**Psychology and discipline analysis of special education based on deep learning**

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**Abstract:** To address the challenges of low recall, poor precision in integration results, and suboptimal recommendation accuracy in the field of special education psychology and discipline analysis, a novel method based on deep learning is proposed. A data collection framework tailored for special education psychology and discipline analysis was developed, employing both manual and data center-based approaches to gather relevant data. The acquired data underwent preprocessing to generate candidate labels, with TextRank scores, TF-IDF weights, and positional information weights calculated independently. A comprehensive scoring mechanism was applied by integrating multiple features, arranging the results in descending order to produce document labels. Utilizing a graph convolutional network from deep learning, a recommendation model for special education psychology and discipline data was constructed based on the generated document labels. This facilitated the effective analysis of special education psychology and discipline resources. Experimental outcomes demonstrate that the proposed method achieves maximum recall and precision rates of 98.8% and 98.7%, respectively, with a consistent recommendation accuracy exceeding 93%. The method exhibits excellent practical application performance.

**Key words:** Deep learning; Psychology of special education; Subject analysis; Acquisition architecture; Candidate label; Recommend model

**1 Introduction**

In recent years, the importance of special education has grown significantly, with society placing greater emphasis on individuals possessing specialized skills. This shift has led to notable advancements in the field of special education. Today, modern education goes beyond the transmission of academic knowledge, focusing on fostering students' psychological well-being and promoting their holistic development [1]. Alongside focusing on the development of students' foundational knowledge and skills, greater attention must be directed toward nurturing their mental health. For students in special education schools, their psychological health is a critical factor that significantly influences their future prospects. Therefore, during the special education process, teachers must prioritize the psychological and self-regulation aspects of students, including their learning habits and attitudes toward life. Efforts should be made to enhance students' psychological characteristics and develop various mental qualities [2-3].

The psychological well-being of students in special education schools is a key educational focus, as it directly impacts their mental health and shapes their academic and personal futures [4]. In these schools, educators must provide tailored psychological health education that aligns with individual needs, enabling students to cultivate a positive mindset and resilient personality. By fostering mental strength and a proactive outlook, students can better navigate social interactions and adapt to challenges in their future personal and professional lives. Analyzing the psychological and subject-related needs of special education students allows for the recommendation of suitable resources, thereby contributing to the enhancement of mental health support and the overall development of students in special education environments.

In view of the above problems, reference [5] puts forward a hybrid recommendation method based on learner model. Firstly, the classification of text information from neural networks is introduced into the recommendation algorithm to alleviate the cold start problem. Secondly, by calculating the learning characteristics and learning ability of old users within the class, the problem of similarity and large computation of traditional collaborative filtering single calculation score is solved, so as to realize the design of hybrid recommendation method. Reference [6] describes an improved collaborative filtering (CF) approach tailored for recommending online learning resources, addressing several limitations of traditional methods. To begin with, this method converts user-resource interactions into rating scores, thereby mitigating the issue of sparse scoring matrices that often reduce the effectiveness of CF systems. Moreover, it introduces user initialization labels into the similarity calculation process, which significantly alleviates the cold start problem, a common challenge when dealing with new users who lack prior interaction data. To ensure accurate recommendations, the method uses RMSE as a metric for evaluating the prediction accuracy of the algorithm. By prioritizing resources with the highest recommendation scores, this approach ensures precise and effective resource suggestions for users. Reference [7] proposes a comprehensive framework for personalized resource recommendations in the context of online education platforms. This framework is designed to integrate multiple data processing and analysis layers to deliver tailored learning experiences. At its core, the system incorporates a data layer that organizes user information alongside a resource library, which contains knowledge databases, behavioral data, and tagging systems. The framework also includes a data analysis layer, where static user attributes, such as demographic details, are combined with dynamic behavioral data, such as learning habits, to construct detailed user profiles. These personalized profiles provide meaningful insights into user learning progress. To further refine recommendations, the system incorporates a recommendation computing layer that applies advanced analytical techniques, including similarity analysis and clustering algorithms, to discern user learning patterns. Reference [8] presents a multi-task feature recommendation technique enhanced by a knowledge graph. This method integrates the knowledge graph into multi-task feature learning, using cross-compression units to establish higher-order connections between latent features and entities. The resulting recommendation model enables accurate course resource suggestions based on learners' goals, interests, and knowledge levels. Reference [9] introduces an online education service recommendation method grounded in social media, leveraging a genomic approach. It extracts user learning information and social gene fragments, behavior genes, and other features. Using the CRITIC weighting method, the approach calculates the importance of each gene to construct a social media genetic map. This helps users quickly access personalized online education services.

But will be found in the above method is applied to the actual, these methods have special education psychology and the recall ratio of subject resource integration result, precision, recommend the problem of low accuracy, this paper designs a new based on depth study of the special education psychology and science analysis method, and the effectiveness of the proposed method is verified by experiment.

**2 Analysis of psychology and discipline of special education**

**2.1 Special education psychology and subject data collection**

The main functions of special education psychology and subject data collection architecture include special education psychology and subject data collection report configuration management, data collection process management, collection result management, etc. The specific special education psychology and subject data collection architecture is shown in Figure 1.

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**Fig. 1 Collection structure of special education psychology and subject data**

The working group personnel should configure the report version of the collected data, determine the types and names of all the reports that need to collect special education psychology and discipline data. The report configuration management is to set and adjust the catalog and report of the existing reports, and set the data items of the reports. Before starting the collection task, it is necessary to define the task scope of the data collection item, delimit the task scope, decompose the data collection tasks for different parts, and assign the tasks to the staff of the parts. After the collection task is started, during the data collection process, the staff fills in or collects data according to the assigned report tasks. If the system is privately integrated with the school's original information system or data, data can also be directly read from the system, or imported information. Once partial data collection is completed, the management personnel must review and approve the data before it can be deemed valid. During the project’s data collection and execution phase, managers can monitor the task's progress in real time, allowing for ongoing oversight of the collection process. This enables them to view all audited data and make adjustments as needed if any issues arise. Afterward, the data collection results can either be directly exported or submitted to the higher department through the system, ensuring streamlined reporting and further analysis.

The collection methods of special education psychology and subject data are mainly divided into two ways: manual input collection and capture from the data center, corresponding to different collection methods, the trend of data flow will be different. For the manual input method, after the data is manually entered into the system, various data collection tables are generated through the self-defined report format [10]. If LPI decision support is to be carried out, the system will obtain data from various data collection tables according to collection requirements, and finally form a dynamic scale by analyzing the scale.

The manual grasping method of special education psychology and subject data is shown in Figure 2.

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**Fig. 2 Manual grasping**

For fetching data from the data center, data from the business system will flow to the data center through the integration of the data center with various business systems, and the system can also capture special education psychology and discipline data from the data center to form data sharing. During data collection, the system directly captures related data items from the data center and forms various data reports based on user-defined report formats. To perform KPI analysis, the system directly captures data from the data center according to the defined data model and forms a dynamic scale through analysis. Figure 3 shows the fetching mode of the data center.

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**Fig.3 Data center capture mode**

**2.2 Resource label generation**

This research introduces a multi-feature fusion algorithm specifically tailored for label generation in the context of special education psychology and related subjects. To ensure the generation of high-quality labels, the collected data undergoes a thorough preprocessing phase, which involves meticulous filtering and refinement to create a pool of potential candidate labels. After preprocessing, the algorithm independently calculates various feature metrics, including the TextRank score, which evaluates word importance by analyzing their connectivity in a graph structure; the TF-IDF weight, which measures the relevance of words based on their frequency in the document relative to the entire dataset; and the positional information weight, which assigns greater importance to words depending on their placement in key sections of the text.

These individual feature scores are then combined through a fusion mechanism to derive a comprehensive final score for each word. Words are ranked in descending order based on these scores to create a prioritized list of document labels. This systematic approach ensures that the most relevant terms are identified and selected. A detailed visualization of the implementation process is provided in Figure 4, highlighting each step from data preprocessing to the final generation of document labels.

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**Fig. 4 Flowchart of multi-feature fusion label generation algorithm**

(1) Document preprocessing

The original web special education psychology and discipline data text is unstructured data, the computer can not directly use label generation algorithm to analyze and process these unstructured data, unable to understand and mine the content of the document itself and then generate labels. Special education psychology and subject materials often include irrelevant information, such as images and hyperlinks, which can hinder the efficiency of text processing. To enable accurate computer recognition and analysis, Chinese documents must undergo preprocessing steps before applying the label generation algorithm. These steps include filtering irrelevant content, performing word segmentation, and removing unnecessary words. The primary steps involved in document preprocessing are outlined as follows:

1) Filtering. Firstly, the irrelevant interference contents such as pictures, videos, hyperlinks and various symbols are filtered out. Filtering and deleting these contents can improve the efficiency of word segmentation and the accuracy of text analysis.

2) Chinese word segmentation. This serves as the foundation of natural language processing, significantly influencing the effectiveness of subsequent tag generation. Unlike English, where words are clearly separated by spaces, Chinese lacks distinct delimiters to differentiate between words. Additionally, complexities such as homophones with different meanings, synonyms with varying usages, and grammatical peculiarities make Chinese word segmentation more challenging.

This paper employs the Jieba word segmentation technology, which integrates rule-based and statistics-based methods. Jieba improves scanning efficiency by utilizing a Trie tree structure to create a word graph. It constructs a directed acyclic graph (DAG) to detail all possible word combinations within the text and applies dynamic programming to identify the maximum probability path for segmentation based on word frequency. For new words absent from the dictionary, a Hidden Markov Model (HMM) based on Chinese characters is applied, leveraging the Viterbi algorithm to deduce the most likely hidden states and achieve the highest probability segmentation results. Jieba’s HMM model effectively handles new and ambiguous words, ensuring segmentation accuracy. Additionally, custom dictionaries can be incorporated to improve recognition of domain-specific terms, preventing unidentified words from negatively impacting segmentation quality. The jieba.posseg.dt method also enables part-of-speech tagging, supporting subsequent processing steps.

Jieba is one of the most versatile Chinese word segmentation tools for Python, offering multiple segmentation modes. It supports traditional Chinese, custom dictionaries, and provides options for precise, full, and search engine segmentation models. The full mode is fast but may encounter more ambiguity issues, while the search engine mode performs a secondary segmentation on longer terms for improved recall. The precise mode prioritizes accuracy, making it more suitable for generating labels in special education psychology and subject data. By enhancing segmentation effectiveness, it improves the overall quality of generated tags.

3) Stop using words. Texts often contain a large number of stop words, such as connectives, prepositions, or pronouns, that add little meaning or context. Following Chinese word segmentation, these irrelevant words must be filtered out, leaving nouns and verbs that best capture the document's central ideas. These selected terms serve as candidate tags, streamlining subsequent processing and enhancing the efficiency of the tag generation algorithm.

(2) TextRank weight calculation

The calculation begins with the construction of a keyword graph. In this graph, edges are formed based on co-occurrence relationships between two nodes, with the frequency of co-occurrence assigned as the edge weights. The original documents to be processed are divided and stored in the list according to sentences, and pairwise pairing is performed. A sliding window of size 5 is selected. When two words appear in the same window, edge weight +1, and the weight transfer matrix  is calculated. Based [11]. We set , . When the error is less than the set threshold, it is considered to converge, and the final score is obtained. Each node and its corresponding score are sorted in descending order by sorting function and stored in dictionary form.

PageRank is a representation method based on graph model. It regards the Internet as a graph and every web page as a vertex, and every vertex will point to another vertex, and there will be other vertices pointing to the vertex [12]. PageRank algorithm is obtained as follows:

(1)

Among them,  to point to a collection of web page  is also called the chain set,  to  points to a collection of web pages is also called the chain set,  for the chain number, each web page will own score average contribution to each chain,  to  to  points, all  into the chain contribution to its scores for  own score, namely for the damping coefficient.

Special education psychology and science data label generation algorithm will page initial score is 1, by formula (1) iterative calculation, update scores, convergence can get page final score, if always not convergence, then set the appropriate number of iterations, and get the final value by the above methods will be included in the calculation. TextRank also adds edge weight ,  to represent the edge weight between word nodes  and  in the calculation process. The co-occurrence times between words are used as edge weight to add to TextRank's calculation [13], and the initial weight is set as 1.The weight transfer matrix is obtained as follows:

(2)

TextRank is a ranking algorithm rooted in graph theory, designed to evaluate the importance of textual elements within a document. The method constructs an undirected graph, where each node corresponds to a potential keyword, and the connections (or edges) between nodes are established based on co-occurrence relationships among words. The strength of these connections is quantified through edge weights, which reflect the frequency of co-occurrence between words within a given context.

Once the graph is constructed, the algorithm employs an iterative process to calculate the relative importance of each word node. This iterative computation adjusts node scores by considering the influence of connected nodes and their corresponding edge weights. The final score for each node is determined using a mathematical formula, which ensures that the ranking reflects the overall contribution of each word to the text. This process effectively highlights the most significant keywords within the document.

(3)

Where  is the node,  is the weight of the edges between  and . The iterative calculation was carried out according to Formula (3) until convergence to obtain the initial TextRank score of . The value of  is generally 0.85.

(3) TF-IDF weight.

he process begins with the creation of a suitable corpus for word segmentation, where each word is assigned a unique ID. Next, the frequency of each word's occurrence across the corpus is analyzed, and its IDF value is calculated and stored in a dictionary. Along with the IDF values, the total number of documents in which each word appears is also recorded, offering a comprehensive overview of word distribution [14]. Following this, the frequency of each word's occurrence within the specific dataset for special education psychology and related disciplines is measured. Using these counts, the TF for each word is calculated and stored in a separate dictionary. By combining the TF and IDF values, the TF-IDF score for each word is computed, reflecting its significance within the dataset relative to the entire corpus [16].

To efficiently rank words based on their computed TF-IDF values, Python’s CMP sorting function is employed. This function sorts words alongside their corresponding TF-IDF scores in descending order, storing the results in a structured dictionary format [15]. The sorted list highlights the most relevant terms for subsequent processing and analysis. The mathematical formula used to calculate the TF-IDF value is provided below, offering a clear representation of the underlying computation:

(4)

Where,  is importance of word  in . The occurrence frequency is

(5)

where  is occurrences number. The calculation of IDF is as follows:

(6)

Among them,  is the total number,  is the number of documents containing word .

(4) Calculation of position weight

We first divided document according to paragraph number . In the calculation of position information weight, regular expression matching method is used to judge the relative position of words. Match words after first appeared in paragraph , a statistics section  of the total number of words  and  words in paragraph  of the relative position , calculate weight the location information of words in paragraph , and the relative position of segment information weight , according to the formula of calculating the position of the words within  in the document information weight , and the normalized processing. Lastly,  is calculated and stored.

Following the principles outlined above, higher weights are assigned to positions near the beginning and end of the special education psychology and discipline documents. Positional weights are adjusted according to the location of the words within the text. The weight of all words in the location  paragraphs is:

(7)

As indicated by formula (7), positions closer to the beginning and end of the text are assigned higher weights, while the middle sections are given relatively smaller weights, all within the range of (0,1). The weights are then normalized to ensure a reasonable calculation of the positional information weight.

(8)

Then the weight of the position information:

(9)

Then,  is normalized:

(10)

The scores are combined to calculate the weighted fusion of potential relationships between words. This process considers the influence of words within the corpus, the overall document, and their positional significance. The final score for each word is determined, and the words are ranked in descending order based on their scores. The final score  is

(11)

Where  and are all greater than 0, respectively.

**2.3 Recommendation based on improved deep learning**

In this study, a GCN, a pivotal deep learning architecture, is utilized to develop a recommendation model tailored for special education psychology and subject data. By integrating document labels, the model facilitates the comprehensive analysis and processing of the dataset, ensuring accurate and efficient resource recommendations. A prominent example of such an approach is the GCNMF model, a social recommendation framework that leverages the capabilities of GCNs for enhanced performance.

The GCNMF model is designed with two primary components. The first is a GCN module, which is responsible for extracting user feature vectors by learning from the complex relational data in the graph structure. The second is a probabilistic matrix factorization framework, which predicts user ratings by modeling latent user-item interactions. Together, these components allow the system to effectively capture and leverage social relationships and user preferences. The detailed architecture of the GCNMF model, shown in Figure 5, illustrates how its modules are integrated and their respective roles in the recommendation process.



**Fig. 5 GCNMF model**

Let  and  represent the potential factor models of users and projects, respectively, and the predicted score can be calculated by the following formula:

(12)

From the perspective of probability, the conditional distribution of the observation score can be expressed as:

(13)

Where  represents the Gaussian density function following with mean  and variance .  is the indicator function.

Like the traditional matrix factorization model, for the latent model  of the project, when mean is 0:

(14)

The potential model is:

(15)

(16)

Where,  represents the user social embedding vector. The Gaussian prior with mean 0 is set as follows.

(17)

The conditional probability distribution is:

(18)

Thus, the joint probability distribution of SCMF is:

(19)

The structure of GCN can be expressed as:

(20)

We use Maximum A posteriori (MAP) to estimate parameter:

(21)

Then:

(22)

Where,  and  are regularization parameters.

The coordinate descent method is employed to optimize the following parameters:

(23)

(24)

Where,  and  represent diagonal matrices, and  and  represent the rating vectors, is used as the equilibrium parameter.  and  are fixed as constants, and the loss function is:

(25)

Where . The parameters ,  and are updated alternately, and the process is repeated until convergence is achieved, completing the entire learning process. This approach is utilized to design and train the recommendation model for special education psychology and subject data. The trained model is then applied to the recommendation process, enabling the provision of more suitable special education psychology and subject data for users.

**3 Experimental design**

**3.1 Environment**

The programming language used in the experiment is Python. The open source library of algorithms in Python provides convenience for the construction of this model. Compared with other programming languages, Python has higher running efficiency. Python is the preferred development language for deep learning and the main programming language for Tensor Flow framework. The special education psychology and subject data recommendation model proposed in this paper is based on the framework of Tensor Flow.

Tensor Flow is a kind of data structure called tensors that represents all of the data. It's a system that takes complex data structures and sends them to artificial intelligence neural networks for analysis and processing. It integrates many existing and implemented classical machine learning algorithms, which are called operators. Each operator is defined and implemented with rules, methods, data types and corresponding output results. Tensor Flow uses a "library" registry to define nodes, which are the movements and implementations of an input in an operator. Tensor Flow interacts through conversations. For a Tensor Flow, you will have to process data like this:

(1) Establish a conversation;

(2) Generate an empty graph;

(3) Add each node and edge to form a graph with connection points;

(4) Start the diagram for system execution.

Table 1 shows the main software and hardware environment requirements of this experiment:

**Table 1 Requirements for the experimental hardware environment**

|  |  |
| --- | --- |
| Environmental parameters | Configuration requirements |
| Hardware environment | CPU:Inter(R)Core(TM)i5-8400 CPU@2.80Ghz |
| Memory: 8G |
| Hard disk 500G |
| The operating system | Microsoft Windows 10 |
| The software platform | Pycharm,jupyter |
| Development of language | Python 3.6 |

The experimental methods encompass those from references [5], [6], and [7], as well as the method introduced in this paper. The effectiveness of these approaches is assessed by comparing their recall rates, precision rates, and recommendation accuracy in the integration of special education psychology and discipline resources.

**3.2 The experimental results**

The methods from references [5], [6], and [7] are compared with the approach proposed in this paper using the same dataset, with a primary focus on comparing the recall rate. The results of this comparison are presented in Table 2.

**Table 2 Recall rate of integration results of special education psychology and subject resources**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Number of experiment | Ref [5] method/% | Ref [6] method/% | Ref [7] method/% | Our /% |
| 10 | 79.8 | 84.7 | 78.9 | 96.8 |
| 20 | 85.6 | 79.8 | 85.6 | 97.5 |
| 30 | 84.7 | 87.9 | 84.9 | 96.3 |
| 40 | 82.3 | 85.6 | 82.3 | 95.8 |
| 50 | 79.5 | 84.7 | 84.7 | 96.7 |
| 60 | 78.4 | 86.9 | 89.6 | 98.8 |
| 70 | 73.6 | 84.7 | 75.5 | 95.9 |
| 80 | 75.8 | 84.7 | 76.3 | 96.7 |
| 90 | 84.6 | 75.6 | 74.8 | 97.2 |
| Average | 80.5 | 83.8 | 81.4 | 96.9 |

From the data in Table 2, the integration of special education psychology and discipline resources using the method from reference [5] achieves a maximum recall rate of 85.6%, an average of 80.5%, and a minimum of 73.6%. In the case of the method in reference [6], the maximum recall rate is 87.9%, the average is 83.8%, and the minimum is 75.6%. The approach from reference [7] results in a maximum recall rate of 89.6%, an average of 81.4%, and a minimum of 74.8%. In comparison, the method proposed in this paper consistently outperforms the others, with a maximum recall rate of 98.8%, an average of 96.9%, and a minimum of 95.8%. This shows that the proposed method delivers significantly better recall rates for integrating special education psychology and discipline resources, reflecting its enhanced practical applicability.

Additionally, the accuracy rates for integrating special education psychology and discipline resources using the methods from references [5], [6], and [7], along with the method introduced in this paper, are compared. The results of this comparison, highlighting the effectiveness of each approach, are presented in Table 3.

**Table 3 Precision rate of integration results of special education psychology and subject resources**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Number of experiment | Ref [5] method/% | Ref [6] method/% | Ref [7] method/% | Method of this paper /% |
| 10 | 74.1 | 89.6 | 75.6 | 98.7 |
| 20 | 76.4 | 85.7 | 78.9 | 95.6 |
| 30 | 78.5 | 84.5 | 75.4 | 94.7 |
| 40 | 82.3 | 82.3 | 78.1 | 98.3 |
| 50 | 74.1 | 86.3 | 79.6 | 97.8 |
| 60 | 75.6 | 84.7 | 74.1 | 96.7 |
| 70 | 73.4 | 85.3 | 72.3 | 98.7 |
| 80 | 75.6 | 84.7 | 75.4 | 93.7 |
| 90 | 72.3 | 86.3 | 85.3 | 97.4 |

The data in Table 3 indicates that the method from reference [5] achieves a maximum accuracy rate of 82.3%, an average accuracy rate of 75.8%, and a minimum accuracy rate of 72.3% for the integration results of special education psychology and discipline resources. The accuracy rates for the method in reference [6] are 89.6%, 85.5%, and 82.3% for the maximum, average, and minimum, respectively. For the method in reference [7], the corresponding accuracy rates are 85.3%, 77.2%, and 72.3%. In contrast, the method proposed in this paper achieves accuracy rates of 98.7%, 96.8%, and 93.7% for the maximum, average, and minimum, respectively. Overall, the proposed method demonstrates higher accuracy and superior integration precision for special education psychology and discipline resources compared to the other methods.

The methods from references [5], [6], [7], and the approach proposed in this paper are also compared in terms of recommendation accuracy for special education psychology and discipline resources. The results are displayed in Figure 6.

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**Fig. 6 Comparison of recommendation accuracy**

An analysis of the data presented in Figure 6 shows distinct differences in the accuracy trends of special education psychology and discipline resource recommendations as the number of experiments increases across the various methods. The method from reference [5] exhibits an accuracy range between 66% and 89%, while the approach in reference [6] shows a slightly lower range, from 61% to 88%. The method described in reference [7] demonstrates even more variability, with accuracy fluctuating between 57% and 77%. In contrast, the method proposed in this study consistently achieves an accuracy above 93%, indicating superior performance. This suggests that the proposed method offers significantly more precise and reliable recommendations for integrating special education psychology and discipline resources, showcasing its strong practical applicability and effectiveness in real-world scenarios.

**4 Conclusion**

As societal attention to education continues to grow, special education schools are gaining a deeper understanding of their roles and responsibilities. These institutions are increasingly incorporating mental health education into their daily curriculum to help students build psychological resilience, manage stress, overcome psychological barriers, and promote overall mental well-being. This approach equips students with the tools they need to better adapt to societal demands and challenges in the future. As a result, the integration and recommendation of special education psychology and academic resources to the appropriate individuals has become a critical focus.

In light of this, this paper presents a method based on deep learning to analyze and integrate special education psychology and academic resources. Leveraging the self-learning capabilities of deep learning algorithms, a model is created to bridge the gap between mental health education and academic subjects, reflecting the dynamics of the special education sector. The experimental outcomes indicate that the proposed method yields a maximum recall rate of 98.8%, a maximum precision rate of 98.7%, and a recommendation accuracy consistently exceeding 93%. These impressive results underscore the method’s strong practical performance and its potential for real-world application.

Despite these promising results, there are areas for future improvement. One key direction for future research involves expanding the model’s dataset to include a broader range of special education contexts, which could enhance its ability to generalize across different educational environments. Additionally, incorporating real-time data could improve the dynamic nature of recommendations, ensuring that the system adapts to changing student needs and educational trends. Finally, integrating more advanced natural language processing (NLP) techniques could further refine the model’s ability to understand and interpret complex psychological and academic data, ultimately enhancing the accuracy and relevance of recommendations. By addressing these areas, future work could lead to even more effective and personalized support for students in special education settings.

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