Wear Fault Diagnosis of Aeroengines Based on Broad Learning System and Ensemble Learning

Mengmeng Wang 1,2, Quanbo Ge 3,*, Haoyu Jiang 4 and Gang Yao 1

1 Logistics Engineering College, Shanghai Maritime University, Shanghai 201306, China; wmm_triumph@163.com (M.W.); gangyao@shmtu.edu.cn (G.Y.)
2 Hangzhou Zhongheng Provincial key Enterprise Research Institute of Powercloud, Hangzhou 310018, China
3 School of Electronics and Information Engineering, Tongji University, Shanghai 201804, China
4 Institute of Automation, Southeast University, Nanjing 211189, China; Jianghy@hzzh.com

* Correspondence: qbge_tju@163.com

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Abstract: An aircraft engine (aeroengine) operates in an extremely harsh environment, causing the working state of the engine to constantly change. As a result, the engine is prone to various kinds of wear faults. This paper proposes a new intelligent method for the diagnosis of aeroengine wear faults based on oil analysis, in which broad learning system (BLS) and ensemble learning models are introduced and integrated into the bagging-BLS model, in which 100 sub-BLS models are established, which are further optimized by ensemble learning. Experiments are conducted to verify the proposed method, based on the analysis of oil data, in which the random forest and single BLS algorithms are used for comparison. The results show that the output accuracy of the proposed method is stable (at 0.988), showing that the bagging-BLS model can improve the accuracy and reliability of engine wear fault diagnosis, reflecting the development trend of fault diagnosis in implementing intelligent technology.

Keywords: aircraft engine; fault diagnosis; broad learning system; ensemble learning

1. Introduction

The engine is the key component of an aircraft, and thus, maintaining its health is a key issue in ensuring civil aviation safety. However, the harshness of the operation environment and the complexity of aircraft engines (aeroengines) frequently cause failures in their inner mechanical structure [1,2]. In addition, the manufacturing costs of aeroengines are quite high, and the replacement of an engine requires large investments, in terms of both manpower and financial resources. It is, therefore, necessary to find an effective method to monitor the condition of and predict the faults in aeroengines [3–6].

Wear failure is a common fault in modern mechanical equipment. As the core part of the aircraft, the engine works under the conditions of large fluctuations: high speed fluctuations, high temperatures, and large load range, which are all prone to causing fatigue faults and accelerating the aging of the engine [6]. A wear fault usually results in different types of wear particles, which can provide a basis for the monitoring and analysis of fatigue failures [7,8]. Oil monitoring techniques have been developed for fatigue fault diagnosis, in which the particles and elements in the engine oil are monitored [9–11]. At present, the main research methods for oil monitoring are ferrography analysis, spectrum analysis, and magnetic plug monitoring [11–13]. The basis of ferrography analysis is to separate abraded iron from an oil sample by using a magnetic method, which is then observed under a microscope, and consequently, a qualitative and quantitative analysis is conducted on it. This method can not only provide detailed information about the abraded particles, such as the type and quantity, but can
also provide their visual features, such as shape, color, and size. However, traditional ferrography analysis usually results in fuzzy decisions and qualitative analysis, where the decision-making mainly depends on expert experience, which has a low efficiency and unreliable accuracy due to differing professional levels.

In view of the above shortcomings, artificial intelligence methods have been introduced to analyze the data obtained from ferrography analysis. Currently, many researchers have applied expert systems, neural networks, and other algorithms to diagnose fatigue faults. In [14,15], an expert knowledge set has been built to diagnose engine oil through fuzzy logic and fuzzy cluster methods. However, an expert system has knowledge acquisition and poor adaptability issues. In [16], an oil-like spectral threshold method has been introduced to estimate the probability density of aircraft engine oil sample spectral data, with which the normal, warning, and abnormal thresholds of the mass fraction ratio of an aeroengine can be calculated. In [4,17–20], different kinds of neural networks were used to diagnose the wear faults of aeroengines; these methods also have high reference values. However, a typical neural network requires a large amount of data, which is impractical as only a small number of oil analysis data are usually obtained (because of the energy cost of oil analysis). It is also easy to for these methods to become trapped in local extrema.

To address the shortcomings of other fault diagnosis methods, an intelligent wear fault diagnosis method based on oil analysis technology is established in this work. A new method for wear fault diagnosis—a broad learning system (BLS) based on ensemble learning (bagging-BLS)—is proposed to deal with the oil analysis data. First, the bagging sampling method is used to prepare the dataset. Then, several BLS models are established and trained using the dataset. Finally, these sub-BLS models are integrated by the ensemble learning method. The proposed model is tested, based on real oil analysis data. The results show that the proposed method can extract the knowledge rules of wear fault diagnosis in aeroengines well and has high recognition accuracy. The whole process is completed automatically (i.e., without human intervention) and has a high degree of automation and intelligence.

The rest of the paper is organized as follows. In Section 2, the analysis of the cause of wear faults, the relationships between abrasive particles and faults, and some previous works related to engine fault diagnosis are given. Section 3 presents the BLS and ensemble models, as well as giving the details of the proposed bagging-BLS model. Section 4 compares the performance of the random forest, single BLS, and bagging-BLS models in aircraft engine fault diagnosis. Additionally, a performance analysis of the proposed bagging-BLS algorithm is addressed here. Finally, discussions and conclusions are given in Section 5.

2. Problem Analysis

2.1. Problem Description

During the operation of an aeroengine, as a result of the high-intensity contact and rapid relative movement, mechanical friction will inevitably occur between the aeroengine and the supporting parts of engine. The products of such friction are mechanical debris and abraded particles, which fall off the surfaces of the parts into the lubricating oil. Then, the lubricating oil carries these abraded particles around. This ‘contaminated’ oil will flow to the other mechanical parts, working as an abrasive to aggravate the wear of the surrounding parts, which consequently leads to large areas of wear and serious scraping [21,22]. By analyzing the content of abraded particles in the lubricating oil, we can infer the worn parts and wear severity before serious faults occur.

For an aeroengine, friction occurring on different components will produce different abrasive particles with different shapes. Ferrography analysis is a reliable method for oil analysis, with which the kinds of abrasive particles in the ‘contaminated’ oil can be determined. A large number of studies based on ferrography analysis technology have shown that abrasive particles generated by the same component have a similar type and shape [23]. In other words, the features of a certain abrasive particle can represent the wear modes of a certain part in an aeroengine, which provides the exciting
prospect for a method for wear fault diagnosis. According to the type and shape characteristics of abrasive particles, they can be divided into eight types: normal abrasive particles, cutting abrasive particles, severe sliding abrasive particles, fatigue stripping, spherical abrasive particles, layered abrasive particles, and black and red oxide abrasive particles. Table 1 lists the characteristics and generation mechanisms of these common abrasive particles [24]. On the basis of these abrasive particles in oil analysis, this paper proposes a new model (bagging-BLS) to diagnose the wear fault modes of an aeroengine. The eight kinds of abrasive particles are the input features for the diagnosis model and the wear modes are the output. The general structure of the new diagnosis model is shown in Figure 1, which demonstrates the main idea of this industrial application.

Table 1. Types and generation mechanisms of abrasive particles [24].

| Type                        | Generation                                      | Wear status                                      |
|-----------------------------|-------------------------------------------------|-------------------------------------------------|
| Normal sliding abrasive particles | Sliding friction cuts the mixed layer            | Good condition                                  |
| Cutting abrasive particles  | Cutting at an acute angle or contact grinding   | Damage of contact surface or grease contamination |
| Severe sliding abrasive particles | High speed or high intensity friction         | Heavy load and high speed                       |
| Fatigue stripping           | Fatigue from rolling                            | Excessive load on rolling bearings or gears     |
| Spherical abrasive particles | Fatigue from rolling, high temperature welding, or cavitation | Quantity increasing means serious failure |
| Layered abrasive particles  | The abrasive particles are formed by rolling parts | A sharp increase in the number indicates a rolling component failure |
| Black and red oxide abrasive particles | Oxidation products from slightly slow wear process | Contact corrosion                              |

Figure 1. The general structure of the proposed model.

All mechanical components operate together and rub against each other to make an engine run effectively; thus, abrasive particles are a necessary product of the operation of an aeroengine, which provide important evidence of the mechanical wear that may cause faults or result in a serious accident. Therefore, the analysis of abrasive particle information provides a valuable method for identifying the wear mode, as well its location in the engine [25–28]. Table 2 shows the correlations between wear modes and abrasive particle characteristics in the important parts of an aeroengine (i.e., gear and bearing), which provides a theoretical basis for engine wear fault diagnosis based on wear particle analysis. In the table, “0” represents that the relationship between an abrasive particle type and a wear mode is weak or nonexistent; “1” represents that an abrasive particle has a direct relationship with the corresponding wear mode.
Table 2. Relationships between abrasive particles and wear modes [25].

| Component of Engine | Characteristic          | Wear Mode | Adhesive Wear | Abrasive Wear | Fatigue Wear | Corrosion |
|---------------------|-------------------------|-----------|---------------|---------------|--------------|-----------|
| Gear and Bearing    | Normal abrasive particles | 1         | 0             | 0             | 0            | 0         |
|                     | Cutting abrasive particles | 0         | 1             | 0             | 0            | 0         |
|                     | Severe sliding abrasive particles | 1         | 0             | 0             | 0            | 0         |
|                     | Fatigue stripping       | 0         | 0             | 1             | 0            | 0         |
|                     | Spherical abrasive particles | 0         | 0             | 1             | 0            | 0         |
|                     | Layered abrasive particles | 0         | 0             | 1             | 0            | 0         |
|                     | Black and red oxide abrasive particles | 1         | 0             | 0             | 1            | 0         |

2.2. Motivation

As condition monitoring and fault diagnosis have become an urgent problem in civil aviation, many studies have attempted to improve the accuracy of wear fault diagnosis methods. Among these studies, the performance of artificial immune system (AIS) methods has stood out in the diagnosis of wear faults [29–31]. An AIS was adopted in [29] to solve the problem of wear fault diagnosis of an aeroengine. In the AIS method, wear failure of the engine is considered analogously to an antigen in biology. Certain antibodies match with certain antigens, just like the generation of particles will certainly cause wear fault. It simulates the biological relationship between antigen and antibody mathematically and then optimizes the antibody continuously, causing it to mature. The mature antibody is used to identify the antigen and outputs the right match as a result.

In the application of fault diagnosis for aeroengines, AIS makes use of an antibody to determine a fault state and its location in the engine, in order to achieve the purpose of fault diagnosis. Several parameters need to be determined when establishing an AIS model, such as the number of initial detectors $n$, inhibition threshold $s$, and diagnostic threshold $r$. In [30], the initial parameters for the AIS algorithm used could only be determined by experience. Moreover, when inputting an unknown set of data, the inhibition threshold and diagnosis threshold are individually determined by the distribution concentration for each dataset. This method, in which the algorithm parameters are determined based on experience, increases the uncertainty and the difficulty in establishing a diagnosis model. Although the method can obtain a satisfying output, it takes too much time in choosing suitable parameters.

In this work, we propose a new algorithm to diagnose wear faults in aeroengines that can provide high accuracy and ease of implementation, while not requiring a tedious initialization procedure. Figure 2 shows this improvements (compared with AIS), where the left side is the algorithm flow chart of AIS and the right side presents that of the method proposed in our work. This study optimizes broad learning system models with ensemble learning and proposes the bagging-BLS model to improve the diagnosis method for wear fault diagnosis in aircraft engines. Although it is not necessary to spend too much time in finding a suitable initial value for the bagging-BLS model, random initial parameters may result in poor accuracy; this can be adjusted by incremental BLS, by adding more nodes to the network. Furthermore, although different initial parameters result in different output accuracies between the BLS models—some good and some bad—the ensemble learning method can reduce this short-board effect by integrating the outputs of all BLS models. By comparing the diagnosis effect of the proposed
model with various algorithms, the effectiveness of the bagging-BLS model is verified. Finally, the proposed model is proved to be a feasible solution for the wear fault diagnosis of aircraft engines.

Figure 2. The difference between artificial immune system (AIS) and bagging-broad learning system (BLS) models [30].

3. Wear Fault Diagnosis Technology for Aircraft Engines

In this paper, the broad learning system (BLS) method is used to model the diagnosis process. Broad learning systems are broad neural networks with a simple construction process and high operational efficiency, which have been widely used to deal with classification and regression prediction tasks [32–34]. For aeroengine wear fault diagnosis, although BLSs have high calculation speeds and high accuracy, their diagnosis results are unstable and their float ranges are larger when the initial parameters are varied. Ensemble learning methods have been designed to solve the overfitting and instability problems in machine learning; therefore, ensemble learning methods may be used to improve broad learning systems, in order to obtain a better diagnosis algorithm with good stability and high precision.

3.1. Broad Learning System

A broad learning system (BLS) is a kind of planar neural network, developed from a function chain neural network [35], which is composed of an input layer, an intermediate layer, and an output layer, as shown in Figure 3. The middle layer consists of two kinds of neurons with different properties: feature neurons and enhancement neurons. The function of a feature neuron is to conduct the feature extraction of data by the feature extraction function $\phi(\cdot)$. The data $X$ of the input layer is transformed, by the feature neuron, to $Z$ under the action of the $\phi(\cdot)$ function, following which $Z$ generates an enhanced node $H$ by the function $\xi(\cdot)$. Together, feature neurons and enhancement neurons form the middle layer $[Z \mid H]$. 
The establishment of BLS is as follows [35]. Assuming that the input of the model is $X$ and that $Y$ is the output:

1. Feature extraction; $Z$ represents feature nodes

   \[ Z = \phi(XW_1 + \beta_1), \]  

   where $W_1$ are randomly generated weights, connecting the input and feature nodes, and $\beta_1$ is the threshold of the function $\phi(\cdot)$.

2. Build intermediate layer; $H$ represents enhancement nodes

   \[ H = \xi(ZW_2 + \beta_2), \]  

   where $W_2$ and $\beta_2$ are randomly generated weights and thresholds, respectively. After obtaining the enhancement neuron $H$, the entire intermediate layer can be represented by $[Z|H]$.

3. Deduce output weight;

   \[ Y = AW, \]  

   \[ W = A^+ Y. \]

Then, the relationship between the intermediate layer and the output layer is established with the connection weight $W$, which can be deduced by (3) and (4). After obtaining $W$, the testing data are used to check the ability of the established BLS.

3.2. Ensemble Learning

Ensemble learning is built by constructing multiple parallel estimators [36,37], combining the learning results of multiple classifiers in order to obtain better generalization ability and robustness than a single classifier. The principle of this method is to build multiple independent learners, and then, take the average of their predicted results. In the paper, the classic method of ensemble learning—bagging—is adopted to improve the performance of the broad learning system for wear fault diagnosis. The structure of the bagging method is shown in Figure 4, in which $X_1$ is the training input, $Y_1$ is the expected training output, $X_2$ is testing input, and $Y_1$ is the output of the ensemble model.
3.3. Broad Learning System Based on Ensemble Learning

Figure 5 shows the structure diagram of the proposed broad learning system based on ensemble learning (bagging-BLS), where \( \{d'_1, d'_2, \cdots, d'_T\} \) represents the feature part of the subtraining set, \( \{d''_1, d''_2, \cdots, d''_T\} \) consists of the subtraining set labels, \( \text{Test}' \) is the feature part of the test dataset, and \( \text{Test}'' \) is the label part of the test dataset. Detailed information of the bagging-BLS model will be given below, based on Figure 5. Suppose the sample dataset of wear particles is \( D = \{S_1, S_2, \cdots, S_N\} \) and \( S_i \) is a sample of the dataset composed of features and labels, as shown in Figure 6. Divide all the samples into a training dataset and a test dataset, the sizes of which are \( N_1 \) and \( N_2 \), respectively. A sample ratio \( p \) is set to decide the number of samples extracted from the training dataset, and a corresponding number of samples are drawn from the training dataset to form a subtraining dataset. The bagging sampling method is applied to draw samples after copying these samples and then putting them back into the training dataset. This sampling method is called sampling with replacement. Finally, \( (O_1, O_2, \cdots, O_T) \) is the output of the test.

Figure 6. Example of a sample.
The establishment of a model includes the following parts:

1. Feature selection

   Feature selection is of great importance in a diagnosis pattern recognition system. Although all the wear features are related to the wear modes, some features are less relevant to the wear modes and may be redundant in the system, decreasing the performance. As the eight features are mutually independent, this paper introduces mutual information (MI) to search for the most relevant nonredundant features [38], which is an effective way to automatically employ the most suitable features. Letting \( I \) be the score function, the score of each feature \( X_k \) is obtained as \( I(X_k, C) \), where \( C \) is the class label. The definition of mutual information is [38]:

   \[
   I(X_k, C) = \sum_{x_i \in X_k} \sum_{c_j \in C} \log \frac{p(x_i, c_j)}{p(x_i) p(c_j)},
   \]

   where \( k \) ranges from 1 to total numbers of features \( M \), \( i \) and \( j \) range from 1 to \( N \), \( p(x_i) \) is the probability density of \( x_i \) in \( X_k \), \( p(c_j) \) is the probability density of \( c_j \) in \( C \), and \( p(x_i, c_j) \) represents the combined probability density of \( p(x_i, c_j) \) and \( c_j \). The larger the value of \( I(X_k, C) \), the stronger the correlation between the feature \( X_k \) and the class label \( C \).

2. Data preparation

   The whole dataset is divided into a training dataset (of size \( N_1 \)) and a test dataset (of size \( N_2 \)). Setting the sampling ratio \( p \) \([N_1 \cdot p]\) (where \([x]\) denotes the largest integer no more than \( x \)) samples are chosen from the training dataset using the bagging sampling method. This sampling process is then repeated \( T \) times. As a result, \( T \) different subtraining datasets are prepared for submodels.

   The \( T \) sub-datasets are, then, \( \{ (d_1', d_1''), (d_2', d_2''), \ldots, (d_T', d_T'') \} \), where the whole feature part is written as \( \{ d_1', d_2', \ldots, d_T' \} \) and the label part is \( \{ d_1'', d_2'', \ldots, d_T'' \} \). Furthermore, the test dataset can be represented by \( \{ Test', Test'' \} \).

3. Build the sub-BLS models [35]

   The main idea of ensemble learning is to combine multiple sublearners into strong learners. In this work, each BLS model is regarded as a sublearner in the ensemble learning model, similar to a decision tree in the random forest method. According to Equations (1)-(2), \( T \) BLS models are established for each training sub-dataset in \( \{ (d_1', d_1''), (d_2', d_2''), \ldots, (d_T', d_T'') \} \). To build a sub-BLS model, features are first extracted using Equation (6). Second, the intermediate layer is built using Equation (7):

   \[
   Z_t = \phi \left( d_t W_{i1} + \beta_{i1} \right),
   \]

   \[
   \begin{align*}
   H_t &= \xi \left( Z_t W_{i2} + \beta_{i2} \right) \\
   A_t &= [Z_t \mid H_t]
   \end{align*}
   \]

   where \( t = 1, 2, \ldots, T \).

4. Train the sub-BLS models

   According to Equations (6) and (7), the submodels are established successively; then, the weights \( W_t \) of the hidden and output layers in \( t \)th BLS model are computed by:

   \[
   W_t = A_t^+ d_t' ,
   \]

   where \( t = 1, 2, \ldots, T \).

5. Test the ensemble model
When testing the sub-BLS models, Test′ is used as an input for each model, obtaining $T$ outputs for each submodel through Equation (9):

$$O_t = W_t \cdot \text{Test}'.$$

(9)

Then, the output of the bagging-BLS model can be computed by Equation (10):

$$Y = (O_1 + O_2 + \cdots + O_T) / T.$$  

(10)

6. Evaluation

After obtaining the result $Y$, it is compared with Test′′ to obtain the accuracy of the bagging-BLS method, accuracy is represented by $acc$

$$acc = (P) / L,$$  

(11)

where $P$ is the number of samples that are correctly predicted, $L$ ($L = N \cdot 36.8\%$) is the number of samples in the testing dataset $\text{Test}$, and $\text{Accuracy}$ is used to describe the reliability of each algorithm. In addition, the $kappa$ value can be used to meaningfully evaluate the diagnosis efficiency of algorithm. The definition of $kappa$ is as follows:

$$kappa = \frac{P_o - P_e}{1 - P_e},$$

(12)

where $P_o$ is the general accuracy of the output and

$$P_e = \frac{a_1 \cdot b_1 + a_2 \cdot b_2 + \cdots + a_c \cdot b_c}{N \cdot N},$$

(13)

where $a_1, a_2, \cdots, a_c$ are the real numbers of each class label, $b_1, b_2, \cdots, b_c$ are the numbers of each class in the prediction output, and $N$ is the total number of samples. The algorithm flow chart of the bagging-BLS model is shown in Figure 7.

![Figure 7. Flowchart of the proposed algorithm.](image-url)
4. Experiment

On the basis of abrasive particle data from the oil analysis of an aerospace engine, a systematic experiment was carried out to verify the proposed bagging-BLS model. In total, 750 sets of sample data were selected, including 300 sets under healthy conditions, 300 sets under bearing wear conditions, and 150 sets under gear wear conditions. Eight features, including normal particles, spherical particles, layered particles, fatigue particles, cutting particles, severe sliding particles, red oxide particles, and black oxide particles were taken as input into the bagging-BLS model to diagnose aeroengine part wear. The data were collected from [7,29,39], all of which were good studies on aircraft fault diagnosis with important reference value for our research. The kinds of aerospace engines used in these studies ranged from turboprop engines to piston engines, which have been widely used in modern airplanes and are prone to experiencing wear faults.

4.1. Feature Selection

There were eight features ($X_k$) in our work, as well as labels $C$. The dimension of $X_k$ and $C$ were both $N \times 1$. We calculated the score of each feature using the MATLAB(2018a) software, based on Equation (5). The score of each feature is shown in Table 3.

| Mutual Information | $I (X_1, C) = 0.6062$ |
|--------------------|------------------------|
|                    | $I (X_2, C) = 0.0485$  |
|                    | $I (X_3, C) = 0.0118$  |
|                    | $I (X_4, C) = 0.0118$  |
|                    | $I (X_5, C) = 0.0118$  |
|                    | $I (X_6, C) = 0.4214$  |
|                    | $I (X_7, C) = 0.1567$  |
|                    | $I (X_8, C) = 0.2273$  |

From the table, it can be seen that $X_3$, $X_4$, and $X_5$ had the same (lowest) MI score, which means that these features were less relevant to the output label. As a result, we selected $X_1$, $X_2$, $X_6$, $X_7$, and $X_8$ as the input features to the diagnosis model.

4.2. Diagnosis Results Based on Random Forest

In order to test the advisability of the application of the proposed model for the wear fault diagnosis of aircraft engines, we used the random forest (RF) algorithm for comparison, in order to illustrate the desirability and superiority of the bagging-BLS algorithm. Random forest is a classical ensemble learning algorithm [40], where decision trees are used as sublearners to obtain better accuracy (over a single decision tree). The trees in RF used the C4.5 algorithm and the depth was 12, including a total of 100 trees in the forest. There were 500 training data samples and 250 test data samples. In the following experiments, random forest is denoted as RF, broad learning system is denoted as BLS, and the proposed model is denoted as bagging-BLS.

Figure 8 shows the diagnosis accuracy test results for the three algorithms. For random forest, 100 decision trees were included, where twelve leaf layers were generated for each decision tree. Figure 8 shows the total test accuracy of the random forest model after the addition of each tree. It can be seen, from the figure, that the highest accuracy was obtained near the 95th iteration, and after 60 iterations, the test accuracy remained stable (at around 0.948). The diagnosis accuracy of the algorithm took approximately 30 iterations to near a stable value.
In order to explore the advantages of the optimization of BLS, we conducted experiments on a single initial BLS model, setting the number of hidden layer neurons to 150 and iterating 100 times. The number of samples in the training set was 500, and the testing dataset included 250 samples. As can be seen from Figure 8, although the accuracy rate of the single initial BLS model was higher than random forest, the accuracy was not stable under the BLS model. The float range of the testing accuracy of the single BLS was between 0.93 and 0.96, where the largest float was up to 3%. After 100 iterations, it was still not stable and kept floating, and so, the performance of the single BLS model was poorer than random forest. In order to combine the merits of the two algorithms, and avoid the shortcomings of each, the proposed method connected the organization method of random forest with the basic principle of BLS, with which we expected to create a maneuverable diagnosis method and obtain a better accuracy for wear fault diagnosis.

For wear fault diagnosis, the learning ability of the random forest model was stable but its accuracy was not satisfactory; furthermore, the single BLS model could achieve better accuracy, but with a large accuracy range and lack of stability. Considering the shortcomings of the above algorithms, a new ensemble learning model based on BLS (bagging-BLS) was developed. For our model, 100 BLS models were prepared (each model’s hidden layer having 150 nodes, the same as in the single BLS). The process for establishing the bagging-BLS model is shown in Figure 7. The sampling ratio \( p \) was set to 0.8, such that each training sub-dataset included 400 samples and the testing dataset included 250 samples. It can be seen, from Figure 8, that the accuracy of the bagging-BLS method was stable at 0.988 and the float range was less than 2%. Compared with the previous two algorithms, bagging-BLS had higher accuracy and faster convergence speed. As shown by the experiment, it performed well for the purpose of wear diagnosis and successfully combined the advantages of the BLS and random forest models.

Figure 8 shows a precision comparison of the three algorithms. It can be seen that, after 80 iterations, the test accuracy of random forest was stable at around 0.94. At each iteration, the test accuracy of the bagging-BLS model was much higher than that of random forest. The accuracy of a single broad learning system was around 0.96, but the accuracy of the improved model was obviously higher (reaching 0.98–0.99) and much more stable. Experiments on the wear failure of aircraft engines have verified the correctness of the broad learning system based on ensemble learning.
(bagging-BLS) model proposed in this work. It has also been verified that the learning effect of the bagging-BLS model was better than that of a single broad learning system model. At the same time, it is also better than the random forest model, a traditional ensemble learning algorithm. Therefore, bagging-BLS can be used as a powerful tool for aircraft engine wear fault diagnosis.

Figure 9 shows the testing results of the three algorithms in the form of a pie chart. There were three types of wear models, represented by different colors. The offset slices in the pie represent the error cases, titled by the corresponding class name; for example, II-error means an error case in category II. The slices that are not offset represent correctly predicted cases. The offset area can be seen to decrease from Figure 9a–c, indicating that the accuracy of the testing result is highest for the bagging-BLS model.

![Figure 9. Pie chart of the test results of the three compared algorithms.](image-url)
On the basis of Equations (12) and (13), we obtained the *kappa* values of each algorithm, which are shown in Figure 10. Clearly, bagging-BLS obtained the highest *kappa* value, which means that it achieved a satisfactory consistency between the real data and the predicted output.

Therefore, it can be concluded that the proposed model achieved the highest accuracy and had the best learning effect for diagnosis applications, among the compared algorithms.

![Figure 10. *kappa* of the three algorithms.](image)

Figure 11 shows the performance of the algorithms under different numbers of inputs (from 3–8). The horizontal axis represents the number of inputs and the vertical co-ordinate represents the test accuracy. It can be seen that, when only three features were input into every model, random forest and bagging-BLS had the same performance (at 0.86) and single BLS performed badly. However, when an increased number of features were input, both the bagging-BLS and single BLS models improved quickly, but the performance of random forest decreased before improving. As is shown in the figure, the performance of bagging-BLS was better than the other models for all numbers of input features. The results show that bagging-BLS obtained the best diagnosis accuracy under different inputs.

![Figure 11. Comparison between three algorithms, with the number of input features ranging from 3 to 8.](image)
5. Conclusions

This paper presents a novel wear fault diagnosis method for aircraft engines based on the proposed bagging-BLS model. In industrial applications, oil analysis is an effective way to monitor the wear fault state of an aeroengine. Oil analysis can obtain the feature information of the wear particles in the oil (such as the type, size, and quantity of wear particles) and then diagnose the working state of the engine. This can not only predict wear faults, but also monitor the development of the faults. The proposed bagging-BLS model provides an efficient method for data processing of such abrasive particle data. Feature selection based on MI was first applied to search for the most relevant features and reduce the redundancy of the model. Experiments were carried out to compare the proposed model to the random forest and single BLS models, in order to verify its learning effect. Finally, the stability and reliability of the bagging-BLS algorithm were determined. The proposed model provides a powerful theoretical basis for the wear fault diagnosis of aircraft engines, and thus, a convenient tool to ensure aircraft safety.

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