

# *Vehicle Engine Fault Identification Method Equipment and System Based on Deep Learning*

**Wei Dong\*, Yan Li, Xing Liu, Hailong Zhu**

*FAW Group Engineering and Production Logistics Department - General Assembly Process  
Department, Changchun City, Jilin Province, China*

*\*Corresponding author: dongwei@faw.com.cn*

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**Abstract:** In the actual driving process of the vehicle, the engine may have a variety of faults. Timely identification or detection of engine faults is an urgent technical problem to be solved. In the existing traditional technology, engineers with rich experience are usually employed to manually detect engine faults. This method is inefficient and has high error rate. This paper presents an engine fault recognition method, equipment and medium based on deep learning to realize the automatic recognition of engine faults.

## **1. Introduction**

Engine failure is the abnormal operation of the engine caused by material and workmanship defects, unreasonable design, manufacturing problems and improper operation during use. In the actual driving process of the vehicle, various engine failures may occur, and timely identification or detection of engine failures is a technical problem that needs to be solved urgently. Aiming at this technical problem, this paper looks for a research solution from the perspective of deep learning. By specifying a specific implementation plan, using machine learning and deep learning to build a model and optimize the model, and finally get a deep learning-based engine failure Identification methods, equipment and media for automatic identification of engine failures.

## **2. Research Content**

This paper provides an engine fault identification method, equipment and medium based on deep learning to realize the automatic identification of engine faults. The innovations of this paper are mainly in three aspects: providing a deep learning-based engine fault identification method, an electronic device and a computer-readable storage medium.

### **2.1. Engine fault identification method based on deep learning**

Obtain the operating data of the engine, and input the operating data into a plurality of fault detection models and a normal detection model, wherein the plurality of fault detection models and the normal detection model are self-encoders based on deep learning, and the The fault detection models are respectively used to encode the features representing different types of engine faults and combinations of different fault types, and the normal detection model is used to encode the features

representing the normality of the engine. If the output features of the normal detection model do not match the features in the normal feature library, compare the output features of the multiple fault detection models with the feature library of the corresponding fault type or combination respectively, and identify the engine according to the comparison results.

## 2.2. Electronic devices based on deep learning

This article provides an electronic device based on deep learning technology, the electronic device includes one or more processors and memories for storing one or more programs; when the one or more programs are stored by the one or more programs The processor executes, so that the one or more processors implement the deep learning-based engine fault identification method described in any one of the embodiments.

## 2.3. Computer-readable storage medium based on deep learning

This paper also proposes a computer-readable storage medium on which a computer program is stored, and when the program is executed by a processor, implements the deep learning-based engine fault identification method described in any one of the embodiments.

In this paper, multiple detection models based on deep learning are used to obtain the features that characterize the operating state of the engine. By comparing the features output by the normal detection model with the normal feature library, it can identify whether the engine is faulty; if a fault occurs, then output the fault detection model. The features of the engine are compared with the feature library of the corresponding fault types or combinations to identify the fault types or combinations of the engine. In this way, on the one hand, automatic identification of engine faults is realized, and on the other hand, fault types and combinations of fault types are subdivided, so as to achieve full coverage of engine fault operating states and improve fault identification accuracy. In addition, the autoencoder is used as the detection model to encode the running data, which can analyze the relationship between the running data while reducing the dimensionality, and retain the key information in the running data.

## 3. Implementation

This paper provides an engine fault identification method based on deep learning, which is suitable for automatically identifying engine faults according to the operating data of the engine. This embodiment is executed by electronic equipment. The flow chart of this method is shown in Figure 1:

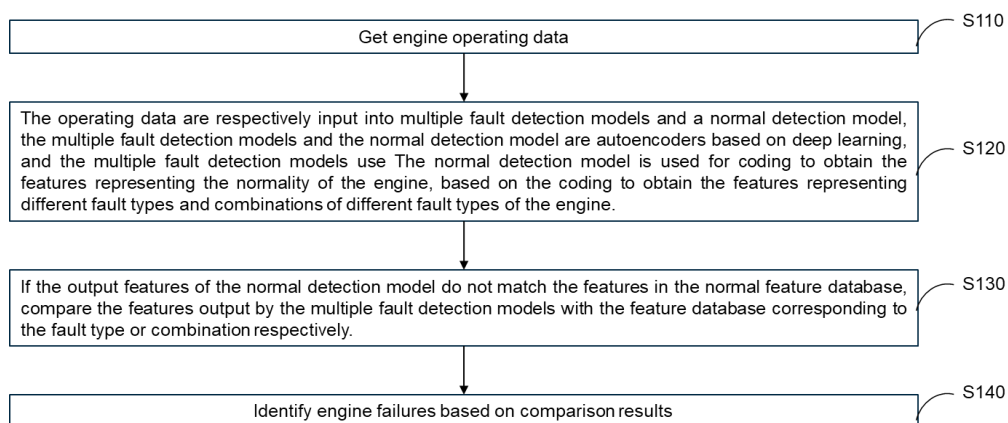


Figure 1: Engine fault data identification process

In addition, the methods of the embodiments herein specifically include:

S110 is the first step that acquiring the running data of the engine. The operating data of the engine can objectively reflect the operating state of the engine. Table 1 shows 10 kinds of operating data of the engine. In practical applications, there are far more than 10 types of operating data, and the more data types, the more accurate the reflection of the engine operating state. The acquired operating data of the engine is used for engine fault identification.

Table 1: Engine operating data

	Data Types
1	final ignition angle
2	throttle valve opening
3	Actual throttle opening
4	speed
5	torque
6	oxygen storage
7	engine downtime
8	Throttle opening duty cycle
9	Cylinder effective injection time
10	ECU power-on flag bit

Optionally obtain the running data of the engine, including: obtaining the running data of the engine within a period of time through the automobile OBS system and the CAN bus system.

S120, Input the operating data into a plurality of fault detection models and a normal detection model respectively, where the plurality of fault detection models and the normal detection model are autoencoders based on deep learning, and the plurality of fault detection models They are respectively used for encoding to obtain features representing different fault types and combinations of different fault types of the engine, and the normal detection model is used for encoding to obtain features representing the normality of the engine.

The types of engine failures include insufficient power, misfire, and sudden flameout. The combination of fault types includes a variety of faults, such as insufficient power + misfire, insufficient power + sudden flameout, insufficient power + misfire + sudden flameout, etc., which means that the engine has multiple faults at the same time. Taking "insufficient power + misfire + sudden flameout" as an example, it shows that the engine has three faults: insufficient power, misfire and sudden flameout at the same time. Table 2 shows the 10 operational data-related fault types or combinations in Table 1. As shown in Table 2, when the final ignition angle is abnormal, the engine will have a failure combination of "insufficient force + misfire + sudden flameout".

Table 2: Fault types and combinations

	Insufficient Power	Misfire	Sudden flameout
final ignition angle	√	√	√
throttle valve opening	√		√
Actual throttle opening	√		√
Speed	√		√
torque	√		
oxygen storage		√	√
engine downtime	√		√
Throttle opening duty cycle	√		√
Cylinder effective injection time	√		√
ECU power-on flag bit		√	

The embodiments mentioned in this paper use detection models based on deep learning to

construct features representing the operating state of the engine. Each detection model is an autoencoder based on deep learning, which is used to reduce the dimension of the input data to obtain the characteristics representing the operating state of the engine. Characteristics. Since there are many types of operating data obtained above, and the various modules of the car are coupled to operate, there are strong interrelationships between various types of operating data, so the operating data retains a lot of noise, details, and repetitive information. So, use auto-encoding to encode the run data, reducing the data type. In order to facilitate the distinction and description, the input of the autoencoder is called data, and the output is called the feature. The dimension of the output feature is smaller than the data type of the input data, that is, the dimension reduction of the data is realized.

In the specific implementation shown in Table 1, it is assumed that the input operational data includes 30 data types (10 of which are shown in Table 1), and after the 30 types of operational data are input into an autoencoder, the obtained feature dimension is 4, which realizes the dimensionality reduction of the data.

In the S130, if the output features of the normal detection model do not match the features in the normal feature library, compare the features output by the multiple fault detection models with the feature library corresponding to the fault type or combination, respectively.

In this embodiment, three types of self-encoders with the same structure but different parameters are used, and each self-encoder corresponds to an operating state of the engine. Specifically, the three types of autoencoders have the following characteristics:

The characteristic of the normal detection model is: if the operating data input to the model is the normal operating data of the engine, the features output by the model match the features in the normal feature library.

The characteristic of a fault detection model of a fault type is: if the operating data input to the model is the operating data of the engine when the fault type occurs, the features output by the model match the features in the feature database corresponding to the fault type.

The characteristic of a fault detection model corresponding to a combination of fault types is: if the operating data input to the model is the operating data of the engine when the combination of fault types occurs, the features output by the model are the features in the feature library corresponding to the combination of fault types.

Therefore, the output features of the normal detection model are used to compare with the normal feature library for the first time. If the output features of the normal detection model do not match the features in the normal feature library, it indicates that the engine is malfunctioning. In order to determine specific fault types or combinations, the features output by each fault detection model are compared with the corresponding feature library.

S140: Identify engine failures based on the comparison results.

If the features output by the fault detection model corresponding to a fault type match the features in the feature database corresponding to the fault type, it indicates that the engine has a fault of the mentioned type.

If the features of the output of the fault detection model corresponding to a fault type combination match the features in the feature library corresponding to the fault type combination, it indicates that the engine has the fault of the combination.

The technical effect of this embodiment is: adopting a plurality of detection models based on deep learning to obtain features representing the operating state of the engine, and identifying whether the engine fails by comparing the features output by the normal detection model with the normal feature library; if a failure occurs, Then, the features output by each fault detection model are compared with the feature library corresponding to the fault type or combination to identify the fault type or combination of the engine. In this way, on the one hand, automatic identification of engine faults is realized, and on the other hand, fault types and combinations of fault types are subdivided, so as to

achieve full coverage of engine fault operating states and improve fault identification accuracy. In addition, the autoencoder is used as the detection model to encode the running data, which can analyze the relationship between the running data while reducing the dimensionality, and retain the key information in the running data.

## 4. Model training and optimization

### 4.1. Training of the normal detection model

This paper presents two specific implementations for training the normal detection model, using different loss functions and training methods respectively.

Embodiment 1: Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are specifically included:

Step1: Build a library of healthy data samples

The characteristic of the normal detection model is: if the operating data input to the model is the normal operating data of the engine, the features output by the model match the features in the normal feature library. In view of this, a normal operation data sample library is constructed for training the model to be trained, so as to optimize the encoder parameters of the model to be trained, so that the autoencoder of the model to be trained satisfies the above characteristics and becomes a normal detection model.

Step2: In the process of training the model to be trained each time to obtain a normal detection model, the first group of normal operation data samples and the second group of normal operation data samples are input into the to-be-trained model successively, and by minimizing the first group of normal operation data samples The distance between the normal operation data samples of the group and the encoded and decoded data, and the distance between the encoded features of the second group of normal operation data samples and the encoded features of the first group of normal operation data samples, to optimize the to-be-trained model the encoder parameters. Optionally, the parameters of the decoder adopt preset parameters, or are optimized together with the autoencoder in each training.

Optionally, the following loss function is constructed during the training process for training the normal detection model:

$$L1 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + a \times \frac{1}{d} \sum_{i=1}^d (z'_i - z_i)^2$$

In here, n represents the total number of data types in a set of normal operating data samples,  $x_i$  represents the encoded and decoded data of the first set of normal running data samples,  $y_i$  represents the first set of normal operating data samples, d represents the total number of dimensions of encoded features for a set of normal running data samples,  $z_i$  represents the encoded features of the first set of running data samples,  $z'_i$  represents the encoded features of the second set of normal row data samples,  $a$  represents the loss weight corresponding to normal operation.

Embodiment 2: Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are specifically included:

Step 1: Build a normal operation data sample library and a faulty operation data sample library.

Step 2: In each process of training the model to be trained to obtain a normal detection model, the first group of normal operation data samples, the second group of normal operation data samples, the first group of faulty operation data samples and the second group of faulty operation data samples are used. The data samples are input to the model to be trained successively, and the distance between the first group of normal operation data samples and the encoded and decoded data is minimized, and

the encoded features of the second group of normal operation data samples are minimized. The distance of the encoded features of the first set of normal operating data samples, minimizing the distance of the encoded features of the second set of faulty operating data samples and the encoded features of the first set of faulty operating data samples, and maximizing the first set of The distance between the encoded features of a group of normal operating data samples and the encoded features of the first group of faulty operating data samples is to optimize the encoder parameters of the model to be trained.

The to-be-trained model includes an autoencoder and a decoder based on deep learning, and the trained autoencoder forms a normal detection model.

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model respectively, the method further includes: in the training of the normal detection model, constructing the following loss function:

$$L'1 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + \alpha \times \frac{1}{d} \sum_{i=1}^d (z'_i - z_i)^2 + \beta \times \frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2 + \gamma \times \frac{d}{\sum_{i=1}^d (z_i - G_i)^2}$$

In here, n represents the total number of data types in a group of normal operation data samples,  $x_i$  represents the encoded and decoded data of the first group of normal operation data samples,  $y_i$  represents the first group of normal operation data samples, and d represents a group of operation data samples The total number of dimensions of the encoded features of the data samples,  $z_i$  represents the encoded features of the first group of normal operation data samples,  $z'_i$  represents the encoded features of the second group of normal line data samples, and  $G_i$  represents the first The encoded features of a group of fault data samples,  $G'_i$  represents the encoded features of the second group of fault row data samples, and  $\alpha$ ,  $\beta$ , and  $\gamma$  represent the corresponding ones, respectively.

In a specific embodiment, constructing a normal feature library according to the plurality of output features includes: selecting at least one output feature with the strongest correlation from the plurality of output features to form a normal feature library. Correspondingly, during the feature comparison process, if a feature has a sufficiently high correlation with any feature in the normal feature library (eg Euclidean distance < 0.01), the feature matches the feature in the normal feature library.

Optionally, if the normal operation data samples input to the normal detection model are the operation data generated by the normal operation of the engine for a period of time, the features output by the normal detection model are multiple curves or a two-dimensional matrix. Among them, each curve reflects the change law of one dimension in the output feature over time. For example, when  $d=4$ , there are 4 curves; the rows and columns of the dimension matrix are different dimensions and different moments of the output feature, for example, When  $d=4$ , the two-dimensional matrix has rows.

Correspondingly, the features in the normal feature library are also multiple curves or two-dimensional matrices. During the feature comparison process, if each curve included in a feature matches every curve of any feature in the normal feature library, the feature matches the feature in the normal feature library; Alternatively, if the two-dimensional matrix corresponding to a feature matches each element of the two-dimensional matrix corresponding to any feature in the normal feature library, the feature matches the feature in the normal feature library.

This embodiment utilizes the characteristics of unsupervised learning of the autoencoder, and can build a corresponding feature library while the model is being trained, without the need for sample labeling, thereby improving the flexibility and application scope of the model.

## 4.2. Training of a fault detection model for one type of fault

Two specific implementations for training the fault detection model are given below, using

different loss functions and training methods respectively.

**Implementation 1:**

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are further included:

Step 1: Build a database of operational data samples for different fault types

The characteristic of a fault detection model of a fault type is: if the operating data input to the model is the operating data of the engine when the fault type occurs, the features output by the model match the features in the feature database corresponding to the fault type. In view of this, a database of operating data samples of fault types is first constructed to train the model to be trained, so as to optimize the encoder parameters of the model to be trained, so that the autoencoder of the model to be trained satisfies the above characteristics and becomes the fault Types of fault detection models.

Step 2: In the process of training the to-be-trained model each time to obtain a fault detection model of a fault type, input the first group of fault operation data samples and the second group of fault operation data samples belonging to the same fault type into the The network to be trained is minimized by minimizing the distance between the first group of faulty running data samples and the encoded and decoded data, and the difference between the encoded features of the second set of faulty running data samples and the first set of faulty running data samples. The distance of the encoded features, and the encoder parameters of the model to be trained are optimized.

Optionally, the following loss function is constructed during the training process for training a fault detection model of a fault type:

$$L2 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + \beta \times \frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2$$

In here, n represents the total number of data types in a group of fault operation data samples of a fault type, xi represents the encoded and decoded data of the first group of fault operation data samples of the fault type, and yi represents the first group of fault types. Fault operation data samples, d represents the total number of dimensions of the encoded features of a group of fault operation data samples of the fault type, Gi represents the encoded characteristics of the first group of fault operation data samples of the fault type, Gi' represents the encoded features of the second group of fault operation data samples of the fault type, and β represents the loss weight corresponding to the fault type.

**Implementation 2:**

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are further included:

Step 1: Build a normal operation data sample library and an operation data sample library of different fault types respectively.

Step 2: In the process of training the to-be-trained model each time to obtain a fault detection model of a fault type, the first group of fault operation data samples and the second group of fault operation data samples belonging to one fault type belong to another fault. The third group of failure operation data samples and the fourth group of failure operation data samples, the first group of normal operation data samples and the second group of normal operation data samples are successively input to the network to be trained, and by minimizing the first group of normal operation data samples to minimize the distance between the encoded features of the second group of malfunctioning data samples and the encoded features of the first group of malfunctioning data samples, minimize the distance between the encoded features of the second group of malfunctioning data samples The distance between the encoded features of the three groups of faulty operating data samples and the encoded features of the fourth group of faulty operating data samples, minimize the distance between the encoded features of the first set of normal operating data samples and the second set of normal operating data samples the distance of the encoded features of the data samples, and

maximize the distance between the encoded features of the first set of faulty operating data samples and the encoded features of the third set of faulty operating data samples, maximizing the first set of faults. The distance between the encoded features of the operating data samples and the encoded features of the first group of normal operating data samples is used to optimize the encoder parameters of the model to be trained.

The to-be-trained model includes an autoencoder and a decoder based on deep learning, and the trained autoencoder constitutes a fault detection model.

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the method further includes: in the training of a fault detection model of a fault type, constructing the following loss function:

$$L'2 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + \beta \times \frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2 + \varepsilon \times \frac{1}{d} \sum_{i=1}^d (G'_{1i} - G_{1i})^2 + \alpha \times \frac{1}{d} \sum_{i=1}^d (z'_i - z_i)^2 + \theta \times \frac{d}{\sum_{i=1}^d (G_{1i} - G_i)^2} + \gamma \times \frac{d}{\sum_{i=1}^d (z_i - G_i)^2}$$

In here, n represents the total number of data types in a group of fault operation data samples of a fault type, xi represents the encoded and decoded data of the first group of fault operation data samples, yi represents the first group of fault operation data samples, d represents the total number of dimensions of the encoded features of a group of operating data samples, Gi represents the encoded features of the first group of faulty operating data samples, G'i represents the encoded features of the second group of faulty operating data samples, G'1i represents The encoded features of the third group of faulty operation data samples, G'1i represents the encoded features of the fourth group of faulty operation data samples, zi represents the encoded features of the first group of normal operation data samples, z' i represents the encoded features of the second group of normal row data samples, and  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\varepsilon$ , and  $\theta$  represent the corresponding loss weights, respectively.

In each training, the encoder parameters are optimized by minimizing the loss function L'2. Specifically, in the loss function L'2,  $\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2$  representing the distance between the first group of faulty running data samples and the encoded and decoded data, Through the minimization of  $\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2$  the loss of fault operation data caused by coding is limited, and the accuracy of fault identification is improved.  $\frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2$  represents the distance between the encoded features of the second group of faulty operating data samples and the encoded features of the first set of faulty operating data samples, Through the minimization of  $\frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2$ , the encoded features obtained from multiple groups of fault operation data samples belonging to the one fault category tend to be consistent, on the one hand, it is beneficial to construct a fault feature library corresponding to the fault type, on the other hand, the coding loss is reduced from the perspective of post-coded features, and the fault identification accuracy is further improved.  $\frac{1}{d} \sum_{i=1}^d (G_{1i} - G_i)^2$  represents the distance between the encoded features of the first set of faulty running data samples and the encoded features of the third set of faulty running data samples, through the maximization of  $\frac{1}{d} \sum_{i=1}^d (G_{1i} - G_i)^2$  (that is, the minimum value of  $\frac{d}{\sum_{i=1}^d (G_{1i} - G_i)^2}$ ) make the coded features of the fault operation data samples of one fault type and the coded characteristics of the fault operation data samples of the other fault type have a long distance, so that the fault operation data of different fault types can be Samples are effectively differentiated.  $\frac{1}{d} \sum_{i=1}^d (G'_{1i} - G_{1i})^2$  represents the distance between the encoded features of the third group of faulty operation data samples and the encoded features of the fourth group of faulty operation data samples, by minimizing  $\frac{1}{d} \sum_{i=1}^d (G'_{1i} - G_{1i})^2$ , the other fault The encoded features obtained from multiple sets of fault operation data samples of different types tend to be consistent, so as to ensure that the encoded features of the third set of fault operation data samples in  $\frac{d}{\sum_{i=1}^d (G_{1i} - G_i)^2}$  can represent all fault operations of the other fault type. The encoded features of the data samples, so that the



operational data samples of the one fault type are effectively distinguished from all the fault operational data samples of the other fault type.  $\frac{1}{d}\sum_{i=1}^d(z_i - G_i)^2$  represents the distance between the encoded features of the first set of faulty running data samples and the encoded features of the first set of normal running data samples, through the maximization of  $\frac{1}{d}\sum_{i=1}^d(z_i - G_i)^2$  (ie the minimum of  $\frac{d}{\sum_{i=1}^d(z_i - G_i)^2}$ ) to make the encoded features of the failure operation data samples of the one kind of failure and the encoded features of the normal operation data samples have a long distance, so that the failure operation data samples of the one kind of failure and the normal operation data have a long distance. The samples are effectively differentiated.  $\frac{1}{d}\sum_{i=1}^d(z'_i - z_i)^2$  represents the distance between the encoded features of the first set of normal running data samples and the encoded features of the second set of normal running data samples, through the minimization of  $\frac{1}{d}\sum_{i=1}^d(z'_i - z_i)^2$ , Make the encoded features obtained from the multiple groups of normal operation data samples tend to be consistent, thereby ensuring that the encoded features of the first group of normal operation data samples in  $\frac{d}{\sum_{i=1}^d(z_i - G_i)^2}$  can represent the encoded features of all normal operation data samples., so that the operating data samples of one type of failure can be effectively distinguished from all normal operating data samples.

At the same time, the training mode is optimized in this embodiment, and the first group of failure operation data samples, the second group of failure operation data samples, the third group of failure operation data samples, the fourth group of failure operation data samples, the first group of failure operation data samples, and the first group of normal operation data samples are optimized. The data samples and the second group of normal running data samples are all encoded once and then updated with parameters. Compared with updating parameters after each encoding, the number of parameter updates is reduced, and the calculation of the overall loss function  $L^2$  is avoided. Invalid parameter fluctuations caused by previous updates make the network converge faster. After training a fault detection model of a fault type, a feature library corresponding to the fault type is constructed by using the fault detection model. Optionally, if the output features of the normal detection model do not match the features in the normal feature library, before comparing the features output by the multiple fault detection models with the feature library corresponding to the fault type or combination, respectively, The method also includes: inputting multiple sets of fault operation data samples of a fault type into the fault detection model of the fault type to obtain multiple output features; and constructing a feature library corresponding to the fault type according to the multiple output features.

In a specific embodiment, constructing a feature library corresponding to the fault type according to the multiple output features includes: selecting at least one output feature with the strongest correlation from the multiple output features to form the fault type feature library. Correspondingly, in the feature comparison process, if the correlation between a feature and any feature in the feature library of a fault type is high enough (for example, Euclidean distance  $< 0.01$ ), then the feature is in the feature library of the fault category.

Optionally, if the fault operation data sample input to the fault detection model of a fault type is the operation data of the engine within a period of time when the fault occurs, then the characteristics of the output of the fault detection model are multiple curves or two characteristics of the fault type. dimensional matrix. Among them, each curve reflects the time-varying rule of the one-dimensional data in the output characteristics of the engine when the fault combination occurs. For example, when  $d=4$ , there are 4 curves; the rows and columns of the two-dimensional matrix are the output characteristics respectively. Different dimensions and different moments of, for example, when  $d=4$ , there are 4 rows in a two-dimensional matrix.

Correspondingly, the features in the feature library of the fault types are also multiple curves or two-dimensional matrices. During the feature comparison process, if each curve included in a feature

matches every curve of any feature in the feature library, the feature matches the feature of the feature library; or, if a feature corresponding to If the two-dimensional matrix matches each element of the two-dimensional matrix corresponding to any feature in the feature library, the feature matches the feature of the feature library.

### 4.3. Training of a fault detection model for a combination of fault types

Two specific implementations for training the fault detection model are given below, using different loss functions and training methods respectively.

#### Embodiment 1:

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are further included:

Step 1: Build a database of operational data samples for different fault types and combinations.

The characteristic of a fault detection model corresponding to a combination of fault types is: if the operating data input to the model is the operating data of the engine when the combination of fault types occurs, the features output by the model are the features in the feature library corresponding to the combination of fault types. In view of this, first construct a database of operating data samples of fault type combinations, which is used to train the model to be trained, so as to optimize the encoder parameters of the model to be trained, so that the autoencoder of the model to be trained satisfies the above characteristics and becomes the fault type Combined fault detection model.

Step 2: In the process of training the model to be trained each time to obtain a fault detection model with a combination of fault types, the first group of all fault operation data samples, the second group of all fault operation data samples belonging to a fault type combination and The fault operation data samples of the first group of various faults belonging to the fault type combination are input to the network to be trained successively, and the distance between all the fault operation data samples of the first group and the encoded and decoded data is minimized. Calculate the distance between the encoded features of the second group of all faulty operation data samples and the encoded features of the first group of all faulty operation data samples, and the encoded features of the first group of faulty operation data samples of various faults. The distance between the feature and the encoded features of the first group of all faulty operation data samples is used to optimize the encoder parameters of the model to be trained.

Optionally, the following loss function is constructed during the training process to train a fault detection model for a combination of fault types:

$$L3 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + \beta \times \frac{1}{d} \sum_{i=1}^d (G'_i - G_i)^2 + \sum_{j=1}^m \left[ \beta_j \times \frac{1}{d} \sum_{i=1}^d (f_j(G_i) - G_i)^2 \right]$$

In here, n represents the total number of data types in a set of fault operation data samples of a fault type combination, m represents the total number of fault types in the fault type combination, and xi represents the first group of all fault operation data belonging to the fault type combination. The encoded and decoded data of the sample, yi represents the first group of all fault operation data samples belonging to the fault type combination, d represents the total number of dimensions of the encoded features of a group of fault operation data samples Gi represents the first group of fault operation data samples belonging to the fault type combination. The encoded features of a group of all fault operation data samples, G'i represents the encoded features of the second group of all fault operation data samples belonging to the fault type combination, fj(Gi) represents the first fault type combination The encoded features of the operating data samples of various faults, β and bj represent the corresponding loss weights, respectively.

### Embodiment 2:

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the following steps are further included:

Step 1: Build a normal operation data sample library and a combination of different fault types.

Step 2: In the process of training the model to be trained each time to obtain a fault detection model with a combination of fault types, the first group of all fault operation data samples and the second group of all fault operation data samples belonging to a fault type combination, The fault operation data samples of the first group of various faults belonging to the fault type combination, the first group of normal operation data samples and the second group of normal operation data samples are successively input to the network to be trained, and by minimizing the distance between the first group of all fault operation data samples and the encoded data, minimizing the distance between the encoded features of the second group of all faulty operation data samples and the encoded features of the first group of all faulty operation data samples, Minimizing the distance between the encoded features of the first group of normal operating data samples and the encoded features of the second group of normal operating data samples, minimizing the encoded features of the first group of faulty operating data samples of various faults The distance of the feature from the encoded features of the first set of all faulty operating data samples, and maximizing the encoded features of the first set of all faulty operating data samples and the encoded features of the first set of normal operating data samples distance, optimize the encoder parameters of the model to be trained.

The model to be trained includes an autoencoder and a decoder based on deep learning, and the trained autoencoder is used to form a fault detection model for the combination of fault types.

Optionally, before inputting the operating data into a plurality of fault detection models and a normal detection model, the method further includes: in the training of a fault detection model combined with a fault type, constructing the following loss function:

$$L' 3 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 + \beta \times \frac{1}{d} \sum_{i=1}^d (G'_{i-1} - G_i)^2 + \alpha \times \frac{1}{d} \sum_{i=1}^d (z'_{i-1} - z_i)^2 + \sum_{j=1}^m \left[ \beta_j \times \frac{1}{d} \sum_{i=1}^d (f_j(G_i) - G_i)^2 \right] + \gamma \times \frac{d}{\sum_{i=1}^d (z_i - G_i)^2}$$

In here, n represents the total number of data types in a group of fault operation data samples of a combination of fault types,  $x_i$  represents the encoded and decoded data of all the fault operation data samples of the first group, and  $y_i$  represents all the fault operation data of the first group samples, d represents the total number of dimensions of the encoded features of a group of operating data samples,  $G_i$  represents the encoded features of the first group of all faulty operating data samples, and  $G'_i$  represents the encoding of the second group of all faulty operating data samples post features,  $z_i$  represents the encoded features of the first group of normal operation data samples,  $z'_i$  represents the encoded features of the second group of normal line data samples,  $f_j(G_i)$  represents the first group of various faults The encoded features of the running data samples, where  $\alpha$ ,  $\beta$ ,  $\gamma$ , and  $\beta_j$  represent the corresponding loss weights, respectively.

In each training, the encoder parameters are optimized by minimizing the loss function  $L'3$ . Specifically, in the loss function  $L'3$ ,  $\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2$  represents the distance between the first group of full-fault running data samples and the encoded and decoded data, Through the minimization of  $\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2$ , the loss of the full fault operation data caused by coding is limited, and the accuracy of fault identification is improved.  $\frac{1}{d} \sum_{i=1}^d (G'_{i-1} - G_i)^2$  represents the difference between the encoded features of the second group of full-fault operation data samples and the first group of full-failure operation data samples. The distance of the encoded features, through the minimization of  $\frac{1}{d} \sum_{i=1}^d (G'_{i-1} - G_i)^2$ , make the operation of multiple groups of full faults belonging to the one fault type combination The encoded features obtained from the data samples tend to be consistent. On the one hand, it is beneficial to build a fault feature library corresponding to the combination of the fault types.

On the other hand, the coding loss is reduced from the perspective of the encoded features, which further improves the fault identification accuracy.

$\frac{1}{d} \sum_{i=1}^d (z_i - G_i)^2$  represents the difference between the encoded features of the first group of full-failure operating data samples and the encoded features of the first group of normal operating data samples. Distance, by maximizing  $\frac{1}{d} \sum_{i=1}^d (z_i - G_i)^2$  (ie  $\frac{d}{\sum_{i=1}^d (z_i - G_i)^2}$  minimize) make the encoded features of the full-fault operation data samples of the one failure type combination have a farther distance from the encoded features of the normal operation data samples, so as to make the full-fault operation data of the one failure type combination Samples and normal operating data samples are effectively differentiated.  $\frac{1}{d} \sum_{i=1}^d (z'_i - z_i)^2$  represents the encoded features of the first group of normal operation data samples and the encoding of the second group of normal operation data samples. The distance of the post-feature, through the minimization of  $\frac{1}{d} \sum_{i=1}^d (z'_i - z_i)^2$  the encoded features obtained from the multiple groups of normal running data samples tend to be Consistent, thus ensuring that the encoded features of the first group of normal running data samples in  $\frac{d}{\sum_{i=1}^d (z_i - G_i)^2}$  can represent the encoded features of all normal running data samples, so that the operating data samples of the one fault type combination can be effectively distinguished from all normal operating data samples.  $\frac{1}{d} \sum_{i=1}^d (f_j(G_i) - G_i)^2$  the encoded features that characterize the first group of jth fault operation data samples belonging to the fault type combination are related to the first distance between the encoded features of all the fault operation data samples in the group limits the loss of each fault type after the encoding of all fault operation data. By minimizing L'3 as a whole, it is possible to keep the main information of all fault types in the guaranteed post-coding feature of all fault operation data, and consider the important information of each fault type in the combination, so as to avoid the faults that users pay attention to. There is a large amount of information missing on the species.

#### 4.4. Model optimization

In this embodiment, the training mode is optimized, and the first group of all faulty operation data samples, the second group of all faulty operation data samples, the first group of faulty operation data samples of various faults, and the first group of normal operation data samples and the second group of normal running data samples are all encoded once and then updated with parameters. Compared with updating parameters after each encoding, the number of parameter updates is reduced, and the update before the overall loss function L'3 is calculated is avoided. The resulting invalid parameter fluctuations make the network converge faster.

Optionally, after constructing the following loss function, the method further includes: acquiring a pre-selected fault type of the engine; and adjusting the parameter  $b_j$  according to the pre-selected fault type, so as to obtain a model focusing on detecting the pre-selected fault type.

In a fault detection model for a combination of fault types, the parameter  $b_j$  determines the loss weight of each fault type in the combination. The larger the weight, the stricter the loss control corresponding to the encoded feature on the fault type in the overall loss function, and the smaller the information loss of the encoded feature on the fault type obtained in the next training. Therefore, by adjusting the parameter  $b_j$ , a model focusing on detecting a certain type of fault can be obtained.

In this embodiment, the parameter  $b_j$  is adjusted by the preselected failure type of the engine. Optionally, the pre-selected fault type is obtained through the user's setting, and the fault type set by the user is the fault type concerned by the user; Misidentification caused by the low proportion of this fault type in the training samples.

After training a fault detection model for a combination of fault types, a feature library corresponding to the combination of fault types is constructed by using the fault detection model.

Optionally, if the output features of the normal detection model do not match the features in the normal feature library, before comparing the features output by the multiple fault detection models with the feature library corresponding to the fault type or combination, respectively, It also includes: inputting multiple sets of full-fault operation data samples of a combination of fault types into the fault detection model of the combination of fault types to obtain multiple output features; and constructing features corresponding to the combination of fault types according to the multiple output features library.

After the training of a fault detection model for a combination of fault types is completed, after inputting multiple sets of full fault operation data samples of the combination of fault types into the fault detection model, the output features tend to be consistent, and the consistent features can be used as representations the characteristics of the engine described failure category combination. At least one feature characterizing the combination of fault types of the engine constitutes a feature library of the combination of fault types.

In a specific embodiment, constructing a feature library corresponding to the combination of fault types according to the multiple output features includes: selecting at least one output feature with the strongest correlation from the multiple output features to form the fault. A feature library for a variety of combinations. Correspondingly, in the feature comparison process, if the correlation between a feature and any feature in the feature library of a fault type combination is high enough (for example, Euclidean distance  $< 0.01$ ), then the feature combined with the fault type will be Feature matching in the library.

Optionally, if the full-fault operation data sample input to the fault detection model of a fault type combination is the operation data of the engine within a period of time when the fault combination occurs, then the output feature of the fault detection model is the number of fault types of the combination. a curve or a two-dimensional matrix. Among them, each operating curve reflects the time-varying law of the one-dimensional data in the output characteristics of the engine when the fault combination occurs. For example, when  $d=4$ , there are 4 curves; the rows and columns of the two-dimensional matrix are the output Different dimensions and different moments of the feature, for example, when  $d=4$ , the two-dimensional matrix has 4 rows.

Correspondingly, the features in the feature library of the fault type combination are also multiple curves or two-dimensional matrices. During the feature comparison process, if each curve included in a feature matches every curve of any feature in the feature library, the feature matches the feature of the feature library; or, if a feature corresponding to If the two-dimensional matrix matches each element of the two-dimensional matrix corresponding to any feature in the feature library, the feature matches the feature of the feature library.

## 5. Conclusion

Engine failure is based on the abnormal operation of the engine caused by material and workmanship defects, unreasonable design, manufacturing problems and improper operation during use. In the actual driving process of the vehicle, various engine failures may occur, and timely identification or detection of engine failures is a technical problem that needs to be solved urgently. In view of the problems existing in traditional engine fault identification, this paper proposes a deep learning engine fault identification method, equipment and medium, so as to realize the automatic identification of engine faults. The engine fault identification method has a good effect in practical application.

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