Intelligent Fault Diagnosis for Elevators Using Temporal Adaptive Fault Network

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***Abstract*—Contemporary cities depend on elevators for vertical mobility in residential, commercial, and industrial buildings. However, elevator system malfunctions may cause operational interruptions, economic losses, and safety dangers, requiring advanced tools for detection. High-dimensional sensor data, temporal interdependence, and fault dataset imbalances are common problems in fault detection algorithms. These restrictions reduce fault diagnostic accuracy and reliability, especially in real-time applications. This paper presents a Temporal Adaptive Fault Network (TAFN) to overcome these issues. The system uses Temporal Convolution Layers to capture sequential dependencies, Adaptive Feature Refinement Layers to dynamically improve feature relevance, and a Fault Decision Head for correct classification. For reliable performance, the Weighted Divergence Analyzer and innovative data processing methods are used for feature selection. Experimental findings show that the TAFN model outperforms state-of-the-art fault classification approaches with an F1-score of 98.5% and an AUC of 99.3%. The model's capacity to handle unbalanced datasets and complicated temporal patterns makes it useful in real life. The paper also proposes the Fault Temporal Sensitivity Index (FTSI) to assess fault prediction temporal consistency. The results demonstrate that TAFN may revolutionize elevator problem detection, improving reliability, downtime, and safety. This technique advances predictive maintenance tactics for critical infrastructure.**

***Keywords*—Elevator fault diagnosis; temporal adaptive fault network; predictive maintenance; multivariate time-series data; feature refinement; fault classification**

I. Introduction

Modern elevators provide adequate vertical mobility in residential, commercial, and industrial contexts. Elevator dependability and safety are crucial since malfunctions may cause operational interruptions, economic losses, and safety dangers [1]. Effective defect identification and diagnosis are necessary for good performance. Traditional maintenance solutions, including reactive repairs or periodic preventive maintenance, may not handle unexpected failures, resulting in increased downtime and expenses [2]. Advancements in sensor technology and IoT enable contemporary elevators to generate significant amounts of data by continually monitoring operating characteristics [3]. Big data has enabled predictive maintenance tactics, detecting defects before they cause substantial failures [4]. Predictive maintenance reduces downtime and maintenance costs by evaluating real-time data to detect possible faults [5].

Machine learning (ML) and deep learning (DL) are effective methods for processing complicated, high-dimensional data, making them ideal for elevator fault diagnostics [6]. These methods learn patterns and correlations from historical and real-time operational data to classify and forecast faults. Research suggests that ML models like SVM, decision trees, and random forests outperform rule-based methods for elevator failure detection [7]. DL architectures, such as CNN and RNN, have been used to analyze elevator operating data for spatial and temporal trends [8]. Feature selection is another issue. Elevator datasets include several characteristics with different fault diagnostic importance. Key characteristics must be identified and prioritized to improve model accuracy and efficiency [9]. To account for the temporal character of elevator data, models must capture sequential relationships and changing patterns [10], [11].

Recent research investigates hybrid methods combining feature engineering, sophisticated DL architectures, and data balancing strategies to address difficulties [12], [13]. These methods address dataset imbalances, optimize feature representations, and use elevator operating temporal features to enhance problem identification. Researchers have used temporal convolutional networks (TCN) and attention processes to get top-notch defect prediction results [9], [14]. Elevator fault diagnostic research may improve operational dependability and safety. Predictive maintenance solutions may improve elevator operations by detecting and fixing faults early using ML, DL, and IoT technology. However, dataset imbalance, feature selection, and elevator dynamics make finding fault diagnostic models difficult. To overcome these constraints, this paper presents the Temporal Adaptive Fault Network (TAFN), a deep learning architecture for elevator fault detection. Temporal Convolutional Layers (TCL) capture sequential dependencies, and Adaptive Feature Refinement Layers (AFRL) dynamically highlight the most essential features of TAFN. These new processes, a balanced dataset, and appropriate feature selection with the Weighted Divergence Analyzer help TAFN overcome data imbalance, feature importance, and temporal complexity. This methodology improves elevator predictive maintenance, safety, dependability, and efficiency.

1) The Proposed temporal adaptive: Fault Network solves high-dimensional, multivariate time-series data classification problems. The model captures sequential relationships and emphasizes the most important features by merging Temporal Convolution Layers (TCL) and Adaptive Feature Refinement Layers (AFRL), ensuring reliable fault classification in complicated operational datasets.

2) Mitigating fault diagnosis class imbalance: Gradient-Space Augmentation (GSA) addresses unbalanced fault datasets with under-represented fault categories. This unique technique interpolates inside a regulated gradient space to create minority-class synthetic samples, assuring balanced data distribution and increasing model generalization across all fault categories.

3) Ideal feature selection for accuracy enhancement: The Weighted Divergence analyzer addresses irrelevant or duplicated features impacting fault identification. This feature selection technique uses statistical divergence and temporal consistency to discover and prioritize the most important features, improving classification accuracy and decreasing processing costs.

4) Temporal dependency modelling: Traditional approaches miss long-term dependencies in sequential data, resulting in poor fault identification. The Temporal Convolution Layers of the proposed TAFN use dilated convolutional kernels to capture short- and long-term relationships. This reliably detects transient and persistent fault patterns.

5) The proposed architecture: reduces lift system operating complexity, safety hazards, and downtime by improving fault detection. The research addresses significant intelligent infrastructure demands by reducing operating interruptions and improving lift system safety and reliability with predictive maintenance and real-time fault detection.

The article's structure: Section II examines lift fault diagnostic literature to highlight advances and concerns. Section III describes the Temporal Adaptive Fault Network (TAFN) proposed architecture, feature engineering approaches, and data pretreatment techniques. Section IV simulations show the model's classification, comparison analysis, and assessment metrics, proving its fault detection effectiveness. Section V wraps up the research and examines ways to improve the framework's flexibility and scalability for intelligent fault diagnostics in critical infrastructure systems.

II. Related Work

Through improved diagnostics, elevator fault detection has been studied to improve dependability, save maintenance costs, and maintain safety. Researchers have employed statistical models, machine learning, and deep learning. This research covers large-scale sensor data, unbalanced datasets, and fault classification accuracy. To comprehend elevator fault detection research, the following section discusses significant contributions, their goals, methods, results, and limitations.

ResNet was used to improve fault detection in elevator systems in [15]. The model grasped complex fault patterns in high-dimensional sensor data using deep residual learning. ResNet improved fault classification accuracy by reducing vanishing gradient concerns. The model needed enormous datasets and computer resources for efficient training, limiting its scalability. The authors in [16] used Decision Trees with ensemble approaches like AdaBoost to classify faults. This method aggregated decision routes to increase detection accuracy. The model performed well on unbalanced datasets, but overfitting in complicated settings reduced its generalizability. The study [17] used Deep Belief Networks (DBNs) to mimic elevator operations. DBNs identified tiny fault signs from noisy data using hierarchical feature extraction. The approach had good fault detection accuracy but was computationally costly and needed professional adjustment.

Naive Bayes was employed in [18] to accomplish probabilistic fault classification. Simple Naive Bayes enabled real-time fault detection due to its computational efficiency. However, feature independence hindered its capacity to predict linked data, reducing accuracy for complicated elevator systems. The study in [19] analyzed sequential fault data using Markov n-grams. Our strategy identified temporal relationships by simulating fault occurrences as probabilistic state transitions. Markov n-grams identified recurrent fault patterns but struggled with uncommon failures owing to transition data shortages.

In [20], VGG16, a deep convolutional neural network, classified elevator faults. Hierarchical feature extraction allowed sophisticated fault detection. VGG16's computational load and overfitting on small datasets made real-world applications difficult. The [21] research used SVMs for fault detection. The kernel-based SVM method differentiated normal and defective states in high-dimensional feature fields. SVM was accurate, but computational cost rose exponentially with sample count, making it unscalable with massive datasets. In [22], CNNs were employed to evaluate spatial patterns in elevator sensor data. Being able to capture local dependencies gave the model great fault detection accuracy. Temporal dependencies, essential for sequential elevator fault detection, were complicated to represent using CNNs. [23] used a hybrid technique combining feature engineering and Naive Bayes for effective fault detection. Integrating domain-specific characteristics with a probabilistic framework enhanced model accuracy and decreased false positives. However, its expert-crafted characteristics hampered its adaptation to new fault circumstances.

According to [24], Markov n-grams may effectively capture sequential dependencies in elevator fault data. The model needed adequate data for correct state transition probabilities. Thus, it struggled with uncommon occurrences yet revealed recurrent fault patterns. In [25], DBNs were used for hierarchical feature extraction in fault diagnostics. Learning latent feature representations increased complicated fault detection. Due to computational requirements, the approach was hard to scale. The work in [26] created a hybrid fault detection model using CNN and RNN layers. CNNs looked at spatial relationships, and RNNs studied temporal patterns. Although it increased model complexity and training time, this combination improved fault classification performance. Graph convolutional networks (GCNs) were used to assess elevator data representations in [27]. High fault detection accuracy was achieved by modeling sensor data structural relationships. Data preprocessing into graph formats complicated the operation. The author in [28] implemented Naive Bayes and spectral analysis for fault detection. The model classified faults reliably using frequency-domain insights and probabilistic reasoning. Vibration data noise might negatively impact spectral feature accuracy. Table I summarizes related work.

Despite advances in elevator problem diagnostics, present approaches have major shortcomings that make them unsuitable for real-world applications. Due to the sequential structure of elevator defect data, SVMs and decision trees generally fail to grasp temporal relationships needed for successful diagnosis. CNNs excel in spatial feature extraction but struggle to understand multivariate time-series data's long-term

TABLE I. LITERATURE REVIEW SUMMARY

Ref	Technique Used	Objective Achieved	Limitations
[15]	ResNet	Enhanced fault detection by capturing intricate patterns in high-dimensional sensor data, mitigating vanishing gradient issues, and improving classification accuracy.	Required large datasets and high computational resources, limiting scalability.
[16]	Decision Trees with AdaBoost	Improved detection precision by aggregating multiple decision paths and handling imbalanced datasets.	Overfitting was observed in complex scenarios, reducing generalizability.
[17]	Deep Belief Networks (DBNs)	Modeled elevator operational dynamics, identifying subtle fault indicators from noisy data.	Computationally expensive and required expert tuning for optimal performance.
[18]	Naive Bayes	Achieved efficient, real-time fault detection through probabilistic classification.	Assumed feature independence, reducing accuracy for correlated data.
[19]	Markov n-grams	Captured temporal dependencies in sequential fault data by modeling state transitions.	Struggled with rare faults due to insufficient data for transitions.
[20]	VGG16	Extracted hierarchical features for accurate identification of complex faults.	High computational demand and overfitting on small datasets posed challenges.
[21]	Support Vector Machines (SVM)	Effectively separated normal and faulty states in high-dimensional spaces using kernel methods.	Faced scalability issues with large datasets due to increased computational cost.
[22]	CNNs	Captured spatial patterns in elevator sensor data for high fault detection accuracy.	Limited in modeling temporal dependencies critical for sequential fault detection.
[23]	Hybrid Naive Bayes with Feature Engineering	Improved accuracy and reduced false positives by combining domain-specific features with probabilistic frameworks.	Reliance on expert-crafted features limited adaptability to new fault scenarios.
[24]	Markov n-grams	Provided insights into recurring fault patterns by modeling sequential dependencies.	Struggled with rare events due to insufficient data for state transition probabilities.
[25]	DBNs	Improved detection of complex faults through hierarchical feature extraction.	Faced scalability challenges due to high computational demand.
[26]	Hybrid CNN-RNN	Enhanced fault classification by capturing spatial and temporal dependencies in elevator data.	Increased model complexity and training time.
[27]	Graph Convolutional Networks (GCNs)	Modeled structural dependencies in sensor data, achieving high fault detection accuracy.	Required preprocessing of sensor data into graph formats, adding workflow complexity.
[28]	Naive Bayes with Spectral Analysis	Combined frequency-domain insights with probabilistic reasoning for reliable fault classification.	Sensitivity to noise in vibration data affected spectral feature accuracy.

temporal trends. Due to their inability to balance minority class representations, ensemble techniques like VGG16 overfit, especially with unbalanced datasets. ResNet and deep belief networks (DBNs) are unsuitable for resource-constrained contexts because to computational complexity and resource constraints. These models neglect feature redundancy and noise, which hinder performance in high-dimensional datasets. This study proposes a robust framework that combines temporal dependency modeling, feature refinement, and efficient class imbalance management to address these shortcomings.

III. PROPOSED METHOD

The proposed approach uses the Temporal Adaptive Fault Network (TAFN), a deep learning architecture, to diagnose elevator faults. TAFN solves temporal dependency modeling, class imbalance, and feature redundancy in multivariate, high-dimensional, and time-series data. Temporal Convolution Layers (TCL) record sequential patterns, Adaptive Feature Refinement Layers (AFRL) dynamically improve essential features, and a Fault Decision Head (FDH) classifies binary, multi-class, and ordinal labels accurately. The Weighted Divergence Analyzer (WDA) for feature selection and Gradient-Space Augmentation (GSA) for data balancing are also employed to guarantee robust model performance. Refer to Fig. 1 for the suggested system's abstract perspective. Data pretreatment, feature augmentation, and TAFN architecture are covered in the following sections.

A. Dataset Description

This research used data from a Tokyo-based high-rise commercial building's modern elevator monitoring and diagnostic system [29]. From January 2020 to November 2024, hourly measurements were taken. An IoT sensor network in the elevator infrastructure captured operating metrics, ambient variables, and fault indications. Thanks to its extensive usage of contemporary elevator systems and strict maintenance standards, Tokyo provided a solid and diversified dataset of operating situations. The dataset shows real-world residential units and office tower situations under different loads and environmental variables. Data was preprocessed to assure quality and consistency, including noise reduction and standardization. Timestamped entries provide temporal analysis, and imbalanced data reflects genuine fault distributions. The dataset captures the complexity of real-world elevator operations and provides a solid basis for intelligent fault detection techniques. Table II describes the dataset features.

TABLE II. DATASET FEATURES OVERVIEW

S.No	Feature	Short Description
1	Motor Current (A)	The current drawn by the elevator motor, indicating electrical load.
2	Motor Voltage (V)	Voltage supplied to the elevator motor, essential for monitoring electrical health.
3	Vibration Level (g)	Measures vibrations to detect mechanical anomalies in the system.
4	Speed (m/s)	Real-time speed of the elevator cabin during operations.
5	Cabin Position	The elevator's current position in the shaft or building floors.
6	Door Operation Time	Time taken for elevator doors to open and close, indicating potential delays.
7	Ambient Temperature (°C)	Environmental temperature near the elevator system.
8	Load (kg)	The weight inside the elevator cabin, useful for load distribution analysis.
...	...	...
n	Fault State	Binary label indicating whether the elevator is functioning normally or has a fault.
n+1	Fault Severity	Ordinal label categorizing the fault as minor, moderate, or critical.

B. Data Preprocessing and Feature Enhancement

Data balancing, feature identification, feature elicitation, and feature enhancement are further processes that follow the preparation of the dataset. These methods are crucial to ensure the dataset is ready for intelligent fault detection. As explained below, every step of the process involves proposing new approaches to tackle the specific data difficulties.

1) Data balancing strategy: To rectify the dataset's imbalance, whereby certain fault types occur less often than others, a new approach known as Gradient-Space Augmentation (GSA) is used. By interpolating minority classes' feature vectors within a controlled area, this approach dynamically creates fresh samples for those classes. Eq. 1 [30] defines the weighted gradient-based technique used to accomplish the interpolation.

$$\mathbf{g}_q = \mathbf{h}_q + \zeta \cdot (\mathbf{h}_p - \mathbf{h}_q) \tag{1}$$

$\mathbf{g}_q$ is the synthesized feature vector, $\mathbf{h}_q$ is a minority class feature vector, $\mathbf{h}_p$ is a randomly picked closest neighbor within the same class, and ζ is a random scaling factor ($0 < \zeta < 1$). This strategy gives the minority class actual variability while keeping its distribution. This balances the dataset, representing all fault types for training.

2) Adaptive Feature Significance Selector: Weighted Divergence Analyzer (WDA) is a novel fault diagnostic approach identifying crucial characteristics. Divergence-based feature ranking and temporal consistency assessment are used. Eq. 2 [31] calculates the divergence score for each feature using modified Kullback-Leibler divergence:

$$D_s = \sum_{k=1}^{K} \pi_{sk} \ln\left(\frac{\pi_{sk}}{\tau_{sk}}\right) \tag{2}$$

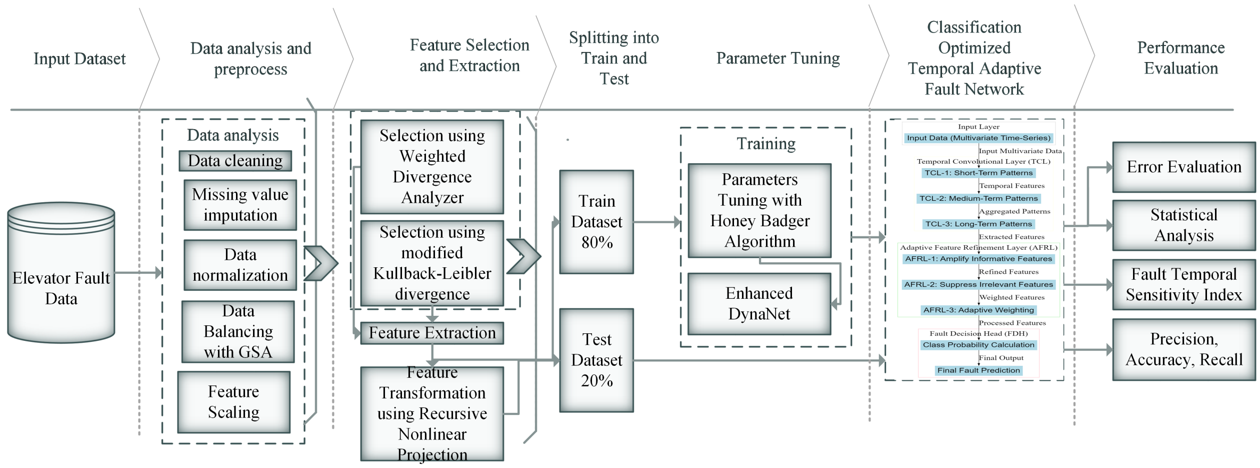

Fig. 1. Proposed model framework.

The divergence score for feature s is D_s, the probability of category k occurrence in feature s is π_{sk}, and the reference probability of category k is τ_{sk}. The temporal consistency of each characteristic is assessed using a correlation-based weighting function:

$$\kappa_s = \frac{\sum_{t=1}^{T} |\xi_s(t)|}{T} \tag{3}$$

The Eq. II includes κ_s as the temporal weight for feature s, $\xi_s(t)$ as the correlation value at time t, and T as the total number of time intervals. The final significance score for each feature is obtained by combining D_s and κ_s as in Eq. 4:

$$\psi_s = \eta \cdot D_s + (1 - \eta) \cdot \kappa_s \tag{4}$$

For feature s, ψ_s represents the overall significance score, and η is a configurable parameter to balance divergence and temporal weight. Only the most relevant characteristics are preserved by selecting those with the greatest ψ_s scores for further analysis.

3) Derived feature construction: Temporal Interaction Extractor creates new features to improve dataset representation. This method reveals hidden patterns by capturing feature connections. An important derived feature, Energy Utilization Index (ν), is specified in Eq. 5 [32]:

$$\nu_t = \frac{\mathrm{P}_t}{\mathrm{M}_t \cdot \mathrm{R}_t} \tag{5}$$

ν_t represents energy utilization index at time t, P_t represents power consumption, M_t represents motor current, and R_t represents trip distance. Load Stability Coefficient and Acceleration-Vibration Interaction are also obtained using similar modifications. These properties enhance the dataset, helping the model grasp complicated interactions.

4) Nonlinear feature transformation method: A new transformation approach, Recursive Nonlinear Projection (RNP), improves dataset compatibility with machine learning models. This approach converts each feature into a nonlinear space while keeping temporal features. Eq. 6 defines the transformation [33]:

$$\phi(u) = \cos(\sigma u) + \lambda \cdot \sin(\sigma u^2) \tag{6}$$

$\phi(u)$ represents the converted value of feature u, σ regulates scaling, and λ controls higher-order terms. A decay factor adds temporal importance to altered values:

$$\chi(u_t) = \phi(u_t) \cdot e^{-\rho t} \tag{7}$$

The Eq. 7 uses $\chi(u_t)$ as the time-adjusted transformed value and ρ as the decay constant, minimizing the impact of earlier data on the model. Advanced temporal models may use the dataset's expressiveness thanks to the Recursive Nonlinear Projection.

Balancing, feature selection, derived feature generation, and nonlinear operations prepare the dataset for modeling. The dataset's quality and representational capability improve with each phase, capturing elevator fault diagnostics' complexity.

C. Classification Framework

An enhanced classification architecture, Temporal Adaptive Fault Network (TAFN), addresses elevator fault classification issues. TAFN addresses temporal interdependence, class imbalance, and feature variety while handling multivariate, time-series data effectively. Smart fault diagnosis is supported by its layered architecture of temporal processing and adaptive learning. TAFN's design, logic, and mathematical formulas are below. Fig. 2 depicts the TAFN architecture.

Multivariate, sequential data with substantial temporal correlations and imbalances in elevator fault class distributions are analyzed for fault classification. Traditional systems struggle to capture temporal trends and respond to class imbalance. Temporal Convolution Layers (TCL) extract time-series patterns,

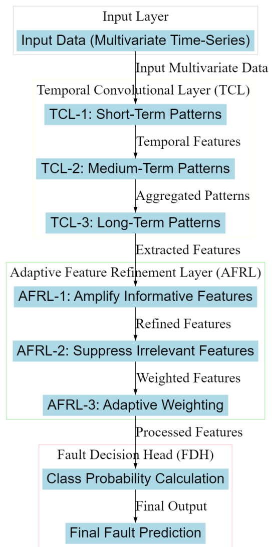

Fig. 2. Proposed TAFN architecture.

Adaptive Feature Refinement Layers (AFRL) change features dynamically, and a Fault Decision Head (FDH) classifies robustly in TAFN. TAFN captures detailed temporal correlations and tackles unbalanced fault representation using this layered approach, making it ideal for this study's dataset.

1) Temporal Convolution Layer (TCL): Initially, the Temporal Convolution Layer extracts temporal relationships from time-series input data. Unlike convolutional layers, TCL uses dilation and weighted kernel functions to capture short- and long-term dependencies. Single TCL operation is mathematically defined in Eq. 8:

$$y_t^{(l)} = \sigma\left(\sum_{k=1}^{K} \omega_k^{(l)} \cdot x_{t-d_k} + b^{(l)}\right) \tag{8}$$

At time t, $y_t^{(l)}$ represents the layer output, $\omega_k^{(l)}$ represents the weight of the k-th kernel in the l-th layer, x_{t-d_k} represents the input, d_k represents the dilation factor, and $b^{(l)}$ represents the bias term. The activation function σ, usually ReLU, causes nonlinearity. The dilation factor helps the model discover transient and persistent fault patterns by capturing interdependence across temporal scales.

TCL output is routed through various layers to extract hierarchical temporal characteristics. Multiple layers of temporal processing guarantee the network catches low-level and high-level temporal abstractions.

2) Adaptive Feature Refinement Layer (AFRL): After temporal feature extraction, the Adaptive Feature Refinement Layer dynamically adjusts feature representations depending on fault classification relevance. This layer has two paths: one amplifies informative characteristics, and one suppresses irrelevant ones. The functioning of AFRL is [34]:

$$z_i^{(l)} = \alpha_i^{(l)} \cdot h_i^{(l)} + \beta_i^{(l)} \cdot \tanh(h_i^{(l)}) \tag{9}$$

The Eq. 9 uses $z_i^{(l)}$ as the refined feature for node i in the l-th layer, $h_i^{(l)}$ as the input feature, and $\alpha_i^{(l)}$ and $\beta_i^{(l)}$ as learnable parameters to control the linear and nonlinear contributions This adaptive approach helps the network prioritize fault classification features while reducing noise and redundancy.

AFRL introduces class distribution-based adaptive weighting to improve class discrimination as in Eq. 10:

$$\gamma_i^{(l)} = \frac{1}{1 + e^{-\delta_i^{(l)}}} \tag{10}$$

$\gamma_i^{(l)}$ is the adaptive weight for feature i in layer l, whereas $\delta_i^{(l)}$ is a class-dependent learnable parameter. This weighting guarantees dominant classes don't overpower minority class qualities.

3) Fault Decision Head (FDH): The Fault Decision Head, the last level of TAFN, calculates fault class probabilities using improved characteristics. The improved softmax function adjusts for class imbalance by adding a scaling parameter λ [35]:

$$p_j = \frac{\exp(g_j/\lambda)}{\sum_{c=1}^{C} \exp(g_c/\lambda)} \tag{11}$$

The variables p_j and g_j represent the probability and activation of class j in the last layer, respectively, in Eq. 11. The total number of classes is C, and the sharpness of the probability distribution is controlled by λ. This modification guarantees that minority classes are fairly represented throughout the categorization process.

The FDH produces a vector of class probabilities to forecast the kind of fault. Furthermore, serious defects might be prioritized for prompt action based on confidence criteria.

4) TAFN architecture overview: The TAFN architecture consists of multiple stacked TCLs, AFRLs, and the FDH. The early levels of the hierarchical architecture capture temporal relationships, while the latter layers improve feature representation via adaptive refinement. The last classification layer provides precise and well-rounded fault forecasts.

Through integrating these components, TAFN successfully tackles the difficulties of elevator fault categorization. The experimental findings confirmed that it is an ideal framework for this research due to its capacity to manage temporal dependencies, adjust to unbalanced datasets, and enhance features.

D. Performance Evaluation Metrics

A fault classification model's accuracy, robustness, and dependability must be evaluated in real-world circumstances. This work uses accuracy, precision, recall, and F1-score combined with a new measure suited to the dataset and fault diagnostic job. Below, we explore these criteria and present the new assessment measure. Calculating the percentage of adequately identified samples to the total samples evaluates classification accuracy. Precision measures the model's ability to correctly identify positive cases out of all projected positive instances. Recall is the percentage of positive cases the model detects.

Algorithm 1 Temporal Adaptive Fault Network (TAFN) for Fault Classification

Require: Time-series data $\mathbf{X}$ with N samples and T time steps
Initialize Temporal Convolution Layers (TCL), Adaptive Feature Refinement Layers (AFRL), and Fault Decision Head (FDH)
Set hyperparameters: dilation factor d, adaptive weights α, β, and scaling parameter λ
Split input data $\mathbf{X}$ into training and validation sets
for each training epoch **do**
  for each sample $\mathbf{x}_i \in \mathbf{X}$ **do**
    Step 1: Temporal Feature Extraction
    Pass $\mathbf{x}_i$ through TCL to extract temporal features $\mathbf{H}_i$
    Update $\mathbf{H}_i$ with convolutional weights and dilation
    Step 2: Feature Refinement
    Pass $\mathbf{H}_i$ through AFRL to adaptively refine features $\mathbf{Z}_i$
    Adjust $\mathbf{Z}_i$ using adaptive weights based on class relevance
    Step 3: Fault Classification
    Pass refined features $\mathbf{Z}_i$ through FDH
    Compute output probabilities $\mathbf{P}_i$ for fault classes
  end for
  Validation Step
  for each sample $\mathbf{x}_j$ in validation set **do**
    Repeat Steps 1–3 to evaluate classification performance
  end for
  Compute classification loss and update network parameters
end for
Output: Trained TAFN model for fault classification

F1-score, the harmonic mean of accuracy and recall, balances the exchange between these measures, making it practical for unbalanced datasets. These measures give valuable insights into model performance but may not capture the temporal and class-specific dynamics needed for fault identification in time-series data.

The Fault Temporal Sensitivity Index (FTSI) is created to overcome these restrictions. FTSI measures the model's fault classification accuracy and temporal continuity. Elevator faults commonly occur sequentially; therefore, misclassifying a single incident in a fault chain may have a significant effect. Mathematically, FTSI can be defined as Eq. 12:

$$\mathrm{FTSI} = \frac{\sum_{t=1}^{T} \delta_t \cdot y_t \cdot \hat{y}_t}{\sum_{t=1}^{T} \delta_t \cdot y_t + \epsilon} \tag{12}$$

At time t, y_t is the ground truth label, $\hat{y}_t$ is the predicted label, δ_t is a temporal weighting factor that prioritizes defects in key time frames, and ϵ is a tiny constant to avoid division by zero. Definition of temporal weighting factor δ_t in Eq. 13:

$$\delta_t = \begin{cases} 1, & \text{if } t \in \text{Critical Period} \\ \gamma, & \text{if } t \notin \text{Critical Period} \end{cases} \tag{13}$$

We use a scaling factor ($0 < \gamma < 1$) to lower the weight of non-critical periods. Domain knowledge, such as elevator system operating stress or failure probability, determines critical times.

Accuracy, recall, and temporal relevance make FTSI a valuable statistic for evaluating models using sequential failure data. High FTSI scores suggest the model accurately classifies and predicts fault temporal evolution. Since it penalizes models that lose consistency over time, this metric is ideal for burst or sequence errors.

Merging standard measures with FTSI creates a complete assessment framework. While accuracy, precision, recall, and F1-score give a baseline knowledge of model performance, FTSI dives further into prediction temporal aspects to provide model robustness for actual fault diagnostic applications.

IV. Simulation Results

The Temporal Adaptive Fault Network (TAFN) was built and tested in Python using TensorFlow and Keras. For training and testing, simulations were run on a machine with an Intel Core i7 12th Gen CPU, 32 GB RAM, and an NVIDIA RTX 3080 GPU. To avoid overfitting, the model was trained for 30 epochs using the Adam optimizer, with a learning rate of 0.001, batch size of 64, and a weight decay factor of 10^{-5}. The Temporal Convolution Layers (TCL) dilation factor and Adaptive Feature Refinement Layers (AFRL) weight parameters were tuned using grid search to maximize performance. Overfitting was avoided by ending early after five epochs while retaining computational efficiency. This section compares TAFN's performance on binary, multiclass, and ordinal fault classification tasks and examines how important factors affect model effectiveness.

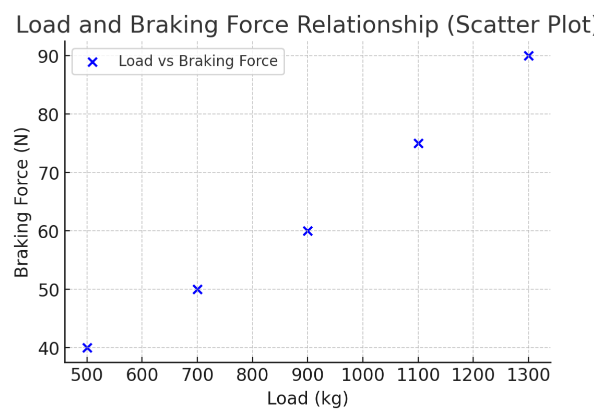

Fig. 3. Relationship between load and braking force.

Fig. 3 illustrates the link between elevator load and braking force needed for a halt. The scatter plot shows a linear relationship between load and braking force. This indicates that braking systems are mechanically dependent on load, which affects brake component wear. Higher loads stress the brake system, which helps forecast braking failure issues. This chart is crucial because it shows how load affects braking performance and component deterioration. Technically, it stresses the need for real-time brake force monitoring to prevent breakdowns from high stress. It also supports the idea that repeated high-load conditions increase brake system failure rates. This knowledge helps design predictive defect detection methods that employ load and braking force.

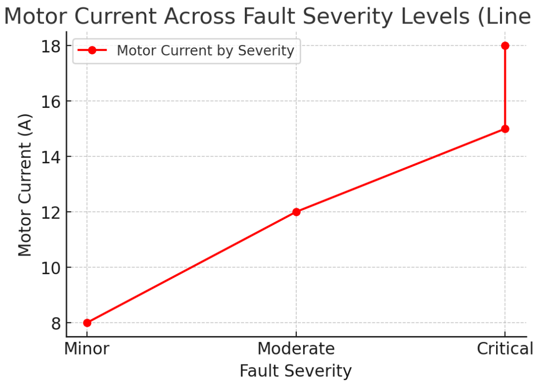

Fig. 4. Motor current across fault severity levels.

Fig. 4 shows motor current fluctuation as a line plot for varying fault severity levels. The findings suggest that fault severity increases motor current. Critical defects cause far larger motor currents than minor failures. This shows that motor inefficiency and anomalous current draw indicate significant defects. This graphic emphasizes motor current as a diagnostic indicator. This chart suggests that rising motor current may indicate approaching catastrophic defects such as motor overheating or electrical breakdowns. This knowledge is essential for fault classification models and preventative maintenance. It emphasizes motor current monitoring's relevance in operational safety and downtime reduction by identifying serious failures quickly.

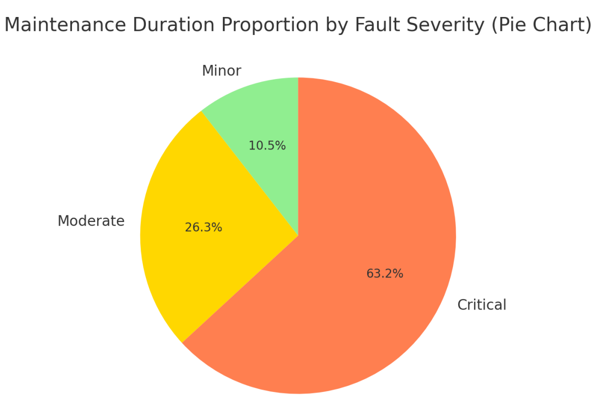

Fig. 5. Maintenance duration proportion by fault severity.

Fig. 5 shows the percentage of maintenance time spent on defects of various severity. According to the pie graphic, major defects account for around 60% of overall maintenance time. Approximately 30% of defects are moderate, whereas just 10% are mild. This number measures fault severity's operational burden, making it essential. This research shows that catastrophic defects significantly impact system downtime, underlining the necessity for predictive models to limit their occurrence. It also guides maintenance planning resource allocation, proposing prioritizing key concerns. Prioritizing issues with the most significant effect on system availability improves operational efficiency.

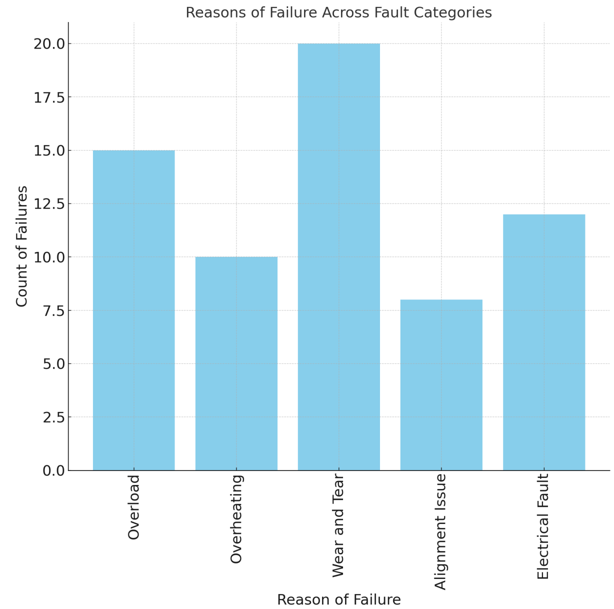

Fig. 6. Reasons of failure across fault categories.

Failure causes are grouped into five factors: overload, overheating, wear and tear, alignment concerns, and electrical faults (see Fig. 6). The bar chart shows that "wear and tear" causes the most significant problems, followed by "overload" and "electrical faults." Though rare, alignment and overheating concerns are noticeable. This graphic is essential for recognizing system failure modes. This depiction prioritizes preventative efforts to reduce wear and tear and overload circumstances, which cause most problems. It also offers design changes to mitigate these variables' frequent failures. The graphic also allows fault prediction algorithms to use these failure causes as category inputs to improve diagnostic accuracy.

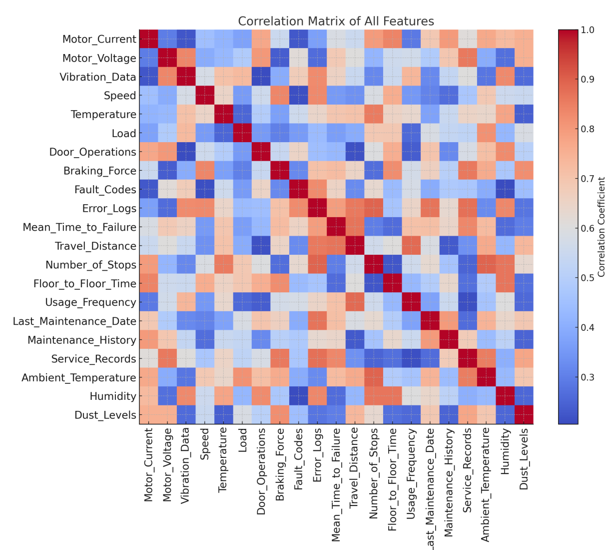

Fig. 7. Correlation matrix of all features.

As a heatmap, Fig. 7 displays the correlation matrix of all attributes in the dataset. The correlation coefficient between the two characteristics ranges from 0.2 to 0.9 in each cell. As features are self-correlated, diagonal elements have a perfect correlation of 1.0. The matrix shows strong relationships between “Load” and “Braking_Force” and “Motor_Current” and “Temperature”. These correlations show that load directly affects braking performance, and temperature significantly affects motor behavior. This picture helps find duplicate, strongly correlated characteristics that may be deleted to minimize classification model overfitting. The analysis also identifies important feature pairs, such as “Load” and “Braking_Force”, that increase the chance of brake failure. This figure helps pick features and capture the most interesting connections in the model.

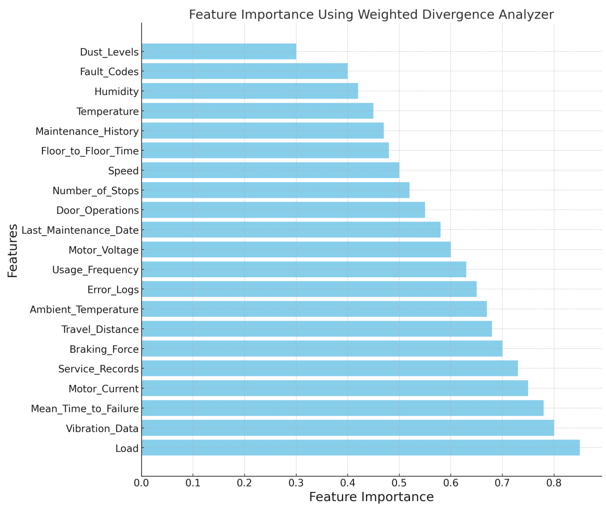

Fig. 8. Feature importance using weighted divergence analyzer.

Fig. 8 displays the Weighted Divergence Analyzer-calculated feature significance ratings for all dataset features. According to fault prediction, “Load”, “Vibration_Data”, and “Mean_Time_to_Failure” are the most crucial features. Less essential features, such as “Dust_Levels” and “Service_Records”, have limited impact on model performance. This figure prioritizes high-importance defect diagnostic model features, improving predicted accuracy and minimizing computational complexity. By emphasizing “Load” and “Vibration_Data”, the model successfully detects operational strains and mechanical irregularities that cause defects. Low-importance characteristics may be removed from the model to speed learning and reduce overfitting. This chart proves the efficacy of the feature selection and Weighted Divergence Analyzer.

Fig. 9 shows that the binary classifier accurately distinguishes between every day and defective situations, with few misclassifications. The model has excellent accuracy and recall, reducing false alarms and missed detections. Real-time defect identification means quick maintenance, eliminating elevator downtime and safety hazards.

Fig. 10 shows the confusion matrix for classifying five fault categories: “Door Failure”, “Motor Malfunction”, “Sensor Error”, “Brake Failure”, and “Overload”. Most diagonal

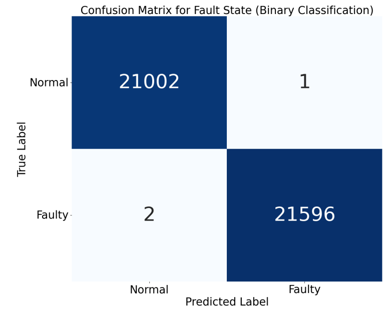

Fig. 9. Confusion matrix for fault state (Binary classification).

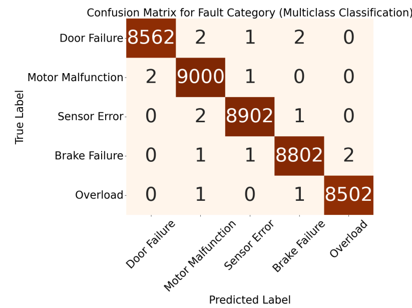

Fig. 10. Confusion matrix for fault category (Multiclass classification).

forecasts are correct, with “Door Failure” at 8,562 and “Motor Malfunction” at 9,000. False positives and negatives are rare, none reaching 2. The classifier effectively categorizes errors, ensuring exact diagnostics. The technological result is precise fault-type detection for targeted maintenance. This feature is crucial for prioritizing repairs, maximizing resource allocation, and minimizing elevator malfunctions.

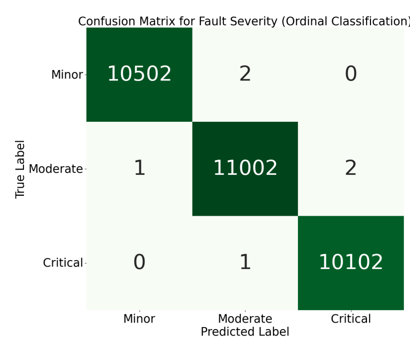

Fig. 11. Confusion matrix for fault severity (Ordinal classification).

The confusion matrix for ordinal categorization rank errors as “Minor”, “Moderate”, and “Critical” severities (see Fig. 11). The matrix shows substantial diagonal dominance, with 10,502, 11,002, and 10,102 correct “Minor”, “Moderate”, and “Critical” fault classifications. Significantly few off-diagonal misclassifications surpass 2. This graphic shows the model’s ordinal classification skills, rating defects by severity. Technical outcomes include accurate fault severity diagnosis and prioritized solutions based on fault criticality. Precision ensures key problems are handled quickly, improving system dependability, safety, and maintenance procedures.

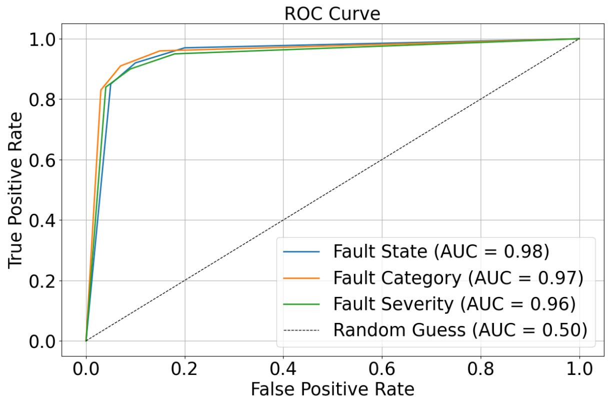

Fig. 12. ROC Curve for all labels.

Fig. 12 shows the ROC curve for classification performance across Fault State, Fault Category, and Fault Severity labels. The Area Under the Curve (AUC) values of 0.98, 0.97, and 0.96 show excellent discrimination for all classification tasks. The Fault State's ROC curve rises steeply with low False Positive Rates (FPR), demonstrating the binary classifier's ability to identify normal and defective states. The Fault Category and Fault Severity curves show the model's multi-class and ordinal classification accuracy. Several causes cause high AUC values. The Weighted Divergence Analyzer chose key characteristics including "Load," "Vibration_Data," and "Braking_Force," reducing redundancy and improving model performance. Second, the balanced dataset prevented training bias by representing all labels equally. Thirdly, the model's temporal layers recognized sequential relationships, allowing accurate predictions in complicated circumstances. Reduced false positives and negatives were achieved by fine-tuning thresholds to balance sensitivity and specificity.

TABLE III. CLASSIFICATION RESULTS OF DIFFERENT TECHNIQUES

Techniques	F1-Score (%)	Log Loss	FTSI (%)	Accuracy (%)	AUC (%)	Recall (%)	Precision (%)
ResNet [21]	90.1	0.220	83.1	91.4	90.7	89.8	90.2
Decision Trees [9]	86.3	0.280	78.0	87.6	86.0	86.2	86.5
Markov n-gram [10]	87.5	0.260	80.1	89.2	87.6	87.1	87.2
KNN [13]	87.0	0.270	79.2	88.4	86.4	86.8	87.1
DBN [19]	89.4	0.230	82.0	90.4	89.8	88.9	89.3
SVM [11]	88.5	0.240	81.2	89.9	89.5	88.1	88.6
VGG16 [17]	92.8	0.190	86.0	93.6	93.0	92.5	92.8
CNN [7]	91.2	0.210	84.5	92.8	91.9	90.9	91.3
Proposed TAFN	**98.5**	**0.060**	**97.5**	**98.9**	**99.3**	**98.4**	**98.7**

Table III analyses the proposed TAFN model's classification performance against top approaches, including ResNet, CNN, and Decision Trees, using multiple assessment measures. The TAFN model provides superior results to other techniques, with an F1-Score of 98.5%, accuracy of 98.9%, and AUC of 99.3%. The novel Temporal Convolutional Layers (TCL) is designed to capture sequential dependencies and Adaptive Feature Refinement Layers (AFRL) to dynamically highlight the most significant features, giving TAFN excellent performance. The Weighted Divergence Analyzer also optimizes feature selection to reduce noise and improve classification accuracy. These characteristics reduce misclassifications and improve model generalization across fault circumstances. Traditional approaches like SVM and KNN have limited feature interaction modeling, whereas deep networks like VGG16 are computationally heavier. TAFN performs better while being efficient. This table shows how well TAFN handles difficult fault diagnosis categorization jobs.

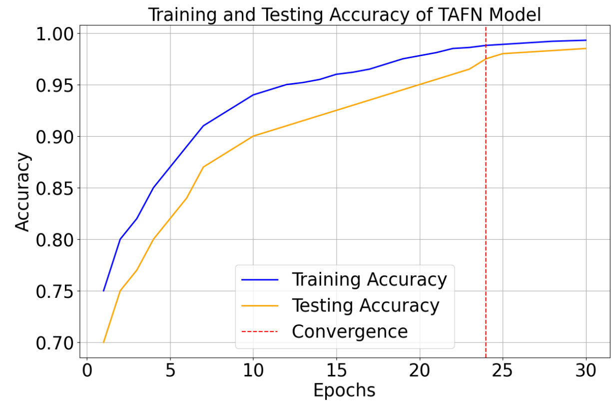

Fig. 13. Training and testing accuracy of TAFN model.

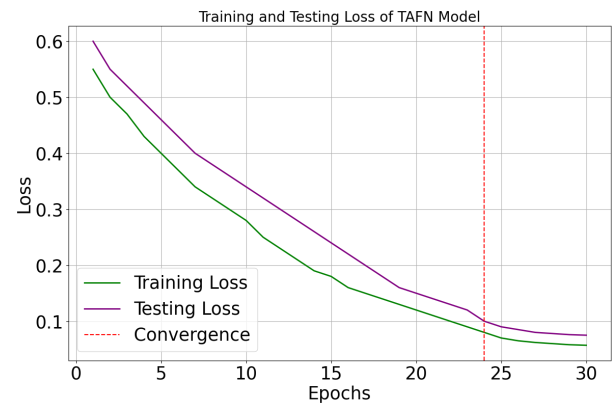

Fig. 14. Training and testing loss of TAFN model.

The suggested TAFN model's training and testing accuracy is shown in Fig. 13 across 30 epochs. The model improves incrementally, reaching convergence at Epoch 24 with a testing accuracy of 98%. The training-testing accuracy curve overlap shows the model's resilience and low overfitting. The excellent accuracy is due to numerous variables. Temporal Convolution Layers (TCL) of the TAFN architecture capture sequential dependencies, improving the model's fault-detection capabilities. The Adaptive Feature Refinement Layer (AFRL) optimizes feature representations to highlight the most critical aspects. Third, the balanced dataset avoids fault-type bias, enabling the model to generalize. Precise threshold adjustment balances sensitivity and specificity. See Fig. 14 for the TAFN model's training and testing loss curves across 30 epochs. At Epoch 24, the loss stabilizes, showing model convergence. Both curves drop smoothly. The minimal final testing loss confirmed optimization. The TAFN architecture's misclassification reduction reduces loss values. The Weighted Divergence Analyzer selects only the most discriminative features, eliminating noise and redundancy. Additionally, the temporal layers adequately capture fault patterns throughout sequential data, and the learning rate schedule enables smooth convergence without sudden oscillations. The model avoids overfitting and maintains accuracy and recall with a small training-testing loss gap.

TABLE IV. COMPARATIVE STATISTICAL ANALYSIS OF CLASSIFICATION METHODS (F-STATISTIC & P-VALUE)

Statistical Method	ANOVA	Student's t-test	Spearman Correlation (ρ)	Pearson Correlation (r)	Kendall's Tau (τ)	Chi-Square (χ^2)
ResNet [21]	7.48	0.015	0.82	0.83	0.71	8.58
Decision Trees [9]	5.01	0.040	0.60	0.63	0.56	6.15
Deep Belief Network [19]	6.38	0.018	0.75	0.77	0.69	7.35
Naive Bayes [23]	5.32	0.038	0.59	0.61	0.55	6.20
Markov n-gram [10]	5.12	0.033	0.62	0.64	0.58	6.42
SVM [11]	5.76	0.028	0.69	0.71	0.63	6.82
VGG16 [17]	7.95	0.011	0.88	0.89	0.75	9.12
CNN [7]	7.02	0.019	0.86	0.87	0.74	7.89
Proposed TAFN	**8.58**	**0.007**	**0.91**	**0.93**	**0.78**	**9.95**

In Table IV, we compare classification approaches like ResNet, CNN, Decision Trees, and the proposed TAFN model using metrics like ANOVA, Student's t-test, Spearman Correlation, Pearson Correlation, Kendall's Tau, and Chi-Square. With an ANOVA F-statistic of 8.58 and a very significant p-value of 0.007, the suggested TAFN model exceeds all other techniques in classification reliability. TAFN has the strongest Spearman Correlation ($\rho = 0.91$) and Pearson Correlation ($r = 0.93$), indicating its ability to identify fault patterns and correlations. Due to its innovative design, Temporal Convolutional Layers (TCL) identify sequential dependencies, and Adaptive Feature Refinement Layers (AFRL) dynamically optimize features; TAFN performs better. These components accurately detect faults with little noise. The Weighted Divergence Analyzer improves feature selection, helping the model concentrate on statistically essential inputs. Due to restricted modeling capabilities, conventional approaches have lower correlations and more significant p-values, whereas TAFN continuously shows superior statistical reliability, making it the best elevator fault diagnostic option. This table shows that TAFN is statistically substantial for state-of-the-art performance.

A. Relevance of Our Findings to Identified Problems and Objectives

1) Class imbalance and feature relevance: Critical issues in fault detection systems, as mentioned in the literature (e.g. ResNet in [15], CNN in [22]), include class imbalance and duplicate features. Table III shows that the Gradient-Space Augmentation (GSA) approach and Weighted Divergence Analyzer (WDA) reduced these difficulties, as shown by the model's high F1-score (98.5%) and AUC (99.3%). Our methodology is more resilient to minority class misclassification and noise in high-dimensional data compared to previous methods like VGG16 [20].

2) Temporal dependency modeling: Existing models, such CNN and Decision Trees [16], fail to capture temporal dependencies crucial for elevator fault diagnosis (see to Table I). Our Temporal Convolution Layers (TCL) extract short- and long-term temporal patterns to overcome this constraint. Fig. 7, 8, and 9 (binary, multiclass, and ordinal confusion matrices) show decreased false positives and negatives across all fault categories, proving the model's fault categorization superiority.

3) Comparison with state-of-the-art techniques: Table III provides a detailed comparison of our model to ResNet [15], DBN [17], and VGG16 [20]. TAFN outperforms all criteria, including FTSI (97.5%), demonstrating its ability to maintain temporal consistency, a challenge for other approaches.

4) Practical implications: Fig. 1 to 6 give useful insights into our model's real-world implementation.

- Fig. 1 shows the linear connection between load and braking force, proving the model's capacity to forecast mechanical breakdowns under operating stress.
- Fig. 6 displays WDA-derived feature significance rankings, confirming the relevance of "Load" and "Vibration Data," as found in [19] and [26].

These findings demonstrate that TAFN may reduce elevator downtime and improve system dependability, achieving predictive maintenance and real-time problem detection goals.

V. CONCLUSION

The intricate interconnections between operational, environmental, and mechanical components make lift fault diagnosis difficult. Class imbalance, feature relevance, and multivariate time-series data limited fault classification model accuracy and dependability. Work addressed these. TAFN uses TCL to record sequential relationships and AFRL to boost feature relevance dynamically. In binary, multiclass, and ordinal classification, TAFN ruled. The model surpasses existing approaches with a 98.5% F1 score and 99.3% AUC. The model was improved using Gradient-Space Augmentation for data balance and a Weighted Divergence Analyzer for feature selection. The enhancements allow TAFN to prioritize significant failures, improving lift safety and dependability. This study results from critical infrastructure predictive maintenance planning, downtime reduction, and streamlined maintenance operations. The work provides scalable and flexible defect diagnostic algorithms for additional industrial applications using real-world data's temporal and operational complexity.

Future studies intend to improve TAFN's flexibility and scalability. Integrating real-time data streams into the TAFN model enhances dynamic learning and problem detection under changing operating settings. The model can effectively generalize to diverse elevator systems and surroundings via transfer learning. Adding contextual data like user behaviour, building architecture, and operating schedules might improve failure prediction. Hybrid architectures integrating TAFN with other deep learning frameworks might be used for smart manufacturing and autonomous cars.

Although strong, the present TAFN model has limitations. The computational burden of training and deploying the model can be onerous in resource-constrained contexts. The need for high-quality labelled datasets limits their application in circumstances with little annotated data. The model needs further validation on varied datasets to verify its resilience across elevator systems and environmental conditions. Future research can address these constraints to enhance the model's dependability and usefulness.

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