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Retraction

Retracted: Harr-NMF Feature Extraction for Multilevel Educational Technology Teaching Big Data System

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Security and Communication Networks has retracted the article titled "Harr-NMF Feature Extraction for Multilevel Educational Technology Teaching Big Data System" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

The authors do not agree to the retraction.

References

[1] S. Fu and K. Mojtahe, "Harr-NMF Feature Extraction for Multilevel Educational Technology Teaching Big Data System," *Security and Communication Networks*, vol. 2022, Article ID 3178763, 12 pages, 2022.
[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

Harr-NMF Feature Extraction for Multilevel Educational Technology Teaching Big Data System

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An essential role in improving educational informatization and encouraging new approaches to education is played by educational technology, a specialist field that supports both theorising and doing in this area. When it comes to learning educational technology, students must have excellent professional knowledge and abilities, as well as a thorough understanding of data. Harr-NMF feature extraction for educational technology teaching large data systems is the focus of this project. With the help of big data technology, the construction of a teaching resource sharing system provides useful solutions for the storage and sharing of current and future massive teaching resources, enables fast and accurate analysis and retrieval of massive teaching resources and data, improves the security and scalability of the system while maintaining system stability, and promotes education teaching informatization to a new level. The system can be used to analyze and retrieve data quickly and accurately. By mapping different types of Harr-NMF features into a gradient matrix using grayscale projection, pattern classification is performed through the simplified gradient matrix as features. The algorithm complexity of feature extraction is eventually reduced to a great extent by the fast advantage of feature extraction by this algorithm. The Harr-NMF algorithm and the similarity relation matrix are used to obtain the optimal parameter values and the corresponding affiliation matrix and class centers, thus providing effective initial values for Harr-NMF, which effectively solves the problems of slow convergence and easy to fall into local minima of the Harr-NMF algorithm. The algorithm of this paper is compared with several improved algorithms of Harr-NMF in terms of convergence, recognition rate, and other performance to verify the feasibility and effectiveness of this paper. With a combination of qualitative and quantitative approaches, the data literacy of teaching educational technology is dissected and constructed to enhance its data literacy and improve the quality of education technology discipline personnel training.

1. Introduction

To enable education to keep pace with economic development, the government has carried out various forms of reforms, and its education budget has reached the level of developed countries such as Europe, America, and Japan, putting the focus of education reform on strengthening vocational education. Government departments have also carried out multilevel and multidisciplinary vocational education for specific national conditions, covering almost most of the industries [1, 2]. Due to the importance the government attaches to vocational education, the adoption of policies and financial resources, and the active introduction and assistance from foreign countries, multilevel education and technical education have achieved rapid development, thus making a great contribution to the development of national power, social progress, and the improvement of national quality and employment opportunities. An educational technology education system that includes public, private, and general secondary schools has been established at this time. As well as educating students in academics, each multilevel educational technology college offers instruction in multilevel educational technology, as well as short-term multilevel educational technology training. [3] Students are able to choose between general and vocational education via the use of a credit system. Its purposeful teaching and emphasis on practical talents, especially the specialties related to agriculture and tourism, are a major feature of multilevel educational technology studies education, which is compatible with resources and markets. To strengthen the guidance of multilevel educational technology education, the ratio of general education to multilevel educational technology education is adjusted to 1 : 1, and the cooperation between the Vocational Education Council and the Basic Education Council, the Non-Formal Education Council, and other institutions and departments is strengthened [4].

As times evolve, education requires reform and innovation. The increasing popularity of information technology in educational applications and the continuous innovation of educational concepts have led to a worldwide trend of educational informatization, and educational technology is a specialized discipline that supports the development of theoretical and practical applications of educational informatization. Students of educational technology will go on to work in schools and other education-related industries, designing, managing, and evaluating educational resources and environments, promoting educational innovation and the development of educational informatization. Such as the effectiveness of various learning software for teaching support, management, and maintenance of online learning platforms, processing, and analysis of data in education teaching, all need to have strong data literacy [5]. Only by mastering solid professional theoretical knowledge and practical skills, and having strong data literacy, can students in Educational Technology meet the needs of the times. The development of educational technology is multidirectional, and as a member of educational technology, I often hear my peers in the same major say that the scope of educational technology is wide but not deep; it thus leads to an awkward situation that nothing can be done, and the theory of education is not as good as the students of education, and the design and development is not as good as the computer science majors, resulting in outsiders who are involved in both majors, and the competition for jobs is quite fierce and the jobs are quite awkward [6]. However, the demand of the society for the professional ability of educational technology is always following the footsteps of social development. It is the development of multilevel educational technology teaching big data system Harr-NMF feature extraction to meet the needs of the society that is the mainstream of the development of educational technology, cultivating talents and also guiding the direction of students' employment [7, 8].

Harr-NMF feature extraction in the era of big data is projected to undergo a paradigm shift, and the current problems and drawbacks of Harr-NMF feature extraction are summarised and explained in conjunction with the theory of Harr-NMF feature extraction from teaching big data systems. The paper also discusses how educational technology can make use of big data to promote the shift to Harr-NMF feature extraction. Big data presents a range of issues for educational technology, including the need to modify ideas and build new technologies, as well as the need to cultivate professional data talent, undertake specific training for instructors, and adhere to ethical norms. Section 1: Introduction. This section firstly overviews the research background and significance, research content, development trend, and application areas of Harr-NMF feature extraction for multilevel educational technology teaching big data system, and finally gives a detailed description of the main research content of this paper and the organization structure of the article. Section 2: Related Work. This section introduces several preprocessing methods, commonly used detection methods and techniques, and finally describes the detection algorithm of Harr-NMF feature extraction for multilevel educational technology teaching big data systems in this paper. Section 3: Research on Harr-NMF feature extraction for multilevel educational technology teaching big data systems. This section first explains in detail the basic algorithm Harr-NMF algorithm to be used in the algorithm of this paper, the calculation of the similarity relationship matrix, the basic Harr-NMF algorithm, and its two different forms of error functions. The initial matrix initialization of the Harr-NMF algorithm is done using the Harr-NMF algorithm and the calculation of the cosine similarity to obtain the similarity relation matrix, and then the principle of the nearest neighbor classifier is explained, by which the extracted features are classified and discriminated. Section 4: Results analysis. With the adaptive Harr-NMF algorithm proposed in this paper as the core, the experimental process and the experimental results are described and analyzed, and the effectiveness of the method proposed in this paper is verified through comparative experiments. Section 5: Conclusion section. This section makes a summary and conclusion of the whole paper, summarizes the main points of the whole paper, and gives an outlook on future work.

2. Related Work

In recent years, many research units continue to engage in the research of Harr-NMF feature recognition technology and have also achieved promising research results. Some goods based on Harr-NMF feature recognition can also be seen in the market and can meet the actual needs in terms of recognition accuracy. However, when the quality of the Harr-NMF feature teaching large system decreases, some traditional algorithms are often unable to carry out an effective solution [9]. The decrease of teaching large system quality includes: the teaching large system is obscured by other organs of the eye, and the Harr-NMF feature teaching large system occurs a certain degree of out-of-focus due to the limitation of the acquisition equipment [10]. Haddadi et al. used the Gaussian–Laplace two-dimensional filter to filter the Harr-NMF feature teaching grand system at multiple scales; to decompose and encode the teaching grand system by Laplace pyramid, firstly apply the teaching grand system alignment technique to the field of Harr-NMF feature encoding, and develop a biometric recognition system based on Harr-NMF [11]. The system was also patented in that year because the algorithm complexity of the method is large and the amount of operations is high because it has not been widely applied to the commercial field. Mohamed A et al. decomposed the normalised Harr-NMF feature teaching large system using a two-dimensional Haar wavelet transform, encoded the quantized high-frequency information, encoded a total of 87 bits, and finally completed the pattern classification by neural network [12]. Huang S et al. processed the Harr-NMF feature teaching macrosystem using a PCA-based algorithm, by which the teaching macrosystem was mapped into a feature vector and quantized these mapping coefficients to form the final feature vector [13].

To this day, many research scholars are still improving the algorithm as the base algorithm; Chen K et al. proposed an improved feature face algorithm and applied it to unrestricted scenes, combining the feature face algorithm with geometric methods for Harr-NMF features [14]. Jiang Y et al. proposed Fisher's method, and Ahonen et al. introduced the LBP operator to Harr-NMF features, based on which an improved LBP descriptor was proposed for Harr-NMF features under strong light irradiation and also listened to a proposed new LBP-based texture analysis method, which uses interpolation to calculate the pixel values in either direction in the neighborhood to improve the accuracy of recognition [15]. Elastic beam map matching was suggested by Yu *J* H et al. for the problem of shifting backdrop and uncontrolled environment. Harr-NMF feature vector extraction is used with the goal of adopting a suitable technique to extract the information that may effectively represent the customised feature vector of Harr-NMF features in the teaching big system [16]. This operation step is extremely important in the Harr-NMF feature system, and the merit of the extracted feature vector directly affects the effect of recognition and classification in the subsequent stage, including recognition accuracy, computational complexity, and convergence of the objective function [17, 18]. Therefore, when extracting the features, it is important to analyze them specifically according to the performance indexes to be studied in the Harr-NMF feature system and to filter out the appropriate algorithm for the extracted feature operation to obtain the optimal recognition results [19, 20].

From the above-mentioned literature and applications, the multilevel educational technology teaching and learning big data system is late in the overall development; although it is fast, the actual landing is also in recent years. From the perspective of the operation of each school, the teaching resource management system has realized the sharing of resources to a certain extent, but in terms of technical architecture, it is still a traditional technical management scheme, and when the scale of teaching resources develops to a certain extent, the defects of this architecture are gradually exposed and it is difficult to expand horizontally. Specifically, most teaching resource management systems "emphasize construction but not management," lack management design, and ignore the sustainable development of teaching resources; the voluntary construction process is single, lacking the support of relevant norms and standards, and ignoring the real-time update and sustainability of resources; in terms of actual investment, the system construction cost is high, the degree of resource sharing is low, there is a lack of compatibility, and duplicate construction exists in large numbers. To address the above problems, this paper, on the one hand, stores massive heterogeneous teaching resources with unified standards, uses big data technology to manage massive teaching resources, improves the horizontal scalability of resources, and reduces the cost of the system in resource management and operation [21, 22]. On the other hand, a well-designed retrieval mechanism for the application can parallelize the search in the massive teaching resources, such that users can quickly and accurately retrieve the resources they want and enhance the application effect of the system [23]. Then, based on the research of related literature and expert consultation, the initial questionnaire of teaching data literacy in educational technology was designed and compiled. Through the prediction of the initial questionnaire, some unreasonable topics were deleted and individual topics were modified and improved, and then the official questionnaire was determined for the survey. The data collected were analyzed by factor analysis and correlation analysis with SPSS software to understand the data literacy of students, and combined with the research and theoretical consideration of literature to construct a model of teaching data literacy in educational technology [24, 25].

3. Research on Harr-NMF Feature Extraction for Multilevel Educational Technology Teaching Big Data System

3.1. Research on Multilevel Educational Technology Teaching and Learning Big Data System. In the multilevel educational technology teaching big data system, the MapReduce framework itself provides parallelized execution. Once there is a retrieval demand, JobTracker starts multiple TaskTrackers and then performs parallel retrieval on multiple DataNodes to obtain the required data resources. The parallelized retrieval process in the multilevel educational technology teaching big data system is shown in Figure 1. In Figure 1, both inverted index generation and parallelized retrieval require the MapReduce framework, because both tasks run on multiple nodes and involve a very large amount of computation. After the inverted index is generated by the resource description, once there is a demand for retrieval, the NameNode forwards the request to the JobTracker, which starts the MapReduce computation task and then runs in each DataNode to perform the specific retrieval, and after the results are returned, the results are merged by the reduce function and returned to the user, thus realizing the parallelized retrieval task. Thus, the parallelization of the retrieval task is achieved.

If you think of a document retrieval system's inverted index as an array of linked tables, which is the most popular data structure, you'll get the idea. The specific index generation process is as follows: read in the data stream, slice the data through Map operation, divide it into each map, process the data into < keyword #resource name, initial word frequency (1)> then merge the local results through Combine operation, convert the key-value pairs into < keyword #total word frequency, resource name>, and achieve global merging through Reduce operation. The output of the result is <keyword * total word frequency, #resource name>.

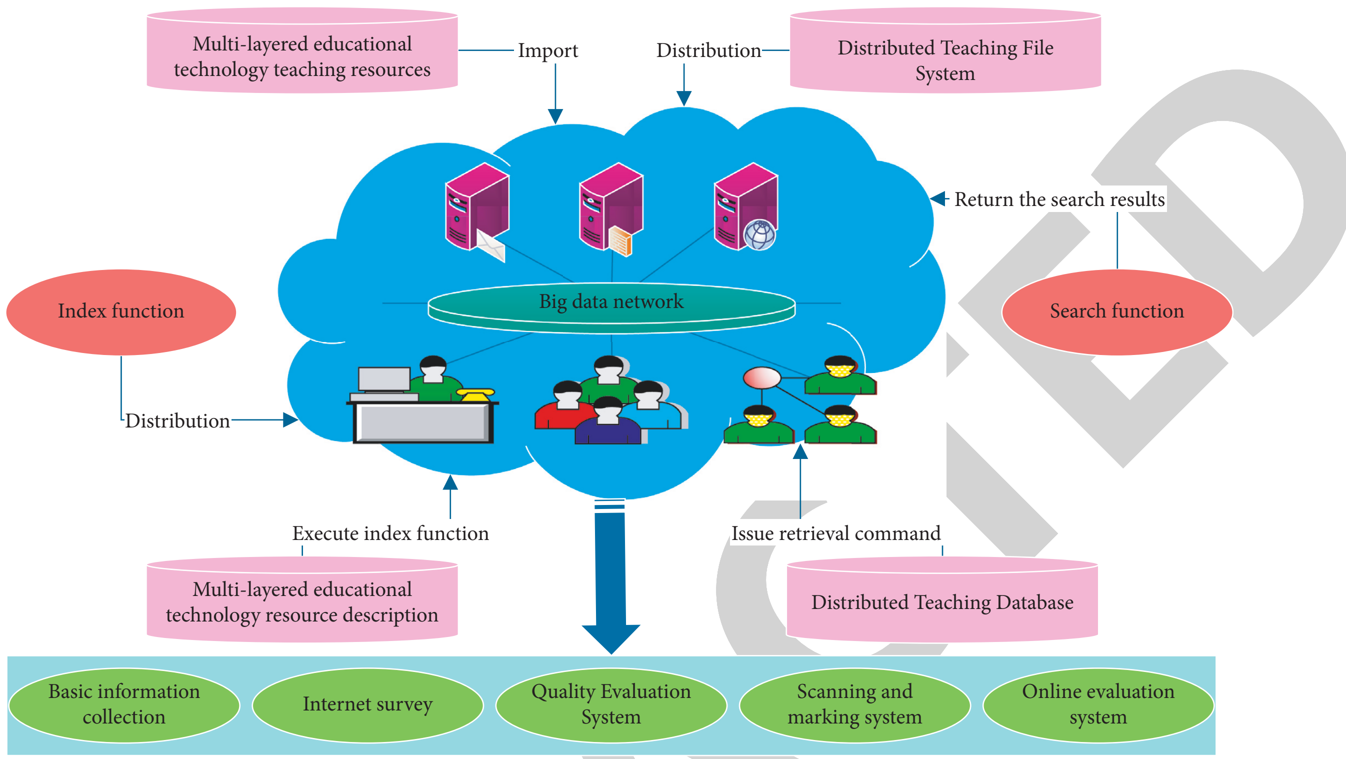

Figure 1: Multilevel educational technology teaching big data system architecture.

In the teaching resource sharing system, all teaching resources are eventually stored on HDFS. Of course, the system provides modification and deletion operations of resources for ordinary users and administrators. It should be noted that the processing mechanism of such modification and deletion is also stored very differently from the modification and deletion of files under ordinary standalone machines. In HDFS, teaching resources are also managed and organized according to categories, and each data resource is established with corresponding redundant data to ensure data loss due to the failure of one storage service development on unreliable storage nodes. To retrieve the required resources in a huge amount of data is fundamentally different from traditional database queries. Therefore, in the Hadoop cluster environment, all the resources uploaded to HDFS are stored in each Data Node, and the index files corresponding to the resources are also generated, which are used for the retrieval of resources. To improve the speed and accuracy of retrieval, the parallelized retrieval design uses a MapReduce program to parallelize the search on multiple Data Nodes, and then merges the retrieval results, encapsulates them into a specific format, and delivers them to the user.

In the repositioning of the objectives of multilevel educational technology education, it is necessary to change the previous over-emphasis on multilevel educational technology skills and combine the emphasis on multilevel educational technology skills with the focus on students' learning ability and the cultivation of comprehensive quality. Change the previous single emphasis on practical hands-on ability, while focusing on the education and training of practical ability and theoretical knowledge, and actively advocate research-based learning to continuously improve the ability to solve complex problems. In addition, multilevel educational technology colleges and universities should also pay more attention to the education of students' moral quality, professional ethics, and humanities, and cultivate highly skilled and innovative talents with high quality.

Colleges and universities with multilevel educational technology education programmes, particularly those at the higher and university levels, should strive to form themselves into a learning community unit, increase development of online courses and distance education, and actively use their research results to provide assistance to society, which is also an important platform for building a life on. The quality of students' comprehensive ability may be improved by enhancing the ideological and moral education courses, as well as professional ethics and humanities education courses. Improve students' capacity to adjust to their jobs by actively collaborating with businesses, enterprises, and diverse units.

We will analyze the strengths and weaknesses of the school's personnel training mode, improve the professional training objectives and curriculum according to the needs, and improve the training direction of educational technology teaching at any time according to the development of information technology to promote the development of educational technology with the times. We strive to cultivate excellent talents that meet the needs of society and narrow the gap between the talents cultivated in colleges and universities and the talents needed by society. At the same time, we strengthen the professionalism of educational technology teaching, guide the development of educational technology undergraduate majors from the development needs of educational technology majors, improve the training plan oriented by market demand to improve the job market of educational technology graduates, promote the development of educational technology, and improve the employment rate of educational technology in the social market at the same time.

3.2. Harr-NMF-Based Feature Extraction Algorithm for Teaching Big Data Systems. Cosine similarity, using the calculation of the cosine of an angle, is derived from the cosine of the angle between two vectors in a vector space, using this cosine as a measure of the difference between two individuals. Two vectors are similar if they have the same direction, and the angle between them is close to zero. In this paper, the cosine similarity between each sample and the class center is calculated, and the cosine value of the angle between the two is used to represent the degree of difference between the objects. The closer the cosine value is to 1, the more similar the two objects are. The vector cosine calculation formula (1) is as follows:

$$f(\overrightarrow{\cos}) = \frac{\vec{m} * \vec{n}}{m * n} * \cos(\theta). \tag{1}$$

According to the range of C values of the FCM algorithm, the continuous cyclic FCM process will get different clustering results and similarity measure matrix, and the optimal parameters of the FCM algorithm will be automatically selected according to the similarity relationship, and the affiliation matrix and the class center corresponding to the optimal parameters will be obtained; then the transpose of the affiliation matrix and the class center will be assigned to the initial matrices M and N of NMF, respectively, and the initial matrix contains the training sample information, which provides a better initial value for the initialization of NMF parameters; the NMF algorithm is applied to obtain the basis matrix by feature extraction, and the algorithm in this paper has obvious effects on improving the recognition rate and accelerating the convergence speed.

NMF is an effective method for extracting local features, ensuring that all components of the decomposition are nonnegative. This nonnegativity restriction makes the data description more realistic, and the pixel value or gray value of a picture loses its meaning if it is negative, and thus this restricted description makes the interpretation of the data more reasonable. At the same time, in nonlinear dimensionality reduction, the construction is based on the fact that the parts constitute the whole. This also meets practical needs, such as the human face is composed of organs such as the eyes, nose, and mouth, and thus this algorithm describes the essential features of things in a sense. Hence, NMF is becoming a more popular research method for dimensionality reduction processing in various fields. The algorithm in this paper is to improve the NMF algorithm as the basic framework and finally achieve the optimization of the algorithm. NMF is used to find two nonnegative matrices $M = F + m \times \mathrm{r}$ and $N = F + r \times \mathrm{n}$, as in (2) where M and N are called the base and coefficient matrices of the teaching large system, respectively; each element value of M and N has to satisfy the nonnegative restriction, and X is a nonnegative matrix training sample. Due to the nonnegative restrictions on M and N, it may lead to the matrix M and N multiplication is not necessarily exactly equal to X. Therefore, it is necessary to make the difference between the two parts as small as possible, i.e., find the smallest M and N and make the equation hold, and represent the high-dimensional data with low-dimensional data, i.e., it serves the purpose of dimensionality reduction of the data, reducing the computation and complexity, and thus improving efficiency.

$$\mathrm{NMF} = M \odot N. \tag{2}$$

In the nonnegative matrix decomposition, the objective function based on the Euclidean distance is defined as

$$F(M, N) = \frac{\mathrm{NMF} - M * N}{2} * \mathrm{NMF}_F^2. \tag{3}$$

The NMF algorithm is mainly used to solve the optimization problem of

$$G(M, N) = \begin{cases} \min\left(F(M, N), M_{\alpha,u}, N_{\beta,u}\right) \\ \sum_{i=1}^{M,N} \forall\left(M_{\alpha,u}, N_{\beta,u}\right) \end{cases}. \tag{4}$$

The above optimization problem can be solved by fixing M and N separately, and in this way, this optimization problem is transformed into two convex optimization problems. By fixing Wk, the iteration step in the gradient descent method is taken as

$$D(x) = \frac{\mathrm{NFM}(x)}{M(x)^T * M(x) * N(x)}. \tag{5}$$

We compose some typical Harr features into some texture cells, and the grayscale distribution of any teaching large system can be represented using these texture cells. These texture cells are composed of binary teaching grand systems of a certain size, with pixel values of 0 in the black region and 1 in the white region. If the texture cells at the x scale are represented using $\mathrm{T}(x_i)$, then the decomposition formula of the teaching large system can be expressed as (6). Formula H(t) needs to analyze the original teaching large system, $\mathrm{a}(x_i)$denotes the coefficients of the texture unit, x denotes the scale of the texture unit, and i denotes the number of the texture unit. When this method is used to analyze the teaching large system with low resolution, the scale of the texture unit can be enlarged, and for those teaching large systems with high subscale rate or texture large system with more detailed information, the scale of the texture unit can be reduced. By approximating the texture units of different scales, we can obtain a large system of textures of any grayscale.

$$H(t) = \iint \sum_{i=1}^{\propto} \left(a(x_i) T(x_i)\right) \mathrm{d}t. \tag{6}$$

In this paper, the projection matrix is designed as a 4×4 size matrix, which includes a total of 16 feature points

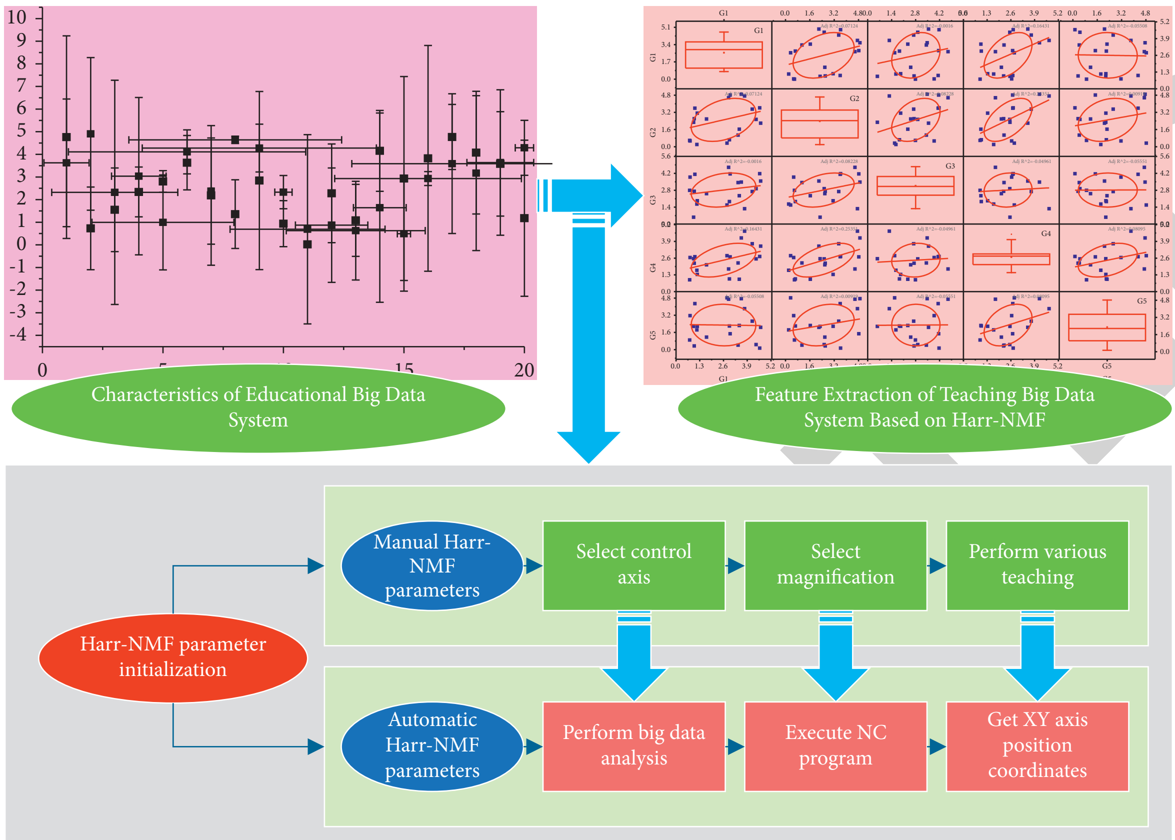

Figure 2: Harr-NMF feature extraction process.

assuming that P represents the intensity of the features corresponding to the different positions in the projection matrix pair. The projection process of the final texture can be obtained by the following (7) where H(A_k) denotes the number of pixels included in the projected texture region A_k. Similarly, H(B_k) denotes the number of all pixels in the selected texture region B_k for projection. The parameter d mainly indicates the intensity of the change in the boundary of the large system for which feature extraction texture teaching is required. This parameter determines when the gradient value of the texture is reached before the texture projection is performed. The texture teaching large system with different step sizes can be extracted separately by changing this parameter according to the needs of the actual situation.

$$P(x) = \sum_{i,k=1}^{\infty} \left(\frac{M(x_i, y_i)}{H(A_k)} + \frac{N(x_i, y_i)}{H(B_k)} \right). \tag{7}$$

In order to determine the total of pixels in a rectangle area, all that is required is to query the integration table, and this is what makes face identification feasible in real time. Moreover, the calculation process of the integral map can also be done quickly by an iterative algorithm, and the integral map is specifically calculated by

$$Q(x, y) = \sum \sum H(m, n), m \subseteq [1, x], n \subseteq [1, y]. \tag{8}$$

The above formula H(m, n) represents the pixel value at the location (m, n) in the original teaching large system. To improve the time of the integral map, calculation can be processed by the following iterative formula; assuming that the integral map of the teaching large system H is Q, then the iterative formula for the calculation is

$$\begin{cases} d(x, y) = d(x, y-1) + d(x-1, y) + H(x, y) \\ Q(x, y) = Q(x-1, y) + Q(x, y-1) + d(x, y) \end{cases}. \tag{9}$$

The original teaching large system features to be feature extracted are assumed to be H(m, n), and since the teaching large system features are rich in texture details, the grayscale projection matrix of the teaching large system is calculated at the ground scale according to the method of this paper. The projection matrix is used as the feature vector of the corresponding region (the simplified projection matrix is used as the feature), and the final eigenvalues are converted into the form of a vector. The summation operation, which takes a lot of time, is converted into a simple table lookup using an integral map, which makes the texture feature extraction time much shorter. The Harr-NMF feature extraction process of the teaching system is shown in Figure 2.

4. Analysis of Results

4.1. Multilevel Educational Technology Analysis. There are specific regulations for teachers of multilevel educational and technical education schools, which require that teachers must meet at least one of the following conditions: hold a university degree and receive vocational training; pass the relevant national test of vocational skills standards and have a relevant diploma or higher specialist; pass the relevant national test of vocational skills standards and have at least 5 years of work experience; specialist in the subject area, with research in his or her field of specialization not less than 5 years; senior technician with not less than 3 years of work experience in their field. This provides the basic basis for the training of teachers of multilevel education and technology education and sets new requirements. The Faculty of Education has developed a Department of Multilevel Education and Technology Education to educate educators in these fields. Multilevel educational and technology education teacher training programmes at the bachelor's degree level are offered by the Faculty of Vocational Education as well as diploma programmes for advanced vocational discipline diplomas for students who have already completed the bachelor's degree programme. In addition, to address the shortage of educational teachers, the Ministry of Education allows educational institutions to hire some retired government officials or technical experts from private companies to teach, but they must pass an examination organized by the Ministry of Education before they are hired. Figure 3 shows the analysis results of multilevel educational technology teachers' professional titles.

As can be seen from Figure 4, the educational requirements for teachers in secondary and higher multilevel educational technology schools have started to increase, and in the case of Bangkok College of Business Administration and Tourism, for example, those with doctoral and master's degrees account for only 34.8% of the total number of teachers, those with bachelor's degrees account for 48.65% of the total number, and those with college degrees or less account for 16.31% of the total number. In contrast, in the multilevel educational technology institutions at the university level, teachers' education is dominated by master's degrees, and in the case of the Royal Panakorn University of Technology, for example, those with master's degrees account for 77.67% of the total. In addition to full-time teachers, these two schools also employ some retired government officials or technical experts from private companies as part-time teachers according to the relevant regulations to introduce the latest production technology into the teaching content, strengthen the connection between enterprises and schools, and help solve problems in production internship, graduation design, and graduate acceptance.

The number and quality of teachers in multilevel education and technology schools have improved greatly compared to the past, but the proportion of specialized teachers is not high enough, the proportion of "dual-teacher" teachers is still small, and the scale of teachers still needs to be expanded. On this basis, the Office of Vocational Education Commission has also put forward new reform requirements to increase the training of multilevel education and technology teachers and improve their professional knowledge and skills.

The questionnaire used in this research was based on the "Likert five-point scale," which uses a scale of 1 to 5, with a higher mean value indicating more competence, and a score of 3 as an intermediate condition indicating a less ideal outcome and a more desirable result. For each dimension, a graph depicting descriptive statistical analysis of the questionnaire is displayed in Figure 4. From the statistical results, it can be seen that the mean value is between 2.6211 and 3.4687, with an overall bias toward the intermediate state. The ranking of the competencies revealed that data acquisition, data needs, and planning competencies were a little higher than the others, followed by data awareness and attitude, data evaluation competencies, and data management competencies, while data analysis and interpretation competencies, data application, and innovation competencies had the lowest mean values. The standard deviation of the total data literacy was 0.5223, and the mean value was 2.952, indicating that the data literacy of educational technology teaching needs to be further strengthened. The results of the multilevel educational technology teaching data literacy analysis are shown in Figure 5.

The ability of data analysis and interpretation refers to the ability to present and communicate data through processing, handling, and analysis of data, mastering the theory and methods of educational information processing and analysis, using the basic data analysis tools of the discipline, processing, and handling data, extracting accurate conclusions based on the analysis results, presenting them with appropriate visualization tools, and communicating and sharing research results with others through various channels. Data evaluation ability is the ability to use various evaluation methods and means to identify data quality and assess the process and results of data manipulation, including evaluation of data perception and identification, formative evaluation, and summative evaluation, including questioning the reliability and accuracy of data sources, differentiating and selecting data collection methods and use processes, as well as recording and monitoring data behavior and interaction processes, and identifying problems based on feedback effects. The evaluation includes questioning the reliability and accuracy of data sources, differentiating and selecting data collection methods and use processes, and recording and monitoring data behaviors and interaction processes, finding problems and shortcomings based on feedback effects, and timely adjustment and reflection. Data management ability is the ability of educational technology undergraduates to develop data management plans according to actual conditions, use basic data management platforms and management tools to achieve effective management of subject knowledge and projects, and update the archived data promptly to keep up with the development of the discipline.

4.2. Analysis of Harr-NMF Feature Extraction Algorithm. The NMF problem itself is nonconvex, and its decomposition results depend on the initial values and are not unique. The selection of the initial values M and N directly affects the iterative results of the decomposition algorithm. To address the drawback that the random initialization of parameters in the NMF algorithm makes the iterative solution slow and

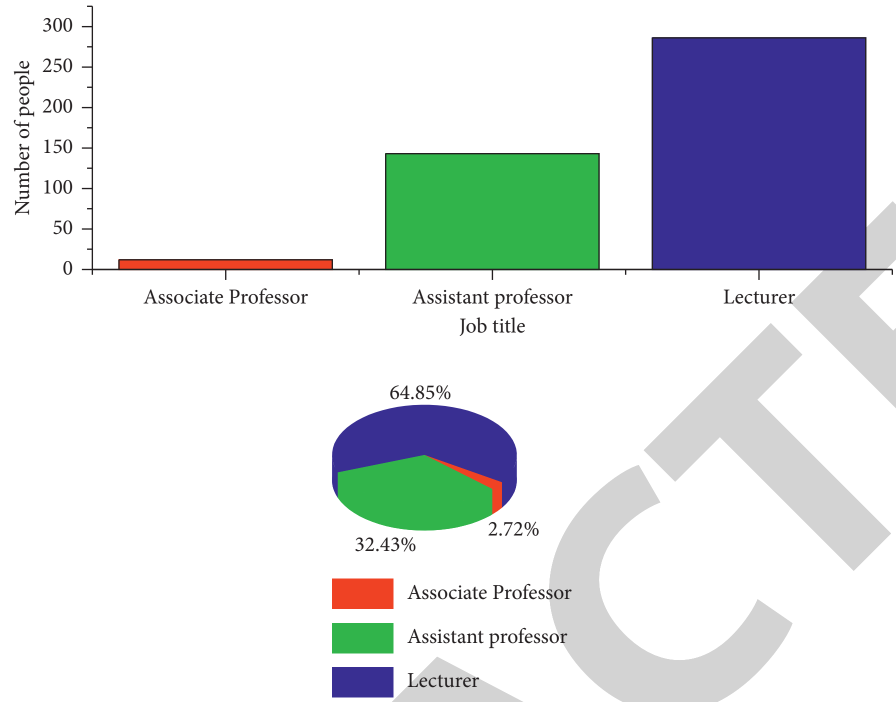

Figure 3: Multilevel educational technology teacher title results.

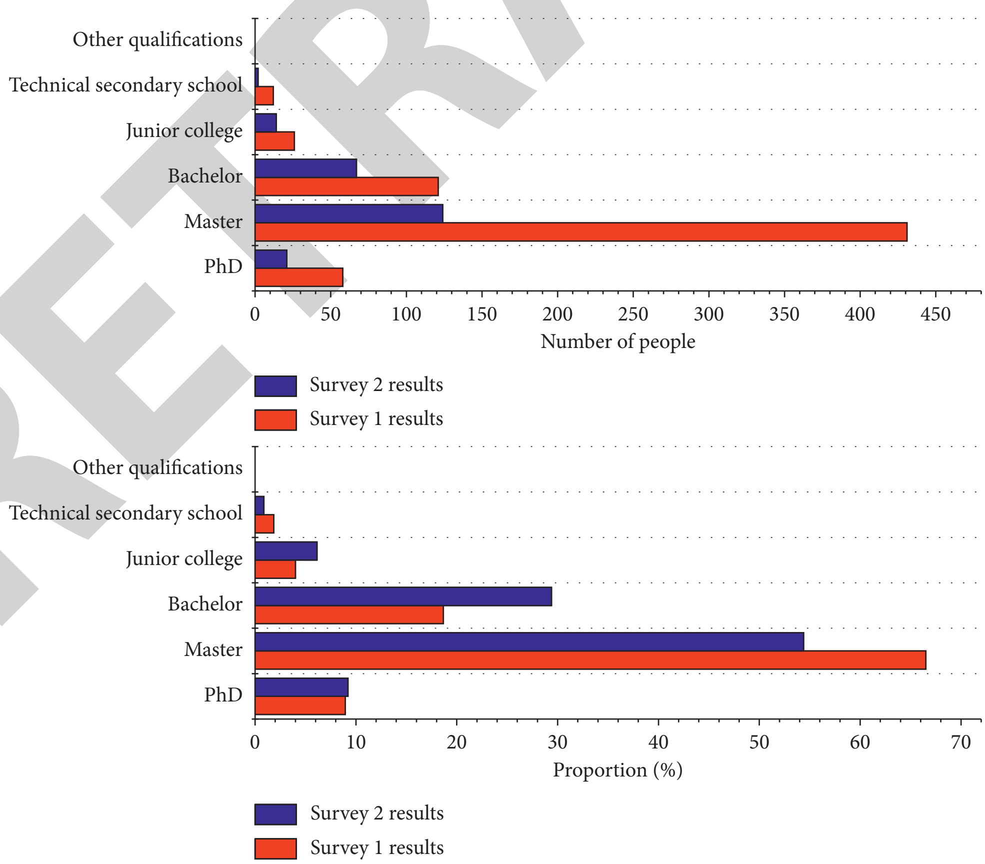

Figure 4: Distribution of teachers' education.

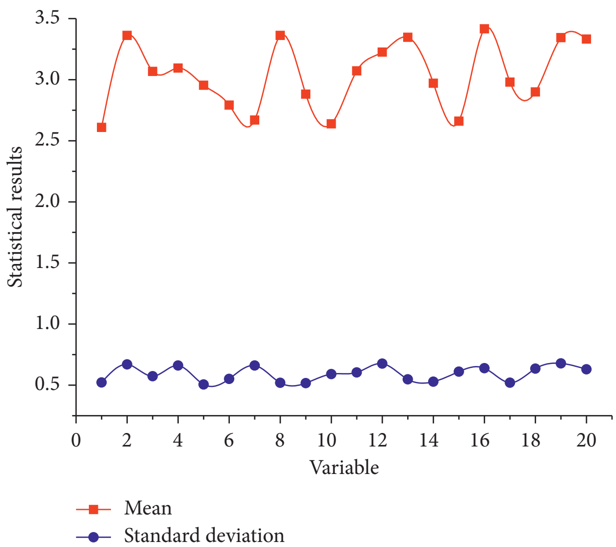

Figure 5: Multilevel educational technology teaching data literacy analysis.

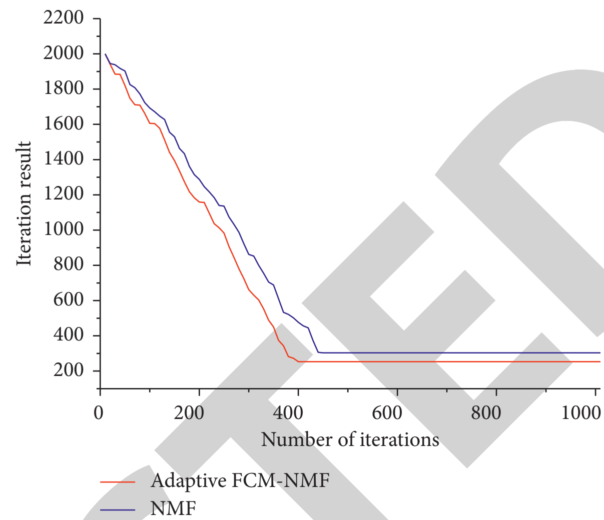

Figure 6: Convergence effect.

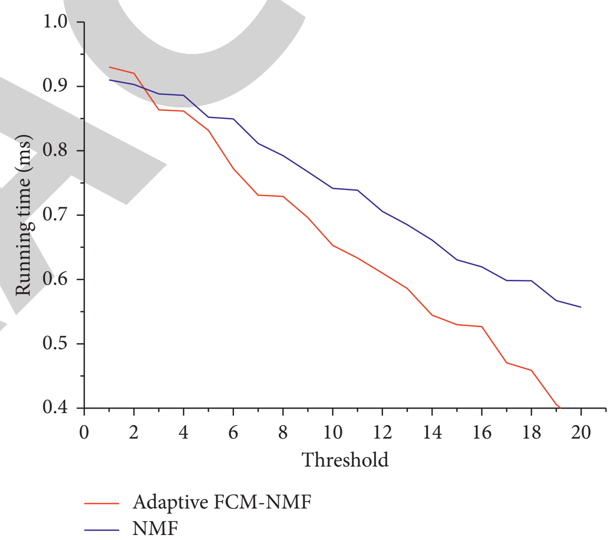

Figure 7: Running time comparison chart.

easy to fall into local minima, the adaptive FCM-NMF algorithm proposed in this paper effectively solves the problem of NMF parameter initialization and speeds up the convergence speed, and the experimental results on the collected face library are shown in Figure 6.

The NMF algorithm and many improved algorithms mostly use the method of randomly assigned initial values of parameters, which makes the iterative solution speed slow. Experimentation shows that the adaptive FCM-NMF method suggested in this research has a reduced starting value, which means that the objective function value is closer to the convergence value after the initialization procedure. Before the curve flattens out, the adaptive FCM-NMF algorithm has a faster-decreasing speed than the original algorithm, which indicates that the algorithm in this paper converges faster than the original algorithm and shortens the convergence time, which shows that the adaptive FCM-NMF can provide a better initial value for the initialization of the NMF parameters, which makes the convergence speed faster, and it can be seen from the figure that the algorithm in this paper can make the objective function converge faster to a smaller objective value.

To better illustrate the time advantage of the adaptive FCM-NMF algorithm proposed in this paper, the NMF algorithm and the running time of the proposed algorithm on the database collected in the laboratory are plotted in the following paper to illustrate the effectiveness of the algorithm in this paper. The line graphs are shown in Figure 7, respectively. The vertical coordinate represents the time in seconds, and the horizontal coordinate represents the threshold value, which represents the difference between the target function values of two adjacent iterations. The algorithm proposed in this paper has certain effectiveness and superiority and is suitable for application to face recognition systems.

In this research, the normalised teaching big system characteristics are 64×512. The classifier is trained on three Harr-NMF characteristics of the same person from a big database. Using a two-dimensional wavelet transform, the normalised Harr-NMF features can be simplified for classifier design. The four Harr-NMF features obtained after the transformation are then decomposed into their approximate counterparts and then subjected to a second wavelet transform. The transformed Harr-NMF features are then used to approximate the original Harr-NMF features for a third two-dimensional wavelet transform. After the three transformations, the Harr-NMF features are 16×128. The horizontal details, vertical details, and approximate Harr-NMF features of this site are summed up according to the weight sequence 0.08, 0.08, and 0.8. All training samples are processed according to the above method. The respective projection matrices M are first obtained by the traditional FLD algorithm, and then each projection matrix is iteratively processed according to the improved RFLD algorithm. Finally, the final projection matrix of each sample can be

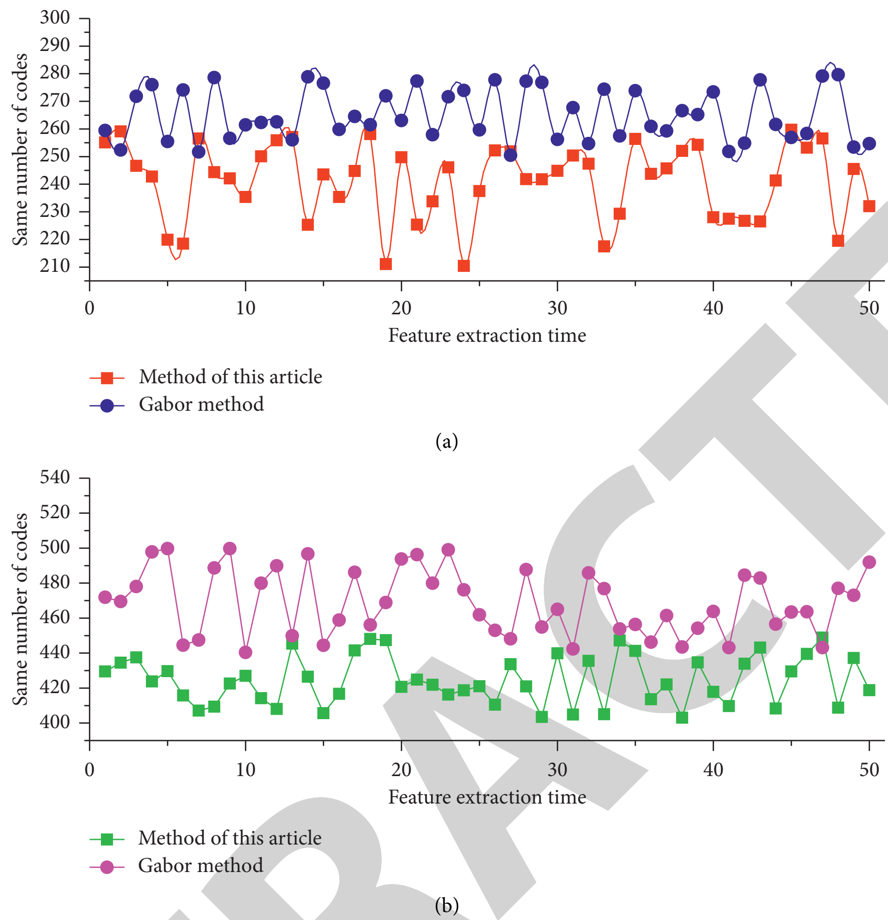

Figure 8: Coding distribution curve. (a) Same number of codes in the class. (b) Same number of codes between classes.

obtained. To verify the stability of the feature extraction method in this paper, we select 10 Harr-NMF features of the same sample in the large database II, extract the features by the method in this paper and the 2D Gabor transform method, respectively, and analyze the stability of the features. The distribution curves of the features within and between classes for the same individual for both methods are shown in Figure 8. Through the above experiments, it can be obtained that the feature extraction algorithm used in this paper is not only effective in identifying the samples, but also has good performance in the stability of features.

Knowledge and skills of educational technology refer to the mastery of basic theories, basic knowledge, and skills of educational technology, understanding the concept of modern education, advanced education and teaching methods, basic theories and methods of integration of information technology and curriculum, knowing the process and laws of knowledge transmission, the nature of learning, etc., familiar with the process of teaching design, analysis and design of teaching strategies according to the needs, learning environment and characteristics of learners, and skills of designing resources and media to support learning and solve teaching problems. They should be familiar with the process of instructional design, analyze and design instructional strategies and structures based on needs, learning environments, and learner characteristics, master the skills of designing, developing, and applying resources and media, be able to use appropriate technologies to support learning and solve teaching problems, and pay attention to the development and frontier trends in their specialties and related fields. Digital environment factors refer to the external conditions that affect students' data literacy, including resources and interpersonal and contextual factors. The context is to provide realistic possibilities for students to develop and improve their skills through authentic practical activities.

5. Conclusion

To expand the scope of resource sharing, improve the efficiency of resource utilization, and solve the problems of uneven distribution of teaching resources among schools and the management and retrieval of massive data resources, this paper designs and implements a teaching resource sharing system under the big data environment. In the teaching big data system Harr-NMF feature extraction, to the teaching big data system Harr-NMF feature extraction, this paper proposes an improved dimensionality reduction method based on adaptive FCM-NMF, which is based on the NMF algorithm as the basic framework, but the random initialization of parameters in the basic NMF algorithm makes the iterative solution slow and easy to fall into the problem of local minima. This algorithm uses the fuzzy C clustering method to obtain the similarity relationship matrix, which can provide better initial values for the initialization of NMF parameters, thus effectively solving the above problems. The experiments on the teaching big data system library show that the algorithm proposed in this paper can provide good initial values for NMF, the recognition rate is also improved, and the algorithm is practical and feasible. Some feature description algorithms with Harr features and improved real-time performance are used in iris recognition by enhancing it after examining the technological backdrop of the teaching large data system Harr-NMF feature extraction method; Harr characteristics are mapped into a gradient matrix via grayscale projection, and the simpler gradient matrix features are used for pattern classification. The complexity of feature extraction is greatly decreased as a result of this algorithm's ability to extract features quickly. After analysing the FLD algorithm's technical aspects, this article builds the matching algorithm of this paper by refining the RFLD algorithm's algorithmic process for Harr-NMF feature extraction in teaching large data systems. As a result of a vast number of studies, this paper's algorithms are shown to be successful in the extraction of Harr-NMF features from instructional big data systems. In terms of curriculum construction, the social demand analysis is not deep enough, only referring to the current situation of teaching big data systems and the needs derived from the survey of frontline teachers, and the curriculum construction is also proposed according to the analysis, lacking the implementation of curriculum construction.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] Y. Sun, Y. Weng, B. Luo et al., "Gesture recognition algorithm based on multi-scale feature fusion in RGB-D images," *IET Image Processing*, vol. 14, no. 15, pp. 3662–3668, 2020.

[2] J. P. Kandhasamy, S. Balamurali, S. Kadry, and L. K. Ramasamy, "Diagnosis of diabetic retinopathy using multi level set segmentation algorithm with feature extraction using SVM with selective features," *Multimedia Tools and Applications*, vol. 79, no. 15-16, pp. 10581–10596, 2020.

[3] H. h Zhao and H. Liu, "Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition," *Granular Computing*, vol. 5, no. 3, pp. 411–418, 2020.

[4] X. Zhang, X. Ming, and D. Yin, "Reference architecture of common service platform for Industrial Big Data (I-BD) based on multi-party co-construction," *International Journal of Advanced Manufacturing Technology*, vol. 105, no. 5-6, pp. 1949–1965, 2019.

[5] Q. Liu and L. Zeng, "Design and application of experimental teaching system driven by big data technology in economics and management majors," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 15, no. 11, pp. 56–66, 2020.

[6] C. Lu and F. Wen, "GIS information feature estimation algorithm based on big data," *International Journal of Information and Communication Technology*, vol. 15, no. 2, pp. 198–209, 2019.

[7] M. V. Ciasullo, O. Troisi, M. Grimaldi, and D Leone, "Multi-level governance for sustainable innovation in smart communities: an ecosystems approach," *The International Entrepreneurship and Management Journal*, vol. 16, no. 4, pp. 1167–1195, 2020.

[8] M. Shi, R. Jiang, X. Hu, and J Shang, "A privacy protection method for health care big data management based on risk access control," *Health Care Management Science*, vol. 23, no. 3, pp. 427–442, 2020.

[9] S. J. Aguilar, "Learning analytics: at the nexus of big data, digital innovation, and social justice in education," *TechTrends*, vol. 62, no. 1, pp. 37–45, 2018.

[10] O. Şen and K. Ç Bayındır, "Big data usage in electrical distribution systems: a review," *International Journal of Applied Business and Management Studies*, vol. 4, no. 2, pp. 2548–0448, 2019.

[11] L. Haddadi, F. B. Dahmani, and N. Guin, "Multi-level computer aided learner assessment in massive open online courses," *International Journal of Knowledge and Learning*, vol. 12, no. 4, pp. 325–351, 2018.

[12] A. Mohamed, M. K. Najafabadi, Y. B. Wah, E. A. K. Zaman, and R Maskat, "The state of the art and taxonomy of big data analytics: view from new big data framework," *Artificial Intelligence Review*, vol. 53, no. 2, pp. 989–1037, 2020.

[13] S. Huang, J. Li, Q. Li, Q. Li, and H. Zhang, "Optimization of big data fusion scheduling in maritime communication based on fuzzy c-means clustering algorithm," *CCAMLR Science*, vol. 25, no. 3, pp. 229–237, 2018.

[14] K. Chen, Y. Zu, and Y. Cui, "Design and implementation of bilingual digital reader based on artificial intelligence and big data technology," *Journal of Computational Methods in Science and Engineering*, vol. 20, no. 3, pp. 889–907, 2020.

[15] Y. Jiang and X. Li, "Intelligent online education system based on speech recognition with specialized analysis on quality of service," *International Journal of Speech Technology*, vol. 23, no. 3, pp. 489–497, 2020.

[16] J. H. Yu and Z. M. Zhou, "Components and development in Big Data system: a survey," *Journal of Electronic Science and Technology*, vol. 17, no. 1, pp. 51–72, 2019.

[17] M. Chen, Y. Jiang, N. Guizani et al., "Living with I-fabric: smart living powered by intelligent fabric and deep analytics," *IEEE Network*, vol. 34, no. 5, pp. 156–163, 2020.

[18] M. Tong, Y. Chen, L. Ma, H. Bai, and X Yue, "NMF with local constraint and Deep NMF with temporal dependencies constraint for action recognition," *Neural Computing & Applications*, vol. 32, no. 9, pp. 4481–4505, 2020.

[19] E. L. Lydia and D. Ramya, "Text mining with lucene and Hadoop: document clustering with updated rules of NMF non negative matrix factorization," *International Journal of Pure and Applied Mathematics*, vol. 118, no. 7, pp. 191–198, 2018.

[20] Y. Meng, R. Shang, F. Shang, L. Jiao, S. Yang, and R. Stolkin, "Semi-supervised graph regularized deep NMF with Bi-orthogonal constraints for data representation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 9, pp. 3245–3258, 2020.

[21] S. R. Bandela and T. Kishore, "Speech emotion recognition using semi-NMF feature optimization," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 27, no. 5, pp. 3741–3757, 2019.
[22] X. Jia, F. Sun, H. Li, and Y Cao, "Hand vein recognition algorithm based on NMF with sparsity and clustering property constraints in feature mapping space," *Chinese Journal of Electronics*, vol. 28, no. 6, pp. 1184–1190, 2019.
[23] C. Wu, Y. Song, and Y. Zhang, "Multi-view gait recognition using NMF and 2DLDA," *Multimedia Tools and Applications*, vol. 78, no. 24, pp. 35789–35811, 2019.
[24] N. Kumar, P. Uppala, K. Duddu et al., "Hyperspectral tissue image segmentation using semi-supervised NMF and hierarchical clustering," *IEEE Transactions on Medical Imaging*, vol. 38, no. 5, pp. 1304–1313, 2019.
[25] Y. Zhang, Z. Zhang, S. Li et al., "Unsupervised nonnegative adaptive feature extraction for data representation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 31, no. 12, pp. 2423–2440, 2019.