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Retraction

Retracted: Data Mining Technology for Equipment Machinery and Information Network Data Resources

Security and Communication Networks

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Zhang, "Data Mining Technology for Equipment Machinery and Information Network Data Resources," *Security and Communication Networks*, vol. 2022, Article ID 5928611, 8 pages, 2022.

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Research Article

Data Mining Technology for Equipment Machinery and Information Network Data Resources

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In order to solve the problem of aviation equipment system maintenance, it is very difficult to judge the faulty finished product according to the fault phenomenon, the author proposes a data mining-based prediction model for aviation equipment failure finished products. The model takes historical fault record data as input, clusters a large number of fault descriptions through text clustering to obtain fault phenomenon clusters, and establishes a many-to-many relationship between "fault phenomenon" and "fault finished product." A probability distribution algorithm for faulty finished products is proposed, and by matching new fault phenomena and fault phenomenon clusters, the probability distribution of faulty finished products is calculated. The experimental results show that after calling the model to complete the clustering of the fault information database, 18966 fault phenomenon clusters are obtained, and each fault phenomenon cluster contains 2.9 fault records on average, the many-to-many relationship between the fault phenomenon and the faulty finished product of the fault information database is successfully constructed. The model can effectively predict the probability distribution of products that may fail according to the fault description, and the prediction accuracy can be improved with the increase of the amount of data to meet the actual security needs.

1. Introduction

In order to maintain high reliability of aviation machinery and equipment, we should ensure the normal operation of the equipment system, carry out efficient and rapid failure analysis on failed components, and find out the cause of failure. Coming up with preventive measures for improvement is a daunting and important task. In the failure analysis of aero-mechanical components, the acquisition and processing of failure information is very important and complex, and it often involves knowledge information in many disciplines [1]. In practical work, the failure information of components is obtained through observation and testing, and there are inevitably many incomplete and inaccurate data, which is limited in analyzing the failure cause [2]. How to effectively use these historical and static information and turning them into dynamic information with analytical decision-making is an urgent problem to be solved in the study of aviation equipment failure analysis.

In recent decades, people have begun to study and apply database and artificial intelligence technology to acquire and discover failure analysis knowledge, and expert systems have been introduced into the field of failure analysis. However, many failure analysis expert systems are based on rule-based reasoning, most of these rules are knowledge described in natural language, they are often qualitative and subjective, and it is difficult to express domain knowledge objectively and rationally. Therefore, there is an urgent need to develop an efficient and intelligent computer knowledge acquisition system to solve the above problems. With the development of database technology, database systems are used to store data and data mining technology is used to extract information with the nature of analysis and decision-making. It can make up for the uncertainty and incompleteness of failure information due to human reasons, thereby improving the efficiency of failure analysis, which is of great significance for the study of aviation equipment failure analysis [3].

2. Literature Review

Data mining technology refers to the use of appropriate intelligent algorithms (such as neural networks, support vector machines, fuzzy algorithms, genetic algorithms, and evidence theory) to build models and the process of obtaining unknown and potentially useful information from the existing data of the research object. Data mining technology plays an important role in aero-engine prediction and health management. Ardehjani et al. have done a lot of research on establishing the engine baseline equation and used the least squares curve fitting algorithm to establish the baseline equation (4). Oropeza and Hart based on test bench test data, established a baseline equation using the cubic polynomial fitting method [5]. Lu et al. made trend prediction based on the regression equation of engine exhaust temperature and other gas path parameters [6]. Shen et al. established a piecewise regression equation between the deviation and the flight cycle to predict the trend of the deviation. However, because the application of data mining technology in China is an interdisciplinary comprehensive research, researchers often ignore the importance of computer technology, intelligent technology, statistics, and other disciplines in data mining research, there is still a gap between many theoretical achievements and practical applications, and it is necessary to further establish a more complete cross-study between disciplines to achieve new breakthroughs [7]. Moayedi et al. automatically adjusted the number of clusters according to the similarity, which reduces the error of the initial number of clusters k [8]. Booker et al. extracted short text topic information with the help of LDA model to determine initial cluster centers in K-means algorithm, the number of iterations of the improved algorithm is significantly reduced, and the clustering accuracy is improved [9]. From the semantic point of view, Li et al. obtained the initial cluster centers by mining the largest frequent words in the short text set and improved the efficiency and quality of short text clustering [10].

The above researches applied various data mining methods to predict equipment failures, but did not perform cluster mining on the fault texts, the research on text clustering mostly focused on social network platforms, there is still a lack of related research on short text clustering of aviation equipment faults. There is a need to study on how to use text clustering technology to analyze finished fault records and unearth hidden value from historical failure records.

3. Research Methods

3.1. Analysis of Failure Records of Finished Aviation Equipment

3.1.1. Features of Failure Record of Finished Aviation Equipment. The failure record of the finished aviation equipment is the maintenance record of the fleet support personnel on the failure of the finished product of the fleet, it mainly includes fleet and location, date of occurrence, aircraft number, name and model of faulty finished product, and fault description, with the following characteristics [11]:

(1) Recurrence of failure phenomenon: before the targeted improvement of the finished product, a certain failure phenomenon corresponding to the failure mode of the finished product often occurs repeatedly

(2) Many-to-one relationship: due to the different habits of recorders, when entering fault descriptions, the fault descriptions corresponding to the same fault phenomenon are not the same [12]

(3) Many-to-many relationship: multiple fault phenomena may correspond to the same faulty product, and multiple faulty products may correspond to the same fault phenomenon

3.1.2. Building Relationships through Text Clustering. Because each fault description corresponds to a fault product, and there is a many-to-one relationship between the fault description and the fault phenomenon, the fault description is divided into multiple types of fault phenomena through text clustering, the many-to-many relationship between the fault phenomenon and the faulty finished product can be constructed, as shown in Figure 1.

3.2. Prediction Model of Aviation Equipment Failure Finished Products

3.2.1. The Composition of the Fault Product Prediction Model. Aiming at the characteristics of finished aviation equipment fault records, the author proposes a finished aviation equipment fault prediction model, it is divided into four-level algorithm modules: text preprocessing, text vectorization, text clustering, and fault product distribution algorithm, the process is shown in Figure 2 [13].

3.2.2. Finished Product Fault Record Text Preprocessing. Text preprocessing is a process of preliminary simplification and normalization of natural language such as fault information, including word segmentation, part-of-speech tagging, feature word discrimination, and useless words filtering for information texts. The feature words obtained after preprocessing can also be used to match relevant technical data and improve the technical support capabilities of the field.

(1) Finished Product Fault Record Text Preprocessing. Words in English are basically strings separated by space characters, while Chinese is a continuous string composed of Chinese characters, there is no obvious separator between words, so the complexity of Chinese word segmentation algorithm is much higher than that of English. The author adopts the PKUSEG word segmentation algorithm, which is based on the classic CRF model and the unique ADF training method and achieves better word segmentation effect and better generalization ability than other word segmentation algorithms [14].

(2) Text Part-of-Speech Tagging. An example fault message is as follows: the left front landing gear shield has scratches and slightly deformed edges. After word segmentation and part-of-speech tagging, the results are as follows: ((no gear, n), (left
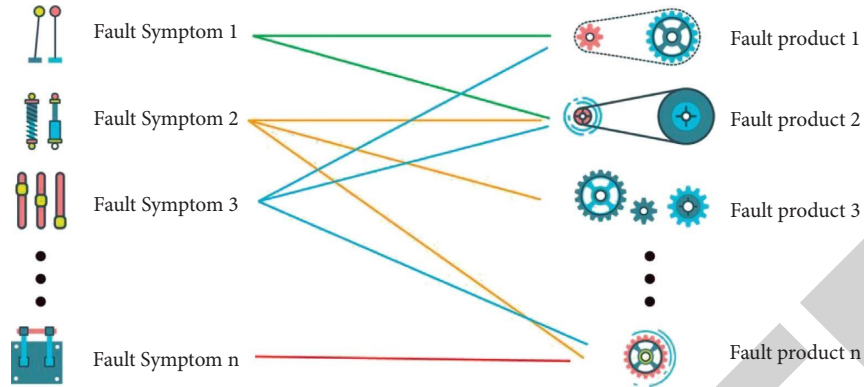
FIGURE 1: The many-to-many relationship between the fault phenomenon and the faulty finished product.
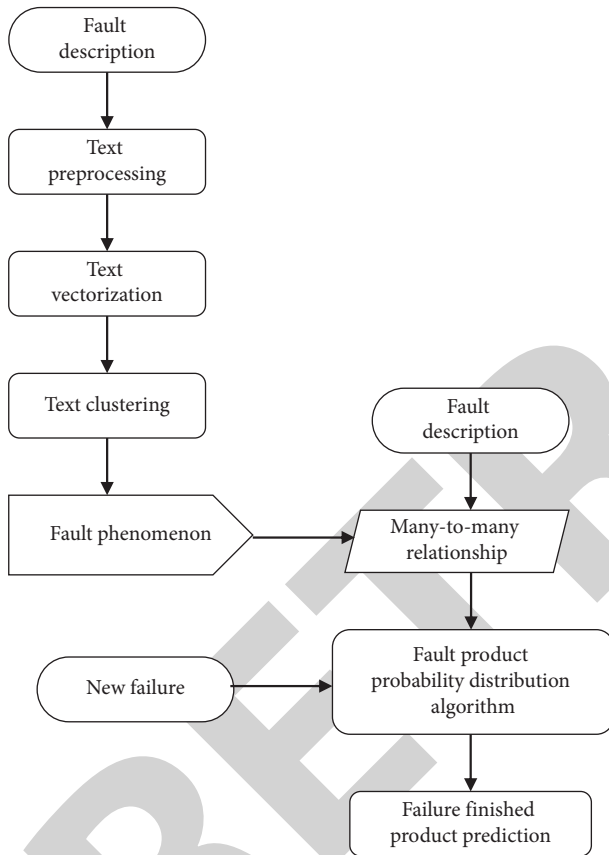

FIGURE 2: Flow chart of the prediction model of aviation equipment failure finished products.

fender, *n*), (yes, *v*), (scratch, *n*), (and, *c*), (edge, *n*), (slight, *a*), (deformation, *vn*), (,*w*)). It can be seen that the word segmentation algorithm can effectively divide and label the fault text, and the meanings of some part-of-speech tags are shown in Table 1.

(3) Fault Feature Words. After filtering the useless words from the above word segmentation results, the results are as follows: ((nog, *n*), (left fender, *n*), (scrub, *n*), (edge, *n*), (deformation, *vn*)). It can be found that nouns and verbs (including gerunds) are the main components of fault information, which determine the subject of fault information, so such words are defined as fault characteristic words.

TABLE 1: Part of the part-of-speech tagging Table.

Code	name	Code	name
a	Adjective	n	Noun
b	Distinguishing word	p	Preposition
c	Conjunction	q	Quantifier
d	Adverb	v	Verb
f	Position of the word	w	Punctuation

3.2.3. Finished Product Failure Record Text Vectorization. After preprocessing, the text is a collection of words, which is still a natural language and cannot be mathematically calculated, it is necessary to convert the text into a mathematical language that can be applied to clustering algorithms [15].

(1) Vector Space Model. Vector space model (VSM) is one of the commonly used text representation models in the field of text clustering, which represents natural language text as a vector in vector space [16, 17].

In the vector space model, the feature words of the text are used as the dimension of the vector, and a vector that constitutes the feature terms is as follows:

$$D_i = \{d_{i1}, d_{i2}, \ldots, d_{in}\}. \tag{1}$$

In the formula, d_{ij} is the feature value of the *j*-th feature word in the text vector D_i. The larger the feature value, the stronger the correlation between the feature word and the text, and vice versa.

(2) Eigenvalue Algorithm. The term frequency (TF) represents the number of times a word appears in the text, that is, TF_{ij} represents the number of times the feature word *i* in the text set appears in the text *j* [18].

The inverse document frequency (IDF) represents the particularity of the feature words in the text collection as follows:

$$\text{IDF}_i = \log_2\left(\frac{N}{n_i}\right). \tag{2}$$

In the formula, *N* is the number of texts in the text set and n_i is the number of texts containing the feature word *i* in the text set. The larger the value of IDF_i, the stronger the ability of feature word *i* to distinguish text.

The TF-IDF algorithm is a combination of word frequency and inverse document frequency, which not only considers the distribution of feature words in the text, but also considers the distribution characteristics of feature words in the entire text collection as follows:

$$TF - IDF_{ij} = TF_{ij} \times \log_2\left(\frac{N}{n_i}\right). \tag{3}$$

In the formula, $TF - IDF_{ij}$ is the feature value of each feature word i in the text j. Based on the TF-IDF algorithm, each feature word in the text can be represented as a statistical feature value, thus realizing the vectorization of the text. If the dimension of the text vector is too high, you can set the eigenvalue threshold, and only select the eigenvalues higher than the threshold as the vector representation of the text, realize text vector dimensionality reduction, and ensure the convergence of text clustering algorithm.

(3) Text Vector Similarity Algorithm. The vectorized texts can be used for clustering algorithms, and the similarity between texts is an important indicator that affects the clustering effect, so the algorithm for calculating text vector similarity is also used [19].

The cosine similarity algorithm is a commonly used text vector similarity algorithm, the similarity between two vectors is measured by calculating the cosine of the angle between them as shown in the following formula:

$$S(D_1, D_2) = \frac{D_1 \cdot D_2}{D_1 \, D_2} = \frac{\sum_{k=1}^{n} d_{1j} \cdot d_{2j}}{\sqrt{\sum_{k=1}^{n} d_{1j}^2 \cdot \sum_{k=1}^{n} d_{2j}^2}}. \tag{4}$$

In the formula, $S(D_1, D_2)$ is the cosine value of the angle between the text vectors D_1 and D_2, and d_{1j} is the j-th eigenvalue in the text vector D_1, It can be seen that the larger $S(D_1, D_2) \in [0, 1]$ is, the higher the similarity of text vectors D_1 and D_2 is, and vice versa.

3.2.4. Clustering Algorithm. Clustering algorithm is a kind of unsupervised machine learning algorithm, according to the similarity between texts and certain rules, a type of texts with high similarity are aggregated into the same cluster, and finally the set of these clusters is obtained.

(1) K-Means Clustering Algorithm. The K-means algorithm was proposed by Stuart Lloyd and is a classical clustering algorithm based on partitioning, it is widely used in the field of text clustering. The basic principle of K-means algorithm is as follows: select k texts from the data set as the initial clustering centers, calculate the distance of each data to these k cluster centers, and assign them to the nearest cluster, then recalculate the center of the cluster and iterate the above process, until the criterion function converges or the maximum number of iterations is reached.

The K-means algorithm is simple, fast in calculation, and has good clustering effect, but it also has some obvious defects: the initial k cluster centers need to be given in advance, but before the clustering results are completed, it is difficult to estimate the appropriate number and configuration of cluster centers, if an inappropriate initial object is selected, it will not only greatly affect the efficiency of the algorithm, but also affect the effect of clustering.

The basic idea of k-means algorithm: a dataset of samples and a given number of clusters are given. Firstly, the following are randomly selected: The samples are respectively used as the cluster centers of the initial division, and then the iterative method is used according to the similarity measurement function, the distance from the undivided sample data to each cluster center point is calculated, and the sample data is divided into the cluster class where the nearest cluster center is located, and for each assigned cluster, the cluster center is continuously moved by calculating the average value of all data in the cluster, and the cluster is redivided until the sum of squared errors within the class is the smallest and there is no change. One feature of this algorithm is that in each iteration process, it is necessary to judge whether each sample data is correctly divided into clusters, if not correct, readjust. When all the data are adjusted, the cluster center is modified and the next iterative calculation is performed. If during an iteration, each data sample is assigned to the correct cluster, the cluster centers are no longer adjusted. The cluster center is stable and no longer changes, marking the convergence of the objective function, the end of the algorithm, and the final evaluation of the clustering results [20]. The flowchart of the K-means clustering algorithm is shown in Figure 3.

(2) Canopy Clustering Algorithm. The canopy algorithm uses the points in the multidimensional feature space as the center to construct clusters, calculates the points in the clusters, and iterates to obtain the clustering results, it is a clustering algorithm that does not need to set the initial clustering center. The principle is to judge whether each point is within the cluster range through the distance thresholds T_1 and T_2, if the distance between the point and the center is $S_i < T_1$, then they are grouped into a cluster, in which the points are removed if $S_i < T_2$, and the remaining points are cycled again as centers to generate clusters until all points in the set are removed.

The canopy algorithm is simple and efficient, and can effectively filter outliers (i.e., individual faults) in the set, and stably obtain the number and center of clusters.

(3) Canopy-K-Means Optimization Clustering Algorithm. From the above analysis of the canopy algorithm and the K-means algorithm, it can be seen that the canopy algorithm is used as the preprocessing algorithm for the initial cluster center of the K-means algorithm, it can solve the problem caused by the random selection of the initial cluster center of the K-means algorithm itself, and this combined algorithm is better than the original algorithm in terms of stability and accuracy.

The brief steps of the canopy-K-means algorithm are as follows:

The text vector set obtained after preprocessing is initially clustered by the canopy algorithm, and clusters of amount of k and their centers are obtained

The k cluster centers obtained by the Canopy algorithm are used as the initial cluster centers of the K-means
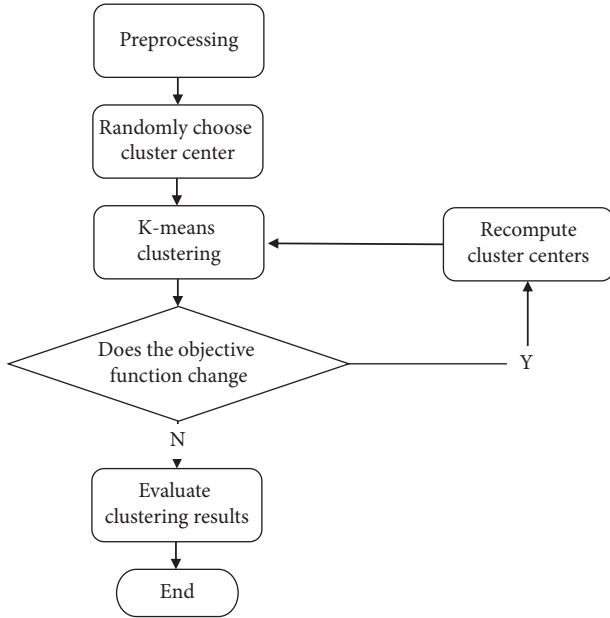
Figure 3: Flow chart of K-means clustering algorithm.

algorithm for secondary clustering, and the final clustering results are obtained after iterative convergence [21, 22]

The clustering flowchart of the Canopy-K-means algorithm is shown in Figure 4 below.

3.2.5. Probability Distribution Algorithm of Faulty Finished Products Based on Historical Data. Through the above clustering algorithm, after completing the clustering of multiple fault descriptions belonging to the same fault phenomenon, a many-to-many relationship between the fault phenomenon and the fault product is established [23].

Because the same failure phenomenon corresponds to multiple finished product failures, and the finished product with a closer failure time is more likely to fail repeatedly in the near future, the following product failure probability distribution formula is proposed.

For multiple finished product failures corresponding to the same failure phenomenon, assuming that this failure phenomenon includes n types of historically faulty finished products, and the number of historical failures of the i-th type of faulty finished product is n_i, the following formula can be obtained:

$$P_i = \frac{\sum_{j=1}^{n_i} \gamma^{t_{ij}}}{\sum_{i=1}^{n} \sum_{j=1}^{n_i} \gamma^{t_{ij}}}. \tag{5}$$

In the formula, P_i is the failure probability of the i-th product, Y is the attenuation coefficient, and t_{ij} is the time since the j-th failure of the first-class failure product (in months, rounded down) [24].

Based on the above algorithm, for each fault phenomenon obtained by text clustering, the probability distribution of each fault product can be calculated and stored in the database. By text clustering the newly-occurring fault phenomenon and each fault phenomenon in the database, the newly-occurring fault can be matched to a fault phenomenon cluster in the database, and then the probability distribution of the faulty finished product can be determined, so as to realize the historical data-based failure finished product prediction [25].

4. Results Analysis

4.1. Realization of Fault Product Prediction Model. The author implemented the abovementioned fault prediction model based on Python and imported the fault information table of a certain model to conduct experiments. The CPU used for the experiment is Intel®Xeon®E7-4820v4CPU@ 2.00 GHz (4 processors), the memory is 128 GB, the experimental environment is WindowsServer2012Standard, and the programming language is Python3.7.

For the text preprocessing module, when the model is specifically implemented, the PKUSEG word segmentation algorithm is introduced to segment the fault description in the fault information item by item, and the fault characteristic words are extracted, at the same time, a special thesaurus for aviation equipment is imported to improve the accuracy of word segmentation. The CountVectorizer function is used in the Scikit-Learn library to vectorize the word segmentation results, and then the TfidfTransformer function is used to calculate the similarity between the vectors.

For the text clustering module, when the model is implemented, the clustering function is independently written according to the principle of the canopy algorithm, at the same time, the K-Means function in the Scikit-Learn library is used and combined with it, the canopy-K-means clustering function is generated to complete the clustering calculation according to the calculated similarity between the vectors, that is, the fault description set is clustered into the fault phenomenon cluster set, and according to the corresponding relationship between the fault description in the cluster and the fault product, a many-to-many relationship between failure phenomena and failed finished products is built successfully.

For the failure product probability module, when the model is implemented, the probability distribution calculation function is written according to the failure product probability distribution algorithm proposed above, and the attenuation coefficient can be customized. For the new fault phenomenon, preprocessing and text clustering are also performed on it, the fault phenomenon cluster with the highest similarity can be obtained, the probability distribution calculation function can be used, and the probability distribution of the suspected faulty finished product of the fault can be obtained.

The fault information database of a certain model used in the test contains a total of 54,996 finished product fault records, covering 10 systems, corresponding to 1,390 types of finished products, with a time span of more than 10 years, and the amount of fault description data is 1,419,584 words. The attenuation coefficient of the probability distribution algorithm of fault products is set to 0.95, and after calling the model to complete the clustering of the fault information database, 18,966 fault phenomenon clusters are obtained, on
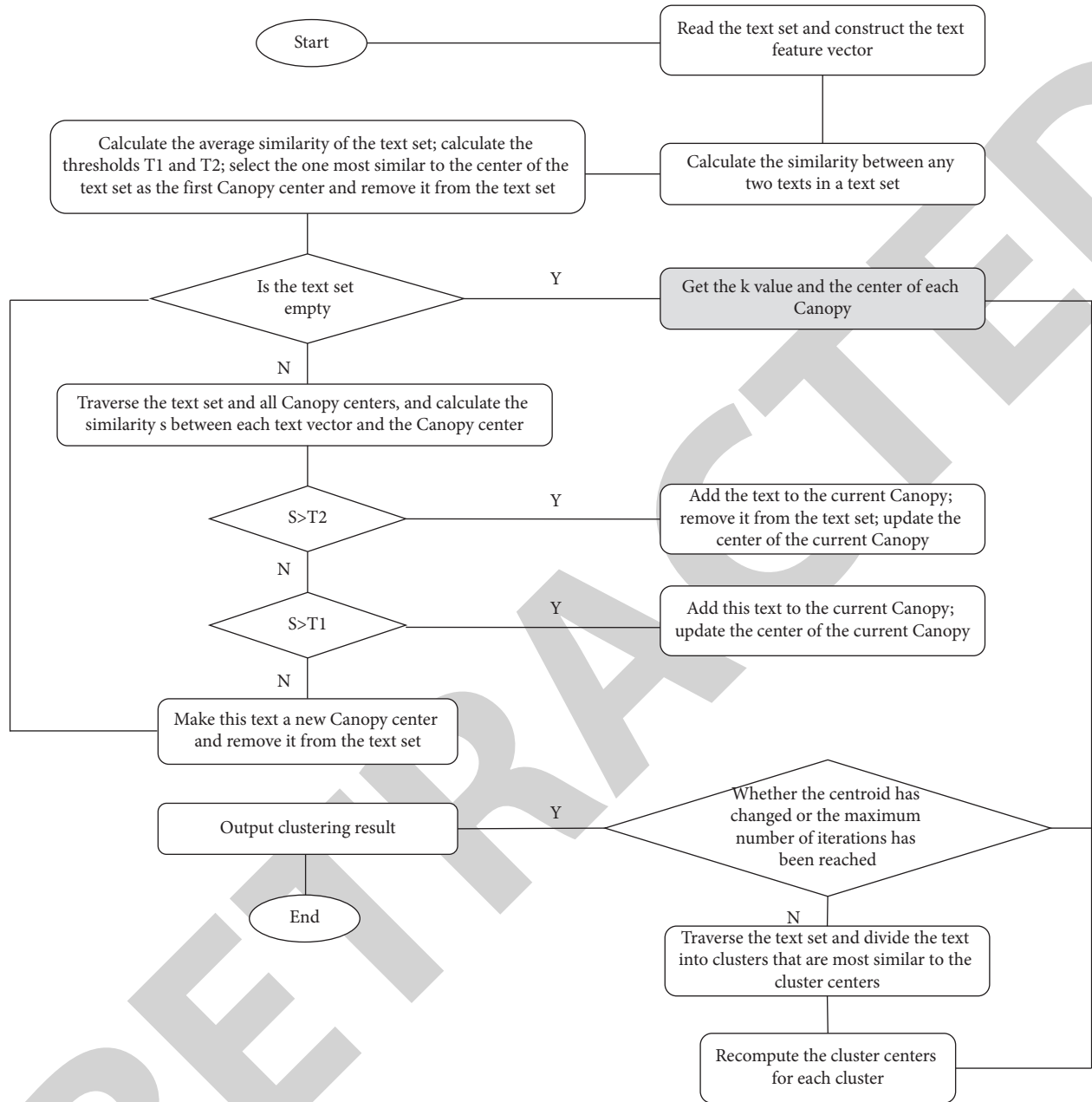
Figure 4: Clustering flow chart of canopy-K-means algorithm.
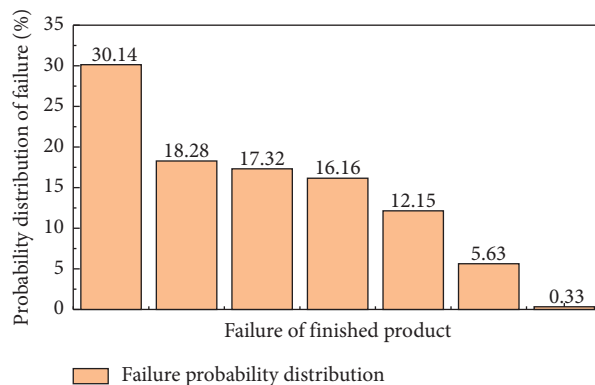

Failure probability distribution

Figure 5: Probability distribution of faulty finished products with high noise in ultrashort wave radios.

average, each fault phenomenon cluster contains 2.9 fault records, and the many-to-many relationship between the fault phenomenon of the fault information database and the faulty finished product is built successfully.

4.2. Validation of Faulty Finished Product Prediction Model. In order to verify the model, it is assumed that the new fault phenomenon is "ultrashort wave radio station is noisy", after importing the model, a fault cluster containing 25 historical faults is matched, and a total of 7 items of suspected fault products are output, its probability distribution is shown in Figure 5.

5. Conclusion

By analyzing the characteristics of the failure records of aviation equipment finished products, the author proposes a prediction model of aviation equipment failure finished products based on data mining. The model takes historical fault record data as input, clusters a large number of fault descriptions through text clustering to obtain fault phenomenon clusters, and establishes a many-to-many relationship between "fault phenomenon" and "fault finished product." A probability distribution algorithm of faulty finished products is proposed and it is calculated by matching new fault phenomena and fault phenomenon clusters. The experimental verification results show that, the model effectively predicts the probability distribution of finished products that may fail based on the failure description. The aviation equipment failure finished product prediction model has the following advantages in the field of aviation equipment support. With the increase in the number and years of aviation equipment in service, the finished product fault record database will be rapidly enriched, and the prediction accuracy of the model will also increase. Failed finished products can be predicted using only finished product failure records without additional maintenance data. The security personnel only need to input the fault phenomenon to realize the prediction of the faulty finished product, and the prediction process is convenient and fast. The next step is to consider applying deep learning techniques, such as leveraging the BERT semantic representation model, in order to improve the text preprocessing techniques of this model.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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