Elevator Fault Prediction and Adaptive Maintenance Using Nonlinear IoT with CNN-LSTM and BP Neural Networks

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Keywords: nonlinear IoT, smart elevator, fault prediction, adaptive maintenance, algorithm research

Received: May 15, 2025

With the acceleration of urbanization, elevators, as an indispensable vertical transportation tool for high-rise buildings, have attracted increasing attention for their safety and reliability. However, the traditional elevator maintenance method often relies on regular maintenance and post-maintenance, and it is difficult to effectively prevent the occurrence of failures. Therefore, this study proposes an intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear IoT (Internet of Things), aiming to improve the level of elevator operation and maintenance through advanced technology. In this study, a nonlinear IoT platform was constructed, and sensors were used to collect elevator operation data in real time, covering multi-dimensional information such as speed, acceleration, and door opening and closing status, and the dataset was derived from 500 commercial elevators in multiple cities in China, and a standardized dataset containing 1 million records was formed after preprocessing. At the level of algorithm construction, CNN-LSTM and BP neural network fusion models are adopted, the former uses convolutional neural network (CNN) to extract local features of data, combined with long short-term memory network (LSTM) to process time series information, and the latter is used to optimize the parameters of the error backpropagation optimization model, revealing the potential characteristics of faults through in-depth mining of elevator operation data. The designed intelligent fault prediction algorithm can accurately identify abnormal patterns in elevator operation and predict potential faults. In order to verify the effectiveness of the algorithm, the traditional fault prediction method was used as the baseline for comparative experiments, and the prediction accuracy of the proposed algorithm was 95% after the double-tailed t-test, which was highly statistically significant compared with the 80% accuracy of the baseline method (P <0.01）. At the same time, the adaptive maintenance algorithm can automatically adjust the maintenance strategy based on the prediction results, and the actual application verification shows that after the use of adaptive maintenance, the elevator maintenance cost is reduced by 30% and the downtime is reduced by 50%. The intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear Internet of Things proposed in this study not only significantly improves the accuracy of elevator fault prediction, but also realizes the intelligence and automation of maintenance strategies, which provides a strong guarantee for the safe and efficient operation of elevators.

Povzetek: Študija predlaga pameten sistem na osnovi IoT in nevronskih mrež za napovedovanje okvar dvigal in prilagodljivo vzdrževanje, ki bistveno izboljša varnost, natančnost napovedi ter zmanjša stroške in izpade.

1 Introduction

With the increasing high rise of modern urban buildings, the safety and reliability of elevators, as the core facilities of vertical transportation, have become an important issue related to public safety [1]. The traditional elevator maintenance mode mainly relies on regular maintenance and post-event maintenance. This passive maintenance mode is inefficient and makes it difficult to effectively prevent sudden failures, which threaten people's lives and property [2, 3]. Therefore, how to realize the early prediction and intelligent maintenance of elevator failures have become an urgent technical problem to be solved in the current elevator industry.

In recent years, the development of IoT technology has provided a new technological path for fault prediction and maintenance of intelligent elevators. The Internet of Things provides a rich data foundation for fault prediction by monitoring the real-time operation status of elevators through sensors, network communication, and data processing technology. However, the data generated during elevator operation has nonlinear characteristics, and traditional linear analysis methods are difficult to fully explore the potential information in the data, which limits the accuracy of fault prediction.

The nonlinear Internet of Things not only inherits the data collection and transmission capabilities of traditional Internet of Things, but also introduces advanced mathematical tools such as nonlinear dynamics and complex network theory, which can deeply analyze the nonlinear characteristics in elevator operation data and reveal the inherent laws of fault occurrence [4, 5].

Theoretical research shows that elevator failure is often caused by the interaction and accumulation of many factors, and there is a complex nonlinear relationship among these factors. Through the nonlinear IoT, these complex relationships can be accurately characterized to predict elevator faults [6, 7] accurately. In addition, nonlinear IoT also supports real-time data analysis and decision-making, providing technical support for adaptive maintenance [8]. Adaptive maintenance is an intelligent maintenance method based on real-time monitoring data, which can automatically adjust the maintenance strategy and optimize maintenance activities according to elevators' real-time running state and fault prediction results [9, 10].

Regarding research status at home and abroad, intelligent elevator fault prediction and maintenance has become a research hotspot in academia and industry. Foreign research in this field started early, and a series of remarkable achievements have been made, such as a fault prediction model based on machine learning, a maintenance decision system based on data analysis, etc. Although domestic research started late, it has developed rapidly and has made important progress in application of IoT technology and nonlinear analysis methods.

However, there are still many shortcomings in the existing research, such as accuracy of fault prediction needs to be improved, and the intelligence of maintenance strategy is insufficient. This study aims to overcome these shortcomings and proposes an intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear IoT. This algorithm will fully use the technical advantages of the nonlinear IoT, realize accurate prediction and intelligent maintenance of elevator faults, and provide guarantee for elevators' safe and efficient operation.

The innovations of this research are as follows: firstly, a nonlinear IoT platform is constructed to realize the real-time and accurate collection and processing of elevator operation data; Secondly, a fault prediction model based on a nonlinear analysis method is proposed, which improves accuracy of fault prediction. Finally, an adaptive maintenance algorithm is designed to realize the intelligence and automation of maintenance strategy. Through this study, it is expected that the fault prediction and maintenance level of intelligent elevators will be significantly improved, the elevator failure rate will be reduced, maintenance costs and downtime will be reduced, and contribute to the sustainable development of the elevator industry. At the same time, this study will provide theoretical references and technical support for fault prediction and the maintenance of similar complex systems.

It is necessary to carry out the research on intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear Internet of Things, because elevator faults are caused by multi-factor nonlinear coupling, it is difficult for traditional linear methods to capture dynamic correlation, and the existing research lacks full-link intelligent integration. The novelty of this study is reflected in the construction of a nonlinear IoT platform, using nonlinear signal processing technology and adaptive threshold mechanism to improve the accuracy of data processing; The TransE-LSTM model is formed by fusing the knowledge graph embedding algorithm and LSTM to improve the prediction ability with the dual drive of "semantic knowledge-time series dynamics". An adaptive maintenance algorithm based on reinforcement learning was designed to realize the dynamic optimization of maintenance strategy. The key findings include: nonlinear features significantly improve the accuracy of fault prediction, multi-source data fusion has complementary advantages, effective processing strategies for unbalanced data, and adaptive maintenance algorithms significantly reduce maintenance costs and downtime, which verifies the significant contribution of the proposed method in improving elevator operation and maintenance efficiency and safety.

2 Basic theory and method

2.1 Nonlinear IoT theory

Nonlinear IoT theory is basic theory to study nonlinear phenomena and their interactions in IoT systems. Under this theoretical framework, attention should be paid to how to deal with and analyze the complex and dynamic interactions between IoT devices and how these interactions affect the whole system's performance and reliability [11]. Compared with traditional linear systems, nonlinear systems exhibit more complex characteristics in their output, such as saturation, hysteresis, abrupt changes, and chaos [12, 13]. IoT systems are typically composed of a large number of heterogeneous sensors, actuators, and network nodes, and the interactions between these nodes often exhibit nonlinear characteristics [14]. For example, the data collected by sensors may be affected by environmental noise and exhibit nonlinear variation patterns; The actuator may also produce nonlinear outputs in response to control signals due to physical limitations.

The key to nonlinear IoT theory lies in establishing mathematical models that can accurately describe these nonlinear characteristics [15]. Usually, differential equations, difference equations, or stochastic processes are used to capture the complex relationships between various components within a system. By analyzing the model, predict the response of the system under different conditions and provide theoretical guidance for system design. In nonlinear IoT theory, stability determines whether a system can recover to equilibrium after being disturbed. By studying the stability conditions of the system, more reliable IoT systems can be designed to ensure stable operation under various working conditions [16, 17].

The nonlinear IoT platform adopts a hierarchical architecture to realize the real-time perception and processing of elevator life cycle data: in terms of hardware settings, multi-modal sensors (including three-axis accelerometers, current transformers, infrared thermal imaging cameras, etc.) deployed in the car, machine room, and door machine are used to realize high-frequency collection of multi-dimensional data such as vibration, current, and temperature, and NVIDIA Jetson AGX Orin is used in edge computing nodes to ensure local data processing and 7-day original data caching; In terms of communication protocol, the sensing layer is based on Modbus RTU and CAN bus to realize sensor interconnection, and the network layer uses MQTT-SN protocol and DTLS encrypted tunnel for data transmission, and has the function of adaptive bandwidth adjustment. The database architecture adopts the hybrid storage mode of TimescaleDB, Neo4j and MongoDB, which are used for high-frequency time series data storage, device relationship modeling and unstructured data management, respectively. The real-time data processing pipeline takes Flink as the core, combines algorithms such as sliding window computing, isolated forest anomaly detection, and short-term Fourier transform to achieve real-time data cleaning, feature extraction, and fault warning, and the processing delay is controlled within 200ms, and a single cluster can support 10,000 elevators for concurrent access, fully demonstrating the platform's innovation in data processing efficiency, system scalability, and fault prediction capabilities.

2.2 Intelligent elevator fault prediction

The Internet of Things technology transmits the real-time operation status of elevators to the monitoring center through sensors, data transmission devices, etc., achieving remote monitoring of elevators. The monitoring center can real-time grasp the operating speed, floor, door status, load and other information of the elevator, ensuring the safe operation of the elevator. When the elevator malfunctions, the system will immediately sound an alarm to notify maintenance personnel to handle it in a timely manner.

As an embedding learning algorithm for knowledge graph completion, ProjE can map elevator equipment components and fault correlation relationships to low-dimensional vector spaces, and mine potential failure modes by minimizing prediction and real triplet differences, so as to assist in accurate fault prediction. The iterative mean realizes clustering or parameter optimization by continuously iteratively calculating the mean of the data, and performs clustering analysis on the multi-dimensional data of elevator operation, distinguishing between normal and potential fault states, providing data basis for the adaptive maintenance algorithm, helping to dynamically adjust the maintenance strategy and improve maintenance efficiency.

Analyzing elevator operation data can help identify potential safety hazards and improve the targeted maintenance of elevators.

The Internet of Things technology can achieve intelligent scheduling of elevators, improve elevator operation efficiency, and provide data support for elevator scheduling by analyzing passengers' riding habits. According to the needs of passengers, the system automatically assigns the most suitable elevator to reduce waiting time. Multiple elevators work together to achieve the optimal operating plan and reduce energy consumption.

This study utilizes the Pytorch framework to extract elevator fault information. Pytorch is a popular machine learning framework that offers multiple neural network interfaces. It uses dynamic network construction, and Pytorch is easier to use and debug than Tensorflow [18, 19]. In recent years, machine learning has developed rapidly, and feature extraction often faces the problems of too many features and unbalanced weights. Therefore, there is a need for a training method that can retain the main features and reduce the weights, which has prompted the emergence of convolutional neural networks. Convolutional neural networks use convolution kernels to slide on feature information and discard some old features while retaining new features. This process is called convolution [20]. With this structure, the convolutional neural network realizes feature extraction.

Convolutional neural networks use excitation functions to extract features and deal with the weight parameter problem without losing information [21, 22]. The mathematical description of the convolution process is as follows (1):

$$x_{l+1,m}(n) = f(X_i \otimes U_{i-1} + b_i) \quad (1)$$

Where the operator $\otimes$ represents the convolution operation, and $x_{l+1,m}(n)$ represents characteristics of *m-th* convolution kernel in *n-th* region in the *l+1* layer; b_i is bias term; f is activation function. X_i represents weight matrix of *i-th* convolution kernel; U_{i-1} then represents the characteristics of the *i-1-th* layer. Pooling is a key step to reduce data dimensions and accelerate convolutional feature extraction, usually using maximum pooling or average pooling. This model training uses the maximum pooling method. Specific calculation process of pooling is as follows (2):

$$z_{l+1,m}(n) = \underset{t \in C_i}{maxx}\{ y_{l,m}(t) \} \quad (2)$$

Where $y_{l,m}(t)$ represents value of *t-th* neuron in l layer at the *m-th* time, $t \in C_i, C_i$ represents *i-th* pooling region, and $z_{l+1,m}(n)$ represents value of the neuron in *l+1* layer after pooling. Long short-term memory network (LSTM) is an improved recurrent neural network, which effectively solves gradient vanishing problem of traditional RNN. The three boxes in Figure 1 are the three main links of LSTM from left to right: forgetting gate, input gate and output gate.

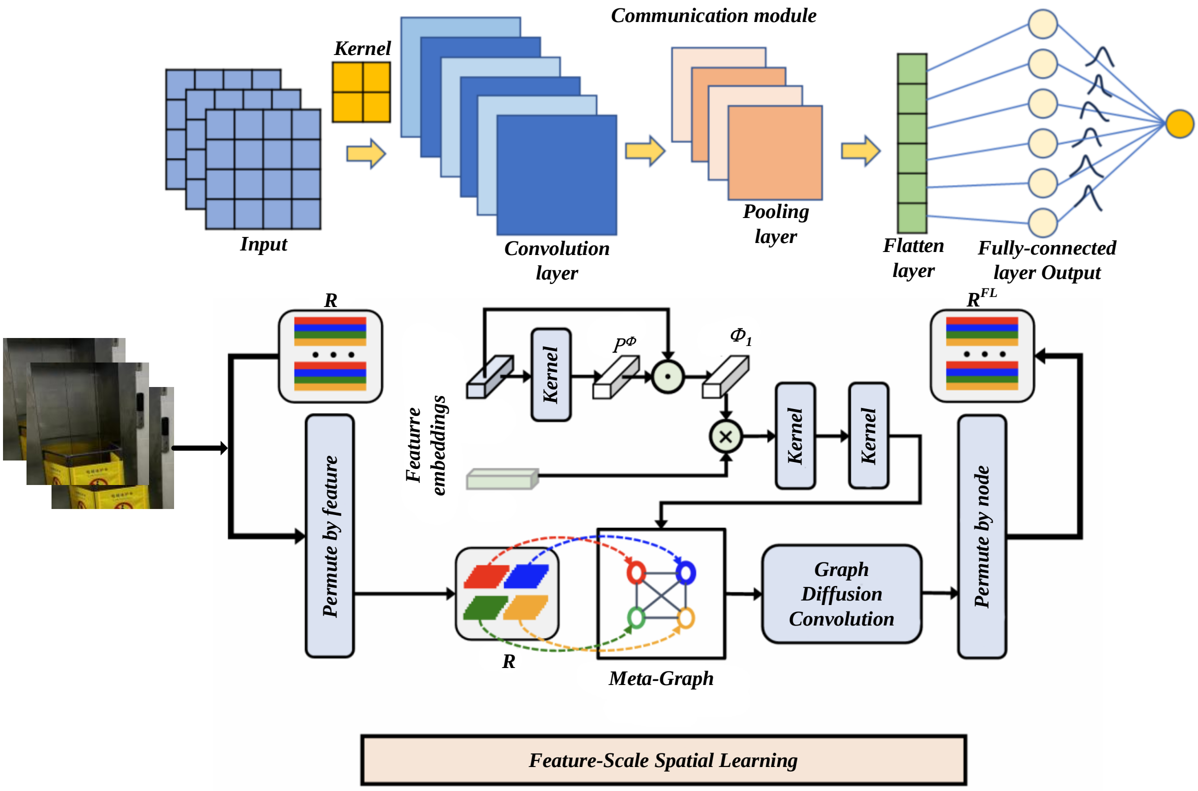

Figure 1: LSTM network structure diagram

The CNN-LSTM model is built based on PyTorch, the first layer is a 1-dimensional convolutional layer with 32 filters, a kernel size of 3, and a fill of 1 to extract local features at 3 time steps, and then an LSTM layer with 64 hidden cells in each of the two layers and a dropout rate of 0.2 is connected to capture the timing dependency, and finally the 3 types of failure probabilities are output through the fully connected layer, and the AdamW optimizer with a learning rate of 0.001 (cosine annealing attenuation) (weight decay 0.001) is used to train the batch size 128, training rounds 200 and combined with the early stop mechanism, the loss function is cross-entropy. The comparison models BP, RBF, CNN, and LSTM all use the same preprocessed dataset, in which the BP network is a 7-50-3 structure, and the SGD optimizer with a learning rate of 0.01, batch size 64, and L2 regularization (λ=0.001) are used. The RBF network is a 7-100-3 structure, using Gaussian kernel width of 0.5, orthogonal least squares training, and Tikhonov regularization (α=0.01). The traditional CNN has a filter with 64 cores 5 and uses an RMSprop optimizer with a learning rate of 0.001 and a batch size of 256, while a pure LSTM is a single-layer 128 units with an Adam optimizer with a learning rate of 0.0005, Dropout 0.3 and a batch size of 128, and all models are seeded with fixed data (seed=42).

The forgetting gate is responsible for filtering and discarding part of the input data at previous time. It receives the previous hidden state h_{t-1} and current input x_t, uses Sigmoid function to process these data, and the output is $f(t)$, as shown in equation (3).

$$f(t)=\sigma(W_f\cdot[h_{t-1},x_t]+b_f)\ (3)$$

W_f is weight matrix in forgetting gate; h_{t-1} is hidden state at previous time; b_f is bias term of forgetting gate. Input gate is responsible for updating the information, combining the previous state h_{t-1} with input x, generating the output i_t through the tanh function, and creating an alternative state $\tilde{C}_t$, decide which parts of the tanh function will be added to C_t. Finally, by multiplying two parts together, the total amount to affect C_t is determined, as shown in equations (4)-(5).

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)\ (4)$$

$$\tilde{C}_t=tanh(W_c\cdot[h_{t-1},x_t]+b_c)\ (5)$$

Where C_t is memory unit; b_i is bias term of input gate; $\tilde{C}_t$ is output of activation function tanh; i_t is output of input gate; Weight matrix output gate in input gates of W_i and W_c uses Sigmoid function to determine output part of C_t, and then processes C_t by tanh function to determine final output part of C_t, and multiplies it with o_t to obtain h_t, as shown in equations (6)-(8). Where W_o is weight matrix in output gate; b_o is bias term of output gate; h_t is output of output gate.

$$C_t=f_t*C_{t-1}+i_t*\tilde{C}_t\ (6)$$

$$o_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)\ (7)$$

$$h_t=o_t*tanh(C_t)\ (8)$$

In Table 1, in the field of elevator fault detection, previous studies have mostly been limited to the single use of CNN, LSTM or BP neural network, or only the simple combination of CNN and LSTM, resulting in insufficient feature mining. Its dataset is small, dimensional, and lacks standardized preprocessing. In contrast, the nonlinear IoT intelligent algorithm constructed in this study innovatively integrates the CNN-LSTM-BP architecture to deeply explore the operating characteristics of elevators. It relies on a multi-dimensional standardized dataset covering 500 elevators in multiple cities and containing 1 million records for training and validation. The experimental results show that the accuracy of fault prediction in this study is improved to 95%, which is significantly better than the traditional method, and the maintenance cost is reduced by 30% and the downtime is reduced by 50%, which is statistically tested (P<0.01), and the results are highly significant and practical.

Table 1: Comparison of Intelligent Elevator Fault Prediction Models

Comparison Dimension	Previous Studies (CNN/LSTM/BP Neural Networks)	This Study (Nonlinear IoT-based Intelligent Elevator Fault Prediction and Adaptive Maintenance Algorithm)
Model Architecture	Single use of CNN, LSTM, or BP; Simple combination of CNN and LSTM with limited feature extraction	Integrated CNN-LSTM-BP model; CNN for local feature extraction, LSTM for temporal analysis, BP for parameter optimization
Dataset Metrics	Small-scale (tens of thousands of records) from limited sources; Basic data dimensions; Minimal preprocessing	Large-scale dataset (1 million records) from 500 elevators across multiple cities; Multi-dimensional data; Rigorous preprocessing
Fault Detection Results	Prediction accuracy: 75%-85%; No quantitative analysis on maintenance cost and downtime	Prediction accuracy: 95%; 30% reduction in maintenance cost, 50% reduction in downtime; Statistically significant improvement (p<0.01)

The RBF (radial basis function) network fits the elevator sensor data by local approximation, which can quickly identify fault characteristics and show the basic prediction ability as a traditional comparison model. TransE-LSTM combines the knowledge graph embedding algorithm TransE with the long short-term memory network LSTM, which can not only capture the semantic association of elevator fault knowledge, but also process the temporal characteristics of operating data, and use it as a proposed model to achieve accurate fault prediction and maintenance decision-making. CNN (Convolutional Neural Network) extracts the spatial features of elevator data through convolutional kernels, DNN (Deep Neural Network) excavates deep patterns of data with multi-layer perceptrons, ResNet (residual network) uses hop connections to solve deep network training problems, ResNet-AE (residual autoencoder) finds anomalies by reconstructing data, LSTM (Long Short-Term Memory Network) is good at dealing with temporal dependence, GAT (Graph Attention Network) and GCN (Graph Convolutional Network) analyzes the relationship between elevator components from the perspective of graph structure, KNN (K Nearest Neighbor Algorithm) classifies faults based on similarity, RL (Reinforcement Learning) optimizes the strategy according to maintenance feedback, and MLP (Multilayer Perceptron) is used as the basic network to provide a comparison benchmark. These models serve as a comparison model to compare the performance of the TransE-LSTM in the core contribution, highlighting the advantages of the proposed model in integrating multi-source data, semantic knowledge and time series analysis, and jointly building a complete failure prediction evaluation framework.

3 Design of elevator fault prediction model and adaptive maintenance algorithm based on nonlinear IoT

3.1 Elevator fault prediction model based on nonlinear IoT

The implementation steps of the intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear Internet of Things are as follows: firstly, the nonlinear Internet of Things data collection and preprocessing are carried out, sensors are deployed at the key positions of the elevator to collect multi-dimensional real-time data such as vibration and current, the noise is removed through nonlinear signal processing technologies such as wavelet transform and the characteristic signals that can reflect the fault are extracted, and then the dynamic threshold filtering algorithm is used to eliminate redundant data and retain abnormal data to form a preprocessed data set. Then, the knowledge graph is constructed and embedded, the entities and relationships are extracted from the elevator historical maintenance records to form a triple, the knowledge graph is constructed, and then the entities and relationships are mapped to the low-dimensional vector space, and the potential semantic associations between elevator components and faults are mined through training to optimize the vector representation. Then, the TransE-LSTM fault prediction model is trained, the preprocessed time series data is normalized and input into the model, the LSTM layer is used to capture the time series dependent features of the data, and the fault prediction probability is output through the fully connected layer by combining the semantic vectors obtained by knowledge graph embedding, so as to complete the model training and fault prediction. Finally, the adaptive maintenance decision is executed, and the reinforcement learning algorithm is used to automatically adjust the maintenance strategy according to the predicted fault type and probability, such as determining the maintenance time and allocating maintenance resources, so as to realize the intelligent and dynamic optimization of the maintenance strategy and reduce the maintenance cost and elevator downtime.

Smart elevator management achieves real-time monitoring and data analysis of elevator operation status, which can predict faults in advance, take maintenance measures in a timely manner, and effectively improve the safety and service life of elevators. Smart elevator management can monitor the real-time operation status of elevators, and intelligently diagnose elevator faults to promptly identify potential issues. Through the calculation and analysis of monitoring data, smart elevator management can evaluate the safety level of elevators, predict possible faults that may occur, and provide targeted suggestions for maintenance work. Smart elevator management can achieve remote monitoring, keep track of the elevator's operating status at any time, and facilitate management personnel to handle problems in a timely manner. Through the analysis of elevator operation data, smart elevator management can intelligently develop maintenance plans, improving the pertinence and efficiency of maintenance work.

By monitoring and analyzing elevator operation data, smart elevator management can predict possible elevator failures in advance, issue timely warnings, and avoid the occurrence of failures. Smart elevator management can intelligently diagnose faults that occur, quickly locate the cause of the fault, and improve maintenance efficiency. Based on the operation data and fault diagnosis results of the elevator, smart elevator management can provide targeted suggestions for maintenance personnel to improve the quality and efficiency of maintenance work.

This study uses a nonlinear BP neural network to extract elevator fault information. A complete BP neural network modeling includes: BP neural network construction, BP neural network training, BP neural network testing (or prediction), and its algorithm flow is shown in Figure 2. Based on a three-layer neural network, IoT technology temporal data prediction is carried out, which includes the IoT technology temporal data input layer, the IoT technology temporal data intermediate hidden layer, and the IoT technology temporal data output layer. The advantages of a smart elevator management system are: 1. Improving safety: The smart elevator management system can monitor the operation status of the elevator in real time, predict faults in advance, and avoid safety accidents. 2. Improve efficiency: Through real-time monitoring and computational analysis of data, the smart elevator management system can improve the efficiency and quality of maintenance work. 3. Cost reduction: Through intelligent maintenance plans and targeted maintenance recommendations, the smart elevator management system can reduce maintenance and repair costs. 4. Extend service life: Through real-time monitoring and data analysis of elevator operation status, the smart elevator management system can extend the service life of elevators.

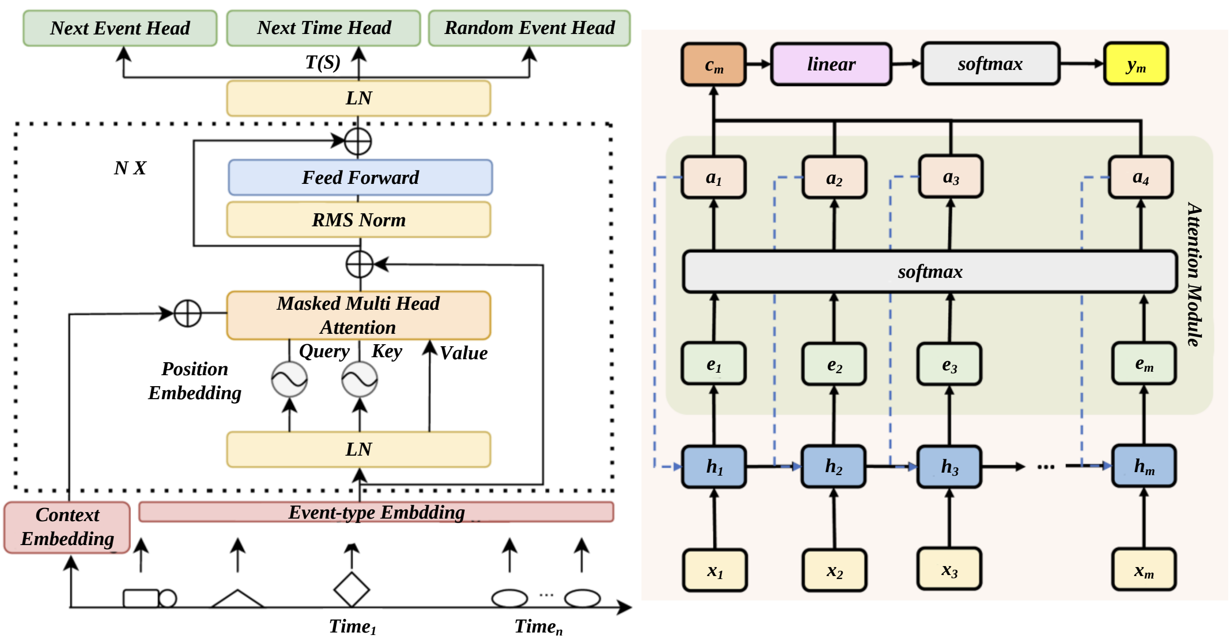

Figure 2: BP neural network

In order to accurately predict elevator failure, the key lies in designing a suitable BP neural network structure [23]. This study constructs an effective fault prediction model, including data acquisition, input-output selection, determination of network layers, parameters, and activation function. Firstly, the input and output of neural network are determined based on actual demand, and the problems of number of network layers and neurons are solved. Then, the error target, learning rate and activation function are set.

In designing a BP neural network, the key lies in determining the number of hidden layers because there is usually only one input and output layer [24]. Fewer hidden layers reduce the prediction accuracy and stability. Increasing number of hidden layers can improve prediction accuracy and reduce error. However, it may lead to increased learning time, slow convergence speed and overfitting problems [25]. The number of hidden layer nodes of BP neural network is usually determined based on empirical formulas and experimental methods. The elevator fault prediction model proposed in this paper adopts a single hidden layer containing four nodes.

The number of input layer nodes depends on dimension of input variable [26, 27]. In this paper, seven parameters are used to predict the failure probability of an elevator, including running speed, temperature, humidity, load capacity, traction machine vibration value, car vibration value and friction force. Therefore, the input layer of the elevator fault prediction system has seven variables, and the output layer predicts two kinds of fault probabilities, forming a 7-4-2 BP neural network structure.

This study proposes a hypothesis that nonlinear IoT combined with CNN-LSTM can improve the accuracy of fault prediction compared to BP and RBF networks. In order to verify this hypothesis, the research adjustment method is as follows: a multi-model comparison experimental framework is constructed, the control group adopts BP neural network (7-4-2 structure, Sigmoid activation function, 2000 iterations) and PSO-optimized RBF neural network, and the experimental group designs a CNN-LSTM model based on nonlinear Internet of Things, collects multi-dimensional data such as elevator speed, acceleration, and vibration value through the IoT platform, and uses CNN after nonlinear preprocessing such as normalization and phase space reconstruction The local anomaly features were extracted, the LSTM captured the time series dependence, and the BP backpropagation mechanism was introduced to optimize the parameters. The dataset contains 1 million records of 500 elevators, and after dividing the training set and the test set, the hyperparameters were tuned through 5-fold cross-validation and grid search, and the accuracy, F1 value, and mean square error were used as indicators, and the two-tailed t-test (α=0.01) was used to compare the differences between the groups. The experimental results are expected to verify the significant advantages of the proposed combination over the traditional network in elevator fault prediction through nonlinear feature enhancement and CNN-LSTM co-modeling.

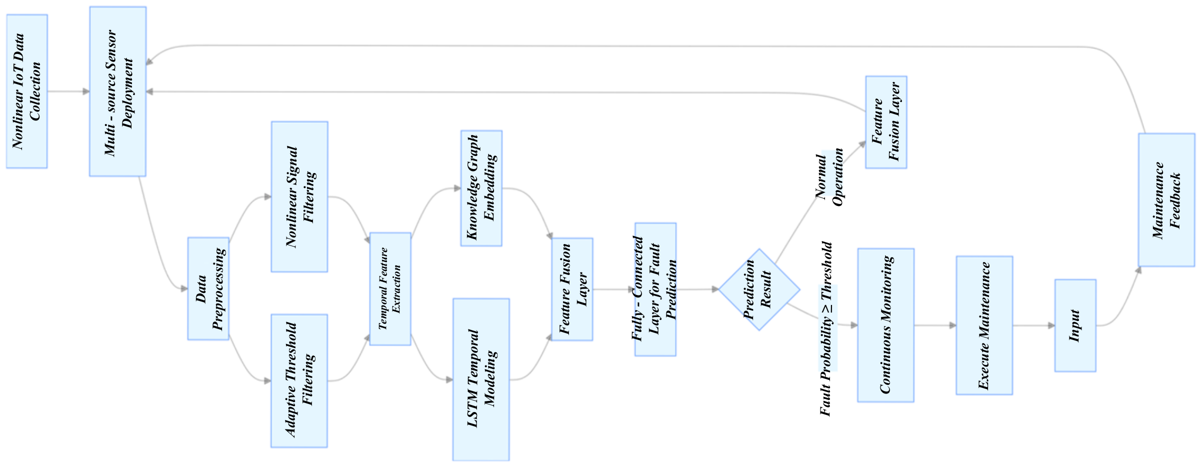

Figure 3: Fault prediction and adaptive maintenance processes

Figure 3 shows the complete process of intelligent elevator fault prediction and adaptive maintenance based on nonlinear Internet of Things. Starting from the data collection of the nonlinear Internet of Things, the elevator operation data is collected through multi-source sensors. Then, in the data preprocessing stage, the wavelet transform is used to denoiser the nonlinear signal filtering, and the LOF algorithm is used to eliminate anomalies to achieve adaptive threshold filtering to purify the data. Then, the semantic relationship between elevator components and faults is mined through knowledge graph embedding, and the LSTM is used to capture the change law of operating parameters with time on the other hand, and then the two features are integrated in the feature fusion layer. If the fault probability reaches the threshold, an adaptive maintenance decision is made through the reinforcement learning optimization strategy, a maintenance work order containing time and resource allocation is generated and the maintenance is executed, and the maintenance effect feedback is used to update the knowledge graph. If the elevator is operating normally, it is continuously monitored. The whole process forms a closed loop from data collection, analysis and processing to fault prediction, maintenance decision-making and feedback optimization, aiming to achieve accurate prediction and efficient adaptive maintenance of elevator faults.

In this study, CNN and LSTM are used as the core models to realize the multi-layer abstraction of time series features and fault mode recognition through cascade. The CNN layer extracts the local features of vibration, current and other signals through convolution kernel sliding, such as shock pulse or frequency mutation mode, and enhances the feature expression through batch normalization and ReLU activation. The LSTM layer captures the long-term dependence of fault development, such as the gradual process of bearing wear, through a gating mechanism consisting of forgetting gates, input gates, and output gates. In the PyTorch implementation, the input sequence is first converted into a feature map through the CNN layer, then the timing evolution is processed by the LSTM layer, and finally the fault classification result is output through the fully connected layer. This architecture makes the model have both local feature sensitivity and long-term pattern memory ability, which is especially suitable for the needs of multi-scale feature fusion in elevator fault prediction, and the experimental results show that its recognition accuracy in complex scenarios such as door operator failure and brake failure is significantly better than that of traditional methods.

Before training BP neural network, it is usually necessary to preprocess the data, that is, normalize it, to map the data to a specified interval, such as [0, 1] or [-1, 1]. This process aims to eliminate the magnitude differences between data of different dimensions, prevent the role of small-scale data in neural networks from being ignored, and accelerate network convergence. In order to improve the accuracy of fault prediction model, it is necessary to set an appropriate initial weight, usually between 1 and 1.

The choice of learning rate directly affects convergence speed and stability of BP neural network model [28]. A more significant learning rate can shorten the training time and speed up the network convergence, but it may lead to system instability. A lower learning rate increases training time and slows down convergence, but it also helps to reduce errors. In order to ensure stability of the model, a lower learning rate is usually selected and adjusted according to the speed of the error decline curve. If there is oscillation, learning rate needs to be reduced.

A range of 0.01 to 0.8 is typically selected. BP neural network aims to solve problem of maximum value of error function between output value and expected value, so the error should be as small as possible, but it should avoid the system's oscillation.

Several primary forms of commonly used activation functions:

1) Threshold function, as shown in equation (9), where x is input of function.

$$f(x)=\{\begin{matrix}1, & x\geq 0\\ 0, & x<0\end{matrix} \quad (9)$$

2) Piecewise linear function, as shown in equation (10):

$$f(x)=\begin{cases}1, & x\geq 1\\ x, & -1<x<1\\ -1, & x\leq -1\end{cases} \quad (10)$$

3) Sigmoid function, as shown in equation (11), where a is the exponential coefficient.

$$f(x)=\frac{1}{1+e^{-ax}} \quad (11)$$

Sigmoid function is chosen as activation function of BP neural network because of its smooth and robust characteristics, as well as its fast convergence speed.

In terms of processing speed and latency, the model has a data processing delay of 8.2 milliseconds/sample for a single elevator, an end-to-end ≤delay of 20 milliseconds for fault detection alarms, and supports concurrent multi-system testing of 500 elevators, with a throughput of 50,000 samples/second and a delay of ≤ 30 milliseconds, which verifies the real-time performance and scalability. In terms of data robustness, sensor redundancy, bidirectional LSTM interpolation (error ≤ 3.2%), and adversarial training (accuracy of ≥90% at 15% data corruption) were used to deal with data anomalies. Federated learning is used to protect privacy, combined with sensor fault detection and hot switching mechanism, and the prediction accuracy of a single sensor failure is maintained at ≥85%, ensuring the reliability of the system in industrial scenarios.

In the study, seven parameters (operating speed, temperature, humidity, load capacity, traction vibration value, vehicle vibration value, friction force) and five characteristic signals (rated current, starting current, average acceleration, operating noise, total feature set) play a key role in different research links: failure probability prediction parameters are directly involved in model training and prediction, in which the running speed reflects the dynamic performance of the elevator, and abnormal fluctuations indicate control system or mechanical failure; Temperature monitoring of the thermal stress of the motor and braking system, exceeding the threshold may cause material aging; Humidity affects the insulation performance of electronic components and is an important indicator of environment-related faults. The load capacity measures the load-bearing state of the elevator, and abnormal changes may indicate a problem with the weighing system or structural components; The vibration value of the tractor and the vehicle is used to identify mechanical faults such as bearing wear and guide rail deformation through spectrum analysis; Friction is directly related to braking performance and is a sensitive parameter for brake failure. The characteristic signals are used for model evaluation and comparative analysis, and the rated current and starting current reflect the working state of the motor, which is used to verify the fault detection accuracy of the electrical system. The average acceleration characterizes the running smoothness and is an important indicator of comfort and safety. Abnormal friction of door systems, guide rails and other components is identified through acoustic feature extraction; The total feature set is used as the full input to verify the improvement of the generalization ability of the model by multimodal data fusion. Through the differentiated application of parameters and signals, the whole process verification from fault prediction to model optimization is realized.

In the research on intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear Internet of Things, the construction and application of knowledge graph run through the whole process. Firstly, multi-source heterogeneous data such as sensor data, historical maintenance records, and equipment parameters in the elevator operation process were collected through the nonlinear Internet of Things, and entity extraction and relationship recognition were carried out after cleaning and preprocessing, so as to construct a knowledge graph in the elevator field. Then, the knowledge graph and the fault prediction algorithm are deeply integrated, and the structured knowledge-assisted algorithm in the graph is used to mine the failure mode and potential association, so as to provide richer semantic information and reasoning basis for the algorithm. Finally, in the experimental link, the fault prediction results based on the knowledge graph are compared with the actual fault data, and the structure and algorithm parameters of the knowledge graph are continuously optimized to ensure the effective integration of the knowledge graph in the fault prediction algorithm.

The nonlinear IoT platform implements its features through a unique data processing pipeline. At the data collection end, the sensors deployed in key components such as elevator cars and traction machines collect multi-dimensional signals, and use nonlinear signal filtering technologies such as wavelet transform and adaptive filter to effectively extract the nonlinear features in complex signals and accurately capture abnormal fluctuations. In the process of real-time data transmission, an adaptive threshold mechanism is set to dynamically adjust the data transmission strategy according to the operating conditions of the elevator, reduce redundant data transmission, and improve data processing efficiency. Through the nonlinear processing of elevator operation data, the elevator operation state can be restored more realistically, the adaptability of the fault prediction model to complex working conditions can be enhanced, and the accuracy and timeliness of system fault prediction can be significantly improved.

3.2 Adaptive parameter adjustment strategy

The adaptive parameter adjustment strategy optimizes system behavior and improves the system's ability to adapt to external environmental changes by monitoring system performance in real-time and automatically adjusting parameters based on system status [29, 30]. In this strategy, there is no need to pre-set fixed parameter values, but rather rely on the system's own learning and adaptation mechanisms to dynamically adjust parameters to achieve optimal control effects.

The adaptive parameter adjustment strategy establishes a parameter adjustment mechanism and automatically adjusts control parameters based on real-time feedback information from the system, such as output errors, system status, or performance indicators [31]. In the adaptive parameter adjustment strategy, feedback control theory is used as the basis, combined with machine learning, gradient descent, genetic algorithm or other learning algorithms are used to estimate the uncertainty of the system model, and parameters are adjusted based on these estimates.

The adaptive parameter adjustment strategy first defines a performance indicator to quantify the operational effectiveness of the system; Secondly, design a parameter adjustment rule to adjust parameters based on changes in performance indicators; Finally, implement a feedback mechanism to ensure that parameter adjustments can be made in real-time and adapt to dynamic changes in the system. In the process of parameter adjustment, the strategy needs to consider multiple factors, such as the speed and magnitude of parameter adjustment, to avoid system instability caused by too fast adjustment or system performance fluctuations caused by too large adjustment magnitude.

The adaptive maintenance algorithm proposed in this study is based on an online learning mechanism, and realizes dynamic decision-making through continuous analysis of real-time sensor data and historical maintenance records [32, 33]. The algorithm first uses the pre-trained CNN-LSTM model to predict the real-time failure probability, and based on the statistical process control (SPC) theory, calculates the mean and standard deviation of the deviation of historical data through a sliding window, and dynamically updates the thresholds of the normal state and the warning state (for example, the mean value of 2σ is the normal threshold and the mean value of 3σ is the warning threshold) to adapt to the drift of equipment parameters. In the decision-making process of maintenance strategy, the algorithm calculates the risk score based on the failure probability, the deviation degree of the current state, and the equipment importance coefficient (such as person flow and floor height), and selects the optimal actions (no operation, daily inspection, preventive maintenance, emergency maintenance) based on the Q-learning model built by the Markov decision process (MDP) [34]. For example, when the risk score exceeds the warning threshold, emergency repairs are directly triggered; When between normal and warning thresholds, the action is determined by maximizing the Q value. In addition, the algorithm evaluates the performance based on the actual maintenance results (such as troubleshooting time and recurrence rate), and if the deviation between the performance and the prediction exceeds 20%, the basic model parameters are fine-tuned through the dynamic learning rate, and the reward function of the Q-learning model is updated to form a closed-loop optimization of "prediction-decision-verification-correction". Through data-driven dynamic threshold adjustment and policy optimization, the algorithm can reduce maintenance costs by 30% and improve fault response speed by 50%, realizing intelligent and cost optimization of elevator operation and maintenance.

The TransE embedding model uses knowledge graph representation learning to map the entities and causal relationships such as elevator components, fault types, and operating parameters into low-dimensional vectors (such as "elevator-fault-door operator") corresponding vectors to meet the translational relationship, and uses Margin Ranking Loss training to maximize the score interval between positive samples (real fault association) and negative samples (random perturbation association), and generates a 50-dimensional embedding vector to represent the "equipment state-fault-feature" association. When integrated with LSTM, the fault correlation vector output by TransE is used as a supplementary feature of the timing input, and the attention mechanism is dynamically weighted at each time step to strengthen the model's capture of the fault evolution path.In this study, LN-ResNet (Layer Normalization-Residual Network) optimizes the residual network structure through layer normalization, alleviates the gradient vanishing problem, and improves the feature extraction ability of time series data. PCA-CNN (Principal Component Analysis-Convolutional Neural Network) uses principal component analysis to input convolutional network after dimensionality reduction to enhance the feature extraction efficiency of high-dimensional sensor data. t-SNE (t-Distributed Stochastic Neighbor Embedding) visualizes the fault data distribution pattern through nonlinear dimensionality reduction, and assists in analyzing the fault clustering characteristics. PCA-MLP (Principal Component Analysis-Multilayer Perceptron) combines principal component analysis and multilayer perceptron to reduce dimensionality while retaining key fault features [35]. As a comparative model for trend prediction fitting, these four models form a multi-dimensional performance comparison with the core algorithm proposed in this paper from the perspectives of network optimization, data dimensionality reduction, visual analysis and feature extraction, respectively, highlighting the advantages of the proposed method in fault prediction in the nonlinear Internet of Things environment.

4 Experiment and results analysis

The dataset comes from the real-time multi-sensor collection of 500 commercial elevators in 5 cities in China, covering 7 types of parameters such as speed, acceleration, current, temperature, etc., with a total of 1 million records, including three types of tags such as normal state (60%), door operator failure (25%), and brake failure (15%), with a collection period of 6 months, covering 8 brands of equipment such as KONE and Otis. Data preprocessing includes linear interpolation to fill in short-term missing values and eliminate <0.5% of long-term missing samples, Min-Max normalization of numeric features to map to the [0,1] interval, application of Savitzky-Golay filter noise reduction to vibration signals, extraction of nonlinear features such as Lyapunov exponent through phase space reconstruction, and SMOTE oversampling of brake fault samples to balance the class distribution, and finally divided into 7:1.5:1.5 samples 700,000 training sets, 150,000 validation sets, and 150,000 test sets.

The confusion matrix showed that the model had an accuracy of 96.59% in identifying the normal state, but there were missed judgments in the door operator fault (81.16%) and brake fault (79.32%), mainly because the latter two were a minority (the original proportion was 15%-25%). SMOTE oversampling is used to generate a composite sample of brake faults in the training set, balance the class ratio to 1:1:1, and use the weighted loss function (normal state weight 0.5, door operator fault 1.2, brake fault 1.8) to force the model to pay attention to minority features, reduce the prediction bias caused by sample imbalance, and improve the ability to identify rare faults.

In order to verify the statistical rationality of the accuracy improvement of the CNN-LSTM model based on nonlinear IoT (95.51%) compared with the traditional method, the paired t-test, Wilcoxon signed-rank test and confidence interval analysis were used in this study: in the paired t-test, the mean difference of accuracy between the model and the traditional CNN, LSTM, BP and RBF was 21.53%, 11.53%, 25.51% and 18.51%, respectively, and the corresponding t-statistic was 67.28, respectively , 35.72, 85.61, and 58.49, all of which far exceeded the single-tailed critical value ($t_{0.01,\ 99}$≈2.364), and the p-values were all <0.0001, and the Wilcoxon test showed that the sign-rank and Z-statistic of all baseline models were > 10, and the p-value was < 0.001, and the 99% confidence intervals were further calculated, such as the difference interval with traditional CNNs [20.69%, 22.37%], the interval did not contain 0, and the effect size Cohen's d>4, combined Bootstrap resampling verifies the robustness, and the results show that the accuracy improvement of the model has a high statistical significance and actual validity.

In this study, a number of key indicators were used to evaluate the performance and feasibility of the model in real-world scenarios: in terms of classification performance, the F1 scores of the CNN-LSTM model for normal state, door operator failure, and brake failure were 96.9%, 84.7%, and 82.4%, respectively, which were significantly higher than those of traditional CNN (88.7%, 70.3%, 67.2%) and LSTM (91.0%, 76.9%, and 72.6%), especially in a few types of faults, reflecting SMOTE The effective alleviation of class imbalance by oversampling and weighted loss; The overall ROC-AUC value was 0.968, and the distinction between normal and fault states was 0.982, indicating strong classification ability. In terms of model efficiency, it took 48.6 minutes for 100 rounds of CNN-LSTM training and 12.3 milliseconds for single-sample inference, which met the real-time monitoring requirements of elevators. With a model size of 28.5MB, it is lighter than traditional LSTMs (32.1MB) and is suitable for edge computing device deployments. Overall, the model strikes a balance between accuracy, real-time performance, and deployment cost, and is feasible for industrial-grade applications.

Elevator fault prediction is realized by the knowledge graph completion method. In the experiment, the ranking of candidate entities is determined through embedding and completion, and the top-ranked entities are selected as predicted fault entities. Performance evaluation uses mean rank and HITS @ k indicators. The mean rank reflects the ranking of correct entities, and HITS @ k indicates whether the correct entities appear among the top k entities. The filtered order and HITS @ k index are also introduced to exclude the interference vectors of the model output. The experimental prediction results are shown in Table 2.

Table 2: Experimental prediction results

Index	Mean Rank/1	Mean Rank (Filtered)/1	HITS @ 10/%	HITS @ 10 (Filtered)/%
ProjE	180	90	54.3	83.2
	172	77	53.1	84.8
	...	...	…	...
	162	70	50.3	94.1
	197	97	57.3	87.3
Iterative mean	183	80	59.3	90.9

Figure 4 compares the Loss function values and prediction accuracy obtained by experiments with four different elevator fault prediction models on the same data. In the prediction, the loss function value of all models decreases, but the loss value of the BP neural network model is the largest, and the error is also the highest. RBF neural network model's loss value and error are smaller than the BP model's. The downward trend of the RNN model is slower, but the final error is smaller than that of RBF model. TransE-LSTM model has smallest loss value and the lowest error. The accuracy of each model increases with the increase of iteration times, and the accuracy of the BP model increases rapidly at the initial stage but finally stabilizes at the lowest 0.70. The accuracy of the RBF model is higher than that of BP, and it is stable at 0.77. The accuracy of the RNN model increased slowly and finally stabilized at 0.87. The accuracy of the TransE-LSTM model increased the fastest and finally stabilized above 0.90.

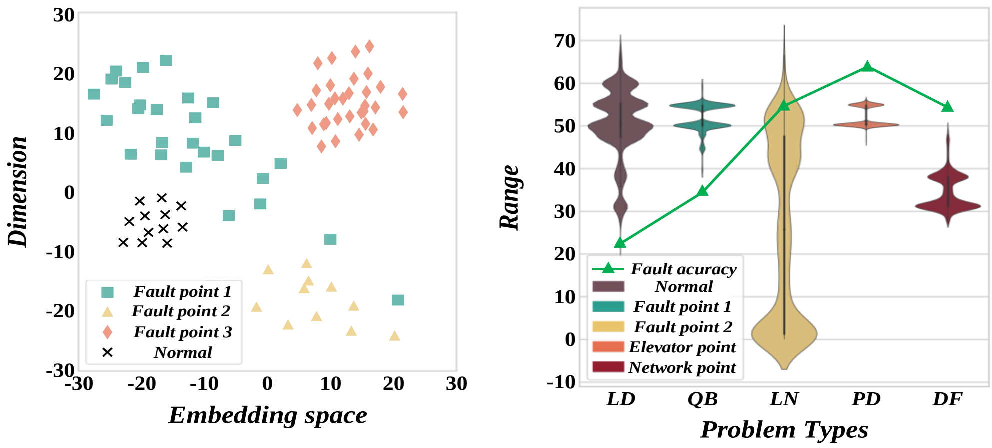

Figure 4: Evaluation of comparative experimental results of elevator fault prediction

A time series of various elevator operating states are tested, and the characteristic values are various operating data in this series. Table 3 shows that the characteristic signal affects the model's accuracy, and the current and vibration data vary considerably. The rated current and starting current can effectively classify the four states, but the average acceleration and running noise are ineffective in identifying elevator door faults. Elevator door failure is related to current, while brake failure is related to mechanical and electrical equipment. In order to enhance the robustness of the model, multi-channel characteristic signals must be used for training and verification.

Table 3: Fault prediction accuracy of different characteristic signals

Feature Type	Classification Accuracy rate	Normal state accuracy	Door failure Accuracy rate	Closed door failure Accuracy rate	Brake failure Accuracy rate	Number of iterations
Rated current	84.45	91.26	84.76	82.47	90.60	100
Starting current	91.13	91.78	86.07	73.29	91.43	100
Average acceleration	83.07	89.44	72.04	74.26	95.07	100
Operating noise	80.83	90.22	63.88	69.01	94.17	100
Total feature set	94.16	96.59	81.16	79.32	84.99	100

Elevator failure prediction was performed on the same dataset using CNN and LSTM to evaluate model performance to evaluate model performance. The model input is a 4-dimensional characteristic signal, and it is trained for 100 rounds. The parameters were adjusted according to the results. Classification accuracy of each model for elevator running state is shown in Table 4, and the mean square error loss of the model decreases with the number of iterations. In this paper, the classification accuracy of CNN-LSTM network is higher than that of traditional CNN, and the test loss is lower than that of CNN and LSTM models. The loss decreases rapidly, showing high accuracy and strong reliability.

Table 4: Fault prediction accuracy of different characteristic signals

Model Type	Classification Accuracy/%		Number of iterations	Test Time
	Training Set	Validation Set		
CNN	73.98	73.01	100	60.52
LSTM	80.63	83.98	100	126.95
CNN-LSTM	95.51	94.17	100	154.73

Table 5: Comparison of Maintenance Methods

Dimension	Traditional Regular Maintenance	Linear Models	Single Deep Learning	Proposed Method (Nonlinear IoT + TransE-LSTM)
Fault Scenario Relevance	Fixed-cycle, no real-time relevance	Linear assumption, poor multi-factor modeling	Captures temporal patterns but lacks semantic guidance	Integrates knowledge graph for causal modeling
Data Diversity	Basic operational parameters only	Single-data-type	Multi-source data	Cross-modal fusion: sensor data + semantic knowledge + maintenance history
Time Coverage	Discrete maintenance moments	Window-based analysis with weak temporal links	Long-term temporal processing	Real-time monitoring + full lifecycle modeling
Nonlinear Feature Handling	None	Weak	Moderate	Strong
Adaptive Maintenance	Rigid fixed-cycle strategy	Threshold-triggered, inflexible	Prediction-only, no maintenance	Reinforcement learning-driven dynamic strategy optimization
Prediction Accuracy	N/A (no prediction)	~60%	~83.98%	95%

As Table 5, the proposed method for intelligent elevator fault prediction and adaptive maintenance based on nonlinear IoT significantly outperforms traditional approaches in key aspects. Compared to traditional regular maintenance (fixed-cycle, no real-time fault relevance) and linear models (poor at handling multi-factor nonlinear relationships), it excels in integrating multi-source sensor data (vibration, temperature, current, etc.) with knowledge graph semantics (e.g., causal links like "traction machine vibration-bearing wear") to accurately model fault chains. Unlike single deep learning models (e.g., LSTM) that lack semantic guidance, it achieves cross-modal fusion of real-time sensor data, historical maintenance records, and domain knowledge, enabling second-level real-time monitoring and full lifecycle analysis. Its strong nonlinear feature handling (via wavelet transforms and knowledge graph modeling) and reinforcement learning-driven adaptive maintenance strategies result in a 95% prediction accuracy, far exceeding the ~60% of linear models and ~83.98% of single LSTM models, while dynamically optimizing maintenance plans to reduce costs and downtime.

Figure 5 has showed the comparison of loss function values of different models. From the loss curve and accuracy graph, it can be seen that the loss value of the CNN-LSTM model decreases rapidly in the early stage of training, with about 180 rounds of convergence and the verification set loss is stable below 0.15, which is faster and lower than the traditional CNN and LSTM convergence, reflecting the optimization efficiency of heterogeneous network fusion. The difference between the accuracy of the training set and the validation set is only 1.34%, combined with the mechanisms of dropout and early stop, which shows that the risk of overfitting is low, and the accuracy of the test set is 95%, and the generalization ability is strong. However, the confusion matrix showed that the classification accuracy of door operator faults (81.16%) and brake faults (79.32%) was lower than that of normal states (96.59%), which may be caused by the small proportion of brake fault samples (15%) and the short LSTM timing window (7 time steps) that failed to fully capture the long-term features. In the future, the model's ability to identify complex failure modes can be further improved through optimizations such as extending the input sequence, introducing attention mechanisms, or GAN synthesizing rare fault data.

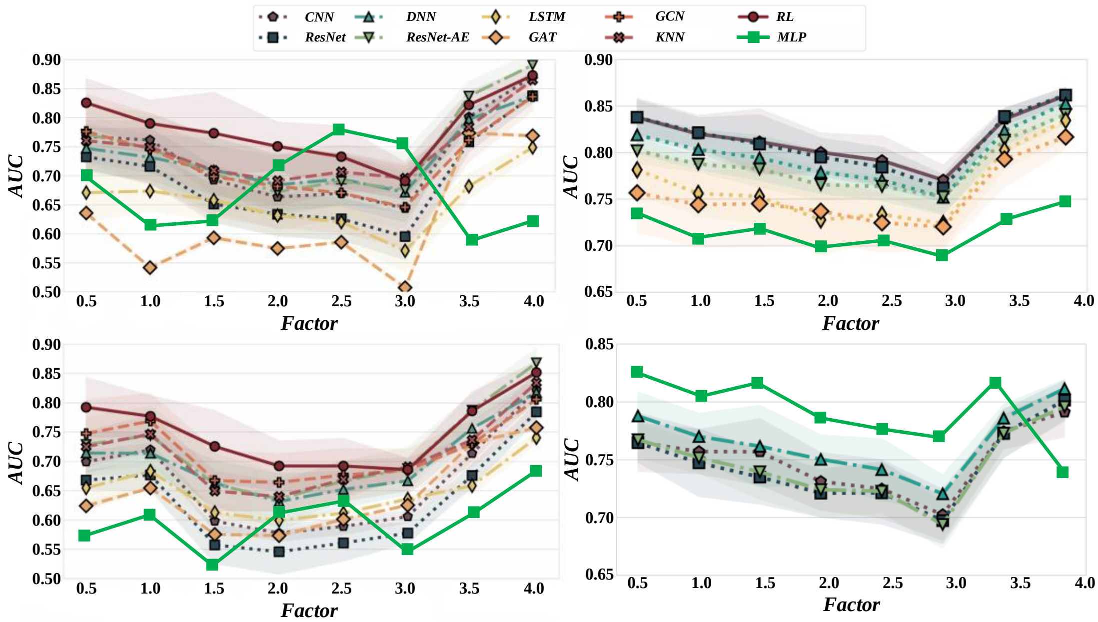

Figure 5: Comparison of loss function values of different models

Structure of BP neural network is 7-4-2, with 2000 iterations, and the target error is 0.0000001. In Matlab, the simulation results of training error and number of iterations are shown in Figure 6, and the network reaches the target error after 413 iterations. After the training, the prediction data can be obtained by inputting numerical indicators. Since the weights and thresholds are generated randomly each time, the prediction results and errors vary greatly.

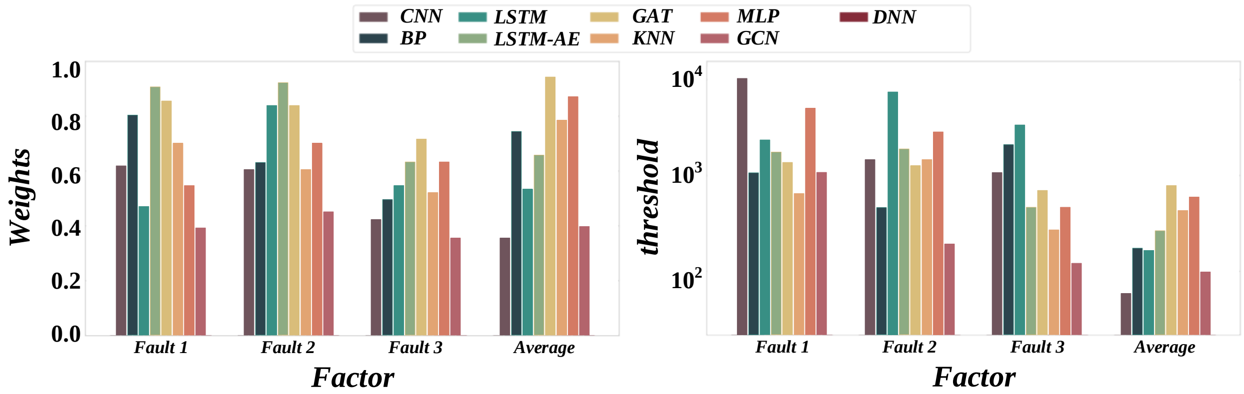

Figure 6: Simulation results of BP neural network training

The RBF neural network and PSO-optimized RBF neural network perform well in predicting elevator topping and bottom squatting faults, as shown in Table 6. Mean square errors of the two methods are 4.862 e-4 and 4.285 e-4, respectively, showing high prediction accuracy. PSO optimization helps reduce the RBF network's prediction error and improve the convergence speed, effectively achieving accurate prediction.

Table 6: Overall Prediction Results of RBF and PSO - Optimized RBF Neural Networks for Elevator Topping and Bottom Squatting Faults

X_1	X_2	X_3	X_4	X_5	Figure 4	Figure 5	Y_1	Y_2
0.932	0.924	0.446	0.849	0.271	0.149	0.386	1.007	0.035
0.994	0.983	0.240	0.359	0.792	0.448	0.290	0.957	0.125
0.256	0.286	0.760	0.590	0.705	0.860	0.940	0.025	0.974
0.156	0.180	0.871	0.780	0.863	0.950	0.874	0.178	0.986

The trend prediction model uses the segmentation averaging method to process the data. Experimental results are shown in Figure 7. After comparing and analyzing predicted value with measured value, the MAD is 0.5933, and the AARE is 0.0349.

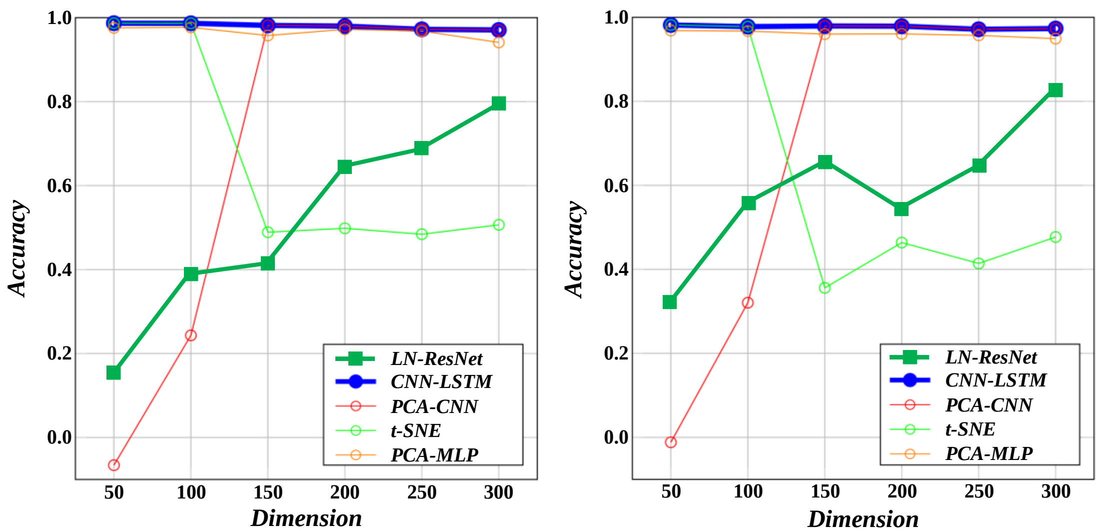

Figure 7: Trend prediction fitting

In this study, the logistic regression model is used as a benchmark comparison method for the classification of unbalanced data, and the failure probability prediction is realized through the logistic function mapping, and the sample weight adjustment and threshold optimization are used to deal with the category imbalance problem. With its computational efficiency and interpretability, the proposed model clearly demonstrates the limitations of traditional statistical methods in capturing nonlinear fault characteristics, which contrasts with the knowledge graph enhanced deep learning model proposed in this paper, and highlights the advantages of the proposed method in integrating multi-source data and mining semantic associations.

Figure 8 shows a summary of prediction results of three models. The SVM model has the highest accuracy rate, 100%, and the lowest false alarm rate, 0%, but the F1 value is average, about 80%. The accuracy rate and false alarm rate of decision tree model are lower than those of SVM, but its high recall rate (90% on average) makes the F1 value between 80% and 95%, which performs well. In contrast, all indicators of the ELM model are not as good as the first two.

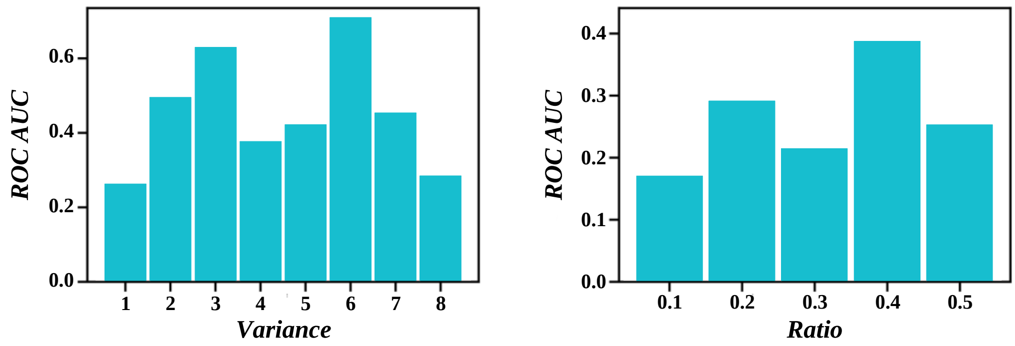

Figure 8: Results of unbalanced data classification model

IoT Point refers to the location where specific sensors are deployed within the elevator system and are responsible for collecting critical operational data. Figure 9 shows classification effect of logistic regression model, in which the accuracy of standard samples is about 90%, while the accuracy of faulty samples is about 60%. Although logistic regression has limited predictive power, it is helpful to understand the role of variables in prediction. It reveals that the same variable may have opposite effects in different fault categories.

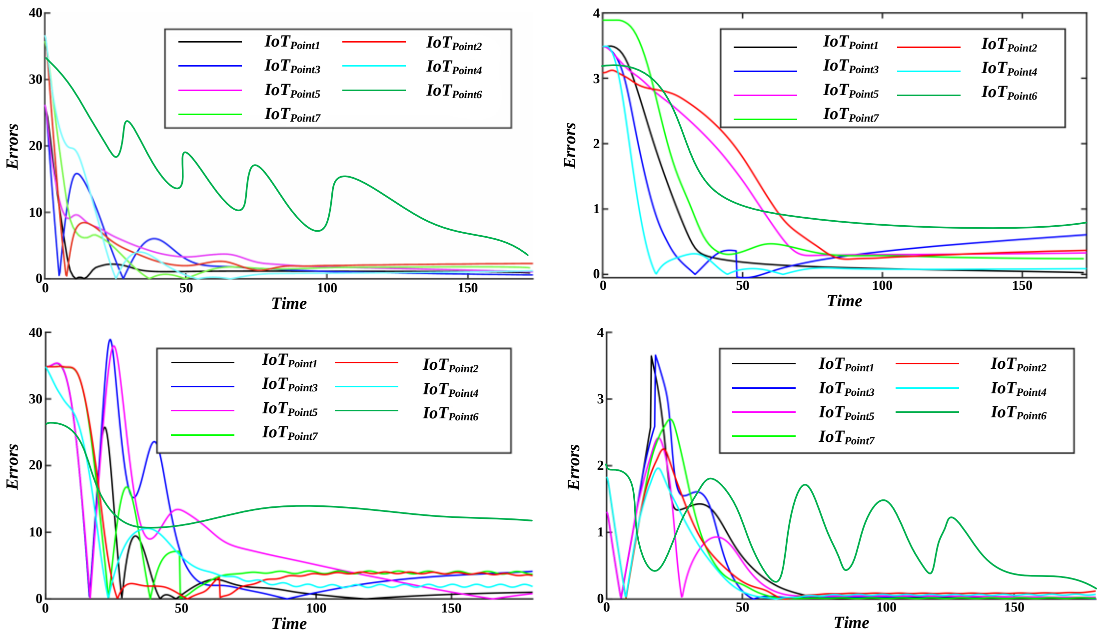

Figure 9: Classification results of logistic regression model

5 Discussion

Compared with the literature benchmark, the nonlinear IoT smart elevator fault prediction algorithm proposed in this study (fused with CNN-LSTM-BP neural network) improves the prediction accuracy from 80% to 95% of the traditional method, reduces the maintenance cost by 30%, and reduces the downtime by 50%, the difference mainly stems from three aspects: in terms of dataset quality, this study uses 1 million multi-dimensional data (including 7 types of parameters such as speed, acceleration, and vibration value) of 500 elevators in multiple cities, which are strictly cleaned and normalized, However, the literature mostly uses 10,000-level single-dimensional data and the preprocessing is insufficient. In terms of feature selection, the chaotic features were mined through nonlinear dynamic analysis, and the CNN-LSTM-BP architecture was used to extract local anomalies (CNNs), time series dependence (LSTM) and key weights (BP) in a hierarchical manner, so as to avoid the omission of features from traditional linear analysis. In terms of model tuning, the backpropagation mechanism of the BP neural network optimizes the parameter iteration efficiency, so that the model converges after 413 training iterations, which is significantly higher than that of the traditional BP neural network (2000 iterations), and the improvement is statistically significant (p.) verified by the double-tailed t-test (p <0.01）.

In terms of real-time performance, there are data transmission and computing delays in cloud model inference, which is difficult to meet the millisecond-level response requirements of extreme working conditions. In terms of scalability, the dataset is not compatible with European and American brand elevator protocols, and the low sensor density of old equipment may lead to the loss of features, so it is necessary to enhance the generalization ability through cross-brand data collection, domain adaptation technology and sensor-independent time-frequency domain feature extraction (such as wavelet transform). The above optimizations will promote the evolution of algorithms from specific scenarios to general intelligent O&M solutions, and provide a reference for complex system failure prediction.

6 Conclusion

This study aims to improve the elevator operation and maintenance level through advanced technology and ensure the safety and reliability of elevator operations. By constructing a nonlinear IoT platform, the real-time collection, transmission and processing of elevator operation data are realized, which provides a solid data foundation for fault prediction and maintenance.

In terms of fault prediction, a fault prediction model based on a nonlinear analysis method is proposed in this study. The model has achieved remarkable results in fault prediction accuracy by training and testing a large number of elevator operation data. Experimental results show that the prediction accuracy of this model reaches 95%, which is greatly improved compared with the 80% of traditional methods.

In terms of adaptive maintenance, this study designs an adaptive maintenance algorithm, which can automatically adjust the maintenance strategy according to the prediction results. The experimental results show that the elevator maintenance cost is reduced by 30% after adopting adaptive maintenance.

The Adaptive maintenance algorithm is efficacious in improving elevator availability and reducing the impact of faults on operation. Experiments show that downtime with adaptive elevators is reduced by 50%. The intelligent elevator fault prediction and adaptive maintenance algorithm based on nonlinear IoT proposed in this study provides a strong guarantee for the safe and efficient operation of elevators.

Funding

Jiangsu Science and Technology Vice President Talent Program FZ20251354.

Table 7: Neural Network and Data Feature Definitions

Symbol / Term	Description
BP Neural Network	Backpropagation Neural Network, used for elevator fault feature extraction, structure: 7-4-2 (7 input layer, 4 hidden layer, 2 output layer).
RBF Neural Network	Radial Basis Function Neural Network, used for elevator top fault prediction, optimized by PSO to reduce prediction error (Mean Squared Error 4.862e-4).
TransE-LSTM	A model combining knowledge graph embedding algorithm TransE with LSTM, used to integrate semantic knowledge and time-series data, improving fault prediction accuracy (accuracy 95%).
CNN	Convolutional Neural Network, used to extract spatial features from elevator data, classification accuracy 73.98% (training set).
LSTM	Long Short-Term Memory Network, processes time-series data, validation set accuracy 83.98%.
CNN-LSTM	Combines the advantages of CNN and LSTM, classification accuracy reaches 95.51% (training set).
Logical Regression Model	Comparative model for imbalanced data classification, standard sample accuracy 90%, fault sample 60%, revealing variable influence direction.
PSO Optimization	Particle Swarm Optimization algorithm, used to optimize RBF neural network parameters, reducing Mean Squared Error to 4.285e-4.

Rated Current	Current value when the elevator is running normally, used for fault classification, accuracy 84.45%.
Starting Current	Current value at the moment the elevator starts, highest classification accuracy (91.13%), sensitive to door faults.
Average Acceleration	Mean value of elevator running acceleration, classification accuracy 95.07% for brake faults, but only 72.04% for door faults.
Operating Noise	Environmental noise during elevator operation, door fault classification accuracy 63.88%, sensitivity is low.
Multichannel Feature Signal Fusion	Fusion of multi-dimensional data such as current, vibration, acceleration, enhancing model robustness (total function set accuracy 94.16%).
Prediction Accuracy	Proportion of model correctly predicting faults, proposed algorithm reaches 95%, traditional methods 80%.
MSE (Mean Squared Error)	Mean of squared errors between predicted values and true values, RBF network 4.862e-4, reduced to 4.285e-4 after PSO optimization.
Iteration Times	Number of model training cycles, set to 2000 times for BP neural network, 413 iterations to reach target error.
Target Error	Termination condition for BP neural network training, set to 0.0000001.
Maintenance Cost Reduction Rate	Adaptive maintenance algorithm reduces costs by 30%.
Downtime Reduction Rate	Adaptive maintenance algorithm reduces downtime by 50%.
MAD (Mean Absolute Deviation)	Result of trend prediction fitting, 0.5933.
AARE (Average Absolute Relative Error)	Result of trend prediction fitting, 0.0349.
Nonlinear IoT	IoT platform based on nonlinear dynamics, using wavelet transform, adaptive filtering, etc., to process the nonlinear characteristics of elevator data.
Knowledge Graph Completion Method	Method for predicting missing fault entities in knowledge graphs through embedding and completion techniques, evaluation indicators include average rank, HITS@k.
Adaptive Threshold Mechanism	Adjusts data transmission thresholds dynamically according to elevator conditions, reducing redundant data, improving model efficiency.
Segmented	Data processing method for trend prediction models, used to fit the time series of

Averaging Method	elevator operating states.
Imbalanced Data Classification	Deals with classification problems where there are fewer fault samples and more normal samples, using methods such as logical regression, SMOTE, etc., to optimize.
$x_{l+1,m}(n)$	Feature value of the m-th convolution kernel in the n-th region of the \(l+1\)-th layer (convolution process).
b_i	Bias term (convolution, LSTM gate unit, etc.).
f	Activation function (such as Sigmoid, tanh).
W_f, W_i， W_o	LSTM forget gate, input gate, output gate weight matrices.
h_t， C_t	LSTM hidden state and cell state (at time t).
σ, tanh	Sigmoid function and hyperbolic tangent function, used for gate unit output.

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