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TimesNet Elevator Accident Prediction Model and Protection Combining DLinear and Deformable Convolution

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Abstract Elevator equipment faces multiple risk factors such as mechanical wear and tear and electrical aging during long-term operation, which leads to frequent failures. The safety of elevator operation is related to the safety of public life and property, and accurate prediction of elevator failures is of great significance in preventing accidents. Aiming at the problems of feature redundancy and low prediction accuracy in existing elevator failure prediction methods, this study proposes a TimesNet elevator operation accident prediction model that integrates DLinear and deformable convolution. Firstly, MIC correlation analysis is used to eliminate feature redundancy, and TimeGAN technique is used to enhance the fault data to balance the sample distribution; then MS-TimesNet model is constructed for feature extraction, and the complex change patterns of the time series data are captured by the dynamic convolution module and the TimesNet module; finally, the DLinear method is applied to reconstruct the features from the two dimensions, namely, the trend and residuals to improve the prediction accuracy. The experiments are validated using the operation data of 30 elevators distributed in 24 different areas, and the results show that the proposed model achieves the accuracy of 0.98, 0.97 and 0.94 on the training, validation and test sets, respectively, which is better than the comparative models of BiLSTM and RNN. The study proves that TimesNet fusing DLinear and deformable convolution can effectively improve the performance of elevator fault prediction and provide reliable technical support for the safe operation of elevators.

Index Terms Elevator operation accident prediction, TimesNet, DLinear, deformable convolution, feature extraction, fault prediction

I. Introduction

Elevator as the people's production and life in the important means of transportation, has always been in the process of economic and social development plays an important role [1]. It is not only an important infrastructure for the protection of people's livelihood needs, but also an important basic equipment for the development of economic industry [2]. According to the classification of the driving method, the elevator mainly includes traction drive elevator, forced drive elevator, hydraulic elevator, rack and pinion elevator, screw elevator and others [3], [4]. The elevator has been integrated into people's daily life, but the elevator also has a greater danger, once the accident will have a serious impact. According to the classification of special equipment, elevator accidents account for a large proportion of the total number of special equipment accidents each year, accompanied by more deaths and lower survival rates [5], [6].

In addition, elevator safety also has the attribute of public safety, and its safety will be highly valued by government departments and the public [7]. At this stage, elevators are facing more and more challenges of accident risks, which are mainly reflected in the increasingly large-scale device, high parameterization of equipment and long operation cycle [8], [9]. Improving the level of elevator safety risk prevention and control, safeguarding the quality and safety of elevators, and reducing the impact of elevator accidents are of great theoretical and practical significance for the promotion of high-quality economic and social development, and the protection of people's lives, health and property safety [10]-[13].

In this study, a TimesNet elevator operation accident prediction model incorporating DLinear and deformable convolution is proposed. The study firstly, for the feature redundancy problem in elevator operation data, MIC correlation analysis method is used to screen out the high correlation features, which lays the foundation for the subsequent modeling; secondly, in order to solve the problem of sparse fault samples, TimeGAN data enhancement technique is introduced to generate high-quality synthetic fault data through generative adversarial network, which balances the ratio of positive and negative samples; and then, the MS- TimesNet feature extraction model, combining the dynamic convolution module and TimesNet module, to fully explore the temporal patterns and spatial features in the elevator operation data; finally, the extracted features are reconstructed by using the DLinear method, and the temporal features are deeply resolved from the trend and residual dimensions, so as to improve the prediction accuracy and generalization ability of the model.

II. Elevator operation accident prediction model incorporating DLinear and deformable convolution

As the most commonly used public transportation tool in urban buildings, elevators bring great convenience to people's life and production, but occasional elevator accidents also bring great harm to the personal safety of users. Based on this, to address the problems of feature redundancy and difficulty in improving the prediction accuracy of existing elevator fault prediction methods, this study will integrate DLinear and deformable convolution to construct an elevator accident prediction model, which will provide support for improving the accuracy and flexibility of elevator fault prediction.

II. A.MIC correlation analysis

To address the problem of feature redundancy in elevator operation data, this paper conducts MIC correlation analysis before feature extraction on the data in order to select features with higher correlation and eliminate the negative impact of feature redundancy on the prediction results.

MIC correlation analysis by finding an excellent discretization way, the mutual information value between the samples into some kind of measurement mode, and then the correlation between the 2 variables can be obtained after normalization, the formula is as follows:

$$M_{\kappa}(X;Y) = \max_{n_x, n_y < B^n} \frac{I(X,Y)}{\log_2 \min(n_x, n_y)} \tag{1}$$

where, n_x and n_y are the number of cells in each axis when dividing the scatterplot grid, respectively; B^n is about 0.6 times the data volume.

II. B.Elevator Failure Data Enhancement

TimeGAN effectively combines the control of supervised training and the flexibility of unsupervised training [14].

The self-encoder network reduces the dimensionality of the input data and utilizes the embedding module to map the original feature space to a latent space containing static and temporal features, the mapping process is as follows:

$$h_s = e_S(s), h_t = e_X(h_s, h_{t-1}, x_t) \tag{2}$$

where, s and x denote the static and temporal feature data respectively, e_S and e_X denote the mapping function from static and temporal feature data to the latent space respectively, and h_s and h_t correspond to the low-dimensional mapping of s and x in the latent space. The embedding module mainly reduces the dimensionality of the input data, while the reproduction module completes the recovery of the data from low-dimensional to high-dimensional by training the inverse mapping function, and the inverse mapping process is as follows:

$$\tilde{s} = r_S(h_s), \tilde{x}_t = r_X(h_t) \tag{3}$$

where, $\tilde{s}$ and $\tilde{x}_t$ denote the static and temporal feature data recovered after inverse mapping. The self-encoder realizes the invertible mapping between feature space and latent space.

In order to improve the learning ability of the embedding and reproduction modules in the selfencoder to the input data distribution, the selfencoder is optimized using the data reconstruction loss function L_R.

$$L_R = E_{s, x_{1:T} \sim p}\left[\left\|s - \tilde{s}\right\|_2 + \sum_t \left\|x_t - \tilde{x}_t\right\|_2\right] \tag{4}$$

In the table: T is the length of the time series and p is the distribution of the data.

The generative adversarial network is designed to achieve a balance between the generator and the discriminator. The generator captures the latent distribution of the real-time sequence and generates a new synthetic sequence. The discriminator provides the correct classification between the real sequence and the synthetic sequence. Its generator function can be defined as:

$$\hat{h}_s = g_S(z_s), \hat{h}_t = g_X(\hat{h}_s, \hat{h}_{t-1}, z_t) \tag{5}$$

where, z_s and z_t denote random static features and temporal features, and $\hat{h}_s$ and $\hat{h}_t$ denote synthetic static features and temporal features in the latent space. In order to improve the generator's ability to learn the temporal correlation of real data and characterize the latent space, a supervised error loss function is introduced:

$$L_S = E_{s,x_{1:T}\sim p}\left[\sum_t \left\| h_t - g_X\left(h_s, h_{t-1}, z_t\right)\right\|_2\right] \tag{6}$$

The discriminator module uses a two-way recurrent neural network (RNN) to distinguish between real and synthetic samples, and the discriminator model is as follows:

$$\tilde{y}_s = d_S(\hat{h}_s), \tilde{y}_t = d_X(u_t^b, u_t^f) \tag{7}$$

where d_S and d_X denote the discriminant functions of static and temporal features, respectively, $\hat{h}_s$ denotes h_s or $\hat{h}_s$, $\tilde{y}_s$ and $\tilde{y}_t$ denote the discriminator labels of the static and temporal features of the synthesized sequences, and u_t^b and u_t^f denote the reverse and hidden states of the forward RNN. The unsupervised adversarial loss function L_U is defined to reflect the competition between the generator and the discriminator:

$$L_U = E_{s,x_{1:T}\sim p}\left[\ln y_s + \sum_t \ln y_t\right] + E_{s,x_{1:T}\sim \hat{p}}\left[\ln(1-\tilde{y}_s) + \sum_t \ln(1-\tilde{y}_t)\right] \tag{8}$$

where, y_s and y_t denote the labels of the static and temporal features of the real sequence.

II. C.Elevator fault data feature extraction

In this section, a new fusion model, MS-TimesNet, will be proposed for elevator fault data feature extraction.

II. C. 1) Dynamic Convolution Module

Let X be the feature samples of the EEG signal, $X = [X^0, X^1, \cdots, X^n]$, and $X^n \in R^{c\times l}$, where n is the number of samples, c is the number of channels, and l is the length of the features of each sample. Let Z_i denote the output of the i th convolution type of the dynamic time layer, $Z_i \in R^{n\times m\times c\times l_i}$, where n is the number of samples, m is the number of channels of the convolution output feature map, c is the number of channels, and l_i is the length of the i th post convolution feature, and Z_i is defined as:

$$Z_i = AvgPool\left(Leaky\,\mathrm{Re}LU\left(Conv1D(X, S_t^i)\right)\right) \tag{9}$$

Due to the covariate shifting problem within the neural network, normalization is added after the dynamic time layer. So the final output of this layer is Z_T and $Z_T \in R^{n\times m\times c\times \sum l_i}$, is defined as:

$$Z_T = f_{bn}\left([Z_1, \cdots, Z_i]\right), i \in [1,2,3] \tag{10}$$

In equation (10), f_{bn} is the normalization operation, and $[\cdot]$ represents the splicing operation of the output of i convolution type in the feature dimension.

In the dynamic space layer, let Z_j represent the output of the convolution type j in the dynamic space layer, $Z_j \in R^{n\times m\times c_j\times l_j}$, where n is the number of samples, m is the number of channels of the convolution output feature map, c_j is the number of channels after the convolution of j, and l_j is the feature length of the first j convolution. Z_j is defined as:

$$Z_j = AvgPool\left(Leaky\,\mathrm{Re}LU\left(Conv1D(Z_T, S_s^i)\right)\right) \tag{11}$$

In Eq. (11) S_s^i is the size of the convolution kernel, Z_T is the output of the dynamic temporal layer, $Conv1D(\cdot)$ is the one-dimensional convolution operation with the convolution kernel of S_s^i and convolutional step of $(1,1)$, $LeakyReLU(\cdot)$ is the activation function and $AvgPool(\cdot)$ is the average pooling operation, and ultimately each output is spliced along the channel dimension, as in the dynamic time layer, where normalization needs to be added, so the final output of this layer is Z_P, $Z_P \in R^{n\times m\times \sum c_j \times l_j}$, are defined:

$$Z_P = f_{bn}\left([Z_1,\cdots,Z_j]\right), j\in[1,2] \tag{12}$$

In Eq. (12) f_{bn} is the normalization operation and $[\cdot]$ is the splicing operation of the outputs of the j convolutional types in the feature dimension.

II. C. 2) Timesnets module

The Timesnets decompose complex temporal variations into intra-cycle and week-to-week variations [15]. The Timesnets layer integrates the data transformation layer, in the data transformation layer, accepts the output Z_P of the dynamic convolutional layer, transforms it into dimensions, and obtains Z_{1D}, $Z_{1D}\in R^{n\times c\times l}$, where n is the number of samples, c is the number of frequency bands after passing through the dynamic convolutional layer, l is the number of features after passing through the dynamic convolutional layer, and for the Z_{1D} sequence, it is converted into Z_{2D} The method of the sequence is defined as:

$$\begin{aligned} &A = Avg\left(Amp\left(FFT(Z_{1D})\right)\right), f_i = \underset{f_i\in\left\{1,\cdots,\left[\frac{c}{2}\right]\right\}}{\arg Topk}\ (A) \\ &p_i = \left\lceil \frac{c}{f_i} \right\rceil, i\in\{1,\cdots,k\} \end{aligned} \tag{13}$$

In Eq. (13), $FFT(\cdot)$ denotes that the Fast Fourier Transform is performed to find the intra-periodic versus inter-periodic variations, $Amp(\cdot)$ denotes that the amplitude is computed, and $A\in R^c$ denotes the amplitude at each frequency, and $Avg(\cdot)$ denotes the averaging from the l-dimension, which requires the DC component to be set to zero, so that the most significant frequencies $\{f_1,\cdots,f_k\}$ are obtained for the first K non-normalized amplitudes $\{A_1,\cdots,A_k\}$, which correspond to the K cycle lengths $\{p_1,\cdots,p_k\}$ as well, due to the frequency-domain covariance, so only the frequencies within $\left\{1,\cdots,\left[\frac{c}{2}\right]\right\}$ are considered, and from this it is possible to take the Z_{1D} time series, and reconstruct it into multiple Z_{2D} tensors, as shown in Eq:

$$Z_{2D}^i = \mathrm{Re}shape_{p_i,f_i}\left(Padding(Z_{1D})\right), i\in\{1,\cdots,k\} \tag{14}$$

In the feature extraction layer, based on the 2D tensor obtained in the data transformation layer, the feature extraction is performed by using a dynamic convolutional layer approach defined as:

$$\bar{Z}_{2D}^i = DCNN(Z_{2D}^i), i\in\{1,\cdots,k\} \tag{15}$$

In Eq. (15), Z_{2D}^i is the i th transformed 2D tensor, and $DCNN(\cdot)$ denotes the same method as the dynamic convolutional layer for feature map extraction. Next, the learned 2D tensor $\bar{Z}_{2D}^i$, converted back to 1D space, is defined as $\bar{Z}_{1D}^i$:

$$\bar{Z}_{1D}^i = Trunc\left(\mathrm{Re}shape_{1,(p\times f)}(\bar{Z}_{2D}^i)\right), i\in\{1,\cdots,k\} \tag{16}$$

In the feature fusion layer, for the output results of the feature extraction layer, K kinds of 1D representations $\left\{\bar{Z}_{1D}^1,\cdots,\bar{Z}_{1D}^k\right\}$ need to be fused to provide the next layer. The amplitude A computed at the data conversion layer can reflect the relative importance of the selected frequency and period, defined as:

$$\overline{Z}_{1D} = \sum_{i=1}^{k} Soft\max(A_{f_i}) \times \overline{Z}_{1D}^{i} \tag{17}$$

II. C. 3) Classification module

In the classification module, the output $\overline{Z}_{1D}$ of the Timesnets module is sent to the fully connected layer to get Output, defined as follows:

$$Output = Linear\left(Dropout\left(GeLU(\overline{Z}_{1D})\right)\right) \tag{18}$$

In Eq. (18), $GeLU(\cdot)$ is the activation function, which helps the gradient descent optimization algorithm to converge more easily because it behaves smoothly in the nonlinear range. $Dropout(\cdot)$ is to randomly set the outputs of a portion of the neurons to zero during the training process, thus reducing the neural network's overdependence on some specific neurons. $Linear(\cdot)$ is the fully connected layer to get the final prediction.

II. D.DLinear feature reconstruction of elevator fault data

Aiming at the problem that traditional elevator failure prediction methods cannot fully resolve complex time series features, this paper analyzes the time series features from the trend and residual of the time series data in order to reconstruct the feature extraction results so that they are more in line with the original features of elevator operation data.

The trend term is the average pooling of the feature data, and the residual term is the difference between the feature data and the pooled data, the formula is as follows:

$$X_t = avgPool(X') \tag{19}$$

$$X_r = X' - X_t \tag{20}$$

where, X_t is the trend term; $avgPool$ is the average pooling operation; X' is the feature data; X_r is the residual term.

Finally, the trend term and residual term are summed and input into the softmax activation function to get the final prediction result [16].

III. Elevator operation accident prediction simulation experiment

In this chapter, the elevator operation accident prediction model fusing DLinear and deformable convolution constructed in this paper will be applied to carry out simulation experiments on elevator fault data enhancement as well as operation accident prediction to explore the fault detection performance of the elevator operation accident prediction model in this paper.

III. A. Experimental data sources

Data is the key link to determine the progress and effect of the experiment, and the elevator as a special equipment, its related data is difficult to obtain and difficult to deal with. For the research direction of elevator fault detection, there are very few open source elevator signal data sets. In order to ensure the effectiveness of the experiment, this paper builds an elevator operation data monitoring platform, in which the platform system simultaneously monitors the operation data of 30 elevators, which are distributed in 24 different areas in Hong Kong, and stores the data in the cloud.

III. B. Quality Analysis of Elevator Failure Data Enhancement

In order to keep the ratio of elevator fault signal data to normal operation data within a certain range, the TimeGAN model proposed in this paper is used to augment the elevator fault signal sample data which accounts for a smaller proportion. Since TimeGAN is composed of multiple modules, in order to focus on adversarial training in the training of the model, the embedding and recovery modules are first pre-trained, so that the embedding module has the ability to map between the input sample features and the potential space, and the recovery module has the ability to map the low-dimensional representations back to the original data, and the loss curves during the training process are shown in Fig. 1. The loss curve achieves convergence at about 200 times.

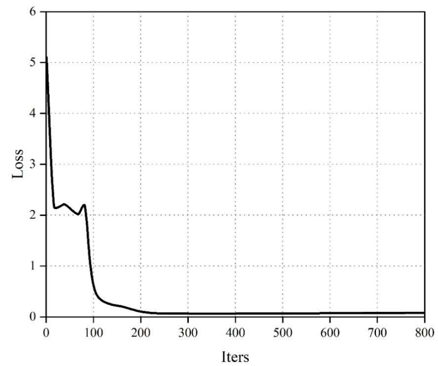


Figure 1: Embedded recovery module pre-training loss curve

Another supervised function introduced in the model for pre-training, which will enhance the learning ability of the generator in the joint training and motivate the generator to capture the distributions in the data, and its loss value curve during the training process is shown in Fig. 2. The loss function achieves convergence at about 95 times. After waiting for the loss value to converge, the function is applied to the joint training.

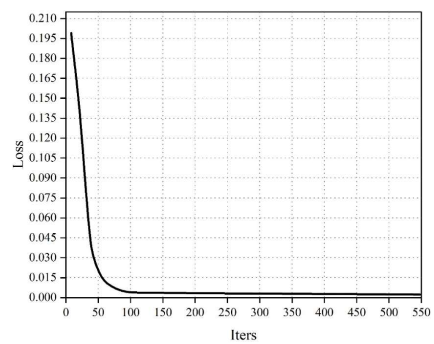
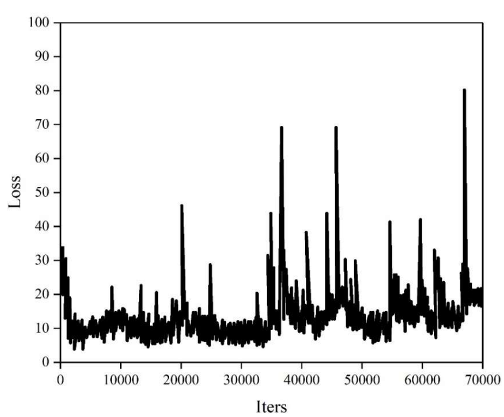
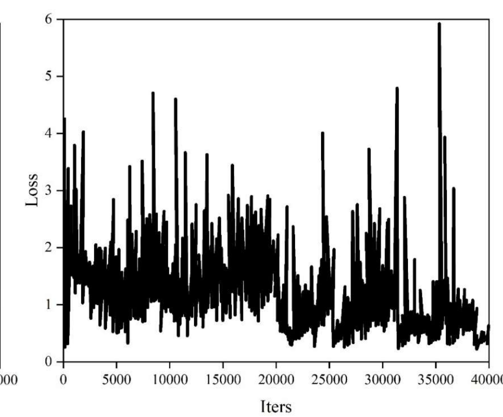


Figure 2: Supervisory function pre-training loss curve

The pre-trained embedding module, recovery module, and supervisory function are added to the joint training process for the generator and discriminator. The loss curves of the generator and discriminator are specifically shown in Fig. 3, and Figs. (a) and (b) correspond to the generator and generator, respectively. The loss curves of the two can be seen that the two have been in an adversarial relationship throughout the training process, and the losses of both the generator and the discriminator are in a state of localized oscillation, which makes them continuously learn and progress during the process of confrontation to make the generator able to generate more realistic data.



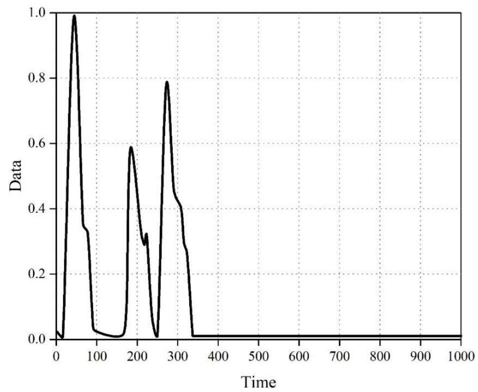
(a)Generator loss curve



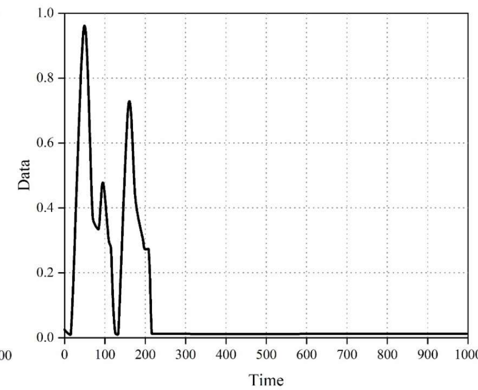
(b)Discriminator loss curve

Figure 3: Loss curve

The data are generated by generating the model, and the generated data are shown in Fig. 4, and Figs. (a) and (b) are the data sample cases 1 and 2, respectively.The characterization of these generated data is carried out, and it can be seen from the data sample case 1 that the data conforms to the scenarios of the elevator when the opening and closing signals are abnormal, and there is a different waveform in the process of opening and closing the door, when the elevator closes the door for the first time, there is a door-opening When the elevator closes the door for the first time, there is an opening action and it does not open completely, which does not match the characteristics of the passengers in the middle of the door opening and closing process, and then there is a normal complete door opening and closing action. There are three raised signals in data sample 2, the first and third waveforms conform to the characteristics of normal door opening and closing, and the second one has a door opening and closing action, but it is not complete, so it can be judged that the elevator door opening and closing at this time has an abnormality.



(a)Data Sample 1



(b)Data Sample 2

Figure 4: Data Sample

III. C. Elevator operation accident prediction effect analysis

In this paper, BiLSTM and RNN model were used as the comparison object respectively, the prediction accuracy of this paper's model with BiLSTM and RNN model in elevator fault diagnosis is specifically shown in Fig. 5. In the training set performance, the model of this paper shows the highest accuracy in the training set, reaching 0.98, which indicates that it is the most effective in modeling and capturing the features of elevator fault data, and it can well identify the fault types in the training data.The accuracy of BiLSTM is 0.93, which is higher in performance, but it is obviously behind this paper's model.The accuracy of RNN is 0.83, which has a relatively low performance The accuracy of RNN is 0.83, which is relatively low, indicating that it is insufficient in learning the features of elevator fault data. In the validation set, the accuracy of this model reaches 0.97, which is the highest among all the models, indicating that it effectively avoids overfitting while maintaining high performance and has good generalization ability.BiLSTM model is slightly inferior to this model, while RNN model has the lowest accuracy and weak generalization ability. In the test set, the accuracy of BiLSTM and RNN models are reduced to 0.9, while the model in this paper still maintains a high accuracy of 0.94, which proves that the model in this paper can accurately diagnose elevator faults in real application scenarios, and it has good practical value.

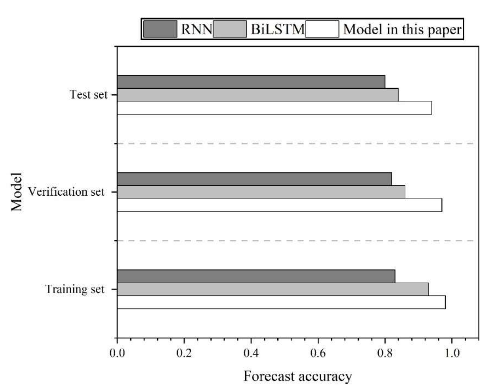


Figure 5: Comparison of prediction accuracy

IV. Conclusion

In this study, by constructing a TimesNet elevator operation accident prediction model that integrates DLinear and deformable convolution, the shortcomings of traditional methods in terms of feature redundancy and prediction accuracy are effectively solved. Experiments verify the superior performance of the model. On a dataset containing data from 30 elevator operations, the proposed model achieves an accuracy of 0.98 on the training set, which is significantly better than the 0.93 of BiLSTM and the 0.83 of RNN, which fully proves the effectiveness of the model in learning elevator fault features. On the validation set, the accuracy of the model stays at a high level of 0.97, indicating that it has good generalization ability and antioverfitting characteristics. What's more, in the test set evaluation of real application scenarios, when the accuracy of BiLSTM and RNN models are both lower than 0.9, the proposed model still maintains a high accuracy of 0.94, which proves its practical value in real environments.

The MIC correlation analysis successfully eliminates the data feature redundancy, and the TimeGAN data enhancement technique effectively balances the sample distribution, generating synthetic data that can accurately reflect the signal characteristics of elevator faults. The MS-TimesNet feature extraction module successfully captures the complex temporal sequential patterns in elevator operation data through the organic combination of dynamic convolution and TimesNet. The DLinear feature reconstruction method further improves the prediction performance by deeply analyzing the time series features from both trend and residual dimensions.

The model provides a reliable technical guarantee for the safe operation of elevators, helps to realize the transformation from passive maintenance to active prevention, and is of great practical significance for improving the safety level of elevator operation and reducing the maintenance cost, and provides a strong support for the development of intelligent elevator management system.

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