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Research on bearing fault diagnosis technology based on machine learning

Yu Xia *, XiaoJun Guo, ErChuan Su, LingPei Kong

Faculty of Mechanical Engineering, Tianjin University of Technology and Education, China
* Corresponding Author: 2228490043@qq.com

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ABSTRACT

As industrial equipment complexity continues to rise, the importance of bearings within these systems has become more critical, given their pivotal role in equipment functionality. Bearing faults can result in severe production accidents and safety issues. Hence, there is an urgent need for advanced bearing fault diagnosis technology. This study concentrates on rolling bearings, analyzing their structural characteristics and key parameters to classify fault types—inner race faults, rolling element faults, and outer race faults. Utilizing a dataset of 80 sets of bearing factory data, time and frequency domain analyses are conducted, establishing seven feature parameters (five in the time domain and two in the frequency domain). This data is organized into a 7-dimensional matrix for subsequent analysis and model development. The K-Means algorithm is chosen for its effectiveness in automatically recognizing fault patterns in rolling bearings. Training on the 7-dimensional matrix identifies four clustering centers corresponding to normal conditions, inner race faults, rolling element faults, and outer race faults. The fault diagnosis system is implemented using Python, and algorithm optimization improves efficiency. The study concludes with insights drawn from the analysis and proposes optimization methods, which contributing to advancing bearing fault diagnosis technology, particularly addressing industrial equipment reliability and safety concerns.

1. Introduction

The second industrial revolution brought the internal combustion engine into people's vision, and then the machinery industry has developed vigorously and gradually developed into the mother of engineering. Since then, the engineering field cannot lack the participation of machinery. As one of the most common components in mechanical structures, the quality of bearings directly affects the regular operation of equipment [1]. However, the traditional method of bearing fault diagnosis still relies on borrowing the experience of the master to listen with the ears and see with the eyes, and to determine the location of the bearing fault through troubleshooting. Most factories currently adopt the traditional training mode of teachers and new employees, which consumes a lot of manpower and resources. And the types of bearings are extremely diverse, and a device may use several or even dozens of types of bearings. The purpose and manufacturing accuracy of each type of bearing vary, which also makes the methods and costs of bearing fault diagnosis different. Taking rolling ball bearings as an example, this paper conducts in-depth analysis of their fault modes using extensive data measured by predecessors in the field of bearing faults, and uses clustering algorithms in machine learning to process the analyzed data, thus achieving automatic recognition of rolling bearing fault modes based on machine learning.

With the continuous development of industrial level, Western society is gradually moving towards Industry 4.0 [2]. While the West proposed Industry 4.0, China also proposed the Made in China 2025 Plan to guide the direction of China's industrial development, which is an industrial development that adapts to China's national conditions. Artificial intelligence technology is the most important direction in the Made in China 2025 plan. Artificial intelligence technology is the major trend and new trend of future development, and machine learning, the most important direction under artificial intelligence, has broad prospects [3]. Especially with the rapid development of computer hardware in modern times, the birth of big data has brought broader development space for models.

As the most core transmission component of electromechanical equipment, rolling bearings are known as the joints in electromechanical equipment, indicating their crucial position in the field of electromechanical equipment. Rolling bearings, as load-bearing components, often need to carry the operation of the transmission shaft. During the operation of the transmission shaft, the rotational speed is extremely high and accompanied by radial and axial runout, so the rolling element always bears variable loads during the working process of the rolling bearing. Therefore, the contact points between the inner and outer race raceways of the bearing and the surface of the rolling element are usually subjected to fluctuating cyclic contact stress [4]. The rolling element of a rolling bearing is in point-and-line contact with the inner and outer rings, which is a high pair connection. Therefore, rolling bearings are highly susceptible to wear and tear in practical use. Once wear and tear expand, the rolling bearing will malfunction. At this time, timely detection of bearing faults and maintenance or replacement can minimize equipment losses.

This paper proposes a clustering algorithm to process the characteristic parameters of bearings automatically to identify rolling bearing failure modes. To achieve immediate maintenance and replacement in the event of rolling bearing failure, reduce equipment loss caused by rolling bearing failure.

In recent years, with the outbreak of a war between Google's Alpha Dog and Go Masters, and the complete victory of artificial intelligence, the argument that artificial intelligence cannot achieve autonomous thinking has been defeated. At this point, artificial intelligence has emerged in a strong posture in front of people, allowing them to appreciate the charm of artificial intelligence. Although people have varying opinions on the development of artificial intelligence, this does not hinder its comprehensive development in modern times. Many countries have made the development of artificial intelligence a national strategy. Machine learning aims to achieve intelligence and intelligence in various products, but the first step towards achieving the goal is data. With the advent of the big data era, the scale of data is no longer what it used to be. Previously, data samples had a capacity of several tens of hundreds, but now the data size is often measured in tens of thousands. This will be a great opportunity for the development of artificial intelligence, but it is also a major challenge. Artificial intelligence urgently needs to seek development in the era of big data and achieve technological leaps in line with the times. To achieve a technological leap in the big data model, it is necessary to make substantive reforms and optimizations to existing technologies from the perspective of combining software and hardware. Using the ideas of Professor Marr, the founder of computer vision, we can categorize the development of artificial intelligence into three stages [5]. The first priority is obtaining the target's data; the second is analyzing the obtained data; And the third is achieving the intelligence of something by using certain ideas or algorithms. The difference between big data technology and machine learning is that big data tends to acquire data, while machine learning tends to process data and how to use data to achieve intelligence in certain things [6].

The first significant leap in machine learning was due to the intersection and integration of the computer and mathematics fields that began in the 1990s, during which many significant scientific research achievements emerged in machine learning. For example, the birth of support vector machines, the proposal of decision forests, and the optimization of Bayesian theory. These scientific research achievements have laid a solid foundation for the rise of machine learning in the future.

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Nowadays, machine learning has penetrated into various industries, and it can be said that artificial intelligence is ubiquitous in the modern world. Machine learning not only has great development in its own field, but also provides favorable tools for the fields of data statistics and data analysis. Machine learning is undoubtedly a hot research field, especially in the field of mechanical engineering. Combining machine learning with traditional machinery can form a new direction, committed to making the manufacturing process intelligent and further liberating people's hands. Therefore, many universities in China have included artificial intelligence and machine learning as compulsory courses in their student training programs.

Machine learning can undoubtedly be seen as the application direction of artificial intelligence. So, machine learning needs to play its role as a tool in engineering. In recent years, machine learning has been widely applied in the field of engineering, such as deep learning and machine vision, which are currently particularly popular. In today's society, machine learning has achieved considerable success in the field of engineering, such as the voice wake-up service on mobile phones and the voice switching function on smart speakers, which are all successful applications of machine learning [7].

Machine learning is a newly established discipline in China, but it has received sufficient attention and achieved significant results quickly. However, very few scholars specialize in machine learning in China, so the cutting-edge research achievements in machine learning in China are indeed not significant enough. This is also an aspect that we urgently need to seek change.

Under the continuous operation of bearings, there will inevitably be vibration and sound generation, and the vibration frequency and sound size generated at different periods are affected by factors such as speed and environment. Therefore, a basis for fault diagnosis of bearings can be obtained by collecting parameters with different operating characteristics and further analyzing and processing the collected data. Due to the various data sources collected, the parameter analysis of bearings can generally be divided into two categories: the sound analysis method using sound analysis, and the vibration analysis method using vibration analysis.

Firstly, we attempt to use the sound analysis method of analyzing sound. However, in the actual operation process, we encountered great obstacles. When we tried to collect sound signals from the running bearings, the measured data was accompanied by a lot of noise. Later, analysis found that the noise other equipment emitted during data collection interfered with our measurement results. Due to the fact that the working environment of bearings is often in complex factory environments, there is inevitably noise around them. Therefore, we cannot use sound analysis method to collect fault data of rolling bearings. After excluding sound analysis method, we have to use vibration analysis method to collect fault data of bearings.

The data in this article is measured by installing a speed sensor to measure the vibration frequency signal of the bearing. After further analysis and processing of the measured data, the operating conditions of the bearings under different conditions and states can be obtained. Because using vibration measurement method can significantly reduce external interference with experimental results, current research on bearing fault diagnosis mainly uses vibration analysis method. This experiment is based on the periodic pulse vibration and amplitude regulation phenomenon of bearing vibration signal, combined with the frequency domain analysis method, time domain analysis method and time-frequency analysis method in classical control theory, to extract the most reliable and representative five dimensionless time-domain characteristic parameters: crest factor, kurtosis, pulse factor, waveform factor, margin factor, and two dimensioned frequency-domain characteristic parameters: root mean square frequency, standard deviation as input [8]. The 80 data groups obtained from the experiment are divided into training set and test set, of which the training set accounts for 80% and the test set accounts for 20%. The K-Means algorithm is trained using the training set first, and then the model is verified using the test set after the training is completed. Further analysis of empirical and generalization errors will finally train a feasible clustering algorithm model to achieve bearing fault diagnosis based on machine learning.

This research identifies a significant gap in the current practices, emphasizing the need for an advanced, automated bearing fault diagnosis system that can address the diverse bearing types, reduce reliance on manual expertise, and minimize the associated resource costs. The primary objective of this study is to develop an innovative bearing fault diagnosis system leveraging machine learning, specifically focusing on rolling ball bearings. The research aims to advance beyond traditional, labor-intensive diagnosis methods by proposing a clustering algorithm to process characteristic parameters automatically. The research seeks to efficiently categorize and identify different failure modes of rolling bearings. By achieving this objective, the research contributes to immediate maintenance and replacement actions in the event of bearing failure, ultimately reducing equipment losses and enhancing overall operational efficiency.

2. Method

According to the national standard, rolling bearings can be divided into radial bearings and thrust bearings. Radial bearings can be divided into radial ball bearings and radial roller bearings according to the different rolling elements [9]. The radial roller bearing comprises a Deep Groove Ball Bearing, an angular contact ball bearing, a four-point contact ball bearing, and a self-aligning ball bearing. Radial roller bearings include needle roller bearings, self-aligning roller bearings, tapered roller bearings, and cylindrical roller bearings. Thrust bearings can be divided into thrust roller bearings and thrust ball bearings according to the different rolling elements. Thrust roller bearings include thrust needle roller bearings, thrust self-aligning roller bearings, thrust cylindrical roller bearings, and thrust tapered roller bearings. The thrust ball shaft contract includes thrust angular contact ball bearings and thrust ball bearings. This article uses a widely used thrust ball bearing as the experimental object, and records its fault situation and data through experiments.

In practical application scenarios, spontaneous vibration of rolling bearings is inevitable. When a certain fault occurs during operation, its vibration frequency and other parameters will significantly change, which is also the fundamental basis for collecting rolling bearing fault data. Although there may be sound signals during the rotation of rolling bearings, many teachers in the past also used the sound characteristics to determine whether the rolling bearings had faults and which type of fault they belonged to. In the actual working environment of rolling bearings, there will inevitably be a large amount of noise (the sound emitted by other surrounding equipment during operation), so it is difficult to collect the sound signal of rolling bearings in practical applications. This article uses the vibration signal of rolling bearings to determine whether there is a fault and what kind of fault exists.

From the perspective of its structural characteristics, the faults of rolling bearings can be divided into bearing outer ring faults, bearing inner ring faults, and rolling element faults. We want to achieve fault diagnosis of rolling bearings. Firstly, we need to know which data these faults are related to. Secondly, we need to extract the features of these faults and compare whether the connection between the faults and the data is close. We need to collect the part of fault data that is most closely related to the fault type. Therefore, when selecting data, the following principles need to be followed:

a. Realizability: The selected data samples should be easy to obtain. Even if a specific characteristic parameter is sensitive enough to the failure mode but is difficult to obtain, this parameter is unsuitable for use as a data sample.
b. High sensitivity: The significance of identifying rolling bearing fault patterns is to detect the presence of faults when there is a slight or even imminent fault in the bearing, but the fault has not yet occurred, reminding technical personnel to handle the faulty bearing and avoid more significant losses.
c. High reliability: The fault data of rolling bearings is measured by simulating the occurrence of bearing faults, but if this data cannot be used as a basis for discovering faults in bearings, then this type of feature parameter cannot be used as a data sample. Therefore, it's crucial to ensure that the simulated fault data accurately reflects real-world scenarios to maintain the reliability of the analysis. Without this reliability, the effectiveness of using such feature parameters as data samples diminishes significantly.

The fault data used in this article comes from the data provided by Hu Jing in his research on rolling bearing defect diagnosis based on the BP neural network, which is the test data of a certain manufacturer's rolling bearing before leaving the factory. Rolling bearings generate sound and vibration during operation, so collecting bearing fault data can start from these two aspects. However, during the experiment, it was found that the data collected using sound analysis method is always extremely insensitive to the fault characteristics of the bearing. This was because the noise generated by the operation of other equipment around the bearing impacted the experimental data. According to the principle of selecting test samples, sound analysis method was excluded, and therefore vibration analysis method was used to analyze the fault forms of rolling bearings. The vibration of bearings can be distinguished between the spontaneous vibration generated by the bearing itself during operation and the vibration generated by the target bearing caused by the vibration of other components on the same equipment during operation. The measurement required for diagnosing rolling bearing faults is the spontaneous vibration generated by the rotation of the bearing itself, so the impact of the second vibration should be minimized as much as possible during the experimental process.

Referring to the data analysis methods in automatic control theory, we can distinguish the data analysis methods into two parts: time-domain analysis and frequency-domain analysis. The advantage of time-domain analysis is that after using sub-method analysis, the characteristic parameters become very sensitive to bearing faults, which means that bearing anomalies can be identified in the early stage of fault occurrence or when the actual fault has not yet occurred. However, nothing can be perfect. The data obtained through time-domain analysis is extremely insensitive to the vibration frequency and amplitude of frequencies. Therefore, it is necessary to use frequency domain analysis combined with time-domain analysis to process the data in order to meet the needs of rolling bearing fault diagnosis. Analyzing frequency domain characteristic parameters such as root mean square frequency RMSF and frequency standard deviation RVF can further improve the accuracy of rolling bearing fault diagnosis.

After the initial phase of data processing, the acquisition of essential data samples for training becomes feasible. Employing machine learning techniques allows for a more profound analysis of the data, thereby enabling the identification of bearing faults through advanced machine learning methods. The utilization of clustering algorithms within the domain of machine learning further contributes to the efficient processing of these data samples, enhancing the overall effectiveness of fault detection.

The principle of bearing fault pattern recognition is to use clustering algorithms as a medium to cluster the obtained bearing fault feature parameters, divide similar training data into the same cluster, and then iteratively optimize by continuously updating the cluster centers until the algorithm iteration ends when the coordinates of all cluster centers no longer change. At this time, the obtained model is relatively optimal. Using the example of Zhao Zhiyong's program, consult relevant materials and compile corresponding training and prediction programs based on one's own dataset. The training program uses training set data, which is then trained using the K-Means algorithm to generate the clustering center and saved in a txt file. The testing program reads the saved cluster center and test set data, and calls the method of calculating Euclidean distance to calculate the distance between the cluster center and the test set. The program prints the distance from each test data to each cluster center, and then analyzes the printed results to obtain the category to which each test data belongs. Finally, the diagnostic category is compared with the original category of the test set, and the test results are used to verify the algorithm's accuracy in diagnosing faults. The program designed in this article is written and run using Python language on the Spyder interface. The process considered in this paper is shown in Fig. 1.

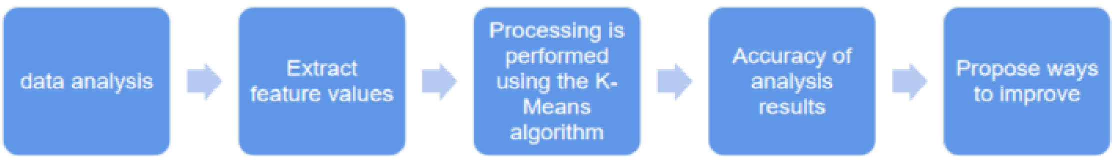

Fig. 1. The research process of this article

3. Results and Discussion

This article's rolling bearing failure data comes from Hu Jing [10]. They are seven-dimensional data under four states of normal state, outer ring, inner ring and rolling element fault. There are 80 groups in total, and each fault state is 20 groups of data. This article divides these eighty sets of data into a training set and a testing set. The training set selects the first sixteen sets of data under four states of rolling bearings, which means the training set consists of a total of sixty-four sets of data; The test set consists of sixteen sets of data selected from the remaining four states of rolling bearings [11-37].

The approximate process of running the training program and prediction program is as follows:

a) Import training set data, read the data row by row and column by column and store the read data in a list variable.
b) Randomly initialize four cluster centers and generate four cluster centers within a reasonable range based on the training set.
c) The algorithm for defining Euclidean distance calculates the distance between data. This step calculates the distance from each set of samples to the initialization cluster center and divides those with similar distances into a fault category. The running results display the fault category and distance.
d) Store the trained clustering center in the txt document for future fault prediction. The training program ends at this point, and the final clustering center after iteration is shown in Fig. 2.

```
[[3.03375000e+00 4.44500000e+00 5.76062500e+00 6.59625000e+00
  1.25562500e+00 3.52543750e+03 1.67875000e+03]
 [1.37057143e+01 7.80761905e+00 1.44195238e+01 1.85900000e+01
  1.52666667e+00 2.92809524e+03 1.36385714e+03]
 [3.37547059e+01 9.62764706e+00 7.78058824e+00 9.80941176e+00
  1.34352941e+00 3.43388235e+03 1.46729412e+03]
 [3.04070000e+01 1.19730000e+01 1.05240000e+01 1.55120000e+01
  1.43900000e+00 3.25430000e+03 1.35750000e+03]]
```

Fig. 2. The final cluster center formed

e) Next, import the test set data into the test program, read the data row by row and column by column, and store the read data in a list variable.
f) The Euclidean distance method is used to calculate the distance between the test sample and the cluster center.
g) After running the test program, the distance from each test data set to each cluster center is obtained. The accuracy of the test results can be determined by checking whether the category to which the minimum distance belongs is consistent with the order of actual test data input. This completes the entire program's operation.

The above training program calculates the distance from each set of samples to the initialization cluster center and divides those with similar distances into a fault category, resulting in the final formation of four cluster centers. The program operation results show the corresponding classification number and the distance from the data to the cluster center, with some classifications shown in Table 1.

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Table 1. Classification of Cluster Centers

Cluster center number	The distance from the training set to the initial clustering center	Cluster center number	The distance from the training set to the initial clustering center
2	3.73324081e+03	0	2.34936634e+04
	2.44274449e+03		1.71988482e+04
	1.72594223e+03		1.64573249e+04
	1.93495224e+03		2.33917214e+04
	1.46131027e+03		1.96017143e+04
	1.14447108e+03		1.55087500e+04
	1.39881896e+03		1.49590580e+04
1	1.47882351e+04	3	1.04242876e+05
	2.43722686e+04		4.28986622e+03
	5.08881561e+03		1.06752045e+05
	1.85738646e+03		1.19004136e+05
	1.13793661e+05		9.66083338e+04
	3.22413096e+03		1.10654642e+05

For the convenience of analysis, each clustering center is defined as 2, 0, 1, and 3 based on the training results. Defined by the data order of the input training set, 2 is the normal rolling bearing cluster, 0 is the outer ring defect rolling bearing cluster, 1 is the inner ring defect rolling bearing cluster, and 3 is the rolling element defect rolling bearing cluster.

The distance from each set of test data calculated in the testing program to each cluster center is shown in Fig. 3. According to Fig. 2 , the test results are classified as follows in Table 2.

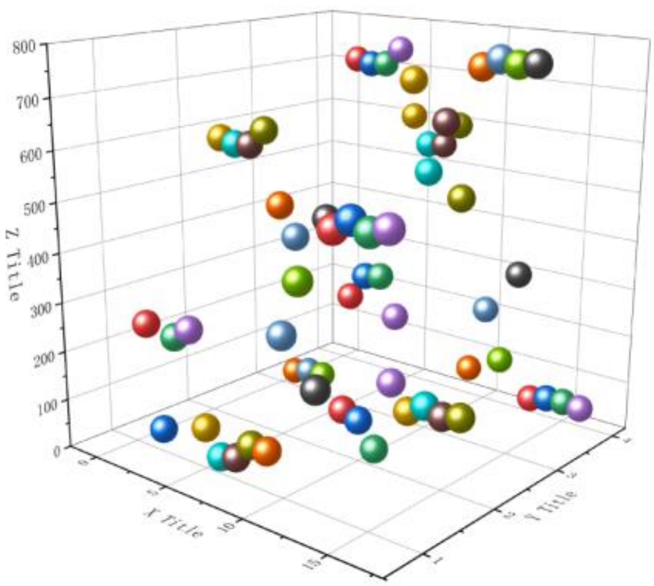

Fig. 3 Distance from the test sample to the cluster center

Table 2. Classification of Test Results

Test data grouping	Category corresponding to the distance from the first cluster center	Corresponding category to the distance from the second cluster center	Corresponding category to the distance from the center of the third cluster	Corresponding category to the distance from the fourth cluster center
	Class 0	**Category 1**	**Category 2**	**Category 3**
Group 1	256.84401433353383	593.2207620580102	34.8703400672	707.0416072674984
	707.0416072674984	585.9583140382364	45.1505754825	703.886717911236
	247.79876880654888	589.5147232569228	45.1245111209	703.886717911236
	271.3013413001717	623.1703530383302	45.2240959434	738.0795475396242
Group 2	83.16181487203531	480.1930149170725	242.545845700	598.5394730292014
	34.821588668899686	423.9265644294941	294.779860962	541.8836901921817
	44.82310623786196	428.1462948462038	302.062088098	545.8595449957462
	81.82110988028359	473.79386992957	223.313442478	592.1536732289335
Group 3	481.62621771584656	95.90813720868654	716.882430940	58.569705922531845
	315.32024686591217	84.45951878627689	540.020127406	202.12675933864065
	423.76119197260306	35.98294892875612	643.587091302	97.10439311876145
	233.24716812305775	182.8457307250532	499.214995058	296.00786882683957
Group 4	530.7057782937255	136.1755315412154	757.017955024	29.63860651745118
	553.5068144870303	157.0774474526017	775.044359120	39.99208972710404
	539.8534258115835	146.8872004888637	768.389369471	42.412009785838706
	552.3478620806983	155.8567615514379	773.704709597	38.64815342242061

Table 2 classifies the test results, clearly indicating the category to which each data group belongs. Find the minimum distance within each group, determine which cluster center is closest to, and classify it as the fault type of that cluster center. Determine whether the test results are consistent with the fault types in the input order of the test set data. Table 3 lists the distances in each group and determines whether the test results are accurate. The detailed classification and accuracy of fault diagnosis are shown in Table 3.

Table 3. Corresponding Data Types and Prediction Results Judgment for the Test Set

Fault Type	Calculated shortest distance	Category to which the test belongs	Determine whether it is accurate
Normal state	34.87034006725845 45.15057548255891 45.12451112096673 45.22409594349289	2	Yes

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Fault Type	Calculated shortest distance	Category to which the test belongs	Determine whether it is accurate
Outer ring defect	83.16181487203531 34.82158866889968 44.82310623786196 81.82110988028359	0	Yes
Inner ring defect	58.56970592253184 84.45951878627689	3	No
	35.98294892875612 182.8457307250532	1	Yes
Rolling element defect	29.63860651745118 39.99208972710404 42.41200978583870 38.64815342242061	3	Yes

The findings presented in Table 3 demonstrate that the K-Means clustering algorithm can precisely identify the specific type of fault defect in rolling bearings. With an error rate of 6.25%, these diagnostic outcomes further substantiate the efficacy of machine learning algorithms in diagnosing rolling bearing faults. Despite the simplicity of the K-Means algorithm's underlying principles, it has limitations. A critical limitation, as highlighted in this study, is the substantial influence of randomly initialized clustering centers on the diagnostic outcomes. Indeed, varying initial clustering centers can result in markedly different clustering outcomes. While executing the algorithm, it was observed that the final clustering centers occasionally exhibited a "nan" value in the results across several training sessions. An account of one such training session is provided, with the initial clustering center, post-execution, depicted in Fig. 4.

```
---------- 2.random center ------------
print first centroids
[[3.63690891e+00 4.33071531e+00 7.52676211e+00 1.01319908e+01
  1.31035278e+00 2.96233881e+03 1.32867333e+03]
 [1.08493346e+01 1.10388610e+01 1.74998266e+01 1.85597338e+01
  1.27640442e+00 3.26227519e+03 1.30003216e+03]
 [1.78936391e+01 7.62553764e+00 1.59771276e+01 8.90403982e+00
  1.40510495e+00 3.44256097e+03 1.32815864e+03]
 [9.59005593e+00 8.99778236e+00 1.76938330e+01 1.20001173e+01
  1.55887495e+00 2.90422766e+03 1.70649461e+03]]
```

Fig. 4 Initializing the cluster center

The subsequent phase involves clustering the samples by calculating the distance from each sample to the initial cluster center and assigning the samples to the nearest cluster center accordingly.

Throughout the intermediary stages of the clustering process, it was observed that none of the data in the training set were associated with the third label, while the other three categories were clustered as expected. Illustrations of some of these clustering processes are presented in Fig. 5.

```
ipdb> [[2.00000000e+00 1.58347748e+05]
 [2.00000000e+00 1.56084768e+05]
 [2.00000000e+00 1.38298383e+05]
 [2.00000000e+00 1.47230296e+05]
 [2.00000000e+00 1.42754288e+05]
 [2.00000000e+00 1.39094393e+05]
 [2.00000000e+00 1.28994620e+05]
 [2.00000000e+00 1.38195297e+05]
 [2.00000000e+00 1.31469033e+05]
 [2.00000000e+00 1.24359958e+05]
 [2.00000000e+00 1.17996919e+05]
 [2.00000000e+00 1.45197341e+04]
 [2.00000000e+00 1.28879065e+04]
 [1.00000000e+00 1.20949678e+04]
 [1.00000000e+00 7.98040859e+03]
 [1.00000000e+00 1.50112295e+04]
 [1.00000000e+00 6.62539859e+03]
 [0.00000000e+00 0.00000000e+00]
 [1.00000000e+00 2.22166104e+04]
```

```
[1.00000000e+00 7.63030243e+02]
[0.00000000e+00 0.00000000e+00]
[0.00000000e+00 0.00000000e+00]
[1.00000000e+00 7.56556091e+03]
[1.00000000e+00 9.67688832e+03]
[1.00000000e+00 2.77873545e+03]
[0.00000000e+00 0.00000000e+00]
[0.00000000e+00 0.00000000e+00]
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[0.00000000e+00 0.00000000e+00]
[0.00000000e+00 0.00000000e+00]
[0.00000000e+00 0.00000000e+00]
[0.00000000e+00 0.00000000e+00]
```

Fig. 5 Clustering process

In the program, 'centroids [j, z]=sum_all [0, z]/r', where r represents the number of clusters. Since no data is divided under the third label, the r value is zero, as shown in Fig. 6.

Name	Type	Size	Value
file_pathdata	str	1	./zhoucheng_moxing.txt
i	int	1	63
j	int	1	3
k	int	1	4
m	long	1	64L
minDist	float64	1	22977.790258290224
minIndex	int	1	0
n	long	1	7L
r	int	1	0
subCenter	float64	(64L, 2L)	[[2.00000000e+00 1.583477 [2.00000000e+00 1.560847

Fig. 6. Zero clusters

The result of this final cycle is the appearance of nan in the cluster center under the third label, as shown in Fig. 7.

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```
ipdb> [[1.37057143e+01 7.80761905e+00 1.44195238e+01 1.85900000e+01
  1.52666667e+00 2.92809524e+03 1.36385714e+03]
 [3.09977778e+01 1.20933333e+01 1.05500000e+01 1.55088889e+01
  1.44222222e+00 3.24422222e+03 1.35444444e+03]
 [1.90429412e+01 7.22588235e+00 6.90382353e+00 8.46588235e+00
  1.30411765e+00 3.47435294e+03 1.56438235e+03]
 [            nan            nan            nan            nan
              nan            nan            nan]]
```

Fig. 7 Cluster centers after the first update

Through the above process, it can be concluded that the problem of having "nan" in the cluster center is caused by dividing by zero when recalculating the cluster center, resulting in the value of the cluster center being "nan". Due to the random initialization of the cluster center in this program, when the initialization cluster center is far from the data, the randomly initialized cluster center may not have any data in the same class as a certain cluster center during the first partition. When the cluster center is updated next, the program will divide by the number of data under the cluster. Since the number of data under the cluster center is zero, the cluster center will become infinite, The occurrence of 'nan' ultimately resulted in unsatisfactory classification results and failure to achieve the expected classification effect.

In academic circles, deep learning serves as a prevalent tool for diagnosing bearing faults. The methodology employed in this study involves utilizing identical bearing fault feature parameters to train both the RBE neural network and GRNN neural network. The outcomes of these training processes are visually presented in Fig. 8 and Fig. 9, which shedding light on the effectiveness of employing these neural networks for bearing fault diagnosis.

0	0	0	-2.29E-08	1.38E-07	1.06E-09	Inf	Inf	Inf
0	0	0	2.58E-07	-1.35E-07	-1.34E-09	Inf	Inf	Inf
1	0	0	0.98925743	-0.002110647	1.75E-06	0.010743	Inf	Inf
0	0	1	3.60E-06	-1.46E-04	1.01E+00	Inf	Inf	0.010306
1	0	0	0.9911013	0.00319822	-1.30E-07	0.008899	Inf	Inf
0	1	0	0.01590531	0.723561935	-1.76E-04	Inf	0.276438	Inf
0	0	1	4.03E-06	-0.00014181	1.00E+00	Inf	Inf	0.002702
0	0	0	-2.83E-07	-3.42E-07	-2.64E-09	Inf	Inf	Inf
0	0	1	1.07E-06	0.00015896	0.99552685	Inf	Inf	0.004473
0	0	1	4.42E-06	-0.000342289	1.02361541	Inf	Inf	0.023615

Fig. 8 The relative error of the precision radial basis (RBE) neural network

1	0	0	-0.010500011	1.050675215	0.00016266	Inf	0.050675	Inf
0	0	1	-1.07E-06	-1.67E-07	-8.19E-10	Inf	Inf	Inf
0	1	0	0.011724618	0.874569752	0.00034067	Inf	Inf	0.999659
0	0	0	4.25E-07	2.31E-07	2.99E-09	Inf	1	Inf
0	0	1	-0.006011777	1.0041647	0.00113747	Inf	0.004165	Inf
1	0	0	-0.018358077	1.044309685	7.79E-05	1.018358	Inf	Inf
0	0	1	0.997339717	-0.00063628	-8.26E-07	Inf	Inf	1.000001
0	0	1	2.26E-07	-2.79E-08	-6.47E-10	1	Inf	Inf
0	1	0	-0.008837833	1.038822248	-0.0001171	Inf	0.038822	Inf
1	0	0	-4.10E-06	0.000361181	0.94299179	Inf	0.999639	Inf

Fig. 9 The relative error of the generalized regression (GRNN) neural network

The outcomes of the bearing fault diagnosis indicate that the K-Means algorithm exhibits superior recognition accuracy for bearing fault diagnosis compared to the RBE neural network and GRNN neural network. Furthermore, unlike neural networks that necessitate extensive data for model training before fault prediction, the K-Means algorithm demonstrates greater efficiency in diagnosing bearing faults [38]. This efficiency is not compromised by factors such as the precision of the training set data or the comprehensiveness of fault condition coverage [39-40].

4. Conclusion

The main task of this paper is to apply clustering algorithms in machine learning to process fault data of rolling bearings, and ultimately achieve bearing fault diagnosis based on machine learning. Divide 80 sets of rolling bearing fault data into training and testing sets, with the training set accounting for 80% of the total data and the testing set accounting for 20% of the total data. Corresponding training and testing programs were designed, and samples were placed in their respective programs to run. The training set data was trained in the training program using the K-Means algorithm to train the clustering center and saved in a txt file. The testing program reads the saved cluster center and test set data, calls the method of calculating Euclidean distance, and calculates the distance between the cluster center and the test set. Print the distance from each test data to the cluster center obtained by the training program, and then analyze the printed results to obtain the category to which each test data belongs. Finally, compare the diagnostic category with the original category of the test set to determine the accuracy of the prediction. After many experiments, it is concluded that the failure prediction accuracy of the K-Means algorithm proposed in this paper for rolling bearings is 94%, which provides a new idea for the research on bearing fault diagnosis that is different from the traditional neural network processing method.

The machine learning model established this time has many shortcomings. For example, during the process of running the algorithm program, it was found that a "nan" value appeared in the results of a training session, and this situation led to the "nan" value appearing in the prediction results of the test set. This is due to the random initialization of the clustering center. Therefore, it can be attempted to select the first K samples of the dataset as the initial center points, Alternatively, select random K sample points as the initial clustering center to see if clustering can be completed normally. Secondly, overfitting will occur when the dimension of training samples is high. Therefore, before applying the K-Means algorithm, you can try to preprocess the data to reduce the dimension, and reduce the seven-dimensional data to two-dimensional data, which can greatly avoid the occurrence of overfitting. However, the importance of each parameter in fault identification varies when performing dimensionality reduction processing on data, which still requires further research. Setting a weight value for each parameter can ensure the original sensitivity of the data sample to fault perception while achieving dimensionality reduction.

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