Retraction

Retracted: Automatic Classification of Basic Nursing Teaching Resources Based on the Fusion of Multiple Neural Networks

Mathematical Problems in Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] T. Hou and Z. Madina, "Automatic Classification of Basic Nursing Teaching Resources Based on the Fusion of Multiple Neural Networks," *Mathematical Problems in Engineering*, vol. 2022, Article ID 7176111, 7 pages, 2022.

Research Article

Automatic Classification of Basic Nursing Teaching Resources Based on the Fusion of Multiple Neural Networks

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Automatic classification is one of the hot topics in the field of information retrieval and natural language processing, but it still faces many problems to be solved. The classic automated classification approach has a sluggish classification speed and poor processing accuracy for resources with a large quantity of data. Based on this, an automated classification approach based on the integration of various neural networks for fundamental nursing teaching materials was presented. The automatic classification method of teaching resources was designed by extracting the characteristics of teaching resources, establishing the model of multiple neural network integration, and designing the classification index of basic nursing teaching resources. The experimental findings suggest that this technique has higher chi-square test parameters and better outcomes for the automated classification of large instructional materials than the classic rough set automatic classification method.

1. Introduction

There are many kinds of mishaps in the Internet, but how to better discover, obtain, and use network text information has become a more and more worthy of attention [1–3]. An excellent collection and classification system can quickly and efficiently obtain relevant network data from the network according to requirements, analyze and extract web information, and then automatically classify the obtained text content in accordance with certain methods for better use by people, which is undoubtedly of great help for rapid discovery, research, and problem solving [4, 5]. In this paper, the problem of collection and automatic classification of massive basic nursing teaching resources is studied deeply with the fusion technology of multiple neural networks, which solves the problem of effective collection and automatic classification of massive basic nursing teaching resources data. Recchia measures the similarity of words and positive and negative words through point mutual information (PMI), calculates the data distribution of teaching resources through this similarity, and then makes judgment and classification by summing up all words in the text. The machine learning algorithm of artificial feature engineering is used to select artificial features from the training samples of labeled classification categories, and then, the machine learning algorithm is used to train the classification model. Online teaching resource library is a kind of independent learning and cooperative teaching system based on the Internet. It has a very wide application prospect. The combination of artificial intelligence and this cooperative system will be its future development direction. The main technical foundation of educational technology includes multimedia technology, database technology, and communication technology. Integrating these three technological foundations is artificial intelligence in education. All kinds of complex technology must be humanized and intelligent in order to be widely used in education. Artificial intelligence categorization technology for educational resources will become a key frontier issue driven by educational technology majors and extensively absorbed by multidisciplinary specialists [6–8]. With the fast expansion of the Internet, the number of online resources has exploded

in recent years. The Internet has a large amount of unique information resources of different forms, such as text, voice, picture, video, and so on. Hundreds of millions of web pages contain rich knowledge and teaching resources [9–11]. It has become a very challenging task in the field of educational resource classification technology to find new resources in the vast and complicated web pages and quickly add them to the resource base. The construction of teaching resource bank is the foundation of higher education informationization. It includes media material database, test question database, case database, curriculum database, resource index database, network course database, etc. As the digital teaching resource center, the online teaching resource library is the core component of developing innovative education and cultivating college students with professional knowledge and information literacy in the era of knowledge economy. Keeping up with the development of the times and constantly updating knowledge is one of its important characteristics. Therefore, it is necessary to constantly excavate the new knowledge and resources on and off the Internet, classify and sort out the mined resources, and add new knowledge and content to the resource base in time. Faced with massive information on the Internet, people generally search for information through search engines, manually select and download online information, and then classify and sort it out. This practice has many disadvantages. First of all, it consumes a lot of manpower, material resources, and energy. Secondly, the consistency of query and classification results is not high. Although classifiers have high professional quality, the results are still not the same when different people come to inquire and classify. Even the same person doing the querying and sorting at different times may have different results. Data mining and classification began as a scientific method to extract hidden predictive information from large-scale databases or data warehouses. It gives people the ability to finally recognize the true value of data, the potentially useable information, and knowledge in data. Data mining and classification are the core steps of database knowledge discovery. Its main research goal is to develop relevant methodology and theoretical tools to support the extraction of useful and interesting knowledge, patterns, and rules from a large amount of data. Its main research contents include basic theory, discovery algorithm, data warehouse, visualization technology, qualitative and quantitative exchange model, knowledge representation method, knowledge classification algorithm, knowledge discovery in semistructured and unstructured data, and online data mining classification.

2. Automatic Classification of Basic Nursing Teaching Resources Based on the Fusion of Multiple Neural Networks

This paper proposes the design of automatic classification method for basic nursing teaching resources based on the fusion of multiple neural networks. The specific design framework is shown in Figure 1.

According to Figure 1, the automatic classification method designed in this paper can complete the automatic classification of teaching resources by extracting the characteristics of teaching resources, establishing the fusion model of multiple neural networks, and designing the classification indexes of basic teaching resources.

2.1. Extracting the Characteristics of Teaching Resources. The indexing words obtained by text expression are called feature terms or attributes in machine learning, which generally has the problem of large dimension. Dimension reduction aims to delete unimportant feature items without affecting the quality of classifier as much as possible. The commonly used dimension reduction includes two processes, feature selection and feature extraction. Feature selection refers to the selection of the important indexing words that can express the topic content of the literature from the initial feature item set. The following are some of the most often used feature selection techniques. The quantity of literature in the training set that include a certain term is referred to as the literature frequency selection feature approach. The hypothesis assumption of the literature frequency approach is that terms with low literature frequency give little useful information for classification prediction and have minimal influence on overall classifier performance; therefore, they may be discarded. Low and medium frequency words are often regarded significant terms to represent the substance of literature in the area of information retrieval. The literature frequency technique merely removes terms with a low literature frequency, leaving the majority of words in the middle and low frequency range [12–14]. As a result, the document frequency technique has no effect on the classifier's performance. It should be noted that stop words must be removed before feature selection and only words related to the theme should be retained. The document frequency method is very simple and has low computational complexity. It can adapt to large-scale automatic text classification tasks, and its performance is basically equivalent to that of information gain method. Information gain refers to the amount of information that a single indexing word can provide for the whole classification [15, 16]. It predicts the category of a document by counting the occurrence or absence of words in the document. Suppose a series of possible categories are $\{c_1, c_2, c_3, \ldots, c_k\}$. Then, the information gain of the indexing word is defined as:

$$\text{IG}(i) = -\sum_{j=1}^{k} P(c_j)\log P(c_j) + p(i)\sum_{j=1}^{k} P(c_j). \quad (1)$$

In formula (1), k is total number of categories and $P(c_j)$ represents the class the term i that is part of the class c_j and the proportion of literature in the entire training set. $p(i)$ represents the proportion of documents that contain terms i. The larger the information gain value of a word, the more likely it is to be selected. Words whose information gain value is less than the specified closed value will be deleted. The information gain method needs to be calculated
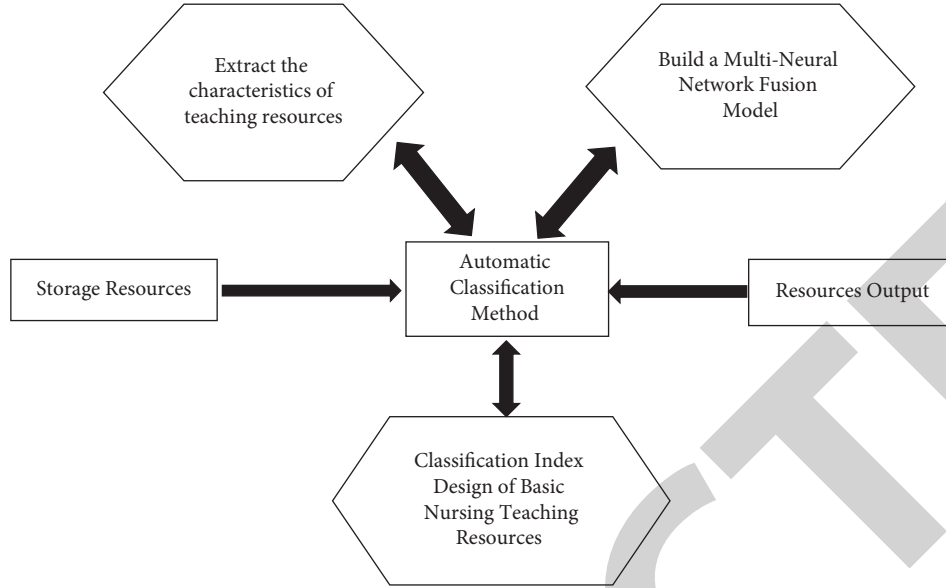
Figure 1: Structure framework of automatic classification method.

separately for each word in the training set. The selection of feature words and weight computation are the most challenging aspects of text feature extraction. If the size of the text feature space is too huge, classification efficiency and accuracy will suffer. As a result, the size of the text feature space must be reduced, and the words that contribute the most to categorization must be chosen. In the categorization process, the weight of a word is determined and processed. The weight represents the effect of a word on classification. The limitation of this method is that it takes into account the situation where the feature words do not appear. When the class distribution and feature word distribution are highly unbalanced, most of the categories are negative and most of the feature words do not appear. At this time, the IG value will be determined by the features that do not appear, and the effect of information gain will be greatly reduced.

Mutual information is a common similarity calculation method in information retrieval and natural language processing, to reflect the degree of correlation between features and categories. Mutual information measures the correlation between a term i and category c_j based on the degree of co-occurrence between them. The higher the MI value, the higher the correlation between category and vocabulary. There are many calculation methods for mutual information, and the most commonly used calculation formula is as follows:

$$MI(i, c_j) = \log \frac{P(i, c_j)}{p(i)P(c_j)} \approx \log \frac{A \times N}{(A + C)(A + B)}. \quad (2)$$

In formula (2), $P(i, c_j)$ represents the probability that word i and category c_j occur together; $p(i)$ represents the occurrence probability of the word i in the entire training set; $P(c_j)$ represents the occurrence probability of category c_j in the entire training set; A represents the co-occurrence probability of words i and categories c_j; B represents the frequency of literature in which word i appears but category

c_j does not; C represents the frequency of documents in which category c_j appears but term i does not; and N represents a literature review of training sets. If there are K classes, then word i will have the number of K and named MI value. And the words whose average value is greater than the threshold value will be selected as the feature item of classification training. The mutual information method only considers the influence of positive correlation attributes on the importance of feature items. The square root fitting test is used to measure the lack of lexical and category independence [17, 18]. The larger x^2 is, the smaller the independence is and the greater the correlation is, which is defined as follows:

$$x^2(i, c_j) = \frac{N \times (AD - CB)^2}{(A + C)(B + D)(A + B)(C + D)}. \quad (3)$$

In formula (3), A represents the co-occurrence frequency of word i and category c_j; B represents the frequency of literature in which term i appears but category c_j does not; C is the frequency of literature in which category c_j appears but word i does not; and D is the document frequency where neither category c_j nor i appears. If $AD \leq CB$, category and vocabulary are independent. If there are K classes, training feature items can be selected according to their average value (in formula (4)) or maximum value (in formula (5)).

$$x^2(i, c_j) = \sum_{j=1}^{k} P(c_j)x^2(i, c_j), \quad (4)$$

$$x^2 \max = \max_{j=1}^{K} x^2(i, c_j). \quad (5)$$

Feature selection method is closely related to experimental data set and classification algorithm, and the advantages and disadvantages of the two methods are compared in practical application. Feature selection generally ignores the semantic relationship between indexing

words. Therefore, the feature term obtained by feature selection is not necessarily optimal. However, the computational complexity of the classifier may be lowered and the classifier's performance enhanced if synonyms and polysemy in the indexing words are integrated or recombined to generate new feature terms [19, 20]. Latent semantic indexing (LSI) and word clustering often utilize special extraction techniques.

In automated text categorization, latent semantic indexing refers to resolving the dimension increase induced by synonyms and polysemy. First, the word frequency matrix is turned into a singular matrix using the singular value decomposition approach in matrix theory. All references in the training set are set to generate a reference matrix, and each component of the matrix represents the number of occurrences of a certain reference in a specific document. Secondly, the matrix is decomposed into singular values, and smaller singular values are removed. The dimension increase method of potential semantic indexing is shown in Figure 2.

In Figure 2, the matrix is used to map the document vector. Word aggregation class collects semantically related words into a group and then uses the group to replace the original feature items, so as to achieve the purpose of dimensionality reduction. The word aggregation class cannot be used to replace the original feature item, but only to complement the original feature item. The similarity of words is determined according to the co-occurrence frequency of words in the text, and the method of clustering literature first and then words is applied to the automatic classification of teaching resources. The flow of the word aggregation class is shown in Figure 3.

As shown in Figure 3, the word aggregation class is processed to control the selection criteria of indexing word conversion relations. Then, other transformation relationships will be filtered out. Traditional feature selection methods can recognize most of the features, but there is a general problem of poor feature recognition. For example, features that rarely appear in the specified category but frequently appear in other categories may be selected, leading to the loss of feature items. However, the extracted features may have errors, so they cannot accurately represent the original data set. In particular, the feature items extracted from the data set with large amount of data and many dimensions are more prone to errors, which ultimately lead to the decline of classification accuracy. The feature dimension reduction method based on multivariate neural network fusion has achieved a better effect than the traditional one. It is widely used in feature extraction, mainly used in feature extraction of dynamic video texture, audio, and image, and also used in medical diagnosis. Noisy data, such as text, may lose precision in processing. In order to eliminate noise interference and obtain more accurate features, a certain probability distribution is used to destroy the original data. After linear transformation and activation function, an implicit coding result is finally obtained. The denoising autoencoder is used to construct a multivariate neural network, which is uploaded layer by layer. Finally, a low-dimensional feature coding of text feature words is obtained, which can be used for text classification combined with the algorithm below.

2.2. Establishing the Multiple Neural Network Fusion Model.
Multivariate neural network is a new research field, developing very rapidly. Different models are constantly proposed and applied. So far, the deep multivariate neural network has formed different models. Deep neural networks may be separated into H classes, generative models, discriminative models, and mixed models based on their structure and principles. The generative depth model is used to explain data with high-order correlation or the joint probability distribution of observed data and related classes [21].

The discriminative multivariate model is capable of pattern classification and usually estimates posterior probability. For example, CNN is a deep neural network framework that minimizes the generation of preprocessed data. The hybrid structure is designed to make the network discriminative, while the generative structure is used to facilitate the optimization of the network. Several models of deep neural networks are introduced below. A special type of Markov random field, in which the upper layer is a random hidden unit which can be seen as some feature extractor, and the lower layer is a random layer of visible or observable units. RBM can also be regarded as a bipartite graph. One layer is the visible input layer, and the other layer is the hidden layer. Nodes of the same layer are not connected, and all nodes are binary variables (value 0 or value 1). And its full probability distribution $p(v, h)$ fits the Boltzmann distribution. Let the input layer of RBM have one node and the hidden layer have m nodes. Since there is no connection between nodes of the hidden layer, when the input layer is known, the nodes of the hidden layer are conditionally independent, namely:

$$p(\mathrm{hv}) = p(h_1 v) \cdots p(h_n v). \tag{6}$$

Since RBM is a symmetric structure, the input layer nodes are also conditionally independent when the hidden layer is known. By adjusting the parameters of RBM network, if the visual layer vl obtained by using the hidden layer h is the same as the original input layer v, the hidden layer h obtained is equivalent to another expression of the input layer v, and the hidden layer h can be regarded as a feature of the input layer v. The schematic diagram of RBM network constructed in this paper is shown in Figure 4.

According to Figure 4, vectors v and h are the states of the input layer and the hidden layer, respectively. The state of the ith node of v is represented by v_i, and the state of the jth node of h is represented by h_j. For state (v, h), the energy formula of RBM model is as follows:

$$p(v, h) = Z(\theta) \sum_{v,h} e. \tag{7}$$

In formula, $Z(\theta)$ represents the normalization factor and e represents the input layer constant.
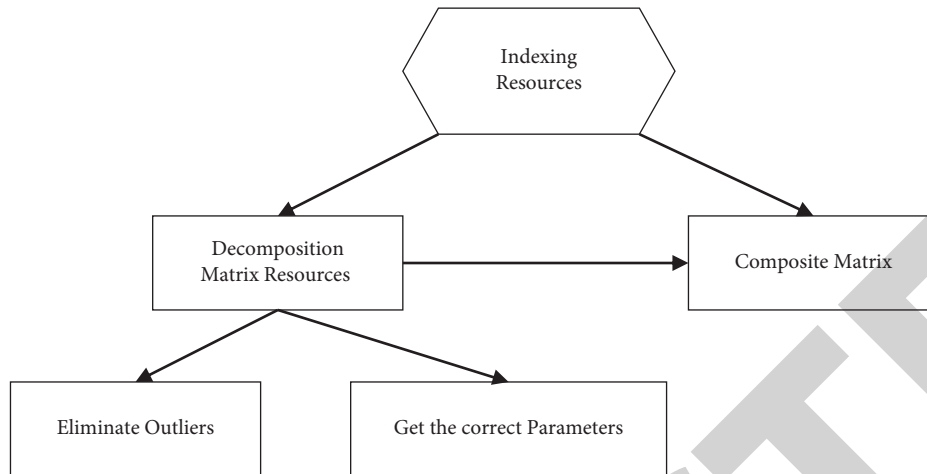
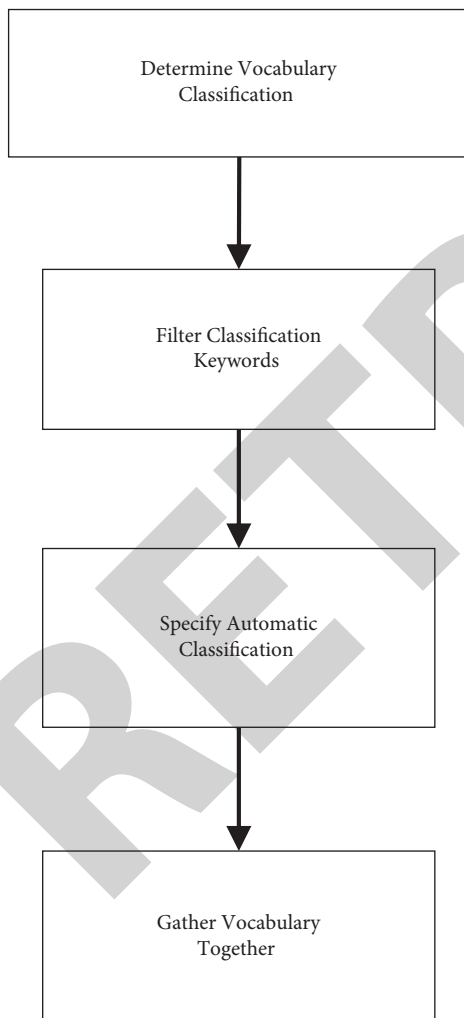Figure 2: The potential semantic indexing dimension adds structure.

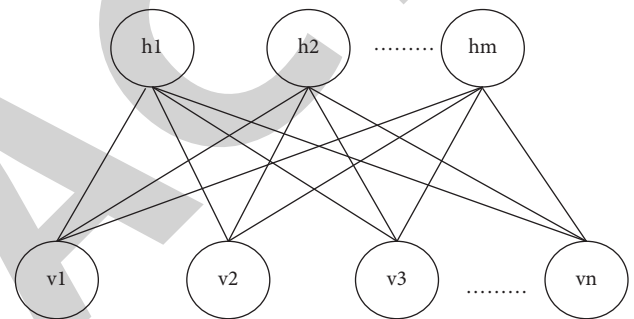Figure 3: Word aggregation class processing flow.

Figure 4: Schematic diagram of RBM network model.

mindset. It also provides the information about good communication with complete cooperation ability. In order to understand the pressure of the education, we need to understand the basic requirement of higher nursing education in detail. Nursing teaching resources mainly include bed-making, handling and protective tools, cleaning, disinfection and sterilization, aseptic operation techniques, isolation and basic nursing techniques, etc. It is one of the key contents of nurses' work to serve patients through nursing basic operation skills. As a result, the quality of nursing service is closely tied to nurses' degree of nursing abilities. Therefore, the necessity of cultivating nursing students' abilities in the process of nursing teaching is a critical link in higher nursing education. To begin, consider the many kinds and properties of indexing languages, such as pregroup or postgroup indexing, indexing depth, and indexing specificity.

A pregrouping language, such as systematic taxonomy, is one in which the indexers are already gathered, or at least the majority of them are assembled, at the time of the indexing language. In a postgrouping language, such as a thesaurus, indexing terms are categorized for real indexing and retrieval. Indexing depth and indexing specificity are key indices that represent an indexing language's features. The number of indexing words in a text is known as indexing length. Indexing duration reflects the content of the indexing language, indexing depth, and indexing specificity to some degree.

2.3. Classification Index Design of Basic Nursing Teaching Resources. Nursing discipline knowledge is updating quickly because clinical nurse must have ability to understand the autonomous learning as well as the critical

When a large number of index languages are integrated, it takes time to perform operations on two index languages.

Document frequency classification index refers to the ratio of the number of documents with feature items in the activity set to the total number of documents. It is the simplest evaluation function. The main idea is to calculate the document frequency of each feature item in the training document set. If the value of the item is lower than the lowest min value or higher than the highest closed value, it will be removed, because they, respectively, represent the two extremes of "no representation" and "no distinction." Document frequency does not depend on class information, so it is a kind of unsupervised feature selection, which is often integrated in text preprocessing to delete words that appear too few or too many times to improve the efficiency of subsequent processing. Although document frequency is much smaller than other evaluation functions, it has a better effect in practice. Text preprocessing is a process of extracting feature words from text to represent the text. Its main task is to segment words and remove stop words. To remove stop words is to remove symbols and words that have little relation with automatic text classification. The general practice is to design a stop word list and remove the words or symbols that appear in the stop word list from the text, leaving only the remaining words for further word segmentation.

In fact, we can take a simpler approach; as long as the index language used by the database has a conversion relationship with the index language used by any other database, users can only use the index language to retrieve other databases or use other index languages to retrieve the database. To achieve the automated categorization of fundamental nursing instructional materials, many classification indices were developed: The proper percentage of assessing resources is represented by specific Spe, which indicates the usual proportion of teaching resources categorization. Sensitivity Sen is a standard parameter for resource classification speed that is used to maintain the automated classification processing speed constant. Accuracy Acc represents the accuracy index of teaching resource classification and judges the accuracy of teaching resource classification. The one-to-one conversion of classification indexes is established, the indexing words in all resource libraries are regarded as an equivalent relation, the conversion classification index parameter F is obtained, and the expression is as follows:

$$F = \frac{\text{The average indexing length of database } B}{\text{The average indexing length of database } A} \times L. \quad (8)$$

In formula (8), L is expressed as equivalent parameters. The classification index is designed by transforming the classification index parameters.

3. Experimental Analysis

3.1. The Experiment to Prepare. This study is a kind of experimental study. All data were carefully checked, used, and

Table 1: Number of teaching resources 1000 chi-square test parameters.

Number of experiments	The experimental group	Reference group
1	87.349	70.164
2	79.168	64.381
3	90.164	84.364
4	88.164	75.169

Table 2: Number of teaching resources 3000 chi-square test parameters.

Number of experiments	The experimental group	Reference group
1	94.167	72.183
2	80.164	67.167
3	68.326	40.189
4	90.197	77.774

Table 3: Number of teaching resources 5000 chi-square test parameters.

Number of experiments	The experimental group	Reference group
1	91.352	74.286
2	89.174	66.349
3	78.266	50.186
4	91.598	74.115

Table 4: Number of teaching resources 7000 chi-square test parameters.

Number of experiments	The experimental group	Reference group
1	90.225	71.035
2	80.143	61.349
3	77.634	55.319
4	95.336	70.167

statistically analyzed by researchers. The results were analyzed by descriptive statistics, two-sample test, paired sample test, chi-square test, rank-sum test, and other statistical methods. The experimental platform of this paper adopts the CPU platform of ULTRAmicro E5 series, the processor is Intel E5-2600 model, the graphics card is GTX TITAN BLACK, the memory is 32G ∗ 8, and the operating system is Linux system. The amount of computation in the fusion training of multiple neural networks is very large, so CPU can speed up the operation. The experiment uses the data of CCDD database, which comes from the basic nursing teaching resources in different regions. The error of the calculation results is small. Increasing the number of training samples reduces the number of functions that training samples can fit, makes it easier to train and get real

decision functions, and improves the prediction accuracy of fitting functions.

3.2. The Experimental Results. In order to the validate the different source of quantity, in Pearson chi-square test parameters, the larger the chi-square test parameter is, the better the effect of automatic classification method is proved. The experimental results are shown in Tables 1–4.

As the theory can be seen, respectively, experimental results show that the chi-square test parameters of the proposed automatic classification method of basic nursing teaching resources based on the fusion of multiple neural networks are higher, and the automatic classification effect is better for a large number of teaching resources.

4. Conclusion

The nursing industry and nursing education to international standards have been imperative, so it is necessary to cultivate a sense of international service and international competitiveness of senior nursing talents, to meet the needs of the society. How to improve the automatic classification of teaching resources and actively promote the reform of nursing education in China is very important. The automatic classification method of basic nursing teaching resources proposed in this paper, based on the fusion of multiple neural networks, can quickly realize the automatic classification of a large number of teaching resources. The experiment proves that the automatic classification method in this paper has higher chi-square test parameters and has a good effect on the automatic classification of teaching resources [22].

Data Availability

The data used to support the findings of this study can be accessed in the repository through the link https://pubmed. ncbi.nlm.nih.gov/32614858/.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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