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Retraction

Retracted: Research on Network Resource Collection and Distribution Strategies in Big Data-Driven Multimedia Teaching

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] J. Han, "Research on Network Resource Collection and Distribution Strategies in Big Data-Driven Multimedia Teaching," *Advances in Multimedia*, vol. 2023, Article ID 7745785, 12 pages, 2023.

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Research Article

Research on Network Resource Collection and Distribution Strategies in Big Data-Driven Multimedia Teaching

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The multimedia teaching information data generated in the era of big data are increasing at a huge scale, but the computing environment used before is difficult to meet users' requirements for data integration. Multimedia information has the characteristics of diversity and structure diversity, which lead to the situation that the storage and processing methods are too complicated and time-consuming to varying degrees. This brings great challenges to big data analysis. Therefore, the fusion of this part of the data information requires a large-scale data parallel framework environment to ensure that multiple data calculation instructions can be executed each time, improve the range of problem solving, and essentially improve the complexity of multimedia teaching information. The main index of large-scale data fusion is computing speed. Aiming at the performance defects of the open source computing framework Hadoop, this paper intends to establish a new computing model. This model uses distributed data sets to replace the previous data structures and solve some problems in the process of data integration, thereby significantly improving the computation efficiency and reducing resource usage. Starting from the network's perception of energy resources and considering that the randomness of energy available to nodes in the energy harvesting cognitive relay different systems will lead to different data volumes such as throughput and resource utilization, this paper takes the network's throughput as the optimization network object for resource collection and allocation research. Experiment description: compared with the previous resource management, this model can reduce the total consumption of the system; compared with the single base station mode, the proposed method can extend the network life cycle to a greater extent; meanwhile, it ensures the use of users. Based on the stability analysis of the data, an optimal solution is obtained that can maximize the stable throughput of cognitive users and effectively improve resource collection and allocation.

1. Introduction

With the advent of the information age, multimedia teaching no longer needs to be limited to individual school networks or a country's network, and education globalization will be realized in the future [1–4]. In such a context, it is particularly important to establish a global platform for sharing resources. Therefore, it is the general trend to build a global educational resource platform [5]. The global educational resources are abundant, various databases are huge, the amount of educational information is large, and the teaching scale is large, which determines that the traditional educational model has certain limitations. Therefore, it is an inevitable trend to use a single network for the collection, analysis, and distribution of educational resources [2, 6, 7].

At present, many domestic colleges and universities spare no effort in the development of this technology, and most of them achieve the purpose of live broadcast education. Moreover, many universities in developed countries are applying live teaching technology on a global scale, that is, using wide-area computers to connect universities around the world for research. This technology has achieved initial results and will slowly mature [8–12]. At the same time, on an international scale, more and more schools have begun to adopt this teaching method and have achieved good results. Live teaching is a new thing; it has many advantages compared with the traditional teaching mode [13]. There is no doubt about that. The live broadcast of education is an era of change. With the popularization of live multimedia teaching in the world, the concept of "world classroom" and the development of knowledge globalization and education globalization trends have put forward higher requirements for live broadcast multimedia teaching technology [14, 15].

Based on the Spark model, users can cache part of the data in memory with the help of elastic distributed data sets, and the execution of parallel computing operations can recycle this part of the cached data [16, 17]. According to the analysis requirements and processing characteristics of media big data, a design method of elastic distributed application system for Spark is proposed. Therefore, the Spark parallel computing architecture supports the access and management of large-scale elastic distributed data sets, and can efficiently process large amounts of data in massive elastic distributed data sets. In this paper, by calling different types of operators and using Spark's own functional tools, the elastic distributed data set parallel operation based on these operators is realized, and a model based on Spark is designed [18–20]. Distributed data is a brand-new structure, which transforms the collection form of data sets into "distributed." In other words, a multimedia network information data set is planned from several data blocks, one of which is a data set. The blocks are distributed and stored in the nodes of the cluster. The Spark framework identifies each multimedia data block with a unique Block ID. By determining the metadata corresponding to the Block ID, tasks such as data block storage and transmission can be flexibly completed. The multimedia data block is divided into several regions for processing [21–24].

The Spark model is a cluster-based computing platform that is mainly used to process relatively large-scale data. The model can perform efficient and high-speed computing, even on disk. The model has four different operating models. This paper mainly uses the framework of the resource management model.

2. Algorithm Model for the Collection and Distribution of Multimedia Teaching Resources Based on Big Data-Driven Research

The model studied in this paper (tentatively named the resource management model) is the basic building block of the education industry and the intelligent industry. As a level of data support, making it understandable by machines is the need of the current information age. The establishment of this resource management model enables better collection and distribution of various resources, and is suitable for all walks of life. Everywhere has a foothold.

Based on the above practical application requirements, this paper designs and establishes a deep learning model with resource management as the core, so that the network resources in multimedia teaching can be brought into play in the field of big data, and the high-efficiency characteristics of big data are used to fully understand, complete, and correct the system In fact, the internal hierarchical structure of the multimedia database is like the resource management model in this paper. The difference is that the internal structure of the library is in the form of classification. According to the scope of semantics, the words and sentence branches are stored in a hierarchical relationship; the resource management model is to build a hierarchy, and to promote the development of the natural language understanding ability of intelligent algorithms based on hierarchical classification and retrieval. Combined with the object of this paper, the model framework under deep learning is divided into the following four levels, and the design problems of the model are discussed, respectively.

The four main points of the embedding layer are character embedding, word embedding, context embedding, and feature embedding. In the connection between the four, there is a subset relationship, that is, the character vector and word vector generated by character embedding and word embedding will be used for the expression elements of context embedding to obtain rich realistic natural language coding information, and then load the coding layer and interactive layer.

Feature embedding is different from word and sentence embedding. The focus of feature embedding is how to convert the inherent features of language or text into one-dimensional vectors.

To sum up, the embedding layer is the process of dataization, and the contrast encoding layer is the context encoding for each word. Since the word vector is still fixed in the embedding layer, when faced with polysemy in the model construction, the specific meaning of the word here can only be retrieved through the common will of the context. In deep learning, in order to realize the understanding of context semantics, the words that have been vectorized are usually used to further process through the neural network to realize vector transfer and then semantic transfer.

2.1. Processing Feature Words. When a neural network analyzes a huge database, it must decide the focus of the analysis, that is, where it needs to be understated and explained in detail. However, the types of parameters have the characteristics of diversification and the nature of time and period, which need to be related to the current situation of network resource development. In the overall situation, the influence of parameter diversification is very small, and the output result of the output layer is also low enough to be affected by the parameters, so it is acceptable that the expected result is consistent with the actual result.

In order to manage the collection and distribution of resources in multimedia education, we must first study how to automatically acquire resources for multimedia education through big data technology. The main methods of acquiring resources are roughly divided into two types, through statistical-based methods as well as knowledge-based methods. But this paper adopts the method based on knowledge network to obtain the teaching resources of multimedia teaching in the whole network.

In feature words, there are many relationships between two or more feature words, such as synonymous relationship, polysemy relationship, and so on. If these relationships can be dealt with, the difficulty of resource management will be greatly reduced. The following takes polysemy processing as an example.

When collecting resources, a feature word contains two or more concepts at the same time, which is often referred to as a polysemy relationship. Assuming that the feature value is t, and the included concept is set to C, then the formula for the feature word to correctly represent its concept is as follows:

$$
\begin{gathered}
C_t = \left\{c_i \,\middle|\, t \xrightarrow{\text{map}} c_i, t \in T, c_i \in C_F\right\}, \\
Q_i = \sum \text{Count}\left(c_i, t_j\right), c \in C_t, t_j \in W \text{且} t_j \neq t, \\
\text{Count}\left(c_t, t_j\right) = \begin{cases} 1, t_j \longrightarrow c_i, \\ 0, \text{others}, \end{cases} \\
c^* = c_i, c_i \in C_i \text{且} Q_i = \max\left\{Q_i, \cdots, Q_i, \cdots\right\}.
\end{gathered} \tag{1}
$$

The final c^* result is the correct concept represented by the eigenvalue t.

Because network resources in the field of multimedia teaching have several obvious characteristics, such as large number of resources, miscellaneous resources, many types of resources, and many professional terms or unfamiliar vocabulary in the article, the model constructed in this paper not only analyzes the content of the article but also analyzes the content of the article. It analyzes the physical structure and logical structure of the constructed article, such as title, paragraph, and literature. The logical structure is the subject content, main level, and main idea of the article. Both structures are considered in subsequent confidence calculations.

2.2. Concept Matching. The purpose of concept matching is to compare network resources and concept networks in a multimedia teaching through concept templates, and match them to knowledge ontology. Then, use this ontology to describe the characteristics of the target teaching resources. Since there are many teaching resources in multimedia teaching, a certain knowledge resource can be represented by a subnetwork in a certain resource network, so concept matching can be carried out through the previously analyzed feature word relationship. Concept matching is calculated as follows:

$$
B = \alpha * \text{Density} + \beta * \text{Dispel}^{-1}. \tag{2}
$$

Among them, α and β are important factors for weight adjustment, and density represents the purity factor in concept matching. Purity represents the gap for matching objects in the calculation process, which is obtained by comparing the initial features and the resulting features. The formula is as follows:

$$
\begin{gathered}
\text{Density} = \frac{\sum_{m \in W} C\text{Value}(m)}{\sum_{n \in W'} C\text{Value}(n)}, \\
C\text{Value}(n) = \begin{cases} 1, n \in W, \\ 2, n \in P, \text{Type}(n) = C.A|C.B|C.R, \\ 3, n \in P, \text{Type}(n) = C, \\ 4, n \in P, \text{Type}(n) = C.A[a]. \end{cases}
\end{gathered} \tag{3}
$$

The dispersion degree dispel represents the distribution of nodes in the model. When the knowledge represented by the eigenvalues of a resource is more dispersed and more niche, the dispersion degree is higher, and the process of collection and distribution is difficult. The dispersion is calculated as follows:

$$
\text{Dispel} = \frac{N \sum_{s_i, t_i \in W} H\left(s_i, t_i\right)}{n \sum_{s_j, t_j \in W'} H\left(s_j, t_j\right)}. \tag{4}
$$

2.3. Confidence Calculation. There is no clear explanation for the description of the confidence level. The general meaning is that, when the data are sampled, a conclusion cannot represent all the meanings, so the conclusion is not very clear. At this time, the credibility of the conclusion is a range value, and this value can be calculated and is called confidence.

After the calculation of the above concept matching, the resource ontology is obtained. Select the corresponding part in the resource ontology as a node to calculate the confidence of resource management. It is calculated as follows:

$$
\text{Trust}(w) = \text{Station}(w) * [\text{Level}(w) + \text{Range}(w)], \tag{5}
$$

where level is called the level confidence and is used to calculate the level value in W:

$$
\text{Level}(w) = \frac{l_w}{l_{\max}}. \tag{6}
$$

The station is called the position confidence, and the position confidence indicates that since most of the data reflecting the topic are usually distributed in the front or the back, the weight given according to the position of the feature word in the teaching resources is called the position confidence as follows:

$$
\begin{gathered}
\text{pos}\left(\text{t}_i\right) = \begin{cases} 0.95, t_i \text{in the header}, \\ 0.85, t_i \text{at the beginning of the paragraph}, \\ 0.8, t_i \text{at the end of the paragraph}, \\ 0.6, t_i \text{others}, \end{cases} \\
P_i = \text{pos}\left(t_i\right), T_w = \left\{t_i \,\middle|\, t_i \xrightarrow{\text{map}} w \text{且} t_i \in T\right\}, \\
\text{Station}(w) = \max\left(P_1, \cdots, P_i, \cdots\right).
\end{gathered} \tag{7}
$$

In the formula, range is called the range confidence, which is the entire range of the feature words in the entire teaching resource library, and it is the coverage of all the meanings of the feature words in the text. The larger the value is, the larger the range covered by the feature word in a certain text is. The formula is as follows:

$$\mathrm{Range}(w) = \sum r(t), t \in T_w, T_w = \{t \mid t \xrightarrow{\text{map}} w \text{且} t \in T\},$$
$$r(t) = \sum \mathrm{length}(l_t), t \in l_t. \quad (8)$$

After the calculation of the confidence level is completed, due to the relatively centralized characteristics of the database, it is easy to appear that the retrieval result has only one word or named entity in the calculation process. Based on this problem, the final output layer needs to use the database classification branch to work together. Indexing technology is used for word vector prediction. Therefore, the resulting index position probability for each character in the library is defined as

$$p = \mathrm{soft\,max}\left(u^Q \cdot W^T \cdot \overline{P}\right). \quad (9)$$

On the obtained probability interval, the probability of the end position is obtained by the same method as the start position prediction. Its mathematical expression is as follows:

$$p_0 = \mathrm{soft\,max}\left(u^Q \cdot W_s{}^T \cdot \overline{P}\right),$$
$$p_1 = \mathrm{soft\,max}\left(u^Q \cdot W_e{}^T \cdot \overline{P}\right), \quad (10)$$

where P_0 is the starting position probability and P_1 is the ending position probability.

The softmax function is the normalization process in the mathematical sense, which is a generalization of the traditional logic function. Combined with the corpus matrix dimension problem in this paper, the normalization process can convert the k-dimensional vector a into a k-dimensional vector b, and at the same time, change the elements of the change. The interval is controlled from 0 to 1, and the value of the matrix determinant is 1.

So far, through the analysis of the text structure in the network resources, the analysis of the feature words, and the calculation of the confidence, and then through the concept matching, the desired target resources are finally obtained. Compared with the previous research, this process considers the previously ignored literature or professional terminology, which leads to the narrowing of the scope of feature words and the reduction of the use of feature words. This process is mainly an improved method for collecting network resources in multimedia, and the core algorithm of this process can be easily run by ordinary computers, and is an algorithm model that can be understood by computers.

$$M_1 = \frac{\sum_{c \in N_0} \{[\mathrm{length}(N_t) - \mathrm{abs}(\mathrm{sort}N_i(c) - \mathrm{sort}N_o(v))]/\mathrm{length}(N_t)\}}{\mathrm{length}(N_o)}. \quad (11)$$

Among them, the length of the response is the length of N_t and N_o, and they refer to two kinds of resource data. Sort represents their ordinal numbers in N.

3. Algorithm Improvement and Optimization on the Core Level of the Model

When dealing with information bottlenecks, attention mechanism selectively filters redundant data, concentrates the core processing points on a certain part with directional characteristics, and speeds up or completes the processing of the target in a qualitative way. At the same time, it is also borrowed from this point, combined with the research object of this paper, to avoid the comprehension error of word and sentence confusion.

Using the model constructed in this paper to build a teaching resource management algorithm focuses on eigenvalues and confidence. To a certain extent, the mechanism is relatively simple, resulting in relatively simple processing methods when faced with actual situations, which makes the model algorithm for the collection of teaching resources, and there will be problems with allocation processing.

In response to the above, this section will propose a variety of big data mechanisms in a supplementary form for improvement.

The vectorization of corpus elements such as words, sentences, and contexts is just a process of converting text information into digital information. This process is not useless, but it is the basic guarantee of the basic structure of big data, using neural networks to efficiently process harmonious text information and vector data-related problems.

First, the word vector is unified as q_n, the context vector is unified as q_m, and the word vector group is a_n. On this basis, the eigenvalue function is set to S as a fixed variable, which is applicable to the following mechanisms. There are four common system mechanisms as follows.

3.1. Dot Product Mechanism

$$S_{i,j} = f\left(p_i, a_j\right) = p_i^T q_j. \quad (12)$$

This mechanism requires that the initial end vector p_i and the end end vector q_j have the same vector dimension. It means that such a mechanism is only applicable to word-only, or context-only vectors in the database.

3.2. Bilinear Mechanism

$$S_{i,j} = f\left(p_i, a_j\right) = q_j^T W p_i. \tag{13}$$

Unlike the dot product mechanism, the parameter matrix W is added, which does not require a square matrix in the same row and the same column. Therefore, the advantage of the bilinear mechanism over the dot product mechanism is that the vector dimensions of the initial end and the end end are allowed to be different.

3.3. Multilayer Perception Mechanism

$$S_{i,j} = f\left(p_i, a_j\right) = W_2^T \tanh\left(W_1\left[p_i; q_j\right]\right), \tag{14}$$

where W_1 is the first-layer weight matrix and W_2 is the second-layer weight vector. This mechanism has a trade-off between the dot product mechanism and the bilinear mechanism because it is much more flexible than the dot product mechanism, but the parameter size is significantly smaller than that of the bilinear mechanism.

3.4. Two-Dimensional Conversion Mechanism

$$S_{i,j} = f\left(p_i, a_j\right) = p_i^T U^T V q_j. \tag{15}$$

Combined with the corpus that needs to be reduced in dimension, the dimension of the context is always higher than the dimension of the word, and the matrix transposition relationship is also determined by the size of the original dimension. According to this, the corrected result of formula (11) is as follows:

$$S_{i,j} = f\left(p_i, a_j\right) = p_i^T W q_j. \tag{16}$$

The advantage of this mechanism is that the initial end vector and the end end vector are converted to the product of low dimensions, reducing the number of parameters involved in the operation. At the same time, after obtaining the calculation score of each word vector, the softmax function is used to normalize the processing to obtain the weight, and its mathematical expression is as follows:

$$\alpha_{i,j} = \frac{e^{S_{i,j}}}{\sum_{k-1}^{n} e^{S_{i,k}}}. \tag{17}$$

Using the weighted sum of weight calculations, the result is as follows:

$$p_i^q = \alpha_{i,1}q_1 + \alpha_{i,2}q_2 + \alpha_{i,3}q_3 + \cdots + \alpha_{i,n}q_n. \tag{18}$$

Use the attention function to express the whole process, namely,

$$\text{Attention}\left(\left(p_1, p_2, p_3, \cdots, p_m\right)\left(q_1, q_2, q_3, \cdots, q_n\right)\right) = \left(p_1^q, p_2^q, \cdots, p_m^q\right). \tag{19}$$

For the optimization of the results, the candidate set of the output results when the database is missing will be considered. Timely reduction and expansion are the key points of the output calculation unit time efficiency. For this, the optimization method is as follows:

$$\alpha_i = \frac{\exp\left(p_i W q\right)}{\sum_t \exp\left(p_t W q\right)}. \tag{20}$$

The attention function is a function used to obtain a weighted average for a given coding layer at different times. The application in this article is to calculate the attention weight. The weight calculation formula is as follows:

$$\begin{aligned} \alpha t' t &= \exp\left(e t' t\right) \sum T k = \exp\left(e t' k\right), \\ u &= \sum_i \alpha_i p_i, \\ P(Y = a \mid p, q) &= \frac{\exp\left(W_a u\right)}{\sum_{\overline{a} \in A} \exp\left(W_{\overline{a}} u\right)}. \end{aligned} \tag{21}$$

In order to predict whether the output result can achieve the expected effect, a number of answers will be introduced to make a trade-off to select the final result. The mathematical formula of the trade-off is as follows:

$$P(Y = i \mid p, q) = \frac{\exp\left(a_i W^1 u\right)}{\sum_{t=1,2\cdots k} \exp\left(a_t W^1 u\right)}, \tag{22}$$

where A is the vector group of word vectors. So far, the optimization and improvement of the model algorithm have been completed. Such processing results enrich the selection principle of the database, expand the capacity of the original model with a single processing capacity, output the huge amount of calculation to be calculated by changing the value interval, and timely change to achieve the collection and distribution of network resources in multimedia teaching.

Assuming that geometry A is a cluttered database that has been constructed and is to be classified, the mathematical formula for the existence of an entropy-increasing region is as follows:

$$A_{ij}(x) = A_i(x) - A_j(x), \tag{23}$$

where x is the element to be processed, if and only if $A_{ij}(x) > 0$ or $A_i(x) > A_j(x)$, the discriminant function parameter i that is not equal to j is established, the discriminant function outputs the result of the classification, and the answer is 0 or 1, and the answer is yes or no to classify each word.

4. Experimental Test

By expanding the selection of attention mechanism, it will directly affect the results of the resource management model on the internal structure design of the network resource library. Therefore, part of the experimental test is to explore the performance of the neural network inside the model for the design and optimization of the resource library, and then determine the improvement or optimization direction of the experimental points in this section.

On the other hand, the experiment selects the resource collection and distribution in a certain school, and the construction model description further illustrates the reliability of the network resource management model under the construction of multimedia teaching.

4.1. Performance Testing. The $f1$ value, also known as the $f1$ score, is an indicator of the accuracy of a model or algorithm using statistical knowledge, and combines precision and recall. It is calculated as follows:

$$F1 = 2\frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}. \tag{24}$$

This paper conducts key performance tests on the resource collection and distribution platform of modern multimedia education based on big data from two performance indicators, data loss rate, and data processing rate.

As shown in Figure 1 and Table 1, under the condition of 1000 G data volume, the data loss rate of the current system is within 0.5%, which can ensure the accuracy of data analysis and meet the stability requirements.

Figure 2 and Table 2 show that the current big data-based modern multimedia education has no obvious difference in the data processing speed of the resource collection and distribution platform within 1000 G, and the current processing speed can meet the real-time performance requirements of the platform.

4.2. Reliability Test. The reliability test is aimed at various functions of the overall architecture of the digital teaching resource management platform. For example, when a single server is powered off, shut down, or shut down by a system crash, the platform system still works normally, and the data remain intact and are not lost. In the event of a hardware failure or the transition to hardware and other hardware in a shutdown state, the computer still works normally, the platform system reaches an automatic load balancing state, and resource data will not be lost. Please refer to the attached Table 3 for the details of the reliability test.

The reliability experiment shows the data packet loss rate when the algorithm model is overloaded due to server disconnection, system crashes, and hardware problems. It can be seen from the results that, when the algorithm is forcibly stopped due to special circumstances, the probability of target teaching resource data loss is smaller than that of other models, indicating that the resource management model in this paper is more reliable. It is shown in Figures 3–5.

4.3. Impact Rate Test. In this experiment, the arrival rate matrix of $p = 0.5$ generated by the uniform distribution of 0 to 1 is multiplied by the scaling factor of 1/5 to 8/5 to simulate the arrival rate matrix of various load conditions. Then, this experiment carried out different load conditions on the MLPI discovery routing strategy and carried out the performance test on 16 switch test networks in each stage.

Figure 6 and Table 4 show the corresponding performance of the routing strategy adopted by the MLPI algorithm under various load conditions. The experimental results show that for any given input traffic, with an increase in load balance, the MLPI algorithm can achieve better results, and the heuristic routing strategy can make the entire network reach better than the undirected routing strategy. No matter how the load conditions change, the routing strategies discovered by the MLPI algorithm consistently outperform the heuristic routing strategies in terms of performance. In the case of 0.8 network load, the MLPI algorithm can reduce the average number of packets by (410 – 253)/410 38 and (356 – 253)/35628, compared to the JSQ and Po2 algorithms.

4.4. Resource Collection. By comparing the student-teacher ratio of each university before and after the assignment, the hypothetical resource allocation through this intelligent assignment model can relatively effectively improve the uneven distribution of educational resources in each university, so that the teacher resources after the assignment to achieve a more general situation, and to improve the phenomenon of uneven educational resources on the teacher's side. Then, configure the collected teacher and student resources as shown in the Figure 7 and Table 5.

It can be seen from the figure that the distribution of students among the six universities is not balanced. However, the student-teacher ratio of 3 schools is 1 : 9 (that is, the ratio of students to the total number of classes), and the student-teacher ratio of the remaining 4 schools is less than 1 : 2, and the gap between these institutions is large. The reason for this is probably that the total number of teachers and students whose resources in these six universities was in the tens of thousands before the allocation, and the number is relatively large. Therefore, the model assumes that the number of teachers and students' resources allocated by each university is relative to the previous number of teachers and students. The number of teacher-student resources is still too small. At the same time, it shows that in order to fundamentally improve the inequality of educational resources caused by an excessively large base, the equalization of the distribution of educational resources should be expected in advance rather than repairing the situation.

4.5. Resource Allocation. The stochastic frontier model mainly uses two methods: the first is called the frontier analysis method, and the second is called the data analysis method. Both methods are well applied with various models. The most commonly used models for frontier analysis are as follows:

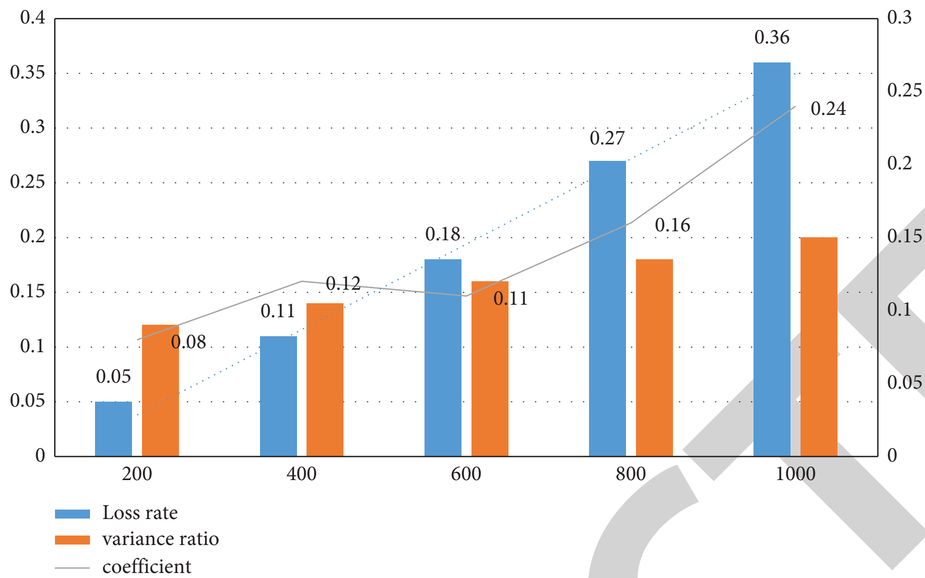

Figure 1: Data packet loss rate.

Table 1: Performance index.

The amount of data	Loss rate	F value	Coefficient
200	0.05	0.12	0.08
400	0.11	0.14	0.12
600	0.18	0.16	0.11
800	0.27	0.18	0.16
1000	0.36	0.2	0.24

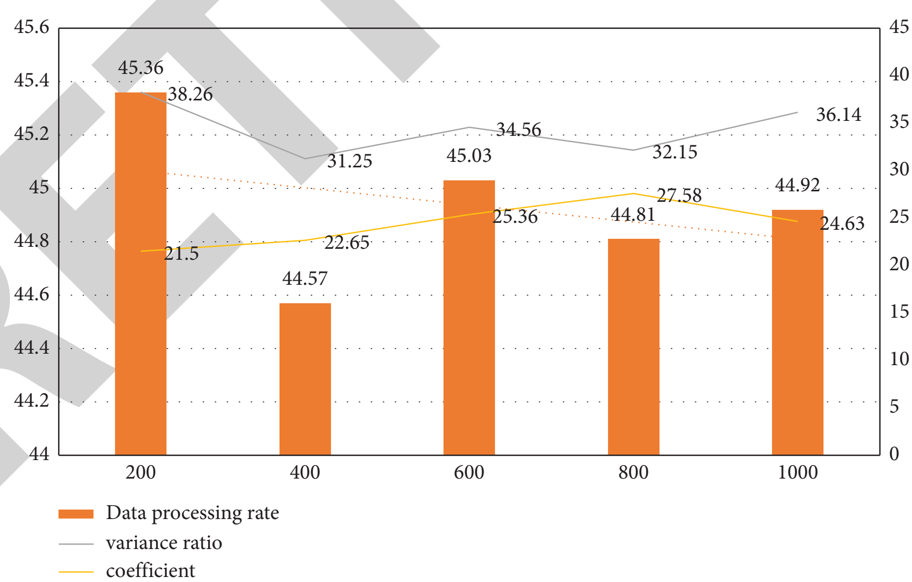

Figure 2: Data processing rate.

$$\ln y_{it} = \ln f\left(x_{it}, B\right) + v_{it} - \mu_{it}, \tag{25}$$

where y represents the actual quantity of a unit, x represents the input quantity of a unit, and f represents a certain calculation function.

Constructing a stochastic frontier analysis model, taking the total resource allocation slack variable on a campus as the explained variable, and taking the allocation of student resources, teacher resource allocation, teacher-student classroom interaction, and teacher-student extracurricular

Table 2: Data processing rate.

The amount of data	Data processing rate	F value	Coefficient
200	45.36	38.26	21.5
400	44.57	31.25	22.65
600	45.03	34.56	25.36
800	44.81	32.15	27.58
1000	44.92	36.14	24.63

Table 3: Reliability test data.

Reason	Server disconnected	Server loses power	System breakdown	Hardware stopped working	Switch hardware
Load	0.56	0.48	0.75	0.68	0.59
Overload	0.43	0.32	0	0.56	0.58
Resource data loss rate	0.12	0.15	0.31	0.22	0.29

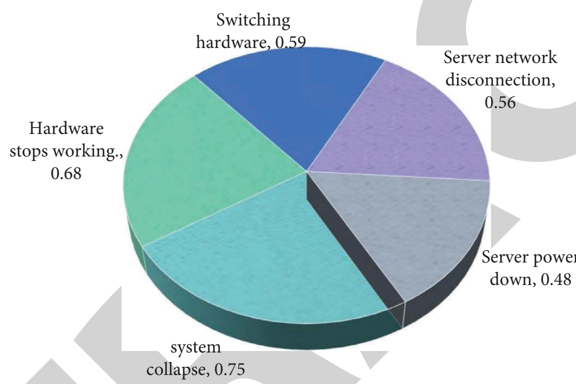

Figure 3: Load factor.

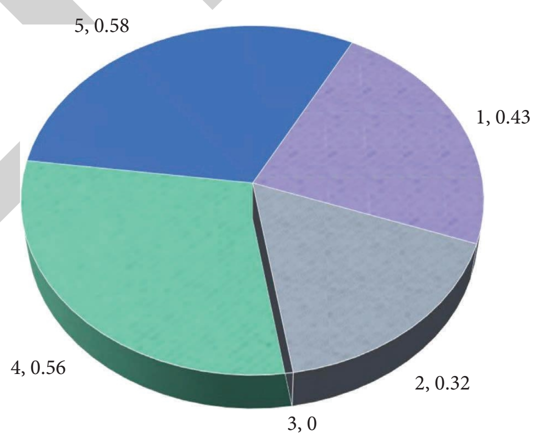

Figure 4: Overload rate.

activities as four external environmental factors. As an explanatory variable, Frontier 4.1 software regression is used to examine whether external environmental factors significantly affect the input slack variable. The results are shown in Table 6.

In Figure 8, the LR unilateral likelihood ratio test is 34.03, 31.77, and 57.28, respectively, all of which have passed the 1% level significance test, indicating that it is appropriate to strip the external environmental factors when multimedia education is used in the efficiency of network resource collection and distribution. The estimated results of the SFA model are acceptable. The three gamma values all passed the significance test at the 1% level, indicating that the selected external environmental factor indicators are more reasonable.

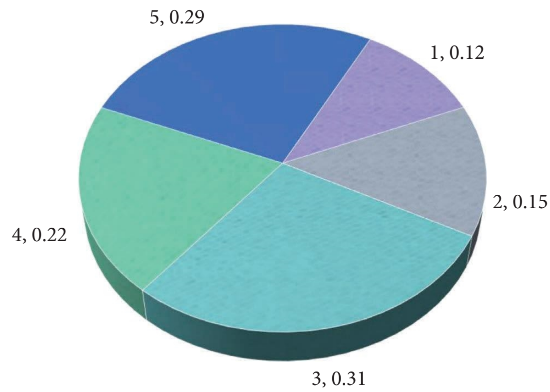

Figure 5: Data packet loss rate.

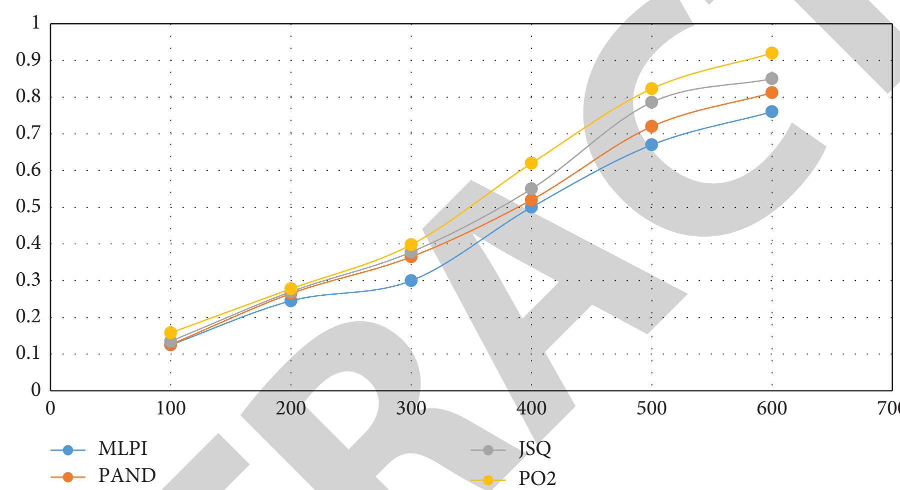

Figure 6: Network load impact rate.

Table 4: Impact rate test data.

Influence rate	100	200	300	400	500	600
MLPI	0.125	0.245	0.3	0.5	0.67	0.76
PAND	0.126	0.265	0.365	0.52	0.72	0.812
JSQ	0.135	0.27	0.378	0.55	0.786	0.85
PO2	0.158	0.278	0.398	0.62	0.823	0.92

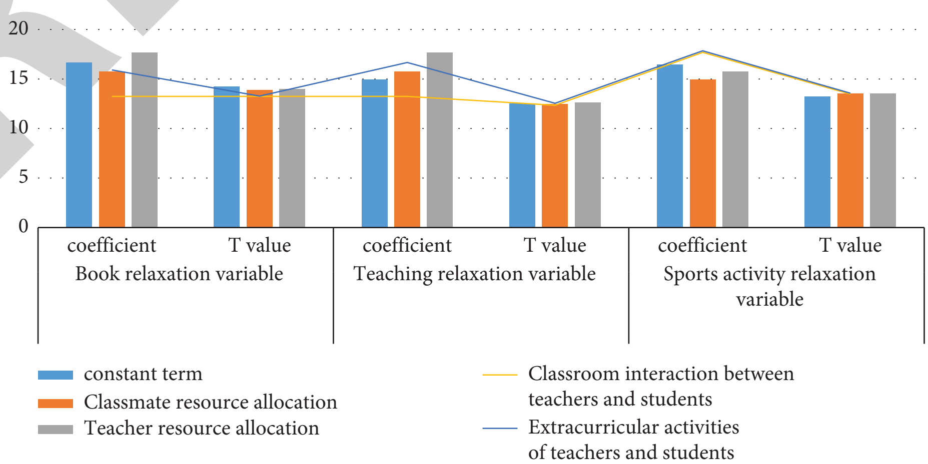

Figure 7: Proportion of resource collection and allocation.

Table 5: Resource configuration.

College	Number of students/thousands	Number of teachers/thousands	Teacher-student ratio (%)	Number of teachers assigned/person	Teacher-student ratio after distribution (%)
1	20	12	16.67	19	14.27
2	26	17	15.76	23	13.87
3	23	13	17.69	34	13.99
4	18	11	13.24	16	13.24
5	19.3	16	15.91	26	13.86
6	25	11	14.95	38	14.45

Table 6: Slack variables.

Variable	Book slack variable		Teaching slack variable		Physical activity relaxation variable	
	Coefficient	*t* value	Coefficient	*t* value	Coefficient	*t* value
Constant term	16.67	14.27	14.95	12.56	16.47	13.24
Student resource allocation	15.76	13.87	15.76	12.47	14.95	13.56
Teacher resource allocation	17.69	13.99	17.69	12.65	15.76	13.52
Teacher-student classroom interaction	13.24	13.24	13.24	12.35	17.69	13.47
Teacher and student extracurricular activities	15.91	13.28	16.67	12.55	17.85	13.56

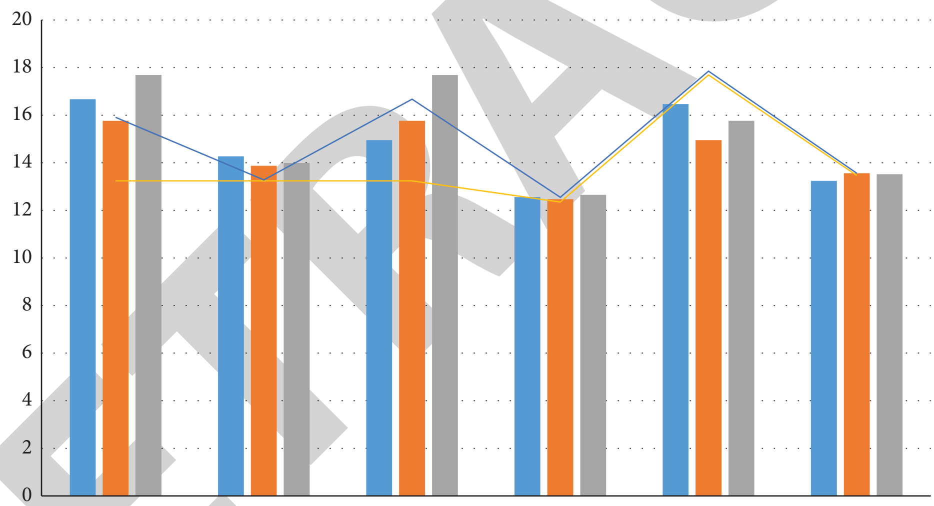

Figure 8: Resource allocation variables.

5. Conclusion

Nowadays, with the increasing maturity of Internet technology, the use of multimedia to collect and distribute network resources has become the habit of most people, but teaching resources are generally numerous and complex, and how to accurately find user needs has become an urgent problem. Because the general teaching mode is relatively backward, people gradually realize the importance of cultivating students' autonomous learning abilities. The emergence of big data technology has laid a technical foundation for the collection and distribution of multimedia education personalized customization resources. Combining big data technology to build a multimedia education resource collection and distribution platform that can accurately detect user needs and comprehensively mine teaching resources has gradually become the current stage of the core issues of research among teaching practitioners and experts. The topic of this paper is that, against this background, the application of big data technology to multimedia education has made a beneficial attempt and contributed to research in the industry of resource acquisition and distribution.

The big data-driven multimedia resource collection and allocation design is based on the establishment of the hierarchical model in this paper to achieve a dynamic balance between the input and output of resources and develop the original inherent normalized storage process into a training experiment under the neural network greatly improving the efficiency. The construction of the interactive layer of the algorithm, the calculation of confidence, and the calculation of eigenvalues are the core levels of this paper. The independent characteristics of resources are fully understood so that they can obtain appropriate classification labels.

Using the previous research experience on the acquisition and allocation of multimedia educational resources, combined with big data technology, this paper proposes the design and application of building a modern multimedia educational resource acquisition and allocation platform based on big data technology to realize the mining of users' personalized teaching requirements. This paper completes the following work:

The main contents of this paper are as follows:

(1) Based on the analysis of many pieces of literature, the current situation of the collection and distribution of multimedia education resources in my country was dissected, and it was found that the collection and distribution of these resources made it difficult for users to obtain teaching resources, and teaching resources were not fully utilized. On this basis, a modern multimedia network resource collection and distribution model based on big data is constructed.

(2) Using big data-driven technology, a multimedia network resource collection and distribution model was constructed. Through the analysis of users' usage and conversion rate, it was found that users had a good evaluation of the model's satisfaction.

The main users of this model are mostly students and teachers. In the future, the characteristics of various network resources in multimedia teaching will be classified in more detail to better serve users, and there will be more and more resource types in multimedia teaching. The classification of resource types is also the focus of this research. Then, make functional improvements based on feedback from the actual use of user objects.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work.

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