can lead to service disruptions, economic losses, and safety hazards, emphasizing the importance of effective fault diagnosis systems to ensure smooth operation and user safety [1].

Traditional maintenance strategies, such as scheduled maintenance or reactive maintenance, often fall short in addressing real-time fault detection and prevention needs. These methods are labor-intensive, costly, and often reactive, meaning faults are addressed only after they occur[2]. Predictive maintenance (PdM), leveraging data-driven approaches and the advancements in the Internet of Things (IoT) and Industrial 4.0, has emerged as a promising solution [3]. PdM relies on real-time data from sensors to predict and prevent potential faults, reducing downtime and improving operational efficiency.

The adoption of machine learning (ML) techniques, particularly deep learning (DL), has revolutionized fault diagnosis systems by enabling automatic feature extraction and accurate fault classification[4]. Models like convolutional neural networks (CNNs) have demonstrated remarkable capabilities in handling time-series data, such as vibration signals from elevator guideway[5]. These signals, often characterized by non-linear and non-stationary properties, require advanced processing techniques for effective analysis. As a result, the integration of empirical mode decomposition (EMD) and machine learning has shown great potential for extracting meaningful features and diagnosing faults in elevator systems effectively[6].

1.2 Problems

Despite the advancements in machine learning and predictive maintenance, several challenges remain in the practical implementation of fault diagnosis systems for elevators [7]:

Limited Data Availability: The collection of fault-related data is often limited due to the rarity of fault occurrences in real-world elevator operations. This scarcity poses a significant challenge for training data-intensive machine learning models.

Diverse Fault Types: Elevator systems encounter a wide range of fault types, including mechanical, electrical, and structural issues. Diagnosing these faults accurately requires robust models capable of handling diverse fault scenarios.

Non-Stationary Signal Characteristics: Vibration signals from elevator guideway are often influenced by operational conditions, environmental factors, and noise, making them complex and non-stationary. Effective fault diagnosis requires methods that can handle these characteristics.

Computational Complexity: Advanced algorithms often demand substantial computational resources, which can limit their real-time applicability, particularly in resource-constrained environments.

Generalization Across Operating Conditions: Models trained on specific datasets often struggle to generalize to new operating conditions or different elevator systems, reducing their practical utility.

Addressing these challenges necessitates the development of innovative frameworks that leverage domain knowledge, transfer learning, and advanced feature extraction techniques to achieve reliable and efficient fault diagnosis[8].

1.3 Objectives

The primary objective of this research is to develop a robust, efficient, and generalizable fault diagnosis framework for elevator guideway. The proposed framework, named Transfer Learning Multi-Channel One-Dimensional Convolutional Neural Network (TL-MC-1DCNN), aims to overcome the limitations identified above. The specific objectives of this study are as follows:

Develop a Multi-Channel 1D-CNN Framework: Design a fault diagnosis framework capable of leveraging multi-channel vibration signals, with empirical mode decomposition (EMD) applied to capture multi-scale fault features.

Incorporate Transfer Learning: Utilize transfer learning to address the issue of limited fault-related data by pre-training the model on a source domain dataset (e.g., the CWRU bearing fault dataset [9]) and fine-tuning it on a small-scale target dataset (elevator guideway data).

Enhance Model Generalization: Ensure the proposed framework performs effectively across diverse operating conditions and fault types by integrating robust preprocessing and training strategies.

Validate the Model's Effectiveness: Conduct comprehensive experiments, including comparison and ablation studies, to validate the proposed framework's accuracy, robustness, and computational efficiency.

By achieving these objectives, this research aims to provide a scalable, reliable, and practical solution for elevator fault diagnosis, contributing to the advancement of predictive maintenance strategies in the elevator industry.

2. Literature Reviews

2.1 Evolution of Fault Diagnosis Techniques

Fault diagnosis has played a crucial role in industrial systems for decades. Traditional methods predominantly relied on signal processing techniques to extract fault-related features from vibration data [10]. These methods include Fourier transform, wavelet transform, and empirical mode decomposition (EMD), which analyze time-frequency characteristics to identify potential issues. For instance:

[11] presented a new multi-speed fault diagnostic approach by using self-adaptive wavelet transform components generated from bearing vibration signals.

[12] proposed a transformer hot spot fault diagnosis method based on the combination of ultrasonic sensing technology and PSO-SVM algorithm.

[13] proposed a rolling bearing fault diagnosis model based on composite multiscale permutation entropy (CMPE) and reverse cognitive fruit fly optimization algorithm optimized extreme learning machine (RCFOA-ELM).

Despite their effectiveness, traditional techniques suffer from two major drawbacks[14]:

Manual Feature Extraction: These methods heavily rely on human expertise to define fault-related features, which may be subjective and suboptimal in capturing complex signal characteristics [15].

Limited Scalability: Their applicability is constrained by the diversity of operating conditions and noise interference, limiting their generalization across domains.

The advent of machine learning has addressed some of these limitations by enabling data-driven approaches for fault classification. Supervised learning algorithms like support vector machines (SVM) and random forests (RF) demonstrated superior performance in scenarios with abundant labeled data but remained limited by their dependency on handcrafted features and domain knowledge.

2.2 Advancements in Deep Learning for Fault Diagnosis

Deep learning has emerged as a transformative approach in fault diagnosis, offering the ability to automatically extract hierarchical features from raw signals

[16]. This eliminates the need for manual feature engineering and enhances scalability across varying operating conditions. Notable advancements include:

Convolutional Neural Networks (CNNs): [17] proposed a novel one-dimensional improved self-attention-enhanced convolutional neural network (1D-ISACNN) with empirical wavelet transform (EWT) for rolling bearing fault classification.

Long Short-Term Memory (LSTM) Networks: [18] introduced a novel deep neural network based on bidirectional-convolutional long short-term memory (BiConvLSTM) networks to determine the type, location, and direction of planetary gearbox faults by extracting spatial and temporal features from both vibration and rotational speed measurements automatically and simultaneously.

Hybrid Deep Learning Models: [19] proposed a fault diagnosis method based on deep learning to alleviate the impact of imbalanced samples on fault diagnosis of rotating machinery.

In elevator systems, deep learning has been applied to key components such as traction machines, guideway, and control circuits:

To fully extract the fault information hidden in the spectrogram, in [20] the vibration signals are transformed into a two-dimensional spectrogram in polar coordinates and used as a sample dataset for training a convolutional neural network (CNN) to achieve fault classification and identification of the rigid guide.

[21] proposed an integrated framework involving state classification, preprocessing, and classification for the fault diagnosis of elevator doors using control state information.

Despite these successes, deep learning models face significant challenges[22]:

Data Scarcity: Deep models require large labeled datasets for training, which is impractical for elevator systems where faults are rare.

Complex Vibration Signals: Overlapping features and non-stationary characteristics in elevator vibration signals complicate fault classification, especially under real-world conditions.

2.3 Transfer Learning in Small-Sample Scenarios

Transfer learning techniques have shown considerable promise in addressing data scarcity by transferring knowledge from a source domain to a target domain with limited labeled data. For instance, [23] 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. [24] 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. [25] proposed a fault diagnosis method for wind turbines with few sample data, combining parameter-based transfer learning and convolutional autoencoder (CAE) to transfer knowledge from similar 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.

2.3 Predictive Maintenance in Elevator Systems

Predictive maintenance (PdM) represents a paradigm shift in elevator fault management, moving from reactive to proactive strategies. PdM leverages IoT platforms, big data, and advanced analytics to monitor elevator health and predict failures before they occur[26]. In particular:

IoT Integration: Sensors embedded in elevators provide real-time data on key components, such as guideway, doors, and traction systems. This data serves as the foundation for predictive models.

Machine Learning Models: Algorithms such as Random Forest and LSTM are used to classify and predict common failures of elevator based on time series data such as vibration signals[27].

Despite its potential, PdM implementation faces challenges, including:

Data Heterogeneity: Variability in sensor data across elevator types complicates model generalization.

Real-Time Processing: Fault diagnosis models must operate within strict time constraints to enable timely maintenance actions.

2.4 Summary

The review highlights significant advancements in fault diagnosis, from traditional methods to deep learning and transfer learning. Each approach addresses specific challenges but leaves gaps in scalability, data efficiency, and robustness under diverse operating conditions. ผิดพลาด! ไม่พบแหล่งการอ้างอิง summarizes key fault diagnosis techniques and their applications:

Table 1 Summary of Fault Diagnosis Techniques and Applications

Technique	**Applications**	**Reference**
Wavelet Transform	Rolling bearing fault detection	[11]
PSO-SVM algorithm	Transformer diagnosis	[12]
Particle swarm optimization optimized variational mode decomposition (PSO-VMD)	Rolling bearing fault diagnosis	[13]
Convolutional Neural Networks (CNN)	Rolling bearing fault classification	[17]
Long Short-Term Memory (LSTM)	Planetary gearbox faults detection	[18]
Deep learning (DL)	Rotating machinery fault diagnosis	[19]
Transfer Learning (TL)	Small-sample wind turbine fault diagnosis	[23-25]

In this paper, By integrating transfer learning with deep learning architectures like CNNs, the proposed TL-MC-1DCNN framework may addresses these gaps, providing a robust solution for elevator guideway fault diagnosis. It combines EMD for multi-scale feature extraction and TL to enhance model performance under small-sample conditions, paving the way for more reliable and efficient predictive maintenance in elevators.

3. Related Theoretical Knowledge

3.1 Elevator Structure and Guideway System

3.1.1 Overview of Elevator Components

Elevators are vital vertical transportation systems in modern buildings, designed to provide safe, efficient, and reliable movement for passengers and goods. The structure of an elevator (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) can be divided into eight primary subsystems, each with specific roles in ensuring its smooth operation [28]:

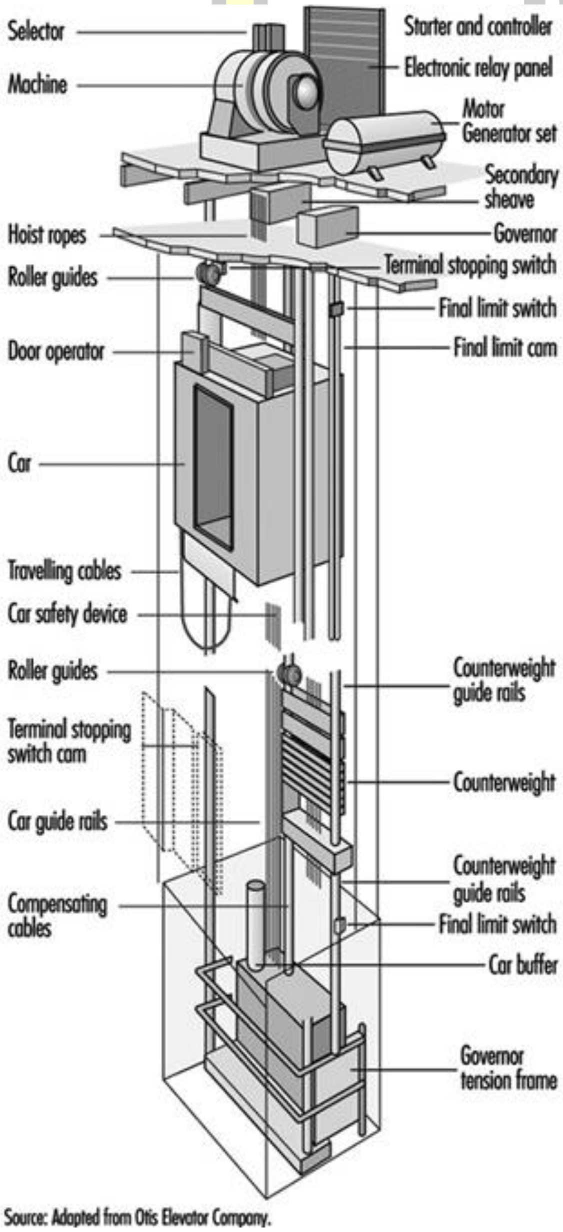

Figure 1 Schematic Diagram Of Elevator Structure

1. Traction System

The traction system is responsible for moving the elevator car up and down the shaft. It includes (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง):

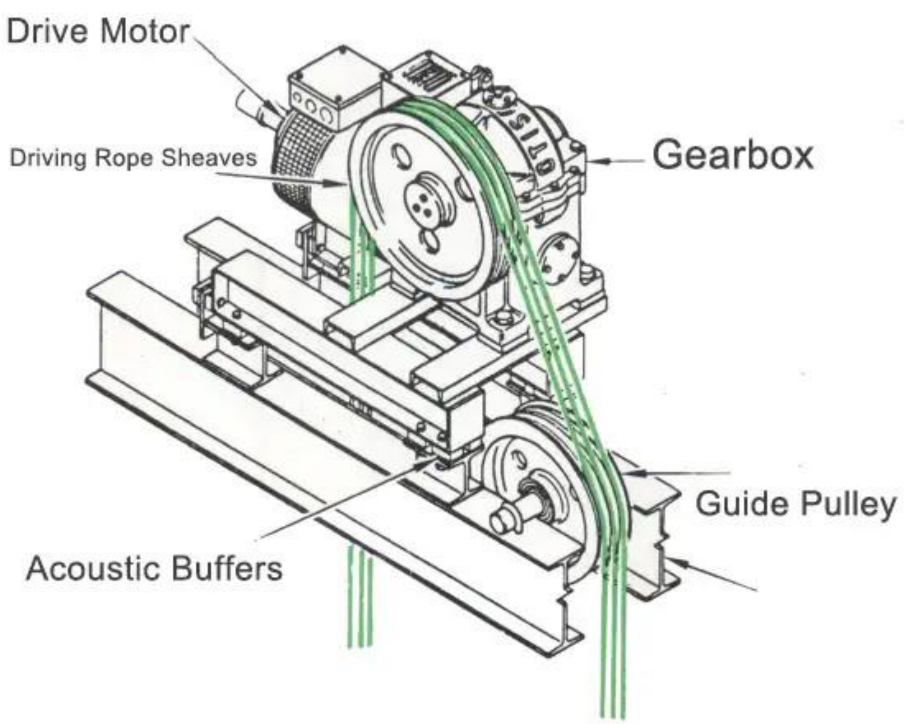

Figure 2 Schematic of Elevator Traction System

Traction Machine: Contains the motor and traction sheave to transfer force to the ropes.

Steel Ropes (Hoist Ropes): Connect the elevator car and counterweight, transmitting motion.

Traction Sheave: Grooved wheel that ensures the proper grip of the ropes.

Counterweight: Balances the weight of the car, reducing energy consumption.

Function: Provides the driving force to lift and lower the elevator car.

2. Guideway System

The guideway system ensures the vertical alignment of the elevator car, preventing swaying and lateral movement. It consists of:

Guideway: Steel tracks mounted vertically on the shaft walls.

Guide Shoes: Attachments on the car and counterweight that slide along theway.

Function: Maintains the stability of the car and counterweight during motion.

Common Faults: Misalignment, bending, and wear, leading to abnormal vibrations and operational instability.

3. Car System

The elevator car is the main compartment that accommodates passengers or goods. It includes:

Car Frame: Structural framework supporting the car platform.

Car Platform: The load-bearing base for passengers and cargo.

Interior Cabin: Equipped with lighting, ventilation, and finishes for passenger comfort.

Function: Provides a safe and comfortable environment for passengers or goods.

4. Door System

The door system ensures secure entry and exit for passengers. It consists of (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง):

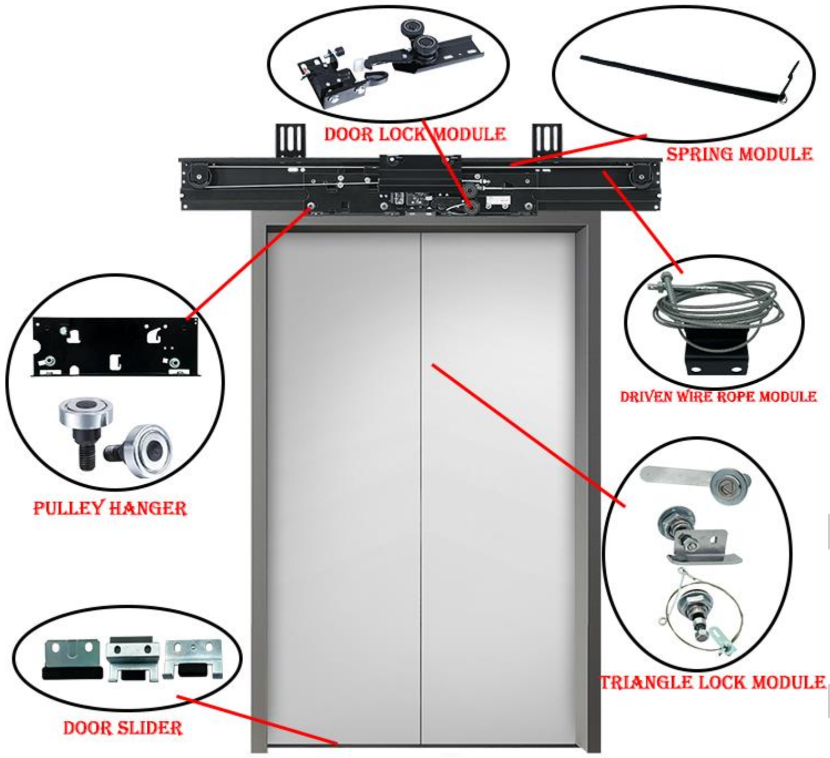

Figure 3 Main Components Of The Elevator Door System

Car Doors: Attached to the elevator car, opening and closing automatically.

Landing Doors: Installed on each floor, aligning with car doors for safety.

Door Operator: A motor-driven mechanism controlling door movement.

Function: Prevents accidents during operation by ensuring synchronized door movements.

5. Weight Balancing System

The weight balancing system reduces the load on the motor by counteracting the elevator car's weight. It includes (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง):

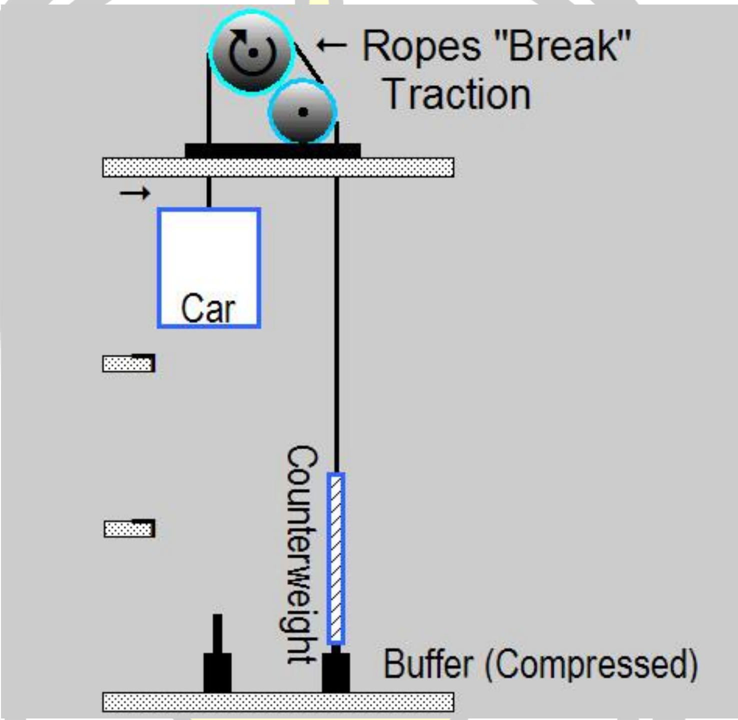

Figure 4 Weight Balancing System of Elevator

Counterweight: A mass that moves in the opposite direction of the car.

Suspension Ropes: Connect the counterweight and the elevator car.

Function: Reduces energy consumption and ensures smooth movement.

6. Electrical Control System

The electrical control system manages the elevator's operations and safety. It consists of:

Control Panels: Located in the machine room, governing car movement.

Sensors: Monitor position, speed, and door status.

Call Buttons: Allow users to summon the elevator.

Function: Ensures precise control of the elevator's movements and interactions.

7. Electric Drive System

The electric drive system powers the traction machine. It includes:

Electric Motor: Provides the mechanical energy required for motion.

Variable Frequency Drive (VFD): Regulates the motor's speed and torque.

Brake System: Ensures the car stops securely at the desired floor.

Function: Converts electrical energy into mechanical energy for smooth and controlled movement.

8. Safety Protection System

The safety protection system ensures passenger safety during abnormal conditions. Key components include:

Speed Governor: Monitors car speed and triggers the safety gear during overspeed conditions (example as ผิดพลาด! ไม่พบแหล่งการอ้างอิง).

Figure 5 Speed Governor of Elevator

Safety Gear: Stops the car in the event of freefall or overspeed.

Buffer: Absorbs energy if the car reaches the shaft's bottom.

Emergency Brake: Activates during power failure or control malfunctions.

Function: Provides failsafe measures to protect passengers and equipment.

These eight systems work together to ensure the elevator operates efficiently, safely, and reliably under various conditions. Among these, the guideway system plays a crucial role in minimizing vibration and ensuring ride comfort, making it a critical focus in fault diagnosis research[29].

3.1.2 Structure and Composition of Guideway System

The guideway system is a critical component of elevator operations, ensuring the stability, alignment, and smooth movement of the car and counterweight within the shaft. It is composed of three main elements: guideways, guide shoes, and guideway brackets, each with specific roles and characteristics[30].

1. Guideways

Guideways are vertical tracks installed along the elevator shaft to constrain lateral movement and ensure smooth and aligned vertical motion of the car and counterweight. They are typically made of steel for strength and durability and are classified into two primary types based on their cross-sectional shapes (shown in ผิดพลาด! ไม่พบแหล่งการอ้างอิง) [31]:

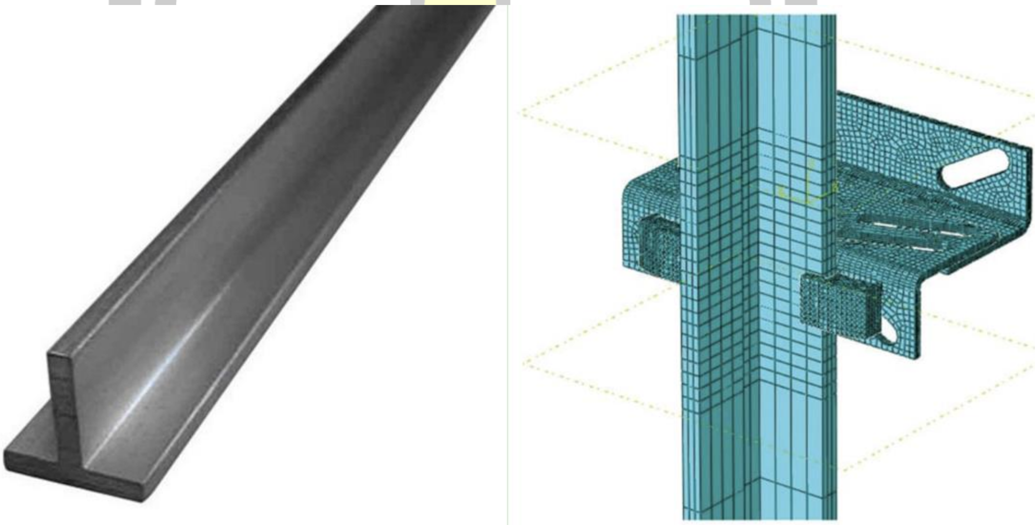

Figure 6 Shape of Elevator Guideway (T- and L-shaped)

T-shaped Guideways:

Structure: These guideways have a T-shaped cross-section.

Advantages: T-shaped guideways offer superior stability and load-bearing capacity, making them suitable for high-rise elevators and heavy-duty applications.

Applications: Commonly used in passenger and freight elevators requiring robust structural integrity.

L-shaped Guideways:

Structure: These guideways have an L-shaped cross-section.

Advantages: L-shaped guideways are lighter and cost-effective, making them ideal for low-rise or medium-duty elevators.

Applications: Frequently used in residential and small commercial buildings where cost and weight are primary considerations.

2. Guide Shoes

Guide shoes are mechanical components attached to the car and counterweight to maintain constant contact with the guideways. They ensure smooth sliding along the guideways, reducing vibration and lateral movement during operation. There are two main types of guide shoes[32]:

Sliding Guide Shoes: These are equipped with inserts, often made of polymer materials, to reduce friction and wear. They are suitable for low-speed elevators.

Roller Guide Shoes: These use rollers to minimize friction and vibration, making them more effective for high-speed elevators and improving ride comfort.

3. Guideway Brackets

Guideway brackets are structural supports that fix the guideways to the shaft walls. They are typically spaced at regular intervals to maintain the alignment and rigidity of the guideways. Proper bracket installation is critical to minimizing vibration and ensuring the longevity of the guideways.

4. Common Faults in Guideways

Guideways are prone to mechanical issues that can affect the stability and performance of elevators. The following are the three most common guideway faults (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง), along with their causes:

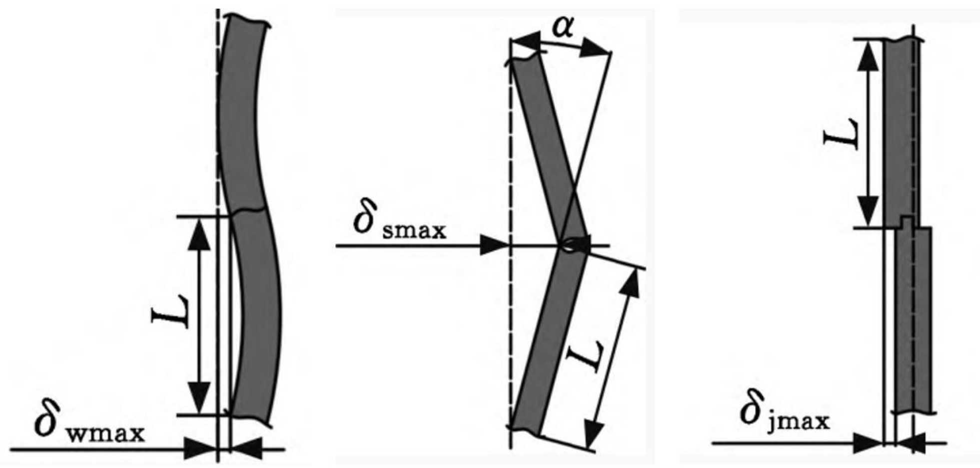

Figure 7 Diagram of Guideway Faults - Bending, Misalignment, and Step [31]

I. Bending Faults:

Description: The guideway deviates from its intended straight alignment, forming a curve.

Causes: Excessive load, improper installation, or material fatigue.

Impact: Leads to increased vibration and uneven motion, affecting ride comfort and system efficiency.

II. Misalignment Faults:

Description: The guideway is not properly aligned with the shaft, causing lateral or angular deviations.

Causes: Improper installation, structural shifts in the building, or wear and tear of brackets.

Impact: Results in abnormal contact between the guide shoes and guideways, increasing wear and vibration.

III. Step Faults:

Description: Sudden changes in the height or level of the guideway, creating discontinuities.

Causes: Poor manufacturing, damage during installation, or structural deformation.

Impact: Causes abrupt jolts during car motion, leading to discomfort and potential damage to components.

The guideway system's faults, including bending, misalignment, and step faults, are primary contributors to elevator vibration issues. Timely detection and accurate classification of these faults are critical for ensuring safe and efficient operation, reducing maintenance costs, and improving passenger comfort. These fault types serve as the primary focus of the proposed diagnostic framework in this study.

3.2 Elevator IoT Monitoring System

The integration of Internet of Things (IoT) technology into elevator systems represents a transformative advancement in predictive maintenance and operational efficiency. IoT-enabled elevator monitoring systems [33] are composed of interconnected sensors, cloud platforms, and data processing algorithms that enable real-time tracking, fault diagnosis, and system optimization. The key components, primary functions, and application characteristics of these systems are outlined below.

3.2.1 IoT System Components

An elevator IoT monitoring system (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) typically comprises the following core elements[34]:

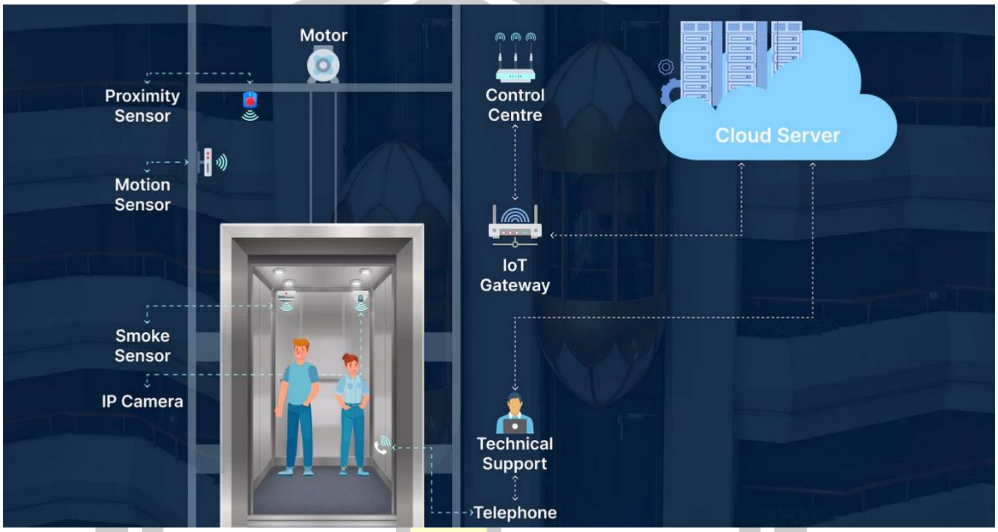

Figure 8 Diagram of Elevator IoT Monitoring System Components

1. Sensors and Edge Devices:

Installed on key elevator components, such as traction machines, guideways, doors, and control panels.

Collect real-time data, including vibration signals, temperature, speed, and load.

Example: Tri-axial accelerometers are used to monitor vibrations for fault detection in guideways.

2. Communication Modules:

Facilitate wireless data transmission between edge devices and cloud platforms using communication technologies like 4G/5G, LoRa, or Zigbee.

Ensure reliable connectivity even in high-rise buildings with complex environments.

3. Cloud-Based Platforms:

Serve as the central repository for data aggregation and processing.

Enable scalable storage, data analysis, and machine learning algorithm deployment.

4. User Interfaces and Mobile Applications:

Provide real-time dashboards for elevator maintenance personnel and operators.

Deliver alerts and reports to facilitate rapid decision-making.

3.2.2 IoT System Functions

IoT-enabled elevator systems are designed to enhance maintenance, safety, and operational efficiency. Key functionalities include (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) [35]:

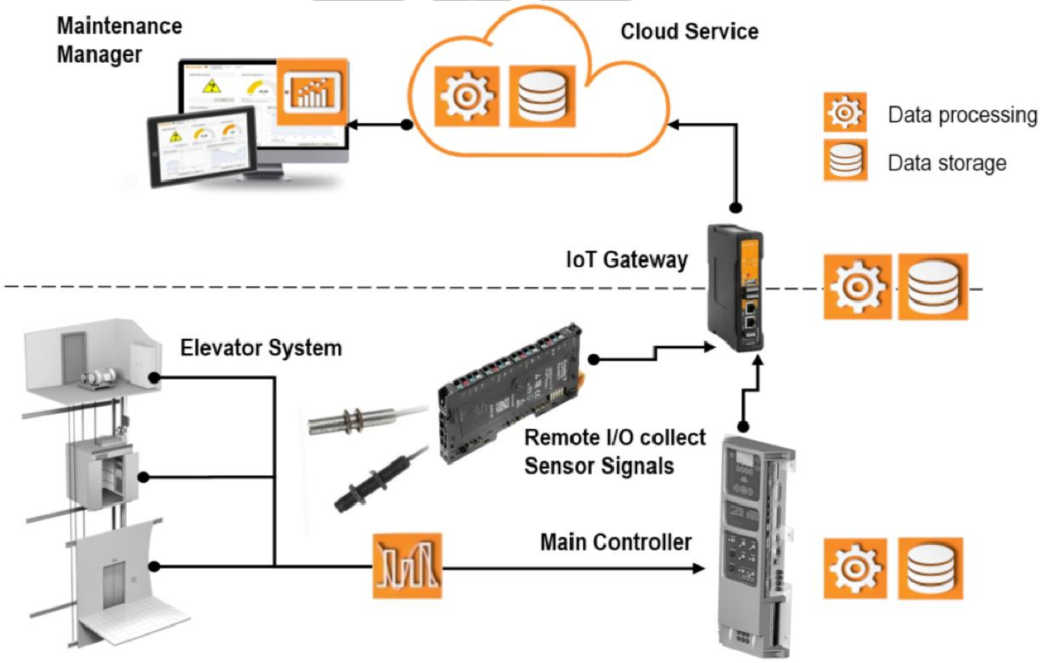

Figure 9 Diagram of Elevator IoT Monitoring System Functions

1. Real-Time Monitoring:

Continuously track critical parameters like vibration, temperature, and operational cycles to assess system health.

Example: Vibration patterns from guideways are monitored to detect anomalies such as misalignment or bending faults.

2. Predictive Maintenance:

Use machine learning algorithms to predict potential faults before they occur, reducing unplanned downtime.

Example: Anomalies in vibration signals can trigger preemptive repairs to prevent operational failures.

3. Remote Diagnosis and Control:

Allow technicians to remotely diagnose faults and initiate corrective actions without physical site visits.

Example: Cloud platforms enable real-time remote fault classification and reporting.

Energy Optimization:

4. Optimize power consumption by monitoring elevator usage patterns and load levels.

Example: IoT systems analyze elevator idle times to minimize energy waste.

3.2.3 IoT System Application Characteristics

IoT systems for elevator monitoring offer several distinctive advantages[36]:

1. Scalability and Flexibility:

Compatible with various elevator types and easily integrated into existing infrastructure.

Adaptable for residential, commercial, and industrial buildings.

2. Enhanced Safety:

Improve passenger safety by providing real-time alerts for system malfunctions.

Example: Emergency notifications for abnormal vibration signals or door operation failures.

3. Data-Driven Decision-Making:

Utilize historical and real-time data for optimized maintenance schedules and system upgrades.

Provide actionable insights to manufacturers and maintenance teams.

4. Cost Efficiency:

Reduce operational costs by minimizing downtime and optimizing resource allocation.

Example: Predictive analytics help avoid costly breakdowns and extensive repairs.

IoT-enabled elevator monitoring systems are integral to modernizing elevator maintenance strategies. By leveraging real-time data, predictive analytics, and remote control capabilities, these systems enhance reliability, safety, and efficiency. In the context of this study, IoT technologies play a foundational role in data acquisition and fault diagnosis, particularly in detecting guideway faults under diverse operational conditions.

3.3 Deep Learning and Convolutional Neural Networks (CNNs)

3.3.1 Deep Learning

Deep learning is a subfield of machine learning that employs artificial neural networks with multiple layers to learn hierarchical representations of data. It automates feature extraction and improves decision-making processes by discovering patterns and relationships in complex datasets (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) [37].

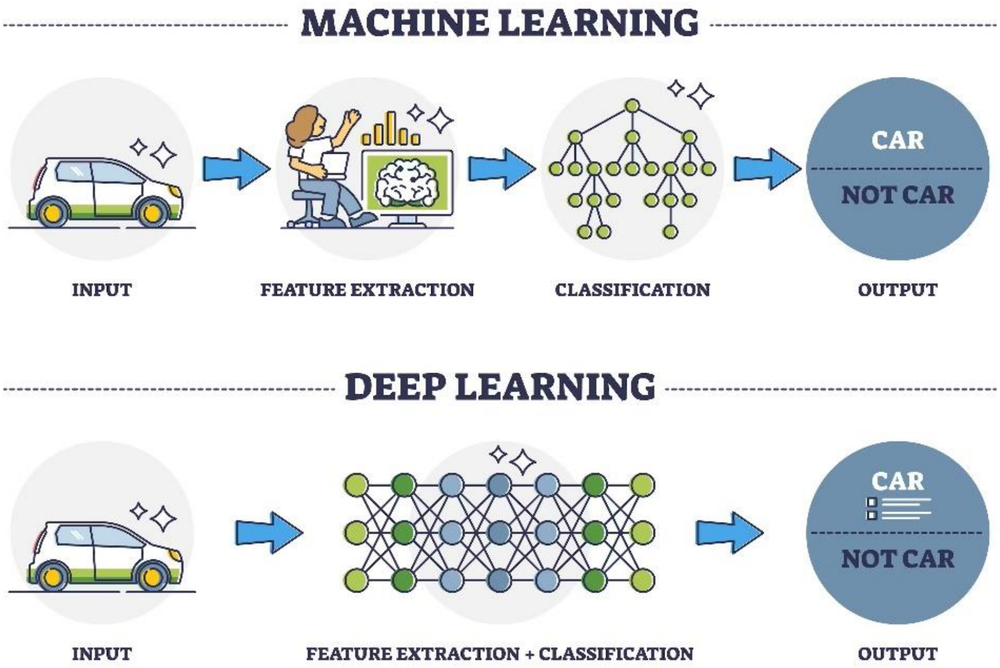

Figure 10 Machine Learning and Deep Learning

1. Application Characteristics

Automation: Eliminates the need for manual feature engineering.

Adaptability: Performs well across a wide range of data types, including images, audio, and time-series signals.

Scalability: Scales efficiently with larger datasets, leveraging advances in computational power and distributed systems.

Performance: Achieves state-of-the-art results in tasks involving pattern recognition, classification, and prediction.

2. Application Scenarios

Deep learning is widely applied in various domains, including:

Healthcare: Disease diagnosis using medical imaging.

Autonomous Vehicles: Object detection and lane tracking.

Natural Language Processing: Sentiment analysis and machine translation.

Fault Diagnosis: Predictive maintenance and anomaly detection in industrial systems.

3. Common Deep Learning Algorithms

Deep learning encompasses various architectures, each tailored for specific tasks. ผิดพลาด! ไม่พบแหล่งการอ้างอิง summarizes commonly used algorithms and their features [38]:

Table 2 Commonly Used Deep Learning Algorithms

Algorithm	**Key Features**	**Primary Applications**
Convolutional Neural Networks (CNNs)	Extract spatial features using convolutional layers.	Image classification, vibration signal analysis
Recurrent Neural Networks (RNNs)	Handle sequential data with feedback connections.	Time-series prediction, speech recognition
Long Short-Term Memory (LSTM)	A specialized RNN for capturing long-term dependencies.	Fault detection in sequential data, natural language processing
Autoencoders	Learn compact feature representations through reconstruction.	Anomaly detection, feature compression
Generative Adversarial Networks (GANs)	Generate new data by modeling data distributions.	Data augmentation, image synthesis

3.3.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a class of deep learning models designed to process structured data, such as images and time-series signals. CNNs leverage local connectivity and weight sharing to efficiently extract features from raw input data.

A typical CNN architecture (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง)consists of the following layers[39]:

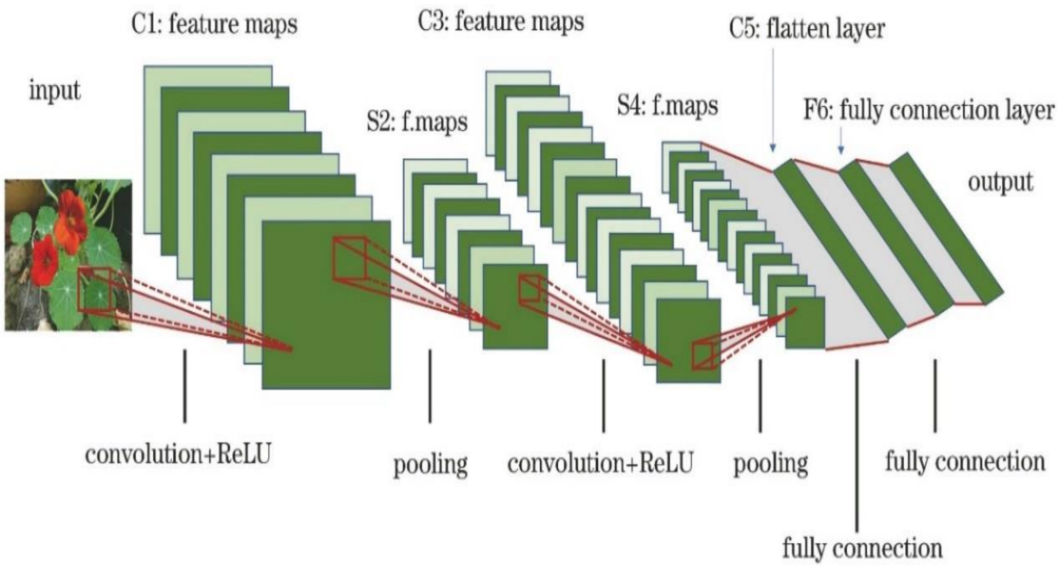

Figure 11 Architecture of a Convolutional Neural Network

Input Layer:

Receives raw data, such as images or vibration signals, and organizes it into a structured format.

Example: A 1D vibration signal is fed into the network as a sequential time-series input.

Convolutional Layers:

Apply kernels (filters) to detect local patterns in the data.

Generate feature maps that represent the presence of features across input dimensions[40].

Activation Functions:

Introduce non-linearity to enhance the network’s ability to learn complex patterns.

Example: ReLU (Rectified Linear Unit) is commonly used for activation[41].

Pooling Layers:

Down-sample feature maps to reduce computational complexity and prevent overfitting.

Example: Max-pooling retains the most prominent features by selecting the maximum value within a window[42].

Fully Connected Layers:

Aggregate extracted features to produce output probabilities or classifications.

Example: Softmax activation converts scores into probabilities for multi-class classification.

Output Layer:

Delivers final predictions, such as fault categories in vibration signal analysis.

Mathematical Formulation

The core operation in a convolutional layer is defined as [43] (3.1):

$$y_{ij} = \sigma\left(\sum_{m=1}^{M}\sum_{n=1}^{N} x_{i+m-1,\,j+n-1} \cdot \omega_{m,n} + b\right) \tag{3.1}$$

Where:

x_{ij} : Input data.

$w_{m,n}$: Convolutional kernel weights.

b : Bias term.

σ : Activation function.

y_{ij} : Output feature map.

Functional Advantages

Feature Localization: Detects spatially invariant patterns in the data.

Dimensionality Reduction: Reduces the computational burden through pooling operations.

Multi-Layer Feature Extraction: Captures both low-level and high-level features, enabling robust classification.

Applications of CNNs

CNNs excel in tasks requiring spatial or temporal feature extraction, making them highly effective in:

Image recognition and object detection.

Sequential data analysis, such as time-series fault diagnosis.

Multi-scale feature learning, particularly in vibration signal decomposition.

This section has introduced the foundations of deep learning and CNNs, emphasizing their adaptability and efficiency in fault diagnosis tasks. The integration of CNNs with advanced preprocessing methods like empirical mode decomposition (EMD) forms the cornerstone of the methodology proposed in this study, enabling accurate fault classification in elevator guideway systems.

3.4 Transfer Learning

3.4.1 Overview of Transfer Learning

Transfer learning (TL) is a machine learning paradigm where knowledge gained from solving one task (source domain) is leveraged to improve performance on a different but related task (target domain) [44]. This is particularly effective when the target domain has limited labeled data, a common scenario in real-world applications.

1. Application Characteristics

Knowledge Sharing: Reduces reliance on large labeled datasets by utilizing information from related domains.

Domain Adaptation: Adjusts pre-trained models to account for discrepancies in data distributions between the source and target domains.

Efficiency: Shortens model training times and enhances performance in data-scarce environments.

2. Application Scenarios

Transfer learning has been successfully applied across various domains (Examples are shown in ผิดพลาด! ไม่พบแหล่งการอ้างอิง), such as[45]:

Natural Language Processing: Adapting language models for specific tasks like sentiment analysis or question answering.

Computer Vision: Fine-tuning pre-trained models for medical imaging or industrial defect detection.

Fault Diagnosis: Transferring knowledge from generic datasets (e.g., CWRU bearing dataset) to specific machinery systems, such as wind turbines.

Table 3 Examples of Transfer Learning Applications Across Domains

Application Area	**Source Domain**	**Target Domain**	**Example**
NLP	General text corpus	Domain-specific text corpus	Fine-tuning BERT for medical text classification
Computer Vision	ImageNet dataset	X-ray images in healthcare	Adapting ResNet for pneumonia detection

Fault Diagnosis	Bearing fault dataset	Wind turbines	Adapting CNN for wind turbines fault classification

3.4.2 Types of Transfer Learning

Transfer learning methods can be broadly classified based on the aspect of the learning process that is transferred. These include (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) [46]:

Table 4 Comparison of Common Transfer Learning Methods

Method	**Key Feature**	**Example Application**
Instance-Based	Reweights source samples	Transfer learning for imbalanced datasets
Feature-Based	Learns shared representations	Fault diagnosis across different machinery
Model-Based	Transfers pre-trained model components	Adapting ResNet for new image classification
Relation-Based	Leverages relational knowledge	Graph-based recommendations

1. Instance-Based Transfer Learning

Instance-based methods reweight source domain samples to align them with the target domain distribution. This approach is particularly useful when the source and target domains share some overlapping data characteristics.

Key Methods:

Importance Weighting: Assigns weights to source samples based on their relevance to the target domain.

Domain Reweighting Algorithms: Algorithms like TrAdaBoost adjust instance weights iteratively to minimize domain discrepancies.

2. Feature-Based Transfer Learning

Feature-based methods aim to learn a shared feature representation that minimizes the divergence between the source and target domains. This ensures that features are equally effective for both domains.

Key Methods:

Domain-Invariant Feature Learning: Extracts features that are common across domains using algorithms like Maximum Mean Discrepancy (MMD).

Subspace Alignment: Aligns feature spaces through linear or non-linear transformations to reduce domain discrepancies.

3. Model-Based Transfer Learning

Model-based approaches transfer pre-trained models or model components, such as weights or hyperparameters, to the target domain[47]. These methods are widely used in deep learning due to their efficiency and adaptability.

Key Methods:

Fine-Tuning: Adjusts specific layers of a pre-trained model while freezing others to retain transferable knowledge.

Model Adaptation: Modifies the architecture or parameters of a pre-trained model to suit the target task.

4. Relation-Based Transfer Learning

Relation-based methods leverage relational knowledge between entities or tasks in the source and target domains. These methods are often used in graph-based data or multi-task learning scenarios.

Key Methods:

Knowledge Graph Transfer: Utilizes relational data from source tasks to improve performance on related target tasks.

Multi-Task Learning: Simultaneously learns multiple tasks, sharing representations across them.

Transfer learning bridges the gap between data-scarce target domains and data-rich source domains [48], making it an invaluable tool in fields like fault diagnosis (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง). The variety of methods available ensures flexibility in addressing domain-specific challenges. In this study, model-based transfer learning is employed, where a pre-trained MC-1DCNN model on the CWRU dataset is fine-tuned for elevator guideway fault diagnosis, demonstrating the practical advantages of this approach.

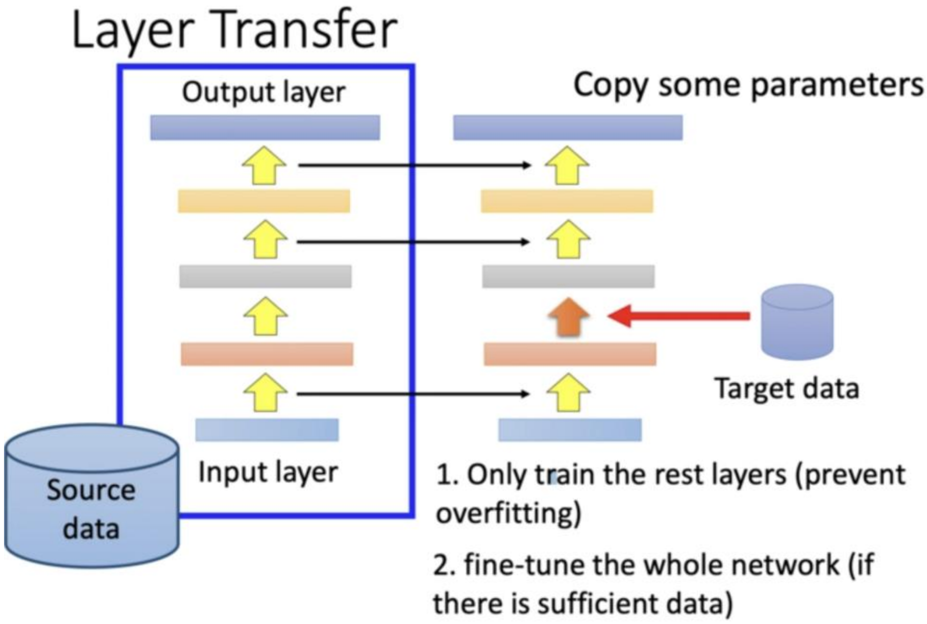

Figure 12 Transfer Learning Process for Fault Diagnosis

3.5 Vibration Signal Processing Methods

3.5.1 Common Methods and Their Characteristics

Vibration signal processing is essential for analyzing mechanical systems' operational conditions and diagnosing faults. Commonly used methods include (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง) [49]:

Table 5 Comparison of Vibration Signal Processing Methods

Method	Strengths	Weaknesses	Applications
Time-Domain Analysis	Simple and intuitive	Limited to stationary signals	Fault detection for abrupt changes
Frequency-Domain Analysis	Identifies periodic components	Assumes stationarity	Bearings, gears
Time-Frequency Analysis	Handles non-stationary signals	Resolution trade-offs	Rotating machinery, transient faults

EMD	Adaptive and data-driven	Computationally intensive for large datasets	Non-linear, non-stationary signals

1. Time-Domain Analysis:

Description: Examines the amplitude, peak, and statistical characteristics of vibration signals over time.

Applications: Identifying abrupt changes or transient events in signals.

Limitations: Limited effectiveness in complex or non-stationary signals.

2. Frequency-Domain Analysis:

Description: Analyzes the signal's spectral components using methods like Fast Fourier Transform (FFT).

Applications: Identifying dominant frequencies associated with specific fault modes.

Limitations: Assumes stationary signals and struggles with transient components.

3. Time-Frequency Analysis:

Description: Combines time and frequency information using methods like Short-Time Fourier Transform (STFT) and Wavelet Transform (WT).

Applications: Effective for non-stationary signals with varying frequencies.

Limitations: Resolution trade-offs between time and frequency domains.

4. Empirical Mode Decomposition (EMD):

Description: Decomposes complex signals into simpler components called Intrinsic Mode Functions (IMFs) without requiring a predefined basis[50].

Applications: Suitable for analyzing non-linear and non-stationary signals, such as vibration data.

Applications of Vibration Signal Processing

Rotating Machinery: Fault detection in bearings, gears, and shafts.

Structural Health Monitoring: Identifying anomalies in bridges and buildings.

Elevator Systems: Diagnosing guideway faults like bending, misalignment, and steps.

3.5.2 Empirical Mode Decomposition (EMD)

EMD is an adaptive signal decomposition method that iteratively extracts oscillatory components, termed Intrinsic Mode Functions (IMFs), from complex signals. Unlike traditional methods like FFT and WT, EMD does not rely on predefined basis functions, making it highly suitable for non-linear and non-stationary signals [51].

The EMD algorithm operates by identifying local extrema within a signal and separating it into IMFs. Each IMF satisfies two conditions:

- The number of extrema and zero-crossings must differ by at most one.
- The mean value of the envelope defined by the local maxima and minima is zero.

The process can be summarized as follows [52]:

- Identify Local Extrema: Locate all maxima and minima in the signal.
- Construct Envelopes: Use spline interpolation to connect maxima and minima, forming upper and lower envelopes.
- Compute Mean Envelope: Calculate the mean of the upper and lower envelopes.
- Extract IMF: Subtract the mean envelope from the signal to isolate the first IMF. Repeat the process on the residual signal until all IMFs are extracted.

Mathematical Formulation

Given a signal $x(t)$, the decomposition process yields (3.2):

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(\mathrm{t}) \tag{3.2}$$

Where:

$c_i(t)$: The i-th IMF.

$r_n(t)$: The residual signal after extracting n IMFs.

Each IMF $c_i(t)$ satisfies the conditions of symmetry and oscillation within a narrow frequency range (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง).

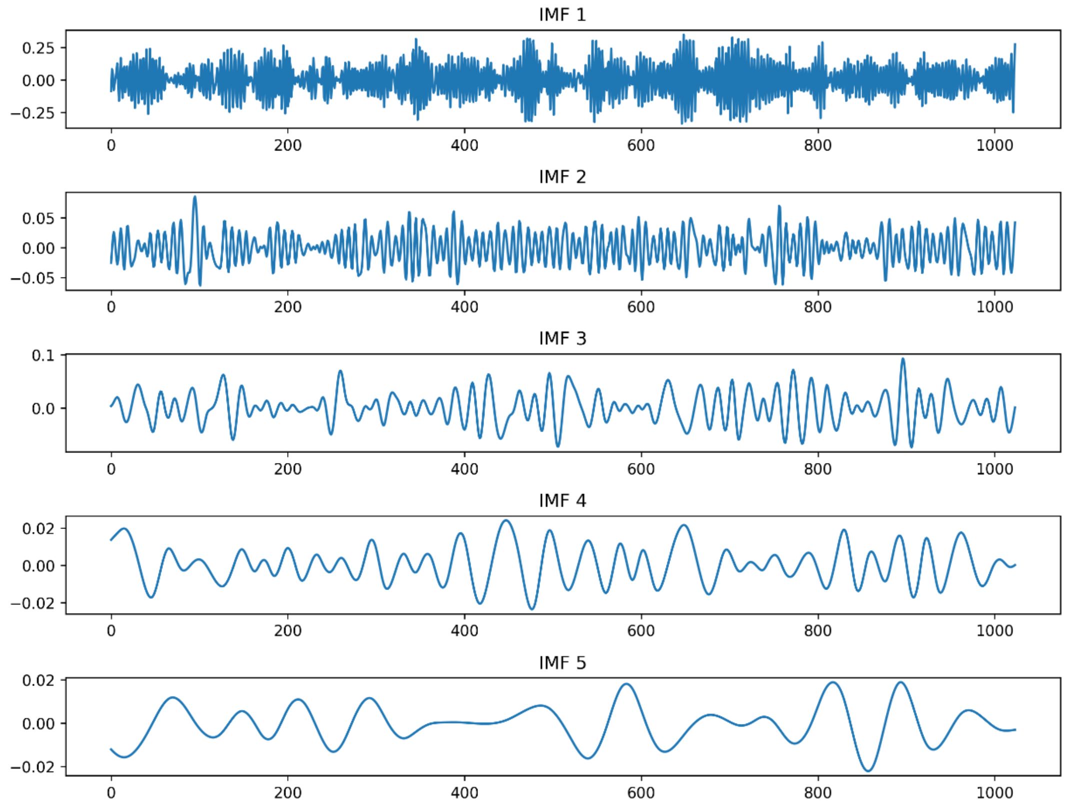

Figure 13 EMD Process Results: IMFs

1. Advantages of EMD

Data-Driven: Does not require prior assumptions about the signal's frequency or basis functions.

Adaptability: Decomposes signals into components that capture local frequency content.

Multi-Scale Analysis: Provides a detailed representation of signals across various frequency bands.

Noise Robustness: Handles non-linearities and noise effectively in practical applications.

2. Potential Applications in Fault Diagnosis

EMD's ability to isolate multi-scale features makes it a valuable tool for analyzing vibration signals in complex mechanical systems[53]. While this study explores its application in diagnosing elevator guideway faults, EMD has been widely considered for:

Decomposing signals from rotating machinery to identify fault-specific frequencies.

Extracting transient features in non-stationary environments, such as structural health monitoring.

EMD provides a robust foundation for processing vibration signals, particularly in scenarios involving complex and non-linear data. Its integration with advanced machine learning frameworks, as investigated in this study, holds promise for addressing the challenges of fault diagnosis in modern elevator systems.

3.6 Summary

This chapter provided an in-depth overview of the theoretical foundations underpinning the proposed methodology. Key insights include:

The role of IoT in real-time elevator monitoring and data acquisition.

The advantages of CNNs and TL in handling complex fault diagnosis scenarios.

The significance of EMD in extracting multi-scale fault features from non-stationary vibration signals.

4 Methodology

4.1 Overall Framework

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

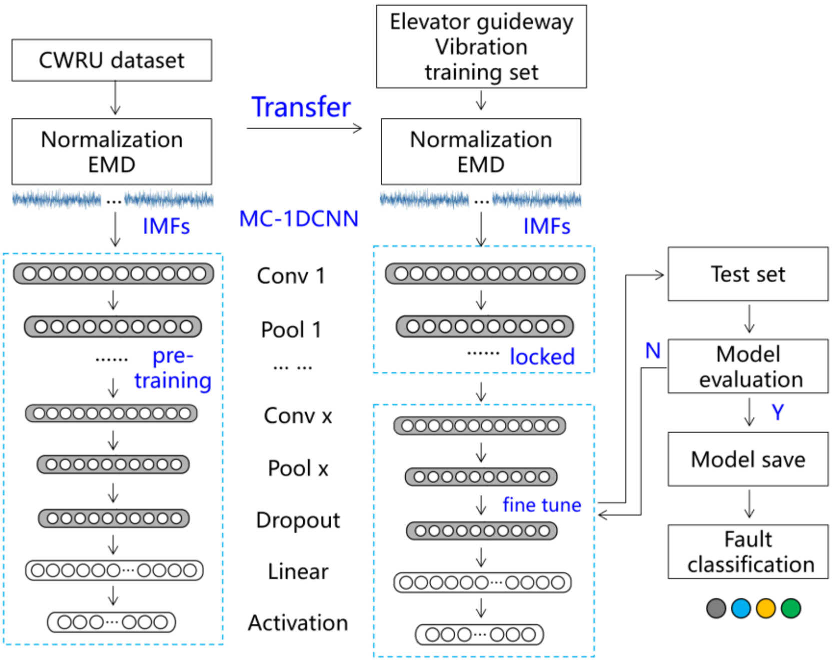

Figure 14 The Proposed TL-MC-1DCNN Framework

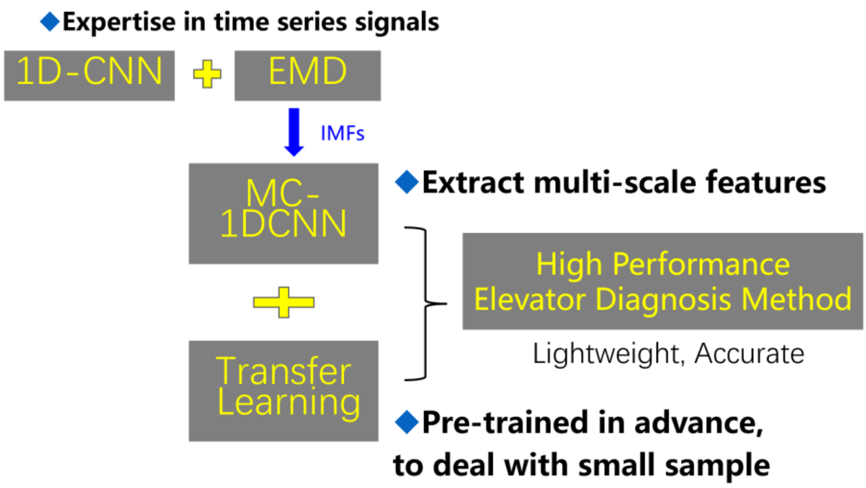

Figure 15 The Proposed TL-MC-1DCNN Framework (simplified version)

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 [54] 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.

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.

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 [55].

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.

4.2 MC-1DCNN Process

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 [56]. These characteristics make 1D-CNN well-suited for elevator guideway fault diagnosis, where vibration signals often exhibit overlapping fault characteristics and non-linear variations [57]. By leveraging convolutional operations, 1D-CNN can robustly learn fault-related patterns, ensuring reliable performance in noisy environments. The basic structure of 1D-CNN[58] is presented in ผิดพลาด! ไม่พบแหล่งการอ้างอิง:

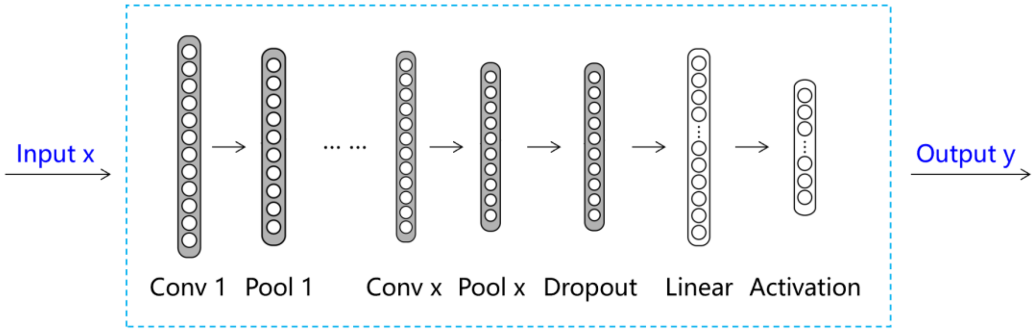

Figure 16 Basic Structure of One-Dimensional Convolutional Neural Network (1D-CNN)

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.

Convolutional Layers:

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

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.

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.

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.

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.

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[59].

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

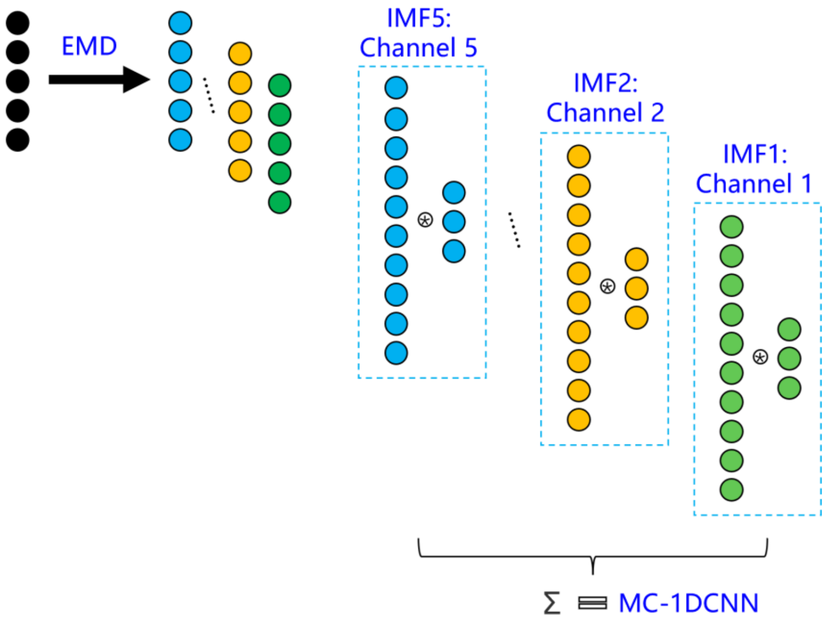

Figure 17 The MC-1DCNN Process and Convolutional Operations

4.3 Experimental Settings

Referring to the empirical practice of common processes (as ผิดพลาด! ไม่พบแหล่งการอ้างอิง), the experiments were performed in a computing environment equipped with a 64-bit Windows 11 system, 64 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.

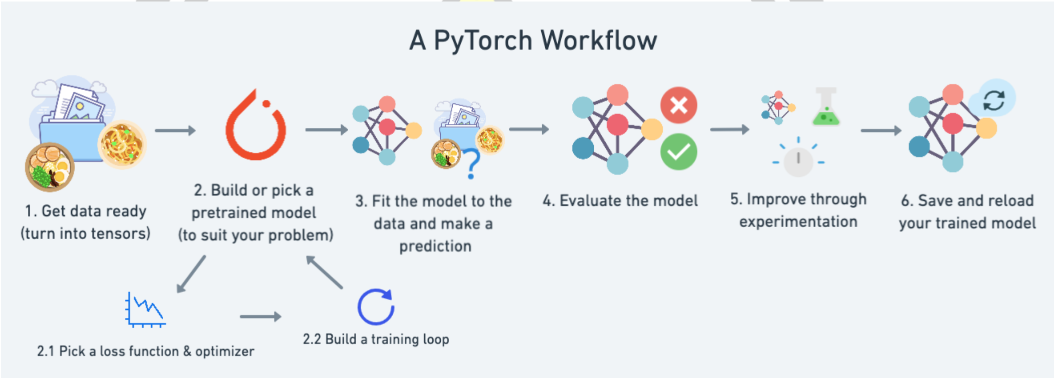

Figure 18 Common Processes of A PyTorch Workflow

The constructed MC-1DCNN (detailed in ผิดพลาด! ไม่พบแหล่งการอ้างอิง) independently processes each of the five input channels, corresponding to the first five IMFs obtained from the vibration signals. Each channel is passed through a separate 1D-CNN module consisting of four convolutional layers, each followed by max-pooling layers with a kernel size of 3×1. The convolutional layers extract hierarchical features with filter sizes of 32, 64, 128, and 256. Outputs from all channels are concatenated after convolution to form a unified feature representation. A dropout layer with a 50% rate is applied to prevent overfitting before the fully connected layer, which predicts the probabilities for the four categories using the Softmax activation function.

Table 6 Parameters of MC-1DCNN

Layer	Parameter Structure	Output Shape
Input (5 channels)	1024 × 1 (sequence length × channels)	1024 × 5
Convolutional Layer 1	1 × 32 @ 3×1, stride=1, padding=1	1024 × 32
Pooling Layer 1	Max Pooling (kernel_size=2, stride=2)	512 × 32
Convolutional Layer 2	32 × 64 @ 3×1, stride=1, padding=1	512 × 64
Pooling Layer 2	Max Pooling (kernel_size=2, stride=2)	256 × 64

Convolutional Layer 3	64 × 128 @ 3×1, stride=1, padding=1	256 × 128
Pooling Layer 3	Max Pooling (kernel_size=2, stride=2)	128 × 128
Convolutional Layer 4	128 × 256 @ 3×1, stride=1, padding=1	128 × 256
Pooling Layer 4	Max Pooling (kernel_size=2, stride=2)	64 × 256
Dropout Layer	Dropout (p=0.5)	64 × 256
Fully Connected Layer	256 × 128 → 128 × 4	4
Activation Layer	Softmax (for classification)	4

To adapt the pre-trained MC-1DCNN to the small-scale target 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 [60] was applied to 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 Dataset Description and Pre-Processing

CWRU Dataset: Publicly available, whose bearing model is SKF 6205-2RS(ผิดพลาด! ไม่พบแหล่งการอ้างอิง). 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 [61] with a 50% overlap, resulting in 1400 samples per category and altogether 5600 samples. The dataset was split 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 [62].

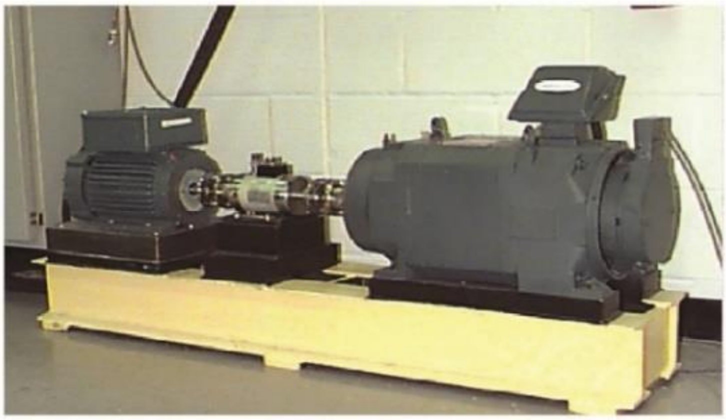

Figure 19 Test Stand of CWRU Bearing Dataset

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 (ผิดพลาด! ไม่พบแหล่งการอ้างอิง), 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 split into training and testing subsets using an 8:2 ratio for fine-tuning and evaluation (detailed in ผิดพลาด! ไม่พบแหล่งการอ้างอิง).

Figure 20 Sensor Mounted on the Elevator Car

Table 7 Dataset List

	Data set	Category	Label	Train sample	Test sample
Source	CWRU	Normal	0	1120	280

domain (pre-train)	bearing	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

The following is a schematic representation of the results of the signal (fragment) pre-processed by EMD, representing the characteristics of the signal at different scales (Shown in ผิดพลาด! ไม่พบแหล่งการอ้างอิง):

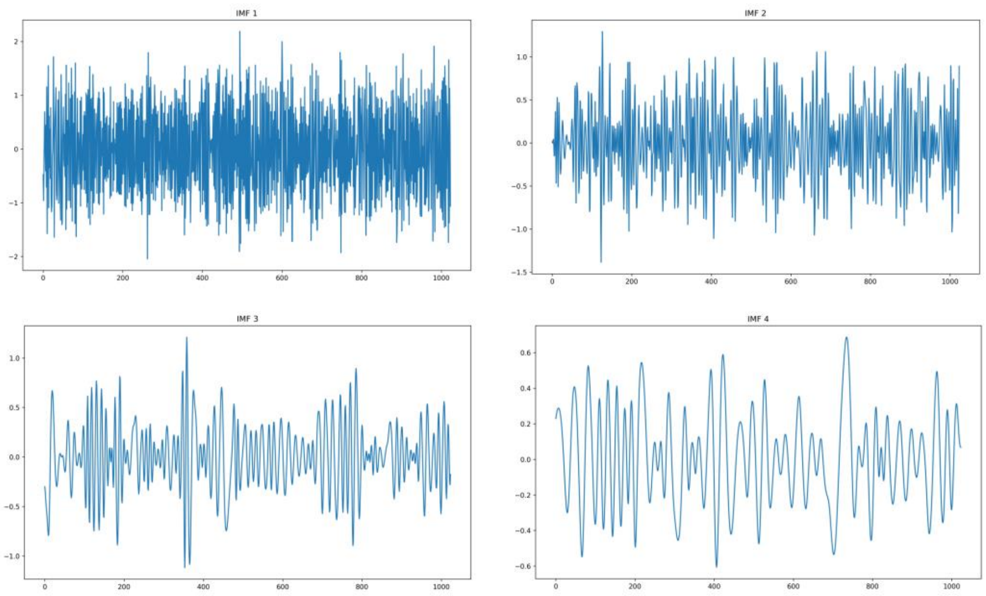

Figure 21 IMFs Of Example Signal

4.5 Evaluation Metrics

The effectiveness of the TL-MC-1DCNN approach was evaluated by commonly adopted indicators of accuracy and confusion matrix. The definitions and formulas are defined [63] as (4.1) and (4.2):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

$$Confusion\ Matrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{4.2}$$

Where:

TP (True Positive): The count of positive samples that are correctly identified as positive.

TN (True Negative): The count of negative samples that are accurately classified as negative.

FP (False Positive): The count of negative samples that are mistakenly identified as positive.

FN (False Negative): The count 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.

5. Results

5.1 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 ผิดพลาด! ไม่พบแหล่งการอ้างอิง). Subsequently, the classification effect of the test samples is given through the confusion matrix (shown in ผิดพลาด! ไม่พบแหล่งการอ้างอิง), and the feature distribution of the test samples visualized using the t-SNE algorithm [64] are presented in ผิดพลาด! ไม่พบแหล่งการอ้างอิง, demonstrating the model's robustness in distinguishing different fault types.

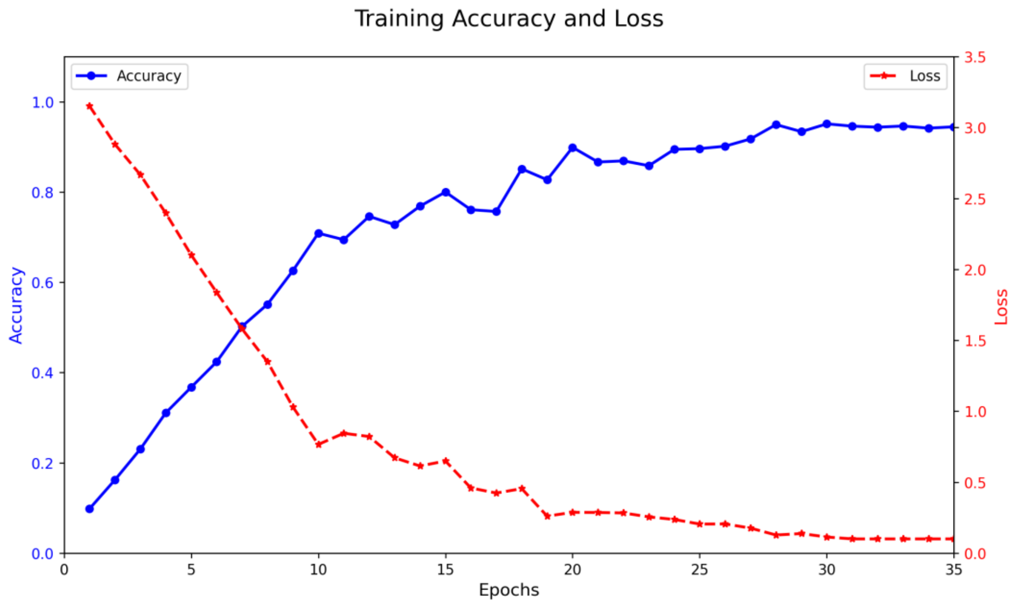

Figure 22 Iterative Convergence of Accuracy and Loss

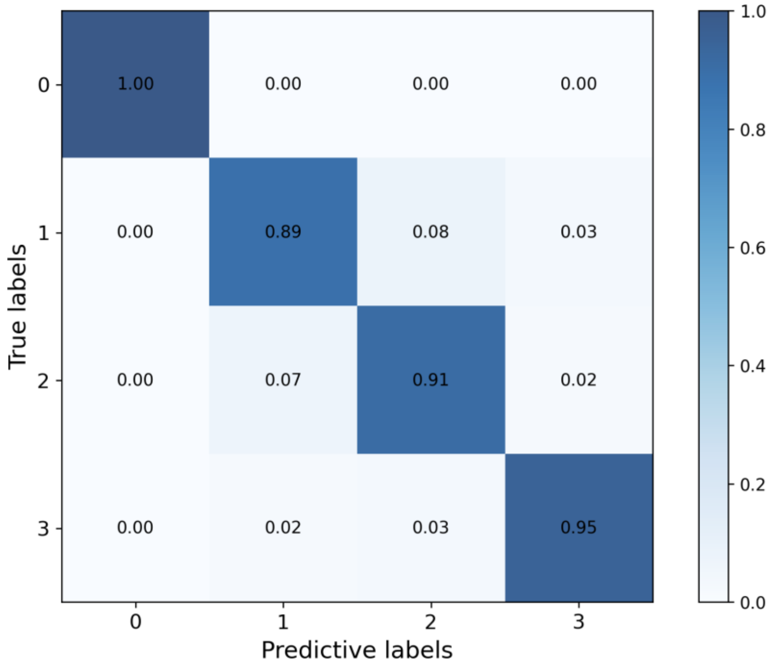

Figure 23 Confusion Matrix for Classification Results

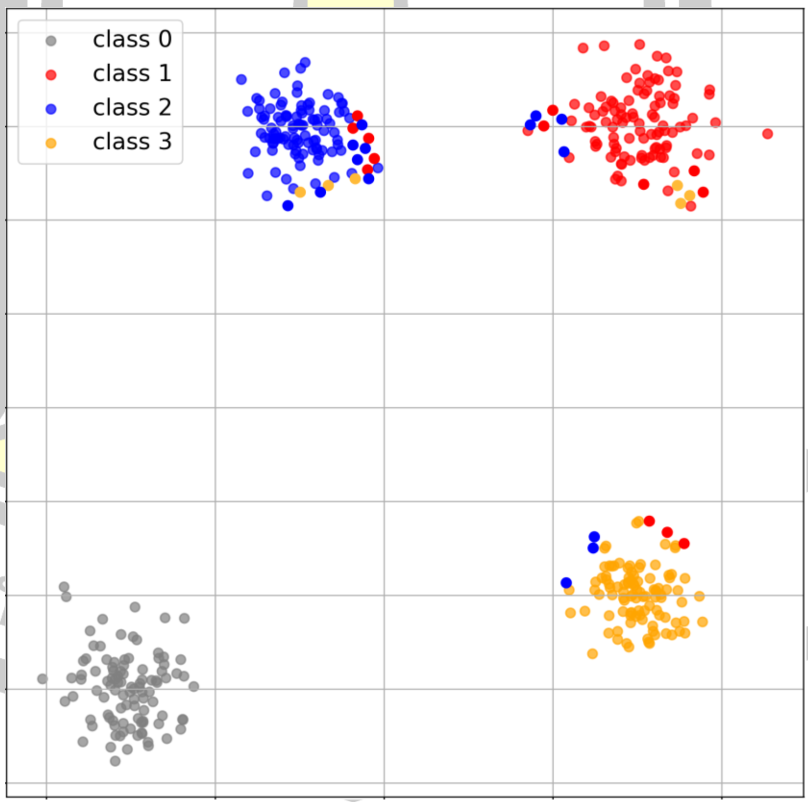

Figure 24 Visualized Feature Distribution

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.

5.2 Comparison Experiment

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.

Comparison Results:

The classification accuracies of the three models, averaged across 5-fold cross-validation on the elevator guideway dataset, are summarized in ผิดพลาด! ไม่พบแหล่งการอ้างอิง. 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 8 Comparative Results of Model Accuracy

	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

5.3 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 ผิดพลาด! ไม่พบแหล่งการอ้างอิง. The constructed method possess the highest classification accuracy, stabilizing after 20 epochs. In comparison:

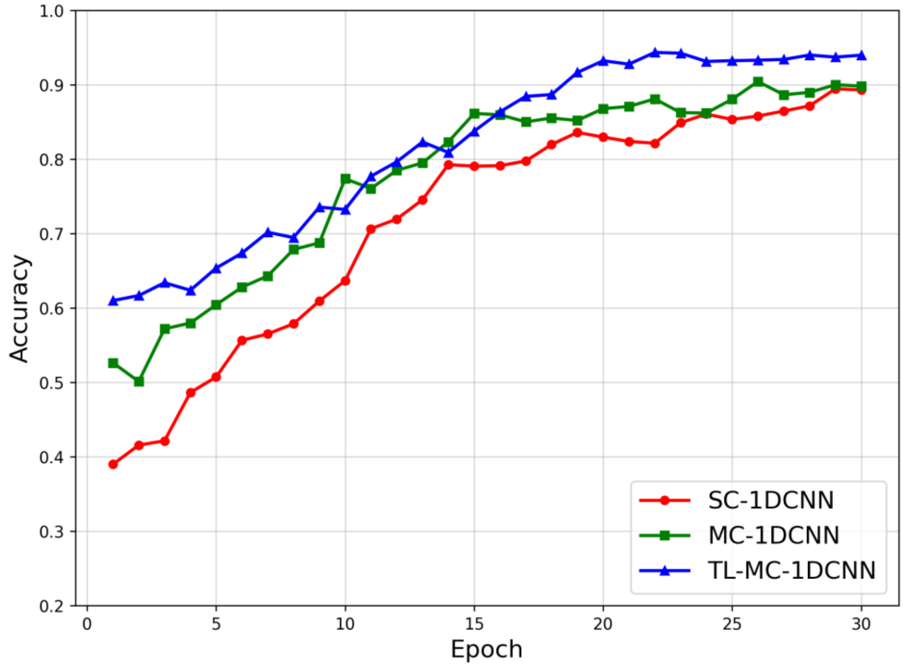

Figure 25 Results of Ablation Experiments

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. Conclusions

6.1 Conclusions

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.

6.2 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.

6.3 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 [65].

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