Elevators Fault Diagnosis Based on Artificial Intelligence

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Abstract. With the rapid development of cities, elevators have gradually been integrated into people's daily life. Therefore, to reduce the occurrence of elevator failures by using the diagnosis methods of elevator failures is of significance to ensure people's lives and property. As an emerging field in the 21st century, Artificial Intelligence (AI) techniques provide an effective elevator fault diagnosis technology. This paper describes the various AI algorithms for elevator fault diagnosis from two aspects: theoretical methods and practical applications. Firstly, several mainstream AI algorithms, including the following algorithms: Back Propagation (BP) Neural Network, Radial Basis Function (RBF), K-Means and Support Vector Machine (SVM) are introduced. Then, a broad literature review of the application of these AI algorithms in elevator fault diagnosis is given. Finally, the possible development trend of AI in elevator fault diagnosis in the future is discussed.

1. Introduction

With the rapid development of science and technology, people have already guaranteed their quality of life, and thus the requirements for the safety performance of daily use implements have also been increased. Elevators are indispensable implements for people today which are no exception. However, in actual conditions, the proportion of accidents caused by elevators such as trapped people and toppings is still high [1]. Therefore, it is of great significance to study how to improve the diagnostic efficiency of elevator faults, to timely rescue and reduce the accident rate.

The traditional way to reduce the accident rate of elevators is to reduce the risk of elevator failure according to the elevator performance evaluation [2], thereby improving the reliability of the elevator and reducing the accident rate. However, in actual life, due to the excessive number of elevators, this method is hard to carry out. Therefore, Chen et al. [3] proposes a new way, which uses a risk calculation method with fuzzy mathematics to calculate the risk value of the elevator system, combines with the elevator failure rate of the monitoring platform and finally establishes a new elevator performance evaluation method.

In the day of big data, with the continuous development of data mining technology [4], artificial intelligence technology is used to mine the real-time information of elevators to effectively diagnose failures and risks of elevators. Therefore, this method must become one of the effective ways to reduce the accident rate. In general, the use of Artificial Intelligence (AI) technology to diagnose elevator faults has four main steps: (1) model selection, (2) feature extraction, (3) model optimization and training, (4) elevator fault pattern recognition. AI technology has been widely used in the diagnosis of various types of mechanical failure. For example, Chang [5] utilizes the improved K-Means algorithm to analyze the failure rate status of different elevators. In [6], Li et al. have been proposed a method for fault diagnosis of the elevator door system based on the Back Propagation (BP) Neural Network. Tian et al. [7] present
an improved ant colony optimization to detect elevator faults quickly through the shortest path to achieve a timely diagnosis of faults. In [8], Gao compares two training results, Radial Basis Function (RBF) Neural Network and BP neural network, which are trained based on the same sample set. It is proved that the RBF neural network is not only better in generalization ability, but also the training speed of the RBF neural network is faster than the BP neural network. Then the RBF neural network is used to verify the fault diagnosis of the air compressor. The test results show that the RBF neural network can predict the fault type of air compressor accurately. Shen [9] combines the real-time status of the elevator operation and uses the finite state machine (FSM) based on streaming data to judge whether the fault occurs during the elevator operation. Then he uses the SeriesNet model based on time series to compare with other machine learning models such as Support Vector Machine (SVM), long short-term memory (LSTM) and undecimated full convolution neural networks (UFCNN). It proves that the SeriesNet model has better generalization and convergence in elevator fault detection.

In this paper, we aim to carry out investigation and research on AI algorithms in elevator fault diagnosis from both theoretical method and practical application. The rest of this paper is organized as follows. Section 2 introduces several mainstream AI algorithms such as K-Means, SVM, BP, and RBF. Section 3 reviews the applications of these AI algorithms in elevator fault diagnosis. Prospects of AI methods in elevator fault diagnosis are discussed in Section 4. Concluding remarks are drawn in Section 5.

2. Introduction of AI algorithm
This section mainly introduces the general algorithms for elevator fault diagnosis at present. Because of the invention and large-scale use of precision sensors today, it can monitor elevator multi-directional information dynamically. And the algorithm does not require prior knowledge and has a strong self-learning ability. These algorithms can efficiently mine information in many useful data sets then diagnose elevator failure accurately.

2.1. BP neural network
BP neural network is the most commonly used algorithm in mechanical fault detection. It consists of an input layer, several hidden layers, and an output layer. The input layer and the output layer are composed of a single layer generally when the hidden layer can be composed of one or more layers.

![Figure 1. The structure of Back Propagation (BP) neural network.](image)

The core formula: $\delta^{(l)} = \left((W^{l+1})^T \delta^{(l+1)}\right) \odot f'(z^{(l)})$
Where $\delta^l$ is the backpropagation offset of $l$ layer, $W^{l+1}$ is the weight matrix of the $l + 1$ layer to the $l$ layer, $\bigodot$ is the matrix operator, and $z^{(l)}$ is the inactive neuron state.

The core idea of the BP neural network is to use backpropagation to propagate the error of the next layer nodes so that the neural nodes of each layer have a good optimization direction. And then use the gradient descent to minimize the cost function so that the neural network has good nonlinear mapping capability with excellent generalization performance [10-11].

2.2. RBF neural network
The RBF neural network is a single hidden layer neural network. Compared with the BP neural network, the RBF neural network has a simpler structure, faster training convergence, and stronger numerical values. It can approximate any nonlinear function without the local minimum problem. Based on the above advantages, the RBF neural network is widely used in the fault diagnosis of operating systems.

The core formula: $\varphi(x) = \sum_{i=1}^{n} w_i K(x, u_i)$

Where $n$ is the number of neurons in the hidden layer, $w_i$ is the linear mapping relationship between the hidden layer and the output layer, $K$ is the kernel function, $x$ is the input data and $u_i$ is the center of the basis function.

Intuitively speaking, the RBF neural network transforms the input data from a lower-dimensional input state to a higher dimensional input state by transforming the input data through a kernel function, thereby transforming the original lower-dimensional nonlinear problem into a higher-dimensional linear separability. Abstractly, the RBF neural network constructs the hidden layer space by using the basis of the hidden layer unit and combines the kernel function which is the central radial point symmetric and monotonically decreasing to map the input data to the higher dimensional linear separable space [12].

2.3. SVM
SVM is a supervised learning algorithm that is often used to solve small sample higher-dimensional fault detection problems because of its excellent processing pattern recognition and regression problems [13,14].

The core formula: $f_i = K(x, l) = \langle \Phi(x) \Phi(z) \rangle$

Where $f_i$ is the new feature parameter, and $K$ is the kernel function.

The core idea of SVM is to use the kernel function to transform the input data of different situations, to map the input features to the higher dimensional linear separability. And find the optimal hyperplane
in this space so that the interval of the closest different data points in space is maximization [15].

As shown in Figure 3, SVM creates the optimal hyperplane to obtain the maximum interval between the closest different data in two-dimensional space.

2.4. K-means
K-means is one of the unsupervised learning algorithms. It is simple and easy to implement, but very effective. The main function of it is to classify similar data samples into the same category.
The core formula:

1. \[ D(X_i, C_j) = \sqrt{\sum_{t=1}^{m} (X_{it} - C_{jt})^2} \]
   Where \( D(X_i, C_j) \) is the distance between \( X_i \) and \( C_j \), \( X_i \) is the \( i \)th point, and \( C_j \) is the \( j \)th Cluster Centroid.

2. \[ C_k = \frac{\sum_{x_i \in k} x_i}{k_n} \]
   Where \( C_k \) is the updated \( k \)th cluster centroid, \( k_n \) is the number of data points in the \( k \)th cluster centroid, and \( \sum_{x_i \in k} x_i \) is the sum of corresponding attributes of all points which are attributed to the \( k \)th cluster centroid.

It generates \( K \) Cluster Centroids randomly and assigns the belonging cluster of each data point according to the principle of shortest distance, and then adjusts the Cluster Centroids’ position based on the average value of each point in the cluster. Next, it continues to iterate according to the principle of shortest distance until the Cluster Centroids don’t change any more. The result of these steps is to minimize the cost function. The process of optimization changes the location of the Cluster Centroids and the attribution of each point [16].

3. Application of AI Algorithms in Elevator Fault Diagnosis

3.1. Application of BP neural network in elevator fault diagnosis

As one of the most popular algorithms, BP neural network is widely used in nonlinear prediction, fault diagnosis, and pattern recognition. Although it may have a problem of slow convergence and easy to get in local minimization value, it can combine with other optimization algorithms such as particle swarm optimization (PSO), genetic algorithm (GA), Principal Component Analysis (PCA), etc. to solve those problems.

Li and Ai [17] use BP neural networks regularized by the Bayesian algorithm and combine with the fuzzified input data. Then based on D-S evidence theory, they fuse the result which comes from the BP neural network. Finally, they complete the decision fusion diagnosis of the elevator drive system and traction. The decision fusion diagnosis of machine failure has achieved a more reliable diagnosis. Wang [18] exploits the wavelet modulus maximum denoising method and the elevator running characteristic parameters which are reduced by rough set attribute reduction to establish a high-speed elevator model for emergency stop fault diagnosis based on the fuzzy BP neural network. It is proved by the simulation experiment that the elevator model has a high accuracy rate at the high-speed elevator. Because the convergence speed of the BP neural network is uncertain, it is easy to get in the local minimization value problem. So, Wang [19] makes use of a genetic algorithm (GA) which has the advantage of global parallel search and strong robustness. The GA is used to optimize the initial weight and the threshold of the fuzzy BP neural network. Then he compares with the neural network training results without genetic algorithm optimization. It shows that the neural network optimized by GA has a stronger generalization ability. Finally, based on the above algorithm, the fault diagnosis of the elevator control system is established. Aiming at the problem that BP neural network convergence speed is uncertain and easy to get in local minimization, Liu [20] utilizes the simulated annealing (SA) algorithm which is one kind of heuristic random search method to obtain the optimal global solution. And she combines the conjugate gradient method to optimize the neural network convergence speed. Finally, she proposes a BP neural network combining the conjugate gradient method with a simulated annealing algorithm with memory. The optimized neural network model shows superior performance in training time, convergence speed, and accuracy. The accuracy of the diagnostic result is almost 100%. Zhang et al. [21] apply the local mean decomposition (LMD) to collect fault feature signals, and then establish a fault diagnosis of rolling bearings based on a simple BP neural network. Wen et al. [22] propose an improved BP neural network based on particle swarm optimization (PSO), which solves the shortcomings of the BP neural network that random initialization of weights and thresholds will reduce prediction accuracy. And then they establish an elevator door system fault prediction model based on PSO-BP neural network.

As one of the widely used algorithms, the main problem of the BP neural network is that there are
local minimum values and random initialization of weights and thresholds. After partial algorithm optimization, it exhibits excellent nonlinear feature fitting, which is quite suitable for fault diagnosis.

3.2. Application of RBF neural network in elevator fault diagnosis

Compared with BP neural network, the RBF neural network has faster training speed and simpler structure. Because it can search for an optimal global solution, there is no local minimum value problem. It is widely used in intrusion detection, fault diagnosis, license plate recognition, etc. However, there are also some shortcomings in the RBF neural network: the initial Cluster Centroids selection is too random, which may have an excellent impact on the later prediction. But at the same time, optimization algorithms such as SA, GA, and so on can be used to optimize them.

Duan et al. [23] combine two selection methods of RBF Cluster Centroid and exploit the elevator dynamic running signal as input to predict the type of elevator fault while the elevator is running. Feng [24] performs discrete standardization on the input data and use K-means to determine the number of hidden layer neuron. Then he combines the strong global optimization ability, fast convergence speed, and no need for excessive parameter adjustment of the PSO to establishes an RBF neural network based on PSO improvement. Finally, the comparison with the common RBF neural network demonstrates the excellent detection of the PSO-RBF neural network. Zhang et al. [25] use the wavelet packet decomposition to extract the characteristic frequency band signal of the non-flat steady of the rolling bearing and adopt the biogeography-based optimization (BBO) to make the model have the strong adaptive ability. They have proposed a rolling bearing fault diagnostic model based on wavelet packet decomposition and BBO-RBF neural network. Aiming at the phenomenon that the gear fault signal is weak and difficult to detect, Zhang and Xiao[26] use the singular value decomposition (SVD) to denoise the gear vibration signal, and then take the energy value of the wavelet packet decomposition as the input of the RBF neural network to realize the gear fault diagnosis. Zhang [27] exploits the characteristics of the Ensemble empirical mode decomposition (EEMD) algorithm which can perform adaptive analysis to scatter multiple gear vibration signals into IMF vector groups and extracts the eigenvalues from the covariance matrix. Then he reduces the dimension of the higher dimensional eigenvectors through the local tangent space arrangement (LTSA) algorithm so that the values are dimensioned to be an input to the RBF neural network for gear fault classification and identification. He also compares the wavelet packet-RBF and LTSA-RBF models after that. Mohammadi et al. [28] propose an algorithm based on hybrid evolution, which can automatically determine the architecture and network state parameters of the RBF neural network.

Although the initialization cluster centroid of the standard RBF neural network is too random which may lead to a long iteration time of the algorithm, many optimization algorithms have been applied to solve such problems. Combined with many efficient data pre-processing technologies, the optimized RBF neural network is very strong in the field of fault diagnosis.

3.3. Application of SVM neural network in elevator fault diagnosis

SVM can be used for multi-classification or data prediction. Its optimization process is to find the optimal hyperplane between different samples. It is mostly through the mathematical method to optimize, and it can also get a good learning effect even when the number of samples is small. Whether the training effect is good or not depends on: (1) the choice of the kernel function, (2) the choice of SVM parameters (mainly penalty factor). For the latter, SVM has many parameter selection methods such as gradient descent method, cross-validation method, artificial immunity, and so on.

Gao [29] uses grid search and cross-validation to determine the SVM parameters, constructs the classifier in a one-on-one manner for each of the two types of samples on the multi-class problem of faults, and then finds the optimal hyperplane. Finally, the generated classifier can classify the fault type, and the experiment proves that the diagnosis result is correct. He et al. [30] obtain the gap signal samples of different faults through the high-precision eddy current displacement sensor and then extract the fault eigenvectors by wavelet packet decomposition. The elevator diagnosis system for brake fault is based on the least square support vector machine (LSSVM). Firstly, Yi [31] decomposes the vibration
acceleration signal of the elevator into the wavelet packet, obtains the energy information of each frequency band of the signal, and constructs the energy eigenvectors. Secondly, by comparing three parameters optimization methods of SVM, it is determined that the PSO with the optimum classification accuracy is used for parameter optimization. Finally, an LSSVM based on PSO is established, which can classify partial elevator faults according to the elevator running signal. For elevator bearing faults diagnosis, Saimurugan et al. [32] exploit 12 vibration signals from piezoelectric sensors to statistical characteristics through the decision tree and compare the effects of four different kernel function SVM models in fault classification. Li et al. [33] propose a fault detection method based on redundant second-generation wavelet packet transform (RSGWPT), neighborhood rough set (NRS) and SVM. This method uses RSGWPT to extract fault features to compose eigenvector and reduces the number of eigenvector dimensions through NRS. Finally, the SVM is used to classify the fault mode according to the key features. The method is applied to the fault diagnosis of the gear reducer, and the results show that it has good classification ability. Yi et al.[34] collect the vibration acceleration signals and noise signals in the three directions X, Y, Z of the car, extract the feature signal by wavelet packet decomposition to train LSSVM, and finally optimize the parameters of the LSSVM through the GA so that the elevator classification model for fault diagnosis has clear recognition efficiency.

SVM has a simple classification principle and a good classification effect. But it will waste a lot of computing time and computing memory when it is used in large datasets. One of the solutions is to reduce the data dimension. For example, using data pre-processing technology such as PCA and SVD. Another way is to divide the big data set into multiple small data sets to train SVM. Both can solve the problem of low efficiency of using SVM in large datasets.

3.4. Application of K-means in elevator fault diagnosis
K-means is a clustering algorithm of unsupervised learning. The algorithm is simple but efficient. It is one of the most widely used algorithms in cluster analysis. For example, it can be used to find the center of the neural node in the hidden layer of the RBF neural network as shown previously. It has favorable effect on clustering, but at the same time it may get in local optimum, and its clustering effect is related to the number of cluster centroids k. There are a variety of optimization methods to the solution of solving the local optimum problem, such as K-means++. For the selection of k, currently, the mainstream method only has the elbow method and contour coefficient method, which are less accurate. But this does not affect it to be one of the mainstream methods of fault diagnosis at this stage.

Aiming at the problem that the K-means algorithm is easy to get in the local optimal problem, Fei [35] proposes a K-means algorithm based on PSO improvement, which can improve the convergence speed of the algorithm while avoiding getting in a local optimum. And then He collects four different types of mechanical fault signal. It is proved that the PSO-K-means model can classify the four mechanical faults better than before. Tzortzis and Likas[36] propose another solution: to minimize variance within the maximum of k clusters and then cluster. Zhang et al. [37] combine this method and kernel function then compare it with ordinary K-means and K-means++. It is shown that the superiority of the new method is obvious. Then a vibrant fault diagnosis model for the hydro-turbine generating unit is established using the minimax kernel K-means algorithm. Du et al. [38] optimize the support vector data description (SVDD) algorithm by using the ant colony algorithm (ACA) which has the advantages of intelligent search and global optimization and solves the problem that the parameter selection of SVDD has a clear influence on the classification performance. Then the SVDD model based on ACA optimization with K-means is established. And the fault diagnosis model for rotating machinery which is using the Davies Bouldin index (DBI) to determine the number of cluster centroids has an outstanding effect. Zhang et al. [39] propose a mechanical fault detection method based on multiscale permutation entropy (MPE) and K-means++. Then they apply this method to on-load tap-changer (OLTC) fault mode classification. In [40], Gong et al. propose an evaluation index based on K-means and PCA algorithm. The evaluation index improves the detection threshold of faults by increasing the number of clusters, and so it can detect fault signals more sensitively. Amruthnath and Gupta [41] compare the clustering effect of different types of clustering methods such as K-means, Fuzzy C-Means,
and model-based clustering.

There are many solutions to the issue that the K-means algorithm may waste time through the iterative computations. For example, Elkan K-means optimize the K-means calculation speed by reducing the calculation of unnecessary distances. And Mini Batch K-means reduces K-means iteration time by regularly reducing the number of samples in the training sample set.

4. Future Trends
With the persistent development of AI technology, the AI technology which can be applied in elevator fault diagnosis is also continuously improving. The above content only mentions the application of partial AI in fault diagnosis, and there are some new trends in future fault diagnosis.

(1) Image Recognition
With the consistent improvement of computer vision, the fault diagnosis model based on image processing will become one of the development directions of elevator fault diagnosis. Moreover, with the emergence of various kinds of optimization Convolutional Neural Networks (CNN), such as ResNet and DenseNet [42, 43], real-time fault recognition based on image processing may transition from fault diagnosis to fault prediction, thereby predicting the occurrence of failures and further preventing property loss. Yaman and Karakose [44] propose a fault detection method for elevator rope based on image processing and perform edge detection on the received elevator rope image to identify the state of the rope.

(2) Association Rule Learning
Nowadays, most of the fault diagnosis technologies of elevators are limited to a component or a certain local system. But due to the correlation between various components inside the system, there will be some deviations in the fault diagnosis result. Accordingly, the accuracy of elevator fault diagnosis can be significantly improved through some machine learning methods to find the association rules of each component and make some adjustments to the diagnostic system. There has been some research on this machine learning method, such as the Apriori algorithm in association rule learning. It can mine association rules in data sets and correlate data.

(3) Intelligent fault diagnosis system based on AI, fault mechanism and prior knowledge
The previous fault diagnosis methods mainly relied on fault mechanism and fault tree or relied on pattern recognition and rule-based expert systems. With the development of AI, the diagnostic system which is mature but not intelligent enough will have new improvements. The intelligent fault diagnosis system which combines AI, fault mechanism, and prior knowledge will be one of the development directions of fault diagnosis.

5. Conclusion
Elevator fault diagnosis is significant to reduce the occurrence of elevator failures and ensure the safety and security of people. The emergence of AI technology has brought a new technical means for elevator fault diagnosis. This paper introduces BP neural network, RBF neural network, K-means, and SVM theoretical background and summarizes the application of them. With the rapid development of AI, it is believed that elevator fault diagnosis will become more and more efficient.

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