ResNet-based Vibration Fault Diagnosis for Aero-engine Bearings

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Abstract. As a key component of the aircraft, the operation of the aeroengine is very important. Traditional fault diagnosis methods face many challenges in dealing with high-dimensional data and complex pattern recognition. The purpose of this study is to compare the fault diagnosis performance of various machine learning and deep learning algorithms in bearing vibration data. By optimizing the algorithms and parameter settings, the classification accuracy and computational efficiency of the models are improved, thus enhancing the operational reliability and maintenance efficiency of the equipment. On the one hand, the time domain and frequency domain features of vibration data are extracted, and then the PCA method is used to reduce the dimension of high-dimensional feature data, and then the model is optimized by grid search and cross validation. On the other hand, the data is directly transmitted to the neural network model for learning prediction without feature extraction. The results show that the classification accuracy of the optimized SVM model on the experimental data set reaches 97 %, and the prediction accuracy of the deep learning algorithm based on Resent-CNN on the data set reaches 100 %. The research method and results can be applied to equipment fault prediction and maintenance in industrial production, and further improve the reliability and safety of equipment operation.

Keywords: Fault Diagnosis, Machine Learning, Deep Learning, 1D-CNN, ResNet.

1. Introduction

Bearing is the key component of aero engines; its running condition is directly related to the overall performance of engines and flight safety. However, given the harsh working environment characteristic of aviation engines, bearings are susceptible to failure, which can result in significant accidents[1]. In view of this, it is particularly critical to implement accurate detection and classification of bearing failures, which not only helps to prevent potential accident risks, but also effectively reduces maintenance costs and guarantees the reliable operation of aircraft.

At present, the identification of bearing faults is chiefly accomplished through the utilization of conventional vibration analysis techniques and the application of manual expertise, with spectral analysis being a commonly employed technique that transforms time-domain signals into the frequency domain to uncover the frequency components indicative of bearing issues. These methodologies are characterized by deficiencies such as low detection efficiency and a high misdiagnosis rate[2].The advent of machine learning technologies, particularly the implementation of deep learning algorithms within the domain of fault diagnosis, has emerged as a promising solution to address these challenges, offering a novel and efficient approach for bearing fault detection[3]. Hai-Rui Liu and colleagues have proposed an aero-engine bearing fault diagnosis and life prediction method based on the adaptive particle swarm optimization algorithm (APSO) optimized least squares support vector machine (LSSVM)[4]. In a related study, Zhang Bowen and colleagues[5] proposed an aero-engine bearing fault diagnosis method based on rotor displacement probability density information (PIRD) and one-dimensional convolutional neural network (1DCNN). In addition, ResNet has excellent performance in image classification, but there has been little research on aeroengine rolling bearing fault diagnosis. This approach effectively addresses the challenges posed by traditional methods in terms of feature extraction and pattern recognition.

In summary, this study aims to explore a more accurate and efficient method for fault diagnosis of aircraft engine bearings. Firstly, this paper extracts time-domain and frequency-domain features from vibration data, and then applies Principal Component Analysis (PCA) to reduce the dimensionality of these features, thereby decreasing data complexity while retaining critical information. Based on this, the paper employs machine learning models for fault prediction and conducts a comparative analysis with deep learning models that directly use raw vibration data as input. The core of this study lies in comparing and evaluating the performance differences and advantages/disadvantages of machine learning and deep learning in fault diagnosis of aircraft engine bearings. Figure 1 illustrates the technical route of this study.

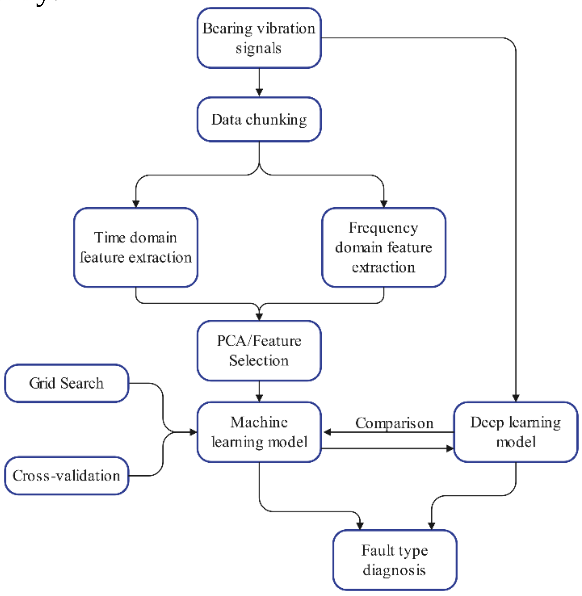


Figure 1. Modeling Process

2. The extraction of features from the time domain and frequency domain

When distinguishing fault types, it is often necessary to combine time domain features and frequency domain features as fault judgment criteria[6]. Some of the formulas for time domain and frequency domain feature parameters are as follows, ranging from Equation 1 to Equation 10.

Where $x(t_i)$ represents a vibration signal sequence, $t_i\,(i=1,2,...,N)$ is the time series, and N represents the sequence length. $s(n_i)$ represents the spectrum sequence corresponding to the signal $x(t_i)$, $n_i\,(i=1,2,...,K)$ is the frequency sequence, and K represents the number of spectrum points; f_i represents the frequency value of the i_{th} spectrum line.

Mean value
$$\overline{X}=\hat{\mu}_x=\frac{1}{N}\sum_{i=1}^{N}x\left(t_i\right) \tag{1}$$

Variance
$$\sigma_x^2=\frac{1}{N}\sum_{i=1}^{N}\left[x(t_i)-\hat{\mu}_x\right]^2 \tag{2}$$

Peak value
$$\hat{X}=\max\left(x(t_i)\right) \tag{3}$$

Effective value
$$\hat{X}_{rms}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x^2\left(t_i\right)} \tag{4}$$

Root mean square amplitude
$$X_r=\frac{1}{N}\sum_{i=1}^{N}\sqrt{|x(t_i)|} \tag{5}$$

margin
$$L=\frac{\hat{X}}{X_r} \tag{6}$$

Pulse value
$$I = \frac{\hat{X}}{\left|\bar{X}\right|} \tag{7}$$

Peak factor
$$C = \frac{\hat{X}}{X_{rms}} \tag{8}$$

Mean frequency
$$MSF = \frac{\sum_{i=1}^{K} s\left(n_i\right)}{K} \tag{9}$$

Center of gravity frequency
$$FC = \frac{\sum_{i=1}^{K} s\left(n_i\right) \times f_i}{\sum_{i=1}^{K} s\left(n_i\right)} \tag{10}$$

3. Machine Learning and Deep Learning for Aviation Bearing Fault Diagnosis

3.1. Data sources

The data set used in this paper is derived from the bearing data center of Case Western Reserve University[7] . The data set records four main fault types: inner ring fault, outer ring fault, rolling element fault and normal operation state, and some diagrams[8] are shown in Figure 2. For each fault type, the dataset provides samples with four different fault diameters (0.007 inch, 0.014 inch, 0.021 inch and 0.028 inch, respectively), and all data are collected at a sampling rate of 12 kHz.

Figure 2. Bearing Fault Illustration

After the data collection work is completed, this paper uses a variety of Python libraries to perform a preliminary visual analysis of the obtained raw data. In view of the limitation of the length of the article, only the visual graphics of some data are presented here, as shown in Figure 3.

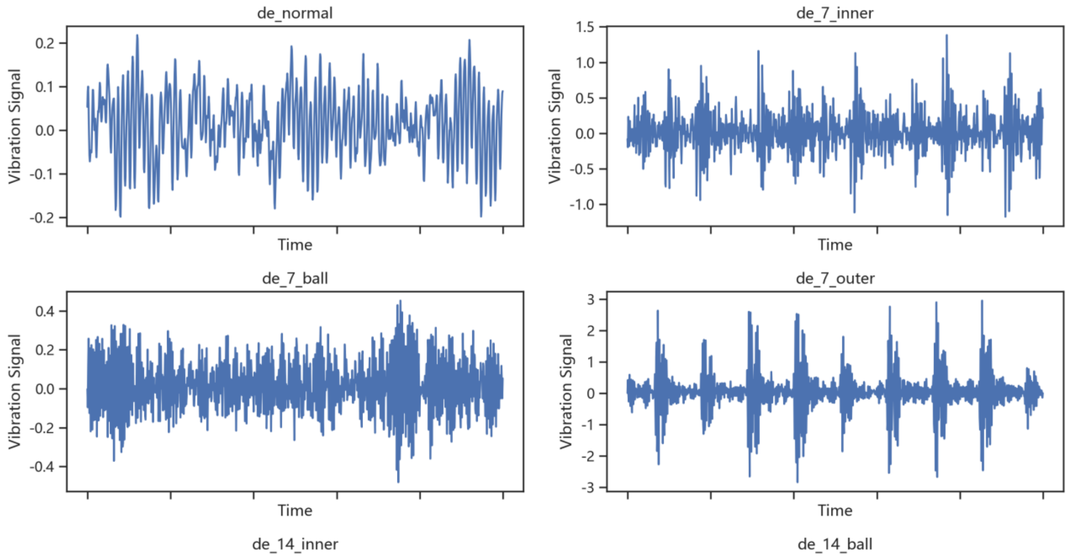


Figure 3. Part of Working Condition Data Visualization

Observe the time-varying curves of four diverse types of vibration signals shown in the above diagram. The amplitude and frequency of these signals show a certain fluctuation, but also show a certain periodicity and repeatability. Therefore, by collecting enough data, a suitable machine learning model can be established to achieve effective prediction and analysis of such vibration signals.

To optimize the processing and analysis of the original bearing vibration data, this paper divides each 1024 data points into a sample block and then extracts the time domain and frequency domain features. This length approximately represents the time interval of the three rotating rings of the bearing, which can not only intercept most of the key vibration information, but also effectively control the data processing scale. Subsequently, to visually display the quantitative relationship of different fault category samples, this paper uses Figure 4. for visual display.

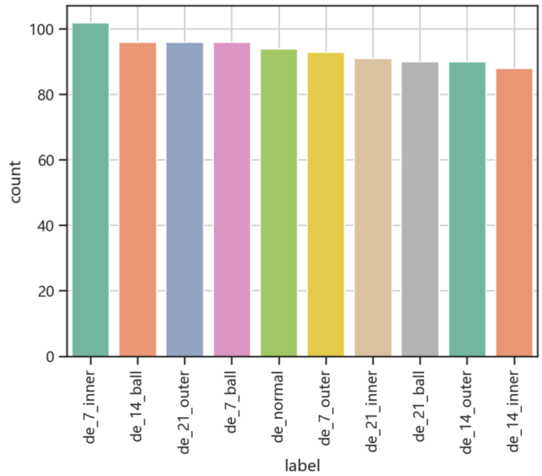


Figure 4. Number of Samples of Different Fault Categories

Observing Figure 4, it is found that the number distribution of various fault samples is balanced. This shows that the distribution of data sets between categories is uniform, and there is no obvious imbalance.

3.2. Data preprocessing

To evaluate whether there are outliers in the time domain and frequency domain features (mean, standard deviation, mean frequency, etc.) extracted from the original data set, this paper uses the box diagram to visually detect. The box diagram corresponding to some features is shown in Figure 5.

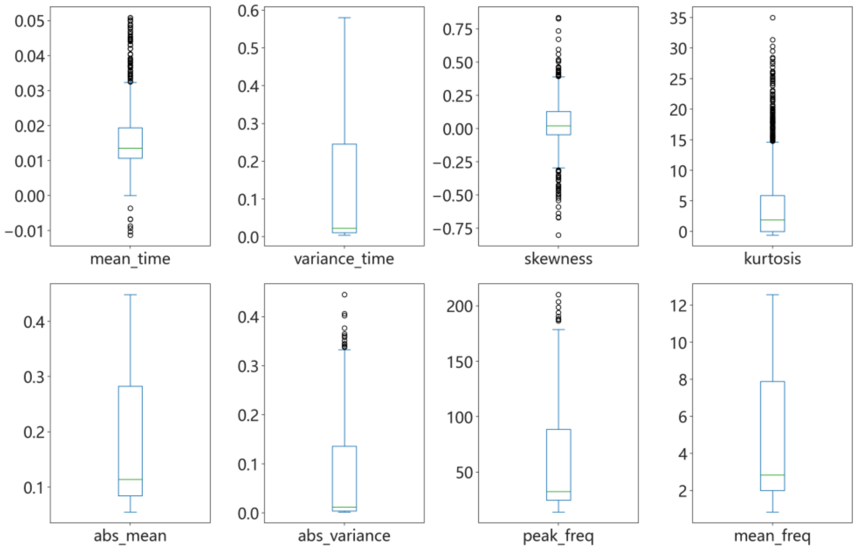


Figure 5 Box View of Some Features

In the in-depth analysis of the data distribution presented in Figure 5, it is noted that there are significant outliers in some variables. For example, among the two features of ' skewness ' and ' kurtosis ', the number of outliers is particularly prominent, and the degree of outlier is much higher than the average level of other variables. The existence of such outliers may adversely affect the subsequent data analysis and modeling process, resulting in inaccurate or biased results.

Therefore, to ensure the reliability and accuracy of the data analysis results, this paper uses RobustScaler to deal with these outliers. RobustScaler is a commonly used data scaling method, which can effectively identify and reduce the impact of extreme values that deviate from the overall trend. By calculating the median and interquartile range (IQR) of each variable in the data set, RobustScaler can determine a reasonable scaling range.

3.3. Feature screening

3.3.1 Analysis of variance (ANOVA)

In view of the considerable number of features involved, if all features are included in the model training without screening, it may cause dimensional disaster problems. To this end, this study adopted analysis of variance (ANOVA) as a means of feature screening[9] to screen out features that have a significant impact on the classification task.

To intuitively show the relationship between salient features and labels, the catplot function in the Seaborn library is used to draw histograms and box plots to show the relationship between category labels and corresponding eigenvalues. For example, Figure 6 shows the difference between the feature abs_mean under different category labels, and Figure 7 shows the distribution of each feature value of the feature abs_mean under different category labels. Through these diagrams, we can intuitively observe the distribution and difference of the observed features between distinct categories.

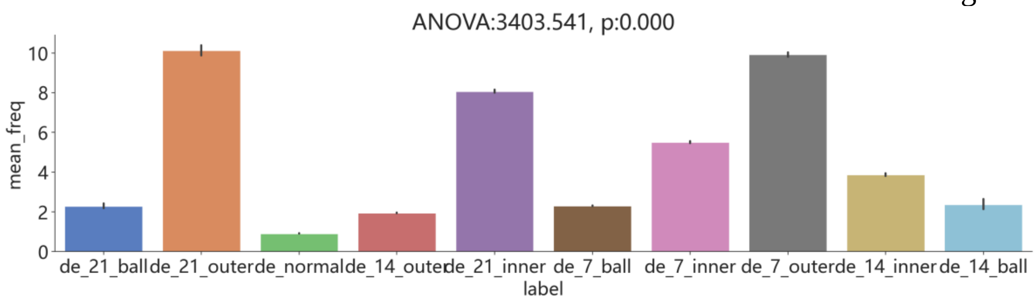


Figure 6. Distribution of Feature mean_freq Across Different Labels (ANOVA Plot)

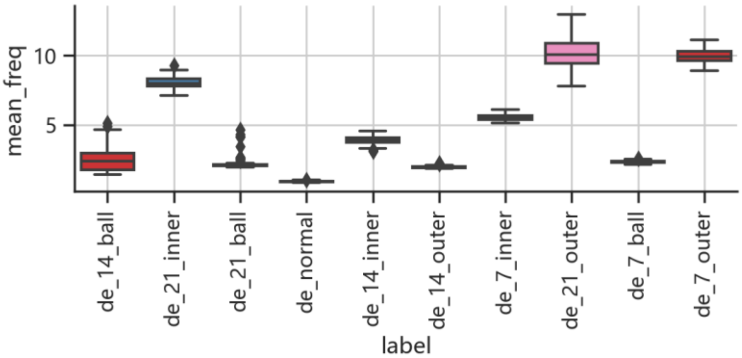


Figure 7. Distribution of Feature mean_freq Across Different Labels (Boxplot)

3.3.2 Principal component analysis (PCA)

In order to further simplify the features and visually display the structure of the data, this paper uses the principal component analysis (PCA) method to reduce the high-dimensional data to a lower-dimensional space[10]. Figure 9 shows the PCA scatter diagram after dimension reduction, through which the distribution of each class in the principal component space can be observed intuitively.

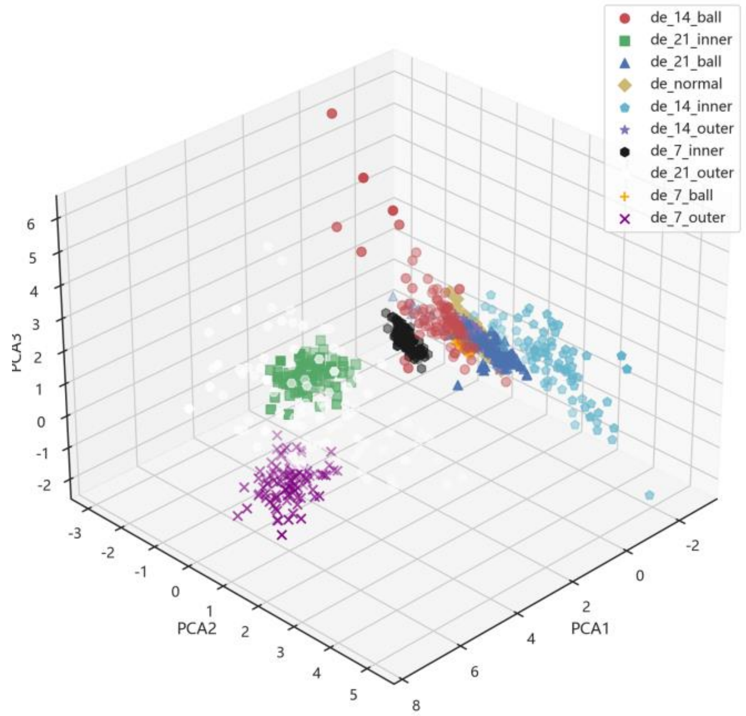


Figure 8. 3D PCA Plot of Bearing Vibration Data

It can be found from Figure 8 that the three-dimensional PCA diagram clearly shows the obvious distinction between different fault types and normal states in the bearing vibration data. Each state type is presented in a unique cluster form in the figure[11], indicating that the principal component analysis effectively captures the basic patterns associated with each state. Although the three-dimensional principal component analysis diagram is easy to represent intuitively, to determine the final dimension reduction, this paper uses the following code method to determine the dimension reduction result. The running result is shown in Figure 9.

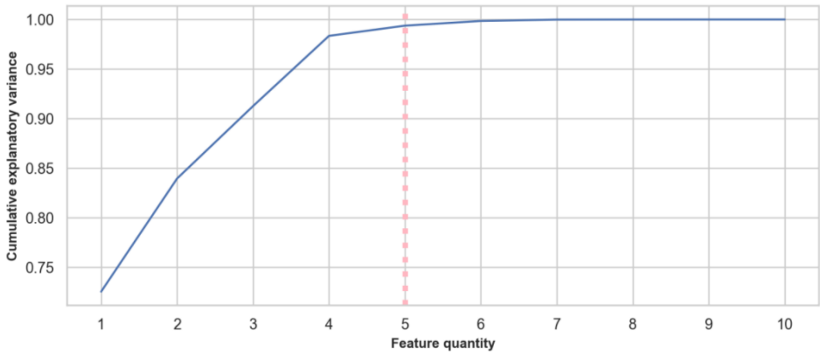


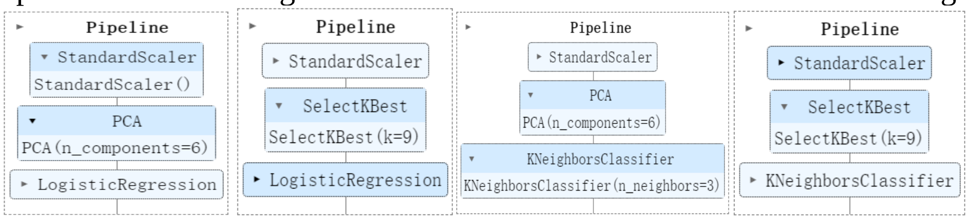
Figure 9. Cumulative Explained Variance of Principal Components

This method determines the optimal dimension reduction by calculating the cumulative interpretation variance. It can be seen from the figure that the first five principal components explain most of the variance. This means that these five principal components have effectively retained the main information of the original data, which is sufficient for subsequent analysis and modeling. Selecting the first five principal components for dimensionality reduction can not only simplify the model calculation, but also reduce noise interference and improve the performance of the model. Therefore, the first five principal components were finally selected for subsequent analysis.

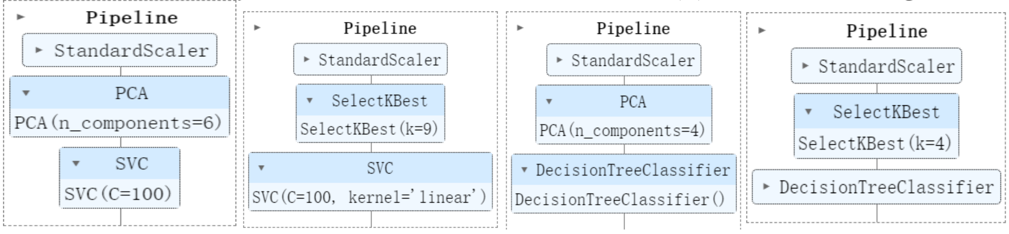
3.4. Predicting Aero-Engine Bearing Fault Classification with Machine Learning

3.4.1 Model structure

When using machine learning related algorithms, the training set is the extracted time domain and frequency domain features. PCA and variance analysis are used for data dimensionality reduction. In model training, logistic regression, KNN, SVM and Decision Tree algorithm are used to train the model, and pipeline is used to integrate the model. The model structure is shown in Figure 10.



(a) Logistic Regression (b) K-Nearest Neighbor



(c) Support Vector Machines (d) Decision Tree

Figure 10. Structure of each machine learning models

3.4.2 Model hyper parameterization

To optimize the hyper-parameters of the model and reduce the accidental factors, this paper uses a combination of Grid Search and Cross-Validation[12]. Specifically, 5-Fold Cross-Validation is used to evaluate the performance of the model. Due to space, only the verification curve of the logistic regression model after PCA dimension reduction is attached here, as shown in Figure 11.

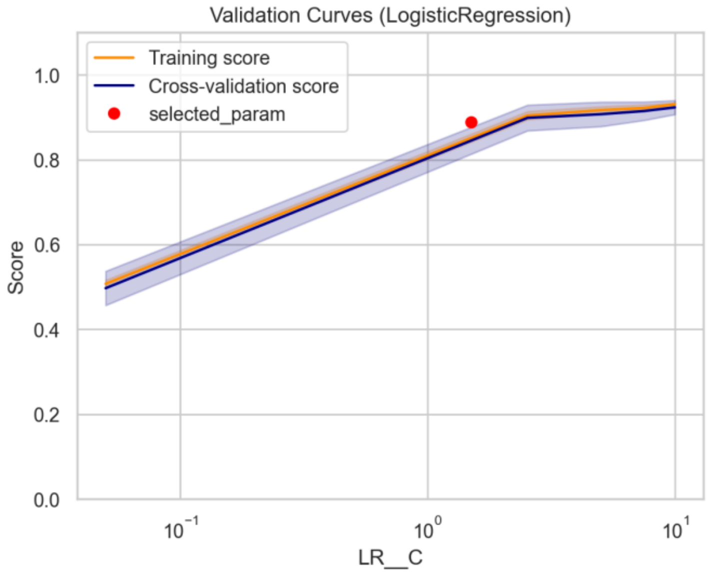
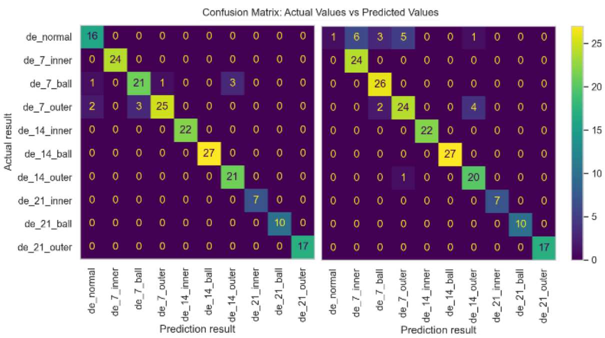


Figure 11. Validation Curve

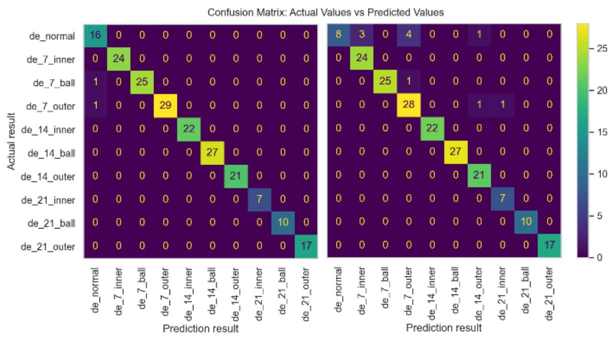
It can be seen from Figure 11 that the verification curve shows the model performance under different hyper-parameter values, which helps this paper to select the best hyper-parameter combination, thus improving the performance and generalization ability of the model.

3.4.3 Model prediction results

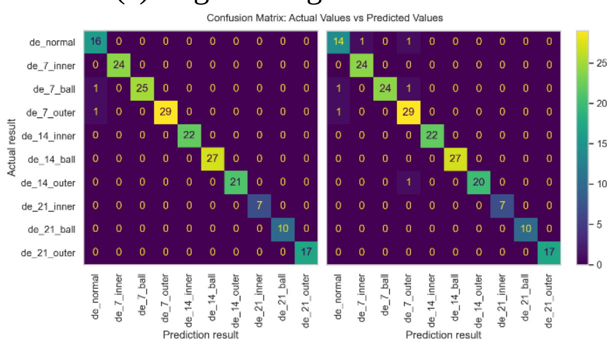
The well-trained model is brought into the test set to obtain the confusion matrix, as shown in Figure 12. In addition, the corresponding Accuracy, Precision, Recall and F1-Score of the model are shown in Table 1 (the left side of each indicator is PCA dimensionality reduction, and the right side is analysis of variance).



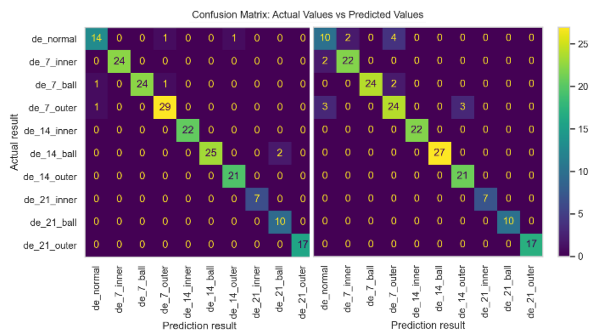
(a) Logistic Regression



(b) K-Nearest Neighbor



(c) Support Vector Machines



(d) Decision Tree

Figure 12. Confusion matrix for machine learning models

Table 1 Performance Comparison of Classification Algorithms

Model	Accuracy		Precision		Recall		F1-Score	
LR	0.95	0.89	0.95	0.90	0.95	0.89	0.95	0.86
KNN	0.96	0.94	0.96	0.95	0.96	0.94	0.96	0.94
SVM	0.99	0.97	0.99	0.97	0.99	0.97	0.99	0.97
DTC	0.96	0.91	0.97	0.91	0.96	0.91	0..97	0.90

After comparison, it is not difficult to find that in the current situation, the Support Vector Machine algorithm has the best comprehensive performance.

3.5. Predicting Aero-Engine Bearing Fault Classification with Deep Learning

This is different from the time domain and frequency domain features brought in by machine learning mentioned above. In the deep learning model, this paper directly substitutes the original vibration data to train the model and obtains the training and verification loss curve in the test set as shown in Figure 13.

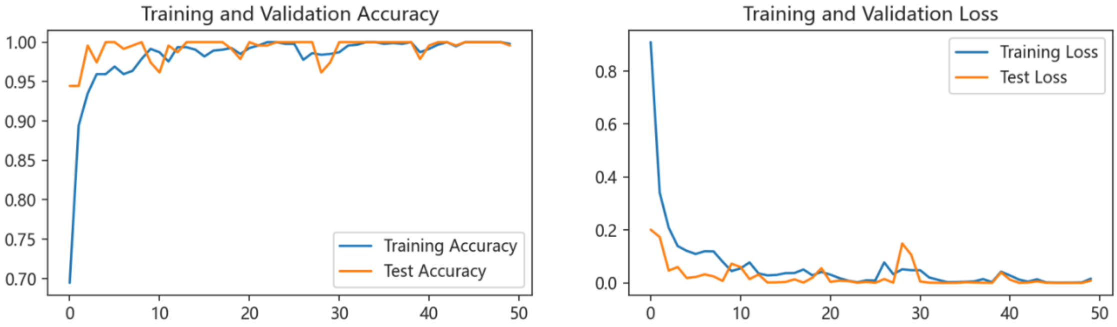


Figure 13. Training and Validation Loss Curves

Figure 14 and Figure 15 are the confusion matrices of 1D-CNN and Resent-CNN models. The performance metrics of the model are detailed in Table 2.

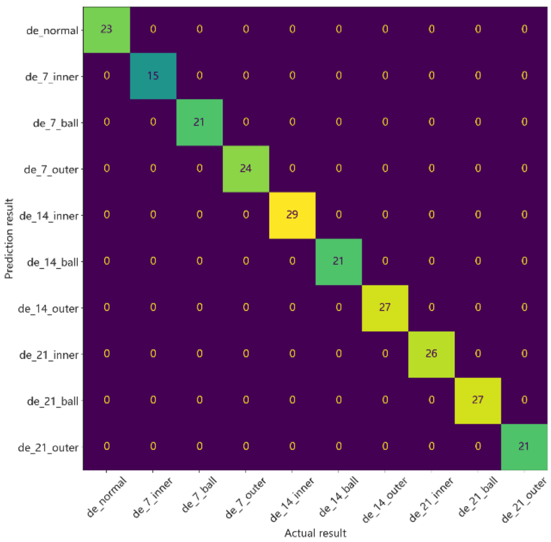


Figure 14. 1D-CNN

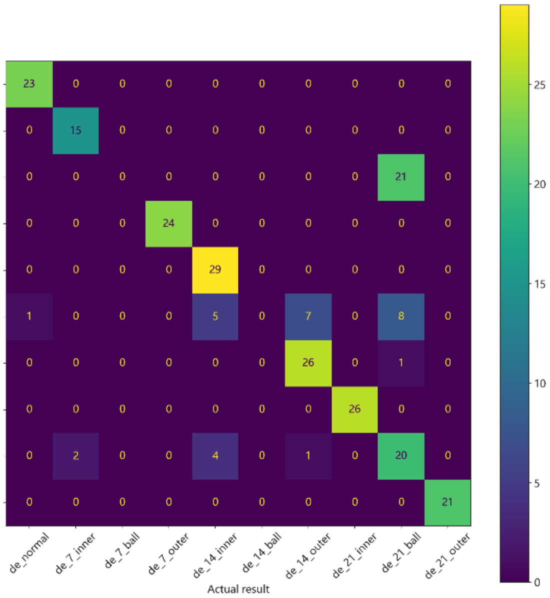


Figure 15. Resent-CNN

Table 2 Performance Comparison of Deep Learning Algorithms

Model	Accuracy	Precision	Recall	F1-Score
1D-CNN	0.786	0.683	0.786	0.725
Resent-CNN	1.00	1.00	1.00	1.00

The residual neural network has obvious advantages over the one-dimensional convolutional neural network on this data set, and compared with the above machine learning algorithms, the residual neural network algorithm is also better in this classification task.

3.6. Performance Comparison of Machine Learning and Deep Learning

In the fault diagnosis of aircraft engine bearings, machine learning and deep learning show different advantages. The machine learning algorithm represented by SVM has the advantage of easy implementation, especially for small sample data and relatively simple feature extraction scenarios. However, it can be seen from the results of Table 2 that the selection of PCA and ANOVA makes the results fluctuate greatly. This shows that machine learning algorithms are highly dependent on feature extraction, and the quality of features directly determines the effect of the model. In the face of complex, multi-dimensional and large amounts of data, the performance of machine learning may be limited.

In contrast, deep learning algorithms such as ResNet-CNN can automatically extract deep features from raw data, reducing the difficulty of feature selection. This type of model performs particularly well when dealing with large-scale data, and has achieved excellent results in the test set. The accuracy comparison between Table 2 and Table 3 shows that deep learning can effectively model and deal with complex relationships.

4. Conclusions

Through in-depth analysis and exploration of bearing vibration data, this study reveals the effectiveness and universality of using main machine learning (such as logistic regression, KNN, SVM, etc.) and deep learning algorithms for fault diagnosis. The results show that the PCA method is used to reduce the dimension of high-dimensional feature data, which not only effectively retains the main variation information of the data, but also significantly improves the computational efficiency and prediction performance of the model. The hyperparameters of the model are optimized by grid search and cross-validation (5-Fold). The application of different machine learning algorithms proves the effectiveness of the method. The experimental results show that the optimal hyper-parameter combination can significantly improve the classification accuracy of the model, indicating that fine parameter adjustment has an important impact on the performance of the model.

In practical applications, the methods and results of this study can be widely used in equipment fault diagnosis and predictive maintenance in industrial production, improve the reliability and safety of equipment operation, and reduce maintenance costs and unplanned downtime. In practical applications, we can also explore how to better apply the model to different industrial scenarios. By constructing a more flexible and scalable system, embedding the fault diagnosis model into the industrial IoT platform, a wider range of online monitoring and predictive maintenance can be achieved, providing a more intelligent solution for industrial production.

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