Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2, 1168-1179
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i2.4722

Research on the construction of outcome-based education platform based on deep learning

LiMengyang[1,2*], Zaida Mustafa[1], Lu Shufang[2]
[1]Faculty of Social Sciences and Liberal Arts, UCSI University, 56000, Kuala Lumpur, Malaysia;
1002165230@ucsiuniversity.edu.my (L.)
[2]Pingdingshan University, 467000 Pingdingshan city, Henan Province, China.

Abstract: The traditional way of enrolling students and organizing teaching by major has been difficult to meet the needs of high-quality development. The OBE (Outcome-Based Education) model emphasizes that everyone can succeed, personalized evaluation, competency-based performance responsibility, and so on. With the continuous development of AI (artificial intelligence) technology and the sharp increase in available data in the era of big data, the application of AI is becoming increasingly important. This paper proposes an OBE platform based on deep learning, which includes personalized learning recommendations and classroom quality evaluations. This paper explores the relationship between users' learning emotions and learning efficiency and uses the content-based recommendation model of CNN (convolutional neural network) to recommend personalized learning methods. It employs the improved SSD (Single Shot MultiBox Detector) algorithm to detect classroom behavior. The research results show that the CNN recommendation model performs very well in the learning resource recommendation platform. The results indicate that the improved SSD algorithm in this paper has a good inhibitory effect on all five actions and shows a significant improvement in the detection effect of small targets, up to 14.805%. This is of great significance for promoting the deep integration of modern information technology with education and teaching and for implementing effective OBE.

Keywords: *Outcome-based education; Deep learning; Learning recommendation; convolutional neural network.*

1. Introduction

In order to meet the new challenges brought by the "new industrial revolution" and adapt to the rise of "public responsibility", higher requirements are put forward for the return of "education investment" and "actual output". With the technological progress and social development, as well as the adjustment and transformation and upgrading of industrial structure, the social demand for technical and skilled talents has changed, and the traditional way of enrolling students and organizing teaching by specialty has been difficult to meet the needs of high-quality development [1]. OBE (Outcome-based Education) model emphasizes that everyone can succeed, personalized evaluation, competency-based, performance responsibility and so on.

With the continuous developmsent of AI (Artificial Intelligence) technology and the sharp increase of available data in the era of bisg data, the application of AI is becoming more and more important. OBE platform is a large-scale intelligent application with universality, which can directly evaluate people, but people are highly intelligent creatures, so it is necessary to evaluate people's learning state in multiple dimensions and in all directions [2]. The concept of deep learning comes from the neural network in computer technology Ouyang, et al. [3]. Hu, et al. [4] puts forward an online course recommendation method based on activity sequence, which uses collaborative filtering to analyze learners' activity behavior sequence, and combines text mining technology to find out resource keywords for matching recommendation. Yang, et al. [5] designed a recognition model of behavior

History: Received: 25 December 2024; Revised: 30 January 2025; Accepted: 3 February 2025; Published: 11 February 2025
* Correspondence: 1002165230@ucsiuniversity.edu.my

features in video images by using deep learning. The video images were divided into two parts by using CNN (convolutional neural network), and the features of two data features with high and low resolution in the data stream were extracted respectively. Finally, the results of the two data features were combined to realize the behavior recognition of the action features in the video images. Chiu, et al. [6] puts forward a new intelligent recommendation platform for online learning, which can analyze all kinds of interactive behaviors between learners and platforms, obtain information about resources from the network to generate causal knowledge of behaviors, and make recommendations accordingly.

The research and application of OBE concept is moving towards diversification, but there are few reform cases of building a platform-based education platform with the advantage of informationization. Constructing the teacher-student relationship scientifically and enhancing the effectiveness of teaching is an important direction of education and teaching reform, and it is also the key to promote teaching and learning [7]. It is difficult for the traditional teaching mode to dynamically monitor the learning process of students, the teaching effect of teachers, and the achievements of the school's goal-oriented talent training stage. The training method of teaching students in accordance with their aptitude and continuous improvement is lagging behind. The achievement is not only what students know and understand, but also the ability to apply it to practice, as well as the values or other emotional factors that may be involved. This paper proposes an OBE platform based on deep learning, which includes personalized learning recommendation and classroom quality evaluation. Explore the relationship between users' learning emotions and learning efficiency, and realize personalized learning method recommendation. Using deep learning to express data, multi-source data are integrated to improve the recommendation effect.

2. Research Method

2.1. Overall Construction of OBE Platform

The basic task of the school's training goal should be to cultivate people by virtue. Based on the school's orientation, philosophy and characteristics, the school level should uniformly plan public general education courses and quality education courses, focusing on the cultivation of students' general ability and moral quality. OBE emphasizes that students' learning achievements are the basis for testing the teaching effect and the standard for judging the quality of education and teaching. OBE tends to examine students' ability changes after learning experience, as well as the management of their own learning perception process, focusing on stimulating students' learning subjectivity, emphasizing the process evaluation of talent training, and paying attention to the satisfaction of relevant groups involved in the output of results. With the support of information technology, the educational and teaching management norms and standards are constantly transformed into computer data resources, which realizes the whole process monitoring and continuous improvement of teaching and learning, promotes the improvement of teaching management efficiency and the achievement of students' core competence, and effectively responds to the concerns of families and society about talent training.

The research-based mixed teaching mode is guided by many teaching ideas or theories such as "students as the main body, teachers as the leading factor", "the nearest development zone" and "learning community", aiming at guiding and promoting students' deep learning. Cooperative learning encourages students to paraphrase and express what they have learned, which has an important impact on the achievement of higher-level goals. "Sharing and reviewing expressions in cooperation is the key behavior that determines learning performance" [8].

There are two problems in the traditional teaching mode. First, the evaluation criteria are single. Teachers have a one-sided grasp of students' learning situation, so it is difficult to accurately understand and control the real learning situation of students in the class, and it is difficult to detect the teaching effect. Second, the way to modify the teaching plan according to students' grades depends very much on teachers' teaching experience. Data is the basis of AI technology, and every data source of the research object can be regarded as a mode, such as the application of deep learning technology in medical imaging. The core goal of multimodal deep learning technology is to integrate many different types of deep learning models, form cooperative learning among the models in the training process, and finally build an accurate OBE platform [9].

Since the development of deep learning, what is the significance of deep learning to the reform and development of our education? In the cognitive field, in addition to requiring students to master the deep content, students need to have the ability of critical thinking, which further embodies the definition of deep learning. In the interpersonal field, students should move to real interpersonal communication through cooperation and communication between groups in the course; In the field of self, students should change from passive learning to spontaneous learning, have and explore the ability to learn, and cultivate good academic habits. The mature application of deep learning in the image field provides the possibility for the realization of a classroom evaluation platform integrating multiple deep learning algorithms.

OBE platform is an intelligent teaching platform which integrates real-time data collection, dynamic modeling and feedback from teachers and students after class. It is composed of classroom monitoring and evaluation model and after-class feedback model. After-class feedback model will be constantly updated and improved according to the feedback data of students and teachers during and after class, making the model more intelligent and accurate [10]. Combining the advantages of personalized education and online education, this paper designs a set of OBE platform based on deep learning. Its platform block diagram is shown in Figure 1.

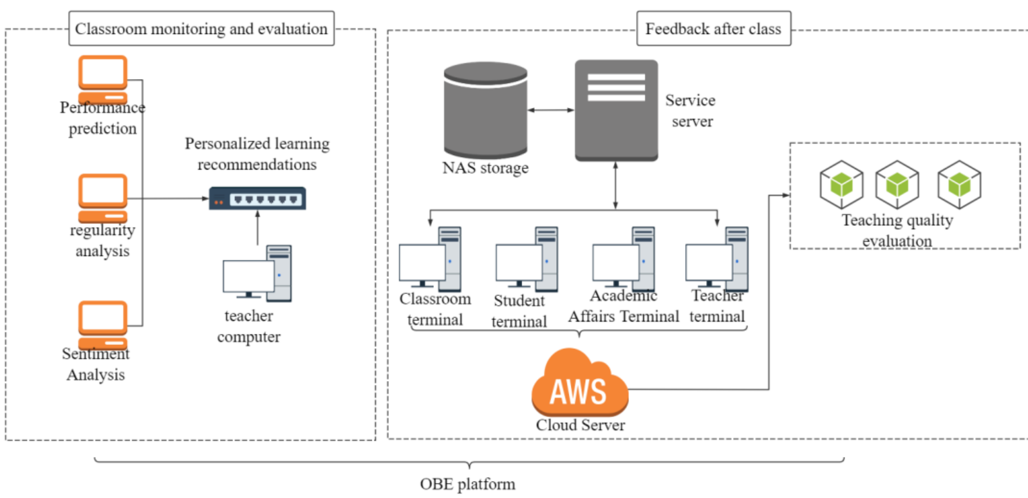

Figure 1.
Block diagram of OBE platform.

This platform mainly combines student behavior recognition and face recognition algorithm to realize the analysis of classroom state. The management end is responsible for randomly viewing the classroom videos at any time and analyzing the classroom state, which can be called the output of the platform. In addition, the algorithm used in this platform is to recognize pictures, so the video needs to be intercepted before recognition, and each recognition in this paper is aimed at a course. The classroom video playing display module is used to play the course video [11] read from the database. In the design, it is required that the platform can correctly read the video and the data corresponding to each state from the database according to the user's choice of viewing mode (divided into class query and teacher query) and the positioning of the search bar information, and play it when clicking the play button.

Different users can enter the teachers' or managers' pages through different login pages, and then upload videos, query class information, classroom information and course information, and view state statistics, attendance information, educational resource information and basic information through page button components. Behavior recognition result information mainly refers to the class state information obtained according to the behavior recognition result of each frame. Face recognition information mainly refers to the face recognition result information of a class. This layer uses MySQL database and SQLAlchemy framework in ORM.

Personalized learning recommendation uses CNN's content-based recommendation model, uses the text information in multimedia resources as the recommendation basis, uses hidden factor model to calculate the feature vectors of users and objects according to historical data, then uses CNN to map and fit the text information in resources with its corresponding feature vectors, and then uses trained CNN to make recommendations.

2.2. Key Technology Realization

2.2.1. Personalized Learning Recommendation

Curriculum is the direct embodiment of professional connotation, the basic element of talent training, and the key factor for schools to meet the talent needs of industry enterprises. The monitoring of teaching process at school level is generally realized by supervising lectures or students' evaluation of teaching. The collation and analysis of evaluation results are often time-consuming and incomplete, which fails to effectively reflect the linkage of "industry demand orientation, students' ability quantification, teaching status analysis, teaching optimization and management adjustment", resulting in weak timeliness of teaching objectives and teaching results. Through information technology, OBE concept runs through the whole process of education and teaching, and integrates information such as educational administration platform, students' autonomous learning space, teaching process, student management service, personnel management, scientific research operation, enrollment and employment process, etc., and unifies them into data standards that can cross the internal and identify each other. Schools, families, society and other subjects perform their duties, cooperate closely and continuously improve around the core and common mission of improving the quality of personnel training.

At present, the online learning platform usually takes the teaching platform as the core, and learners take the learning resources preset in the platform as the main learning content in the learning process, but at the same time, there are homogenization problems. Personalized resource recommendation service technology can automatically recommend educational information and educational resources that learners may be interested in by analyzing learners' historical behavior data and constructing their interest model. In today's information explosion, personalized resource recommendation service can effectively solve a series of problems such as "information loss" and "information overload" [12]. Among them, recommendation algorithm is the most critical link, and its success directly affects the types and performance of this technology.

With the great success of deep learning algorithm in computer vision, speech processing and natural language processing, how to introduce it into recommendation algorithm has become a research hotspot in recent years [13]. Aiming at the problem of "cold start" in traditional recommendation algorithm, this paper proposes a content-based recommendation model using CNN, which uses the text information in multimedia resources as the recommendation basis, uses the hidden factor model to calculate the feature vectors of users and objects according to historical data, then uses CNN to map and fit the text information in resources with its corresponding feature vectors, and then uses the trained CNN to make recommendations. The overall structure is shown in Figure 2:

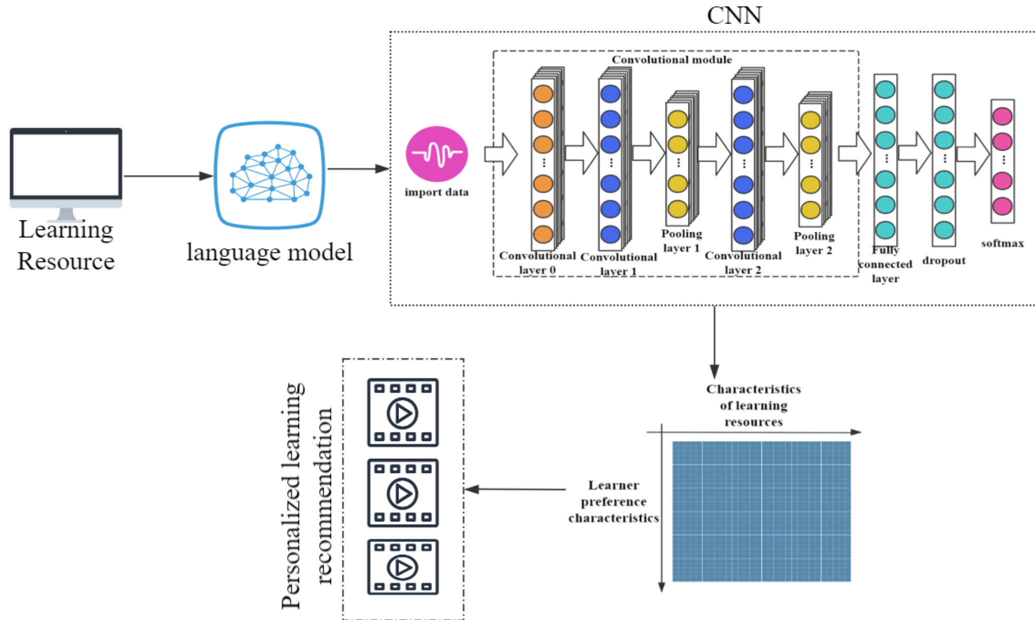

Figure 2.
Overall structure of personalized learning recommendation.

The content-based CNN recommendation model includes three main aspects: content-based recommendation framework, CNN and implicit factor model. The recommendation process depends on CNN provided in the training process to work effectively. The training data of language model comes from the text information in learning resources [14].

CNN model is a four-layer neural network model with two convolution layers, a local sampling layer and a fully connected layer. A convolution layer contains a convolution filter $w \in R^{sk}$, which is applied to s word vectors to calculate their eigenvalues.

$$c_i = f\left(w * x_i + b\right) \quad (1)$$

$b \in R$ is a bias term in neural network, and f is a nonlinear activation function such as sigmoid function.

The convolution operation will produce new eigenvalues at $b = \left[b_1, \cdots, b_\lambda\right]$.

$$a = f\left(w * b + b\right) \quad (2)$$

The above formula deduces the process of extracting features from a convolution filter. In this model, a large number of convolution filters are used to extract a large number of features, and these features are input to a fully connected layer whose output is an implicit factor, that is, the last layer of the network [15].

Implicit factor model is used to obtain the characteristics of learners and learning resources. In the traditional hidden factor model, vector two norm is used as the regularization factor, but this regularization factor will bring the problem of over-smoothness. An improved matrix decomposition method is proposed, and sparse prior is used to constrain the results. The objective function of the model is:

$$J(U,V) = \sum_{ij}\left(U_i * V_j - r_{ij}\right)^2 + \lambda_1 \|U\|_1 + \lambda_2 \|V\|_1 \quad (3)$$

The matrix U represents the correlation matrix between users and implicit factors, and V represents the correlation matrix between learning resources and implicit factors. r_{ij} represents the scoring data given by the i th learner to the j th learning resource, and λ_1, λ_2 is the regularization factor to control the relative strength between the constraint term and the fidelity term in the objective function.

2.2.2. Classroom Evaluation

For general classroom teaching, whether it is the traditional manual evaluation method or the existing classroom evaluation platform, the observation points of classroom teaching evaluation mainly include students' attendance in class, attention in class, classroom activity and the design of classroom links. Based on objective evaluation, this paper studies the evaluation methods of classroom concentration, classroom activity and classroom link richness, and constructs an information evaluation system of students' learning process and classroom quality.

The platform needs to analyze all the collected classroom-related indicators, and get the comprehensive evaluation results of the classroom through weighted calculation, so that teachers and staff can analyze and summarize. Therefore, it is necessary for the platform to have the ability to analyze and calculate the result data obtained from attendance and classroom behavior recognition, and objectively evaluate each class. It is also necessary to make statistics on students' personal classroom behavior, and the statistical results can provide a basis for teachers to evaluate students' personal grades.

The platform adopts the improved version of MobileNet-V2 network, and carries out face recognition on the Inference Engine in the OpenVINO development tool suite. Every time face recognition is carried out, the folder name of face recognition results is read, and the tag file corresponding to the relevant course ID is selected as the reference image library file through the time in the folder name [16].

Classroom behavior is helpful to analyze students' listening quality and teaching effect. This section puts forward an improved SSD (Single Shot MultiBox Detector) algorithm by analyzing the characteristics of students' classroom behavior. The design flow of the behavior recognition model is shown in Figure 3.

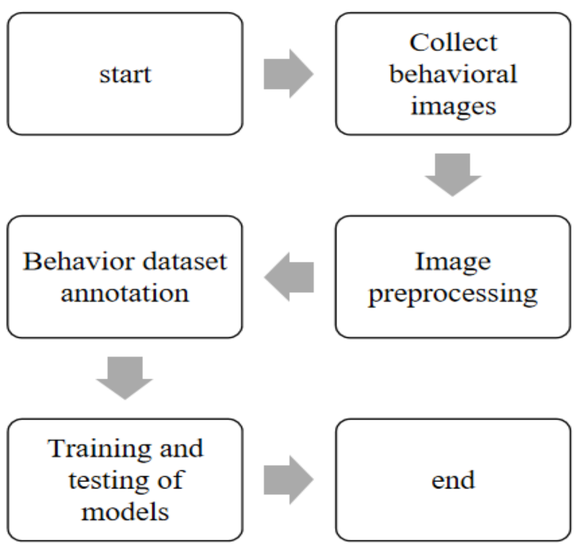

Figure 3.
Classroom behavior identification process.

On this basis, a target detection method based on improved SSD is proposed. SSD method uses a basic neural network, plus an additional convolution layer, and then selects several feature layers to realize the detection of objects. Because of the difficulty of training, it requires high computer configuration and poor real-time performance. On this basis, a lightweight network is used to replace VGG16, which reduces the number of parameters and improves the detection speed [17].

When an image is put into a convolutional network, the image information obtained at different levels of the network is different. Because superficial and deep surface have their own advantages, they can only make up for their shortcomings, so there is a new idea of combining these two technologies. In this paper, add feature fusion method is used to fuse the network [18]. Conv11, Conv13, Conv14_2 and Conv15_2 are selected for fusion operation, so as to improve the detection accuracy of small targets.

Add feature fusion method:

$$R_{add} = \sum_{i=1}^{N}(X_i + Y_i)K_i = \sum_{i=1}^{N} X_i * K_i + \sum_{i=1}^{N} Y_i * K_i \quad (4)$$

Where X, Y stands for the channel to be fused; K_i represents the weight of the i channel; R_{add} stands for fusion result.

In order to accelerate the degradation, it is often required to use the optimal algorithm. On this basis, the RMSProp (Root Mean Square Prop) optimization method is proposed. The specific calculation formula is as follows.

$$S_{dR} = \beta S_{dR} + (1-\beta)(dR)^2 \quad (5)$$

$$R = R - \rho \frac{dR}{\sqrt{S_{dR} + a}} \quad (6)$$

Where β is the decay rate; S_{dR} is a cumulative gradient variable; ρ is the learning rate; a is a constant to prevent the denominator from being 0; R is the parameter.

In the process of updating parameters, the learning rate is used to classify the calculation results. Using this method, the direction of gradient can be changed continuously on a small scale, and the convergence of neural network is improved.

3. Results Analysis and Discussion

This paper collects the online learning behavior data of users from the open data interface provided by the network platform. Then, choose 400 from the training set, totaling 2800, and 500 from the 500 test sets. Set epoch to 100, that is, 6500 times.

Using Spearman's correlation analysis method, this paper makes a quantitative analysis of the relationship between the time and effect of online teaching. According to the real information of users, the real information of users is obtained and sorted accordingly. On this basis, according to the real performance level of users, the Spearman correlation scatter diagram between actual entropy and performance ranking is drawn, as shown in Figure 4.

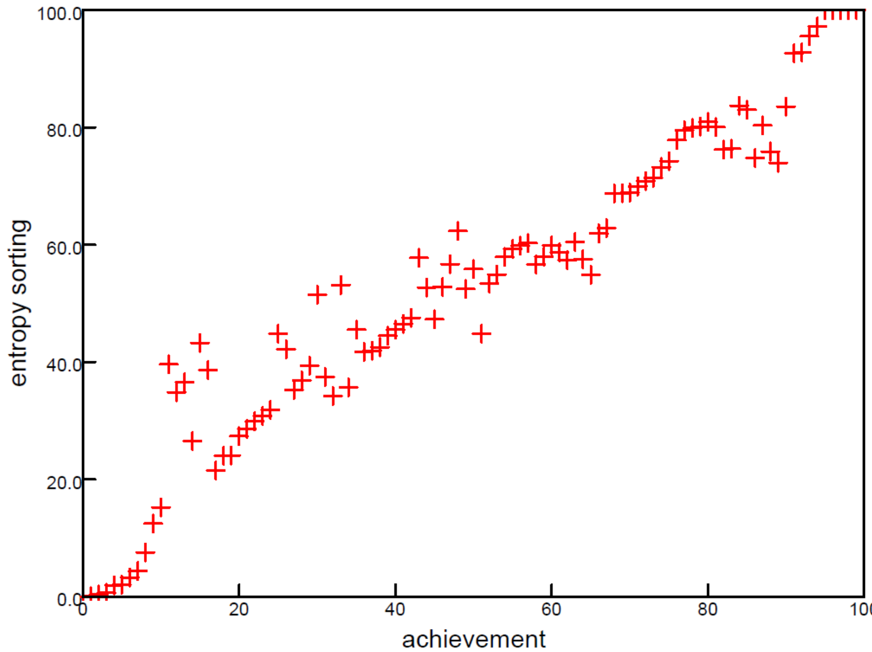

Figure 4.
Spearman correlation scatter.

Users who have a fixed study time will have a higher degree of self-discipline, which is manifested in reviewing what they have learned frequently and will have a better performance in performance evaluation. On this basis, the entropy value of real information is added to the model as the dimension of time regularity, and it is trained accordingly, and the correct rate is improved to 75.761%. This method deeply studies the users in the network and analyzes the users in the network, and finally gets better results.

In this experiment, two common off-line test indicators are used to evaluate the accuracy of the model: RMSE (Root mean square error) and Mae (Mean Absolute Error). In order to evaluate the proposed method CNN recommendation model, the experiment will be compared with some classic recommendation methods and some latest methods: CTR (Collaborative topic regression), BPMD (Bayesian probability matrix decomposition), CFNN (Collaborative filtering based on nearest neighbor). Table 1 and Figure 5 show the experimental results of all the comparison methods of user-based models.

Table 1.
Experimental result.

model	MAE	RMSE
CTR	4.141	4.949
BPMD	2.865	3.962
CFNN	3.284	4.966
Proposed scheme	2.415	3.23

DOI: 10.55214/25768484.v9i2.4722

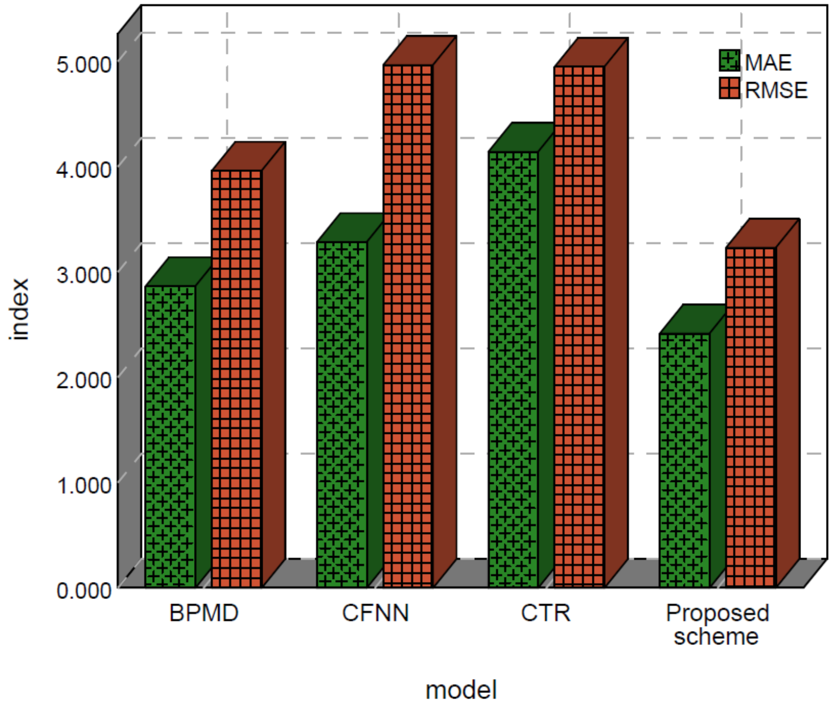

Figure 5.
Statistics of experimental results.

MAE and RMSE measure the difference between the predicted score and the real score. The experimental results show that the algorithm can get the best results under both MAE and RMSE. Experiments show that this method has a good effect. This also shows that CNN model is better than topic model in extracting text features. Through experiments, it can be found that CNN recommendation model will have a very good performance in learning resource recommendation platform.

This paper evaluates this model from two aspects: single frame image detection time and image detection mAP (mean Average Precision). AP value refers to the area under the curve with precision and recall as indicators. The classic SSD method is to judge the training difficulty of the model according to the change of damage function under the same experimental conditions and different experimental conditions. Set epoch to 100 and make 50,000 iterations, as shown in Figure 6.

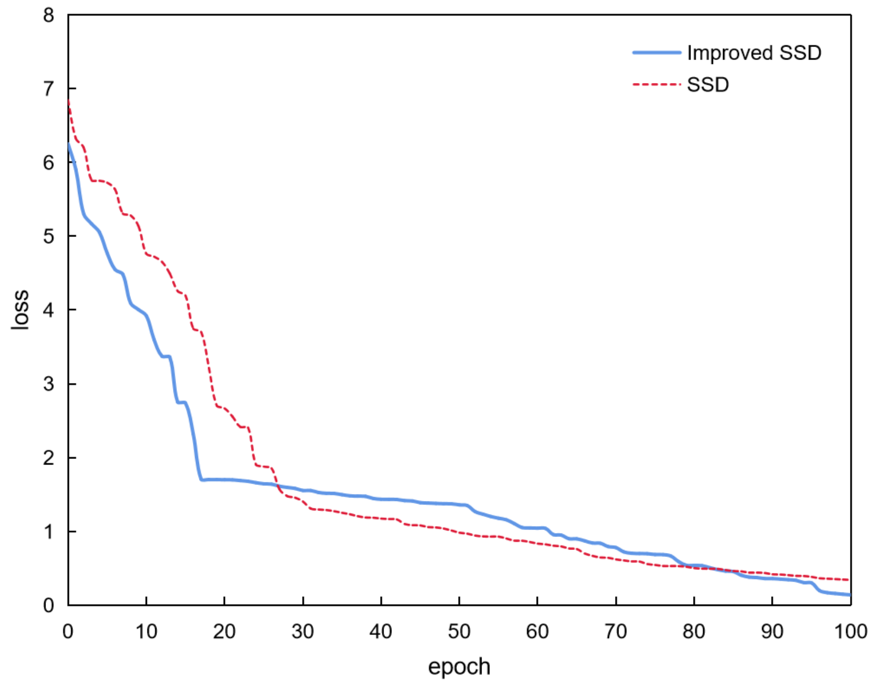

Figure 6.
Loss trend.

The results show that the loss values obtained by these two models have a decreasing trend, which shows that these two models are reasonable to some extent. From the chart, we can see that the improved SSD algorithm can reduce the loss faster, so it is easier to train than the conventional SSD algorithm.

Using the improved SSD and classic SSD model, five actions of students in the test set are detected, and the AP of each action is shown in Table 2 and Figure 7.

Table 2.
Five kinds of classroom behavior detection AP (%).

Classroom behavior	SSD	Improved SSD
Listening to classes	80.155	88.859
Playing with mobile phones	76.315	86.897
Raise your hand	73.846	88.651
write	85.097	89.829
sleep	83.386	90.165

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2: 1168-1179, 2025
DOI: 10.55214/25768484.v9i2.4722

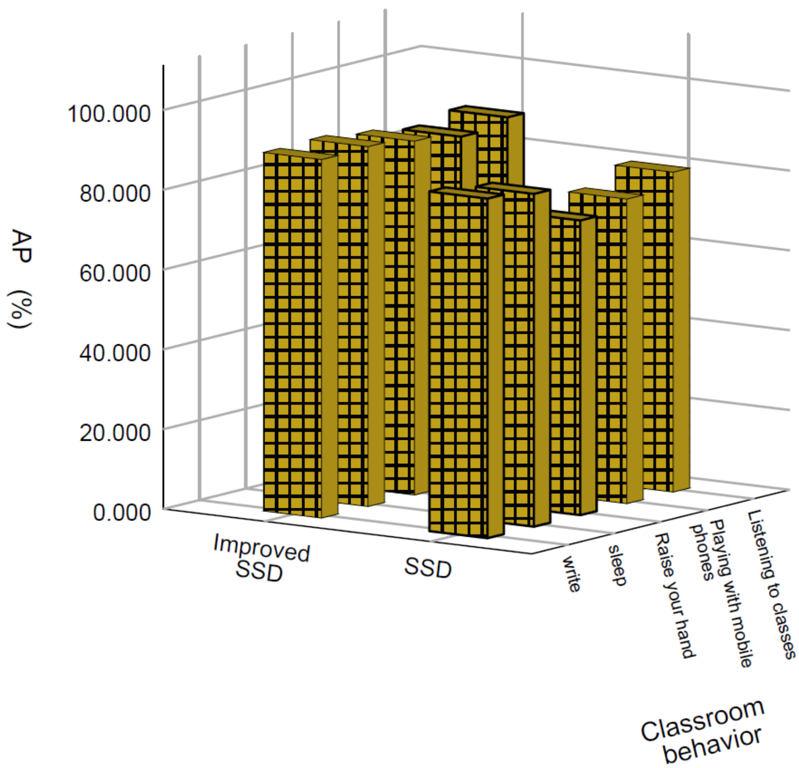

Figure 7.
AP statistical chart of five kinds of classroom behavior detection.

Compared with the original SSD method, the improved SSD method has greatly improved the detection effect of small targets, with an average improvement of 14.805%, which shows that the improved SSD method has greatly improved the recognition of small targets. Compared with the original SSD algorithm, the new algorithm has great improvement in small target recognition.

4. Conclusion

This paper proposes an OBE platform based on deep learning, which includes personalized learning recommendation and classroom quality evaluation. Explore the relationship between users' learning emotions and learning efficiency, and realize personalized learning method recommendation. Using deep learning to express data, multi-source data are integrated to improve the recommendation effect. The entropy value of real information is added to the model as the dimension of time regularity, and it is trained accordingly. This method deeply studies the users in the network and analyzes the users in the network, and finally gets better results. Finally, this paper verifies the recommendation algorithm based on CNN. Compared with the original SSD method, the improved SSD method has greatly improved the detection effect of small targets, with an average improvement of 14.805%, which shows that the improved SSD method has greatly improved the recognition of small targets.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References

[1] M. Li, X. Bao, L. Chang, and T. Gu, "Modeling personalized representation for within-basket recommendation based on deep learning," *Expert Systems with Applications*, vol. 192, p. 116383, 2022. https://doi.org/10.1016/j.eswa.2021.116383

[2] L. Zhou and C. Wang, "Research on recommendation of personalized exercises in English learning based on data mining," *Scientific Programming*, vol. 2021, no. 1, p. 5042286, 2021. https://doi.org/10.1155/2021/4795379

[3] Y. Ouyang, B. Guo, X. Tang, X. He, J. Xiong, and Z. Yu, "Mobile app cross-domain recommendation with multi-graph neural network," *ACM Transactions on Knowledge Discovery from Data*, vol. 15, no. 4, pp. 1-21, 2021. https://doi.org/10.1145/3447817

[4] Z. Hu, J. Wang, Y. Yan, P. Zhao, J. Chen, and J. Huang, "Neural graph personalized ranking for Top-N Recommendation," *Knowledge-Based Systems*, vol. 213, p. 106426, 2021. https://doi.org/10.1016/j.knosys.2020.106426

[5] X. Yang, Z. Zhou, and Y. Xiao, "[Retracted] Research on Students' Adaptive Learning System Based on Deep Learning Model," *Scientific Programming*, vol. 2021, no. 1, p. 6593438, 2021. https://doi.org/10.1155/2021/6526145

[6] M.-C. Chiu, J.-H. Huang, S. Gupta, and G. Akman, "Developing a personalized recommendation system in a smart product service system based on unsupervised learning model," *Computers in Industry*, vol. 128, p. 103421, 2021. https://doi.org/10.1016/j.compind.2020.103421

[7] Z. Ali, G. Qi, K. Muhammad, P. Kefalas, and S. Khusro, "Global citation recommendation employing generative adversarial network," *Expert Systems with Applications*, vol. 180, p. 114888, 2021. https://doi.org/10.1016/j.eswa.2021.114888

[8] M. Unger, A. Tuzhilin, and A. Livne, "Context-aware recommendations based on deep learning frameworks," *ACM Transactions on Management Information Systems*, vol. 11, no. 2, pp. 1-15, 2020. https://doi.org/10.1145/3387013

[9] C. Chen, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Efficient neural matrix factorization without sampling for recommendation," *ACM Transactions on Information Systems (TOIS)*, vol. 38, no. 2, pp. 1-28, 2020. https://doi.org/10.1145/3375652

[10] J.-H. Chang, H.-H. Chiang, H.-X. Zhong, and Y.-K. Chou, "Travel package recommendation based on reinforcement learning and trip guaranteed prediction," *Journal of Internet Technology*, vol. 22, no. 6, pp. 1359-1373, 2021. https://doi.org/10.3966/160792642021062206002

[11] N. Nassar, A. Jafar, and Y. Rahhal, "A novel deep multi-criteria collaborative filtering model for recommendation system," *Knowledge-Based Systems*, vol. 187, p. 104811, 2020. https://doi.org/10.1016/j.knosys.2019.104811

[12] Z. Liu, X. Feng, Y. Wang, and W. Zuo, "Self-paced learning enhanced neural matrix factorization for noise-aware recommendation," *Knowledge-Based Systems*, vol. 213, p. 106660, 2021. https://doi.org/10.1016/j.knosys.2020.106660

[13] F. Yuan and Y. Nie, "Online classroom teaching quality evaluation system based on facial feature recognition," *Scientific programming*, vol. 2021, no. 1, p. 7374846, 2021. https://doi.org/10.1155/2021/3498487

[14] L. Jiang and X. Wang, "Optimization of Online Teaching Quality Evaluation Model Based on Hierarchical PSO-BP Neural Network," *Complexity*, vol. 2020, no. 1, p. 6647683, 2020. https://doi.org/10.1155/2020/8857751

[15] C. Lu, B. He, and R. Zhang, "Evaluation of English interpretation teaching quality based on GA optimized RBF neural network," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 3185-3192, 2021. https://doi.org/10.3233/JIFS-189295

[16] S. Qianna, "Evaluation model of classroom teaching quality based on improved rvm algorithm and knowledge recommendation," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 2457-2467, 2021. https://doi.org/10.3233/JIFS-189276

[17] H. Wenming, "Simulation of English teaching quality evaluation model based on Gaussian process machine learning," *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 2, pp. 2373-2383, 2021. https://doi.org/10.3233/jifs-189233

[18] P. Liu, X. Wang, and F. Teng, "Online teaching quality evaluation based on multi-granularity probabilistic linguistic term sets," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 1-20, 2021. https://doi.org/10.3233/JIFS-189302