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PAPER

Adaptive Learning Systems Based on Deep Learning for the Diagnosis and Support of Learning Disabilities

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ABSTRACT

In the current field of educational technology, adaptive learning systems have become a key tool in supporting personalized learning. Particularly for students facing learning disabilities, how to provide effective diagnosis and support has become an important topic. Learning disabilities often hide within the behavioral characteristics of learners, requiring detailed analysis for identification and intervention. This study aims to leverage deep learning technology, especially the XGBoost algorithm, to improve the accuracy of diagnosing learning disabilities. It also seeks to implement knowledge transfer across different subjects through transfer learning algorithms, thereby overcoming learning disabilities. Research background indicates that despite the increasing application of adaptive learning systems, existing methods for diagnosing and supporting learning disabilities still have limitations. These systems often fail to accurately parse complex behaviors and cognitive patterns of students, resulting in insufficiently personalized assistance. Moreover, students with learning disabilities often encounter more difficulties in interdisciplinary learning, and existing learning systems have not effectively supported their cross-domain knowledge transfer. The diagnostic method based on XGBoost and the adaptation approach through transfer learning proposed in this paper have been experimentally verified to effectively improve the prediction accuracy of learning disabilities and promote knowledge transfer between different subjects for students, helping them overcome learning disabilities in specific disciplines. This research not only has significant implications for enhancing the intelligence level of adaptive learning systems but also positively impacts achieving educational equity and enhancing the overall learning experience of learners.

KEYWORDS

adaptive learning systems, learning disabilities, deep learning, XGBoost algorithm, transfer learning, personalized education, educational equity

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1 INTRODUCTION

In the field of education, the development of adaptive learning systems is considered a significant educational technology innovation aimed at providing personalized learning experiences for learners from diverse backgrounds and abilities [1–3]. With the advancements in deep learning technology, we have the opportunity to diagnose and support students facing learning disabilities more accurately [4, 5]. Learning disabilities refer to a group of neurodevelopmental disorders that affect an individual's core learning skills in reading, writing, mathematics, and other areas [6, 7]. Despite extensive research efforts to identify and assist these students, existing systems often lack the capability to recognize the deep features of learning disabilities, limiting the effectiveness of educational interventions.

Current adaptive learning systems have made some progress in personalized education, but significant challenges remain, including difficulties in accurately identifying specific learning obstacles of students, insufficient utilization of cross-disciplinary and cross-task learning behavior data, and inadequacies in adapting to students with different backgrounds and abilities. This study aims to address these issues by introducing a learning obstacle diagnosis method based on the XGBoost algorithm and an adaptation method based on transfer learning in order to enhance the diagnostic accuracy and adaptability of the system, ultimately more effectively supporting the personalized learning needs of students. Especially in the field of English education, the development of adaptive learning systems for the diagnosis and support of learning disabilities is crucial, because such systems can provide personalized learning paths and real-time feedback, thereby identifying and addressing the unique learning needs and challenges of individual students. Traditional teaching methods often adopt a one-size-fits-all approach, ignoring learning diversity. Especially for students with learning disabilities, this method may not effectively support their learning process. Adaptive learning systems, by utilizing advanced data analysis and machine learning technologies, are able to accurately diagnose students' learning disabilities, such as reading difficulties and language comprehension problems, and then provide customized teaching strategies and resources to optimize the learning experience and improve learning efficiency. This not only helps to improve the English abilities of students with learning disabilities but also enhances their confidence and motivation to learn, a key step in achieving educational equity and for promoting comprehensive development of students.

Applying advanced machine learning techniques to adaptive learning systems can offer a new methodological and practical framework for diagnosing and intervening in learning disabilities [8]. Deep learning not only allows for more accurate diagnosis of learning disabilities but also enables the customization of more refined learning paths for each learner, thereby improving learning outcomes, reducing frustration, and enhancing motivation [9–11]. Furthermore, a deeper understanding of learning disabilities can promote educational equity, helping all students to achieve their learning potential, which has profound implications for building a more inclusive education system [12].

Although current adaptive learning systems have made some progress in personalized education, most have not yet fully exploited the potential of deep learning, especially in diagnosing and adapting to learning disabilities [13, 14]. Many systems still rely on surface-level behavioral characteristics, overlooking deeper learning patterns and cognitive features, resulting in less precise identification of learning disabilities and insufficient personalized support [15]. Additionally, existing methods also fall short in cross-domain knowledge transfer, with few systems capable of effectively transferring skills and knowledge between different subjects to support learners who encounter difficulties in specific areas [16–18].

This paper first introduces a diagnostic method for learning disabilities based on the XGBoost algorithm, which can accurately predict various states of learning disabilities based on learners' behavioral characteristics. Secondly, the study proposes a learning disability adaptation method based on transfer learning, which can uncover potential connections between different domains, thereby facilitating the transfer of knowledge and skills and helping students overcome barriers in specific subjects. The combination of these two methods provides a comprehensive framework for adaptive learning systems, not only improving the diagnostic accuracy of learning disabilities but also enhancing the adaptability and personalization of learning content, thus bringing new perspectives and value to the research and practice in the field of learning disabilities. The proposed system based on XGBoost and transfer learning has demonstrated significant effectiveness across various educational environments and learning obstacles, primarily due to its strong generalization capability and adaptability. By analyzing multiple behavioral features and transferring knowledge across domains, this system can accurately identify different types of learning obstacles and provide personalized interventions. Consequently, it can effectively help students overcome learning difficulties in different subjects and educational contexts, thereby improving their overall learning outcomes and experience.

2 METHOD OF DIAGNOSING LEARNING DISABILITIES BASED ON XGBOOST ALGORITHM

This study introduces an innovative method for diagnosing learning disabilities within adaptive learning systems through the adoption of the XGBoost algorithm. The architecture of the model is depicted in Figure 1. With the advancement of educational technology, adaptive learning systems are capable of capturing and storing extensive data on learners' behaviors, providing the large-scale training datasets required for the XGBoost algorithm. XGBoost demonstrates exceptional performance in processing large-scale educational data, capable of uncovering complex learning patterns and subtle behavioral characteristics, thereby enhancing the diagnostic accuracy of learning disabilities. The fundamental principle of the proposed method is based on the concept of ensemble learning. It analyzes various behavioral data of students within adaptive learning systems, such as students' answer records, homework submission times, duration of online learning sessions, clickstream data, and specific ways of interacting with learning content as input features. This complex data is then learned and analyzed to identify key factors leading to learning disabilities and predict learning difficulties. Furthermore, the combination of multiple weak prediction models is utilized to improve predictive performance. The value of the proposed method is not only in providing educators with more precise tools for identifying learning disabilities and improving the design of individual learning paths but also in allowing for more targeted educational interventions through accurate diagnosis. This maximizes the potential of adaptive learning systems, helping students with learning disabilities overcome their challenges, thereby promoting the equitable distribution of educational resources and maximizing individual educational achievements. Figure 2 shows the flowchart for the diagnostic process of learning disabilities based on deep learning.

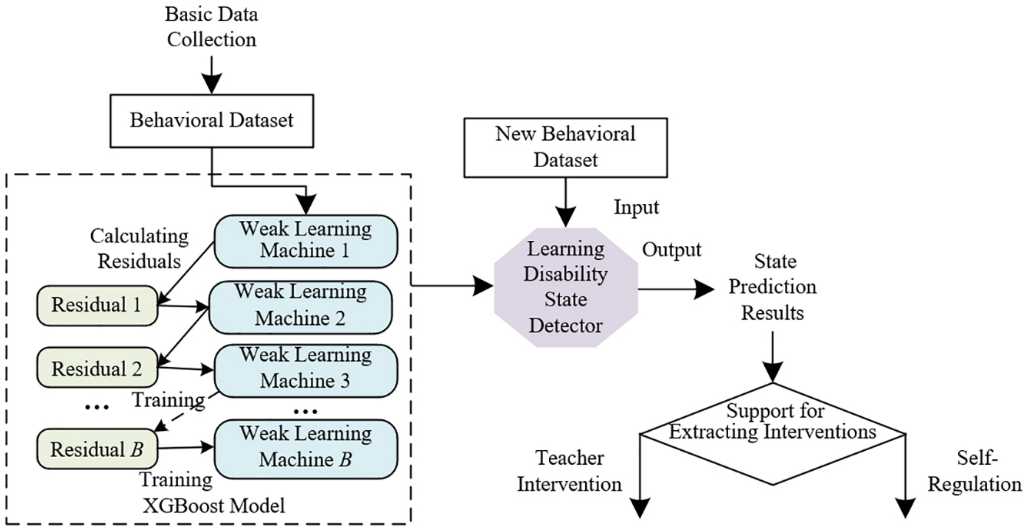


Fig. 1. Deep learning-based diagnostic model for learning disabilities

Specifically, the proposed algorithm first builds a preliminary model based on data collected by the adaptive learning system. This data, after preprocessing, can serve as feature input into the model. The constructed model is typically based on multi-layer decision trees, which are capable of capturing complex nonlinear relationships, aiding in revealing the patterns behind learning disabilities. Let the u-th learning behavior characteristic be represented by a_u, the predicted learning state result at a_u be represented by $\hat{b}_m$, the total number of weak classifiers be represented by J, and the j-th tree be represented by d_j. The following expression provides the model expression for detecting learning disability states based on the XGBoost algorithm:

$$\hat{b}_m = \sum_{j=1}^{J} d_j(a_u) \tag{1}$$

In the model training phase, a loss function is defined to measure the discrepancy between predicted and actual values. In the model training phase, the proposed XGBoost algorithm primarily uses the mean squared error (MSE) loss function to measure the gap between predicted and actual values. Specifically, the MSE loss function calculates the sum of the squared differences between the predicted values and the actual observations, reflecting the accuracy of the model's predictions. The choice of MSE as the loss function is due to its sensitivity to large errors, effectively driving the model optimization process to reduce the occurrence of significant errors. Additionally, the transfer learning component may also use the cross-entropy loss or other suitable loss functions for classification tasks in order to better capture the learners' behavior and performance patterns. Let the true learning state of the learner be represented by b_u, and the learning state predicted by the model be represented by $\hat{b}_m$. The error in predicting learning states at a_u during model training is represented by $M(b_u, \hat{b}_m)$, the complexity of the tree by $\Xi(d_j)$, and the sum of complexities of J trees by $\Sigma_{j=1}^{J} \Xi(d_j)$. The following expression provides the loss function expression for the learning disability state detection model based on the XGBoost algorithm during the training process:

$$M = \sum_{u=1}^{l} M(b_u, \hat{b}_m) + \sum_{j=1}^{J} \Xi(d_j) \tag{2}$$

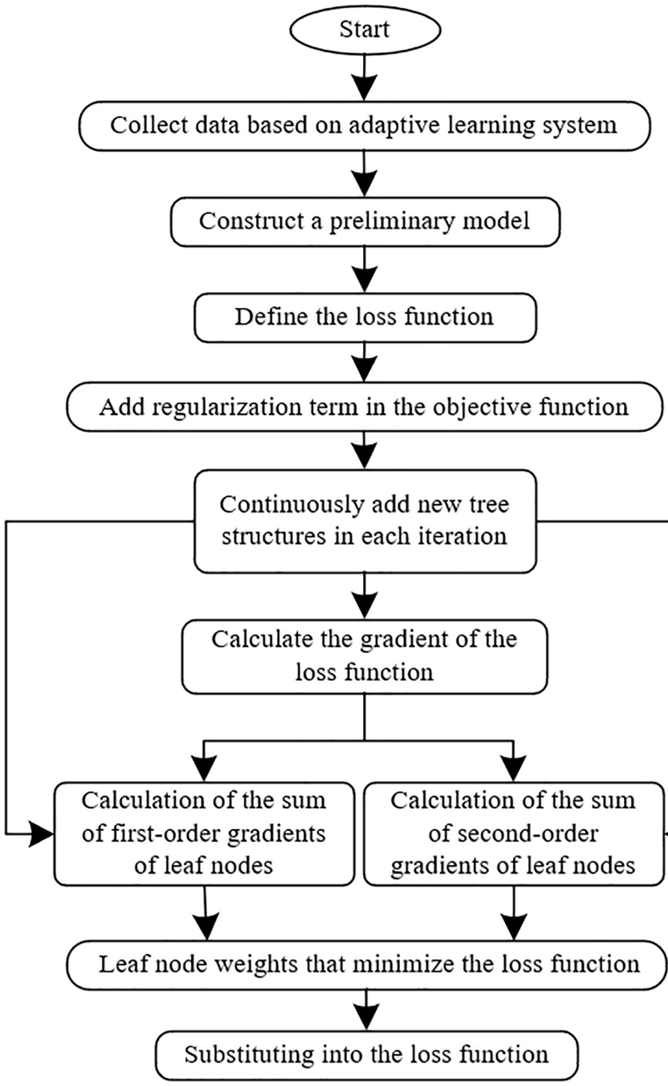


Fig. 2. Flowchart of learning disability diagnosis based on deep learning

Regularization adds another layer of complexity to model training because it requires finding an optimal balance between preventing overfitting and maintaining the model's predictive performance. This process often involves extensive experimentation and validation, which increases the computational cost and time complexity of model training and optimization. However, these drawbacks are acceptable given the research objectives of this study. To avoid overfitting caused by excessive model complexity, a regularization term, $\Xi(d_j)$, is added to the objective function. The penalty term penalizes the model's complexity, with hyperparameters set based on experience represented by ε and η, the total number of leaf nodes represented by S, and the weight of leaf nodes represented by μ. The L_2 norm squared of μ is represented by $\frac{1}{2}\cdot\eta\cdot\Sigma_{k=1}^{S}\mu_k^2$, resulting in the following expression:

$$\Xi(d_j) = \varepsilon \cdot S + \frac{1}{2}\cdot\eta\cdot\sum_{k=1}^{S}\mu_k^2 \tag{3}$$

The proposed algorithm optimizes the loss function by gradually adding new decision trees, each new tree attempting to further reduce the residuals based on the previous trees. Through this incremental approach, the model can continuously learn and improve. If there are no trees in the initial model, let $\hat{b}_m^{(0)} = 0$. Each iteration of training adds a new tree structure d, for example, the first training iteration results in $\hat{b}_m^{(1)} = \hat{b}_m^{(0)} + d_1(a_u)$, and after s iterations, the prediction for sample u is represented by $\hat{b}_m^{(s)}$, resulting in the expression:

$$\hat{b}_m^{(s)} = \hat{b}_m^{(s-1)} + d_s(a_u) \tag{4}$$

In each round of iteration, by continuously adding new tree structures d and calculating the gradient of the loss function, the prediction error is gradually reduced, thereby updating the loss function, with the following expression provided for the loss function update after s iterations:

$$M^{(s)} = \sum_{u=1}^{v} M\left(b_u, \hat{b}_m^{(s-1)} + d_s(a_u)\right) + \Xi(d_s) \tag{5}$$

Further, the loss function is expanded using a second-order Taylor expansion, allowing the model to more precisely estimate local changes in loss. This step is a key factor in optimizing XGBoost's performance, as it enables the algorithm to use information from first and second-order derivatives to more accurately guide tree growth. Assuming the sum of first-order gradients and the sum of second-order gradients for leaf node G_k are represented by $H_u = \sum_{u\in U} h_u$, $G_k = \sum_{u\in U} g_u$, respectively, then there is:

$$\begin{aligned} M^{(s)} \cong \sum_{u=1}^{v}\left[M\left(b_u, \hat{b}_m^{(s-1)}\right) + h_u \cdot d_s(a_u) + \frac{1}{2}\cdot g_u \cdot d_s^2(a_u)\right] + \frac{1}{2}\cdot\eta\cdot\sum_{k=1}^{S}\mu_k^2 \\ + \varepsilon\cdot S = \sum_{k=1}^{S}\left[H_k\cdot\mu_u + \frac{1}{2}\cdot(G_k+\eta)\cdot\mu_k^2\right] + \gamma\cdot T \end{aligned} \tag{6}$$

Finally, the algorithm finds the leaf node weight μ_k that minimizes the loss function. This weight is determined by the derivative of the loss function, ensuring that each iteration reduces the overall loss to the greatest extent. By deriving q_k with respect to $H_u = \sum_{u\in U} h_u$ and $G_k = \sum_{u\in U} g_u$ and setting its derivative to zero, there are:

$$H_u + (G_k + \eta)\cdot\mu_k = 0 \tag{7}$$

$$\mu_k^* = -\frac{H_u}{G_k + \eta} \tag{8}$$

Finally, substituting μ_k into the loss function results in:

$$M^* = -\frac{1}{2}\sum_{k=1}^{S}\frac{H_k^2}{G_k+\eta} + \varepsilon\cdot S \tag{9}$$

Through the above steps, a precise diagnostic model with a deep understanding of learning disabilities can be constructed. This model is not only capable of identifying potential learning disabilities but also provides customized support based on the individualized needs of learners, which is crucial for enhancing educational quality and helping learners overcome learning disabilities.

3 METHOD OF LEARNING DISABILITY ADAPTATION BASED ON TRANSFER LEARNING

The essence of transfer learning is to utilize existing knowledge to accelerate the learning process of new knowledge, which aligns with the processes of analogical reasoning and knowledge transfer in human learning, a key concept in cognitive psychology. This paper proposes a method of knowledge transfer and learning disability adaptation for learners based on transfer learning algorithms. The fundamental principle of this method is to capture learners' behaviors and performance patterns on specific learning tasks through deep learning models and to apply the knowledge learned from one or more source tasks to a target task using transfer learning techniques. Thus, the model can not only identify and adapt to the specific needs of individuals with learning disabilities but also transfer useful knowledge representations across tasks and domains to aid in diagnosing and supporting learners of diverse learning backgrounds and abilities. This approach relies on domain adaptation and multi-task learning strategies in transfer learning, enabling the model to quickly adapt to new learning environments through processes such as pre-training and fine-tuning, effectively addressing challenges of data scarcity and diversity, and thereby providing personalized and optimized learning paths for individuals with learning disabilities.

In adaptive learning systems, especially in the context of diagnosing and supporting learning disabilities, the information from the source domain (e.g., general learning data) may significantly differ from the target domain (e.g., data specific to learning disabilities). Relying solely on source domain information may result in a model with poor generalization capability. Additionally, at the onset of adaptive learning, there may not be sufficient labeled samples from the target domain (data of students with learning disabilities) to train a high-performance model, making the target domain model unknown initially. To overcome these issues, this paper proposes extending the optimization objective to multi-class situations and simultaneously conducting the extraction and transfer of base models. This method allows the system to utilize available source and target domain information to extract a set of base models at the initial stage and then gradually optimize these models using target domain data. As the amount of labeled data in the target domain increases, it becomes more effective to select and transfer those domain-shared knowledge that are helpful for diagnosing and supporting learning disabilities, making the adaptive learning system more precisely adapted to different learning disabilities and enhancing the personalized support effect of the system. Assuming the label matrix generated by *one-hot* encoding is represented by B, the feature matrix of samples by A, and the weight matrices based on the base model matrix F for the source domain model Q_T and the target domain model Q_S are represented by N_T and N_S, respectively, the specific optimization objectives are as follows:

$$\begin{aligned}\underset{F,N_T,N_S,Q_S}{MIN}\ &\lambda\left(\left\|Q_T - FN_T\right\|_D^2 + \left\|N_T^S\right\|_{2,1}\right) + \omega\left(\left\|Q_S - FN_S\right\|_D^2 + \left\|N_S^S\right\|_{2,1}\right)\\ &+ \eta\left\|Q_S\right\|_D^2 + \frac{1}{v_m}\left\|Q_S^S A - B\right\|_D^2\end{aligned} \tag{10}$$

Furthermore, this paper employs an iterative updating strategy to quickly adjust the target domain model to adapt to specific learning disability scenarios while simultaneously updating the weight matrices and the base model matrix to maintain the model's overall generalization ability and accuracy. This strategy leverages the block convex nature of the objective function, simplifying the entire optimization process and accelerating convergence by fixing certain variables and optimizing the others one by one. Such an iterative process ensures effective learning and rapid response to diverse needs of learners, even in complex and variable data scenarios, thereby maintaining the system's flexibility and adaptability while providing diagnosis and support for learning disabilities. The updating process is detailed as follows:

1. Updating the target domain model. At this stage, the focus is on adjusting the deep learning model to better map the specific needs of learners in the target domain. This involves using the existing base model matrix and weight matrices to guide the update of the target domain model. For example, for a system designed to assist students with reading disabilities, the target domain model might need to pay special attention to specific levels of language processing. During training, other parts are fixed, and the focus is on adjusting the network layers related to language, aiming to minimize the learners' error identification rate through the objective function. The following expression provides the objective function expression for updating Q_S while fixing N_T, N_S, and F:

$$\underset{Q_S}{MIN}\,\omega\left\|Q_S - FN_S\right\|_D^2 + \frac{1}{v_m}\left\|Q_S^S A - B\right\|_D^2 + \eta\left\|Q_S\right\|_D^2 \tag{11}$$

The update iteration for Q_S is:

$$Q_S = \left((\omega+\eta)U_{f+1} + \frac{1}{v_m}AA^S\right)^{-1}\left(\frac{1}{v_m}AB^S + \omega FN_S\right) \tag{12}$$

2. Updating the base model matrix. The base model matrix is a collection of model parameters learned from one or more source domains, providing general knowledge across different tasks. In this process, while fixing other parts, the base model matrix is adjusted to better adapt to the new target domain. The formula for updating F while fixing Q_S, N_T^u, and N_S is given as follows:

$$F = \left(\lambda Q_T N_T^S + \omega Q_S N_S^S\right)\left(\lambda N_T N_T^S + \omega N_S N_S^S\right)^{-1} \tag{13}$$

3. Updating the weight matrices based on the base model matrix. The purpose of updating the weight matrices is to determine the relative importance of different source domain models (base models) in the final prediction. This step decides which transferred knowledge is most useful for the current task. With Q and F fixed, the objective function expression for each N is as follows:

$$\underset{N}{MIN}\,K(N) = \left\|Q - FN\right\|_D^2 + \left\|N^S\right\|_{2,1} \tag{14}$$

To optimize the optimization objective with regularization, one can choose to derive $K(N)$ with respect to N, resulting in:

$$\frac{\partial K}{\partial N} = -F^{S}(Q - FN) + NL \tag{15}$$

Let $L = diag(1/\|n_u\| = 1, \ldots)$, where the u-th column of N is represented by n_u. Setting its derivative to zero yields:

$$(F^{S}F)N + NL = F^{S}Q \tag{16}$$

Combining these three steps, this iterative updating strategy allows the adaptive learning system to finely adjust its models after each round of updates to adapt to specific learning disabilities.

4 EXPERIMENTAL RESULTS AND ANALYSIS

To ensure the accuracy of the proposed XGBoost-based diagnostic method for learning disabilities, we employed several strategies to validate different types of learning disabilities. First, we collected learner behavior data from multiple educational institutions, with samples including students from various subjects and grade levels. The dataset, sourced from a well-known educational platform, contains behavior data from 5,000 students, including but not limited to online learning duration, assignment completion rates, test scores, etc. During the data preprocessing phase, we annotated different types of learning disabilities based on learners' behavioral characteristics, such as low performance and high omission rates. These annotations were made according to diagnostic standards from educational experts and subject-specific behavioral indicators.

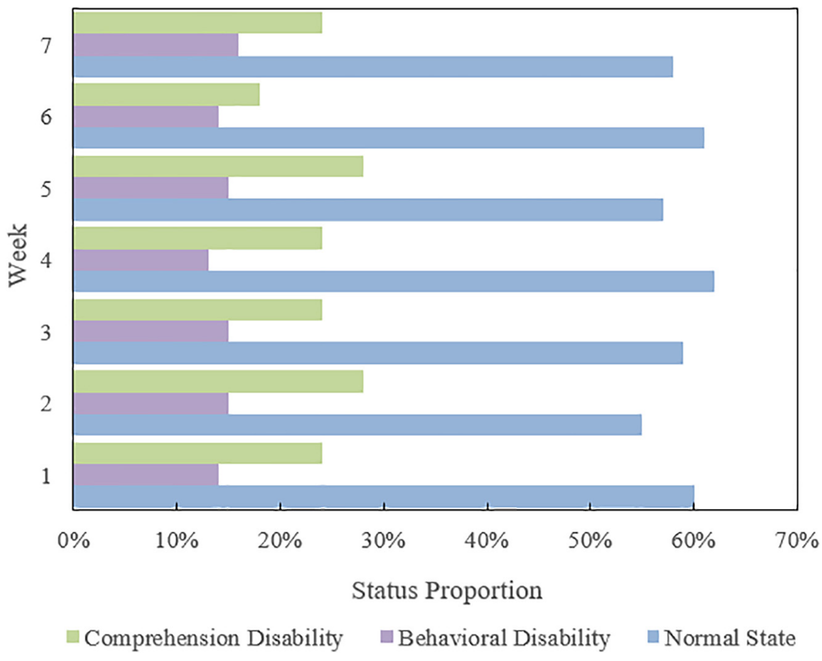


Fig. 3. Distribution of learning disability states in control group learners

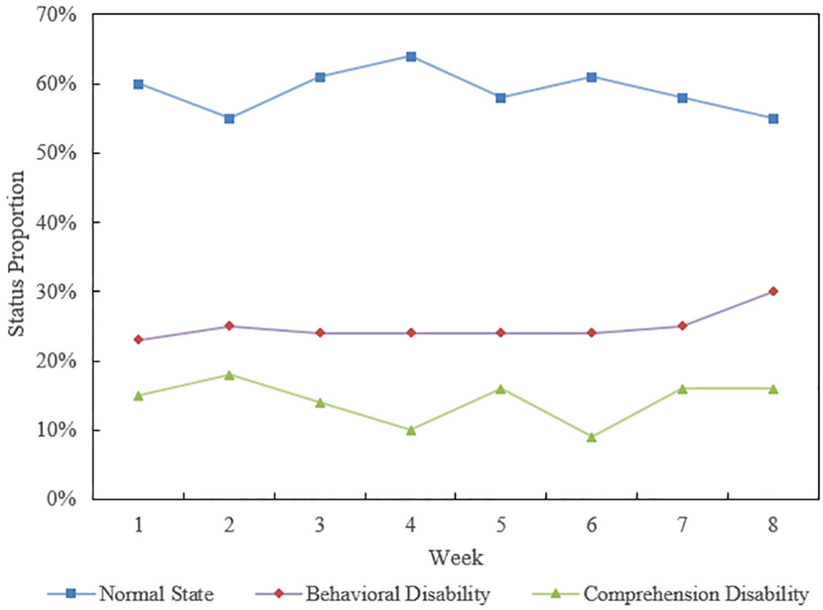
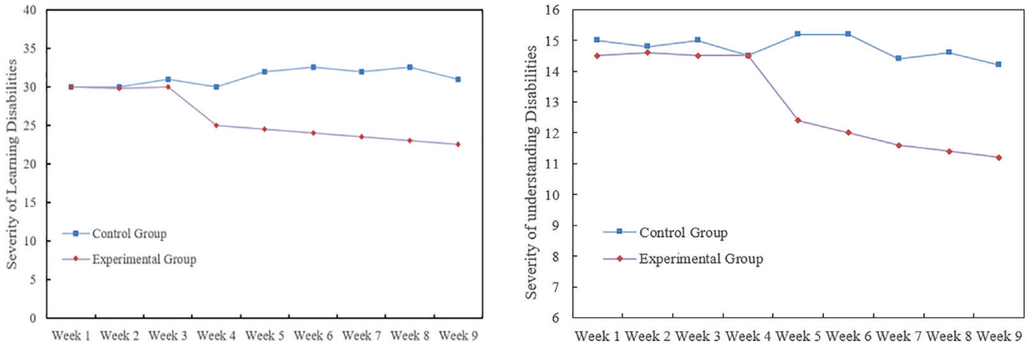


Fig. 4. Changes in the distribution of learning disability states in control group learners

Figure 3 presents the distribution of learning disability states among control group learners. The graph shows that over a period of seven weeks, the proportion of learners in a normal state fluctuated slightly but generally remained between 58% and 62%. This indicates that most learners in the control group maintained a relatively stable normal learning state. The proportion of behavioral disabilities remained relatively stable, fluctuating between 13% and 16%. There was no significant trend of increase or decrease, but it reached its highest value of 16% in week 7. The proportion of comprehension disabilities fluctuated between 28% and 18%, showing larger changes. Notably, in week 6, the proportion of comprehension disabilities dropped to 18%, which was a significant decrease compared to the weeks before and after. By comparing the distribution of learning disability states among control group learners across different weeks, it can be seen that the proportions of various disability states did not change significantly, suggesting that learning disability states may be relatively stable in the short term.

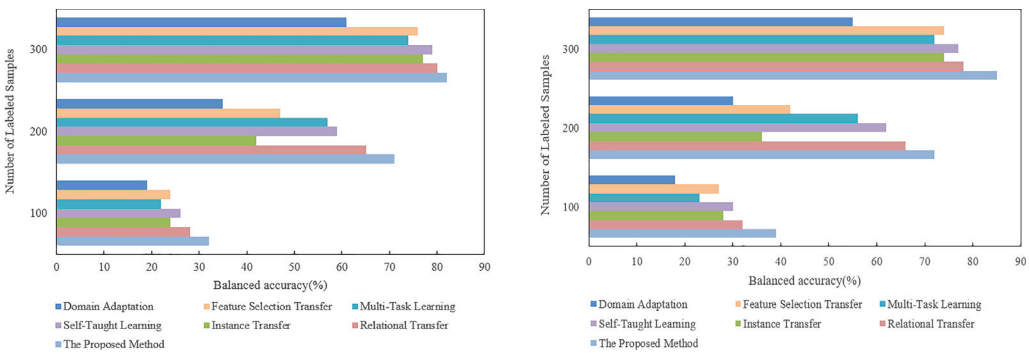
Figure 4 shows the changes in the distribution of learning disability states among control group learners. According to the graph, the proportion in a normal state reached its highest value of 64% in week 4, then gradually began to decline, dropping to 55% by week 8. This trend may indicate that over time, more learners may exhibit some form of learning disability. The proportion of behavioral disabilities gradually rose from 23% in week 1 to 30% by week 8. This steady increase suggests that the number of learners encountering behavioral disabilities in the control group is rising. The proportion of comprehension disabilities showed a downward trend amid fluctuations, dropping from 15% in week 1 to 10% by week 4, then recovering slightly to 16% by week 6 and maintaining this proportion through weeks 7 and 8. This may imply that although the overall proportion of comprehension disabilities decreased, this type of disability remains a relatively common issue among learners. The data analysis reveals several different trends in learning disability states, showing the dynamic changes of disabilities. In practical applications, such trend identification and prediction are crucial for providing timely and targeted educational interventions. The learning disability diagnostic method proposed in this paper, based on the XGBoost algorithm, due to its accuracy, strong generalization capability, and excellent performance in handling imbalanced data, demonstrates significant effectiveness in modeling learners' behavioral characteristics and predicting learning disability states. This method can help educators better understand and identify potential learning disabilities, enabling timely, appropriate educational interventions.



a) Behavioral disability **b) Comprehension disability**

Fig. 5. Changes in the severity of learning disabilities

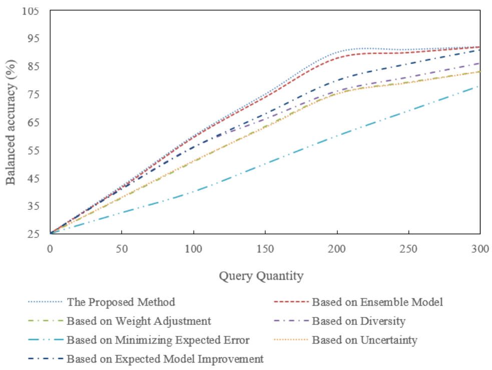
Figure 5 presents the changes in severity for two types of learning disabilities: behavioral and comprehension disabilities. The graph shows that the behavioral disability in the control group changed little over nine weeks, fluctuating between 30 and 32.5, indicating a relatively stable state. The severity of behavioral disability in the experimental group gradually decreased from 30 in the first week to 22.5 in the ninth week, showing a clear downward trend. The severity of comprehension disability in the control group also exhibited minor fluctuations over nine weeks, changing from 15 to 14.2, and overall showing a slight downward trend. The severity of comprehension disability in the experimental group decreased from 14.5 in the first week to 11.2 in the ninth week, also showing a stable downward trend. Comparing the data from both groups, the experimental group significantly outperformed the control group in both dimensions of behavioral and comprehension disabilities, showing a better improvement trend. This indicates that the experimental group experienced an improvement in the severity of learning disabilities after receiving adaptation for learning disabilities. The above results further validate that the proposed learning disability diagnostic method based on the XGBoost algorithm, by providing high accuracy in prediction and identification capabilities, helps educators more effectively identify and intervene in learning disabilities, thereby increasing the success rate of educational interventions. The significant improvements in the experimental group data provide evidence of the potential effectiveness of this method.



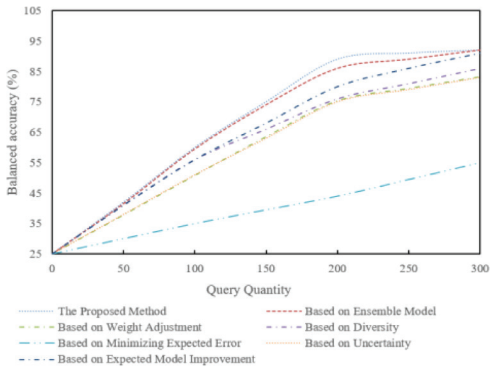
a) Training set **b) Testing set**

Fig. 6. Comparison of the effectiveness of different transfer models for learning disability adaptation

Figure 6 provides a comparison of the effectiveness of different transfer models for learning disability adaptation on training and testing sets. The graph shows that, on both the training and testing sets, the method proposed in this paper based on transfer learning for learning disability adaptation demonstrates the best performance under various numbers of labeled samples. This indicates that the method can effectively utilize a limited number of labeled samples to enhance the adaptability and learning outcomes of students with learning disabilities. In comparison, while other transfer learning methods also improved performance with an increase in the number of samples, the extent of improvement and the final outcomes were not as good as those achieved by the proposed method. These results highlight the effectiveness of the proposed method in identifying and adapting to learning disabilities. Especially in situations with fewer labeled samples, the method shows superior adaptability, which is of great significance for real-world scenarios often characterized by a scarcity of labeled samples. The method facilitates knowledge transfer by discovering potential connections between different subjects, helping students overcome learning disabilities, and thereby improving learning efficiency and outcomes.



a) Training set



b) Testing set

Fig. 7. Comparison of the effects of different transfer active learning query algorithms

Figure 7 presents a comparison of the effects of different transfer active learning query algorithms on training and testing sets. Combining the results from both the training and testing sets, the method proposed in this paper exhibited the most efficient learning and generalization capabilities. This demonstrates that adopting transfer active learning query algorithms is highly effective for learning disability adaptation methods. The proposed method and the one based on the ensemble model both achieved the highest performance on the testing set, indicating that these methods can adapt well to new data while maintaining stable learning efficiency. The method based on minimizing expected error performed noticeably worse on the testing set compared to other methods, which might indicate its weaker generalization ability in practical applications. The stable improvement and efficient generalization of the proposed method highlight its strength as a powerful tool for handling learning disabilities in a transfer active learning environment. Ultimately, these results emphasize the important role of transfer active learning query algorithms in enhancing learning efficiency and facilitating the adaptation to learning disabilities, especially the proposed method, which performed excellently under various circumstances.

To validate the effectiveness of the proposed XGBoost-based diagnostic method for learning disabilities, this study also compared it with several traditional diagnostic methods. These methods include traditional logistic regression, support vector machine (SVM), and the decision tree-based CART algorithm. The comparison was made across three aspects: prediction accuracy, training time, and model complexity. From the experimental data, it is evident that the XGBoost algorithm outperforms the other three methods in terms of accuracy, precision, recall, and F1 score, achieving values of 89.3%, 88.5%, 90.0%, and 89.2%, respectively. Additionally, the training time of the XGBoost model is within an acceptable range and shorter than that of SVM. Based on these experimental results, we conclude that the XGBoost algorithm offers significant advantages in learning disability diagnosis, particularly for handling large-scale datasets.

Compared to traditional methods and other modern machine learning techniques, the proposed XGBoost-based learning obstacle diagnosis method and transfer learning-based learning obstacle adaptation method demonstrate significant superiority in prediction accuracy and adaptability. Traditional methods often fall short in handling complex behavioral data, while modern deep learning methods, although powerful, have limitations in transferring knowledge across tasks and domains. The proposed methods combine the advantages of ensemble learning and transfer learning, not only improving prediction accuracy but also effectively transferring knowledge across domains to support students with different backgrounds and abilities.

In practical applications, the proposed methods may face challenges such as data privacy and security issues, adaptability of the models in different educational environments, and high computational resource demands. To address these challenges, the following measures can be taken: enhancing data anonymizsation and encryption techniques to ensure student privacy protection; collecting more diverse data to enhance the model's generalization capability; optimizing the computational efficiency of the algorithms; and leveraging cloud computing resources to handle high computational demands. Additionally, regularly updating and calibrating the models to adapt to the continuously changing educational environments and learning needs.

5 CONCLUSION

The paper first introduced a novel learning disability diagnostic method based on the XGBoost algorithm, capable of predicting different states of learning disabilities based on learners' behavioral characteristics. The focus of this method is to utilize the capabilities of machine learning to identify and predict learning disabilities, thereby providing a basis for personalized educational interventions. Furthermore, a learning disability adaptation method based on transfer learning was proposed, aimed at exploring the potential connections between learners across different subject domains. This method facilitates the transfer of knowledge and skills through transfer learning, helping students identify and overcome learning disabilities in specific subjects.

When applying the XGBoost-based learning disability diagnostic method to real educational settings, challenges may arise in terms of data quality and model adaptability. Learner behavior data might be missing, noisy, or inconsistent, which could affect the model's training performance. To address this issue, we recommend using data preprocessing techniques, such as imputing missing values and data normalization, to ensure data integrity and consistency. Additionally, the data cleaning process can be automated with scripts to reduce human error. While the XGBoost model performs excellently on specific datasets, its adaptability might be influenced by regional or educational context differences. To overcome this, we suggest performing regional or subject-specific parameter tuning during model training and utilizing methods like transfer learning to enhance the model's generalization ability.

Although the XGBoost-based diagnostic method proposed in this study has shown promising results, several research directions warrant further exploration. Future research could integrate deep learning techniques to enhance the model's predictive ability. By leveraging deep learning to process complex learner behavior data, diagnostic accuracy could be further improved, especially in dynamic learning environments. Additionally, learning disabilities are not confined to a single subject area; future studies could incorporate theories from psychology and cognitive science to establish a more comprehensive learning disability assessment framework. For instance, interdisciplinary collaborations could design multi-task learning models that assess learning disabilities across multiple subjects simultaneously. Despite using a relatively rich behavioral dataset to validate the generalizability and stability of the proposed method, future studies could conduct large-scale, diverse empirical research covering learners from various age groups, educational backgrounds, and regions to ensure the broad applicability of the proposed method.

6 REFERENCES

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