Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 1, pp. 271–284, DOI 10.12694/scpe.v25i1.2294

CREATION OF DEEP LEARNING SCENARIOS IN THE NETWORK TEACHING OF PHYSICAL EDUCATION TECHNICAL COURSES

FANGYU LI*

Abstract. The network teaching evaluation of sports professional technical courses has positive significance for the sustainable development of education. And how to establish an effective evaluation model is the key part. The research introduces the creation of in-depth learning scenarios (LS) into the network teaching of sports professional technical courses, and then constructs a new network teaching mode of sports professional technical courses. The Particle Swarm Optimization algorithm - Attention- Long Short-Term Memory network (PSO-Attention-LSTM) Chinese Emotion Classification Model (ECM) is constructed to classify the online evaluation text to realize the evaluation of online teaching. This model combines the improved PSO, Attention and LSTM classification models. The optimal number of hidden layer nodes for LSTM model is about 100, and the optimal data size for batch processing is 25. The overall error rate of online teaching teachers of male and female sports professional skill courses is 10.1%, and the overall error rate of online teaching teachers of general and advanced sports professional skill courses is 12.8%. The application effect of the creation of in-depth learning scene in the network teaching of physical education technical courses is shown. When the classification threshold is 0.6 and 0.8 respectively, the AUC of PSO-Attention-LSTM Chinese ECM is 0.821 and 0.809 respectively. The research institute has put forward that the online teaching platform of sports professional technical courses has extremely high practical application value and has been unanimously praised by network users.

Key words: DL; LS; Sports major; Network teaching; PSO; Attention mechanism; LSTM

1. Introduction. With the development and popularization of network technology, more and more physical education courses have begun to adopt the network teaching mode. This teaching mode can provide more flexible learning time and place, which is convenient for students to conduct independent learning and course selection. And due to the uneven distribution of teaching resources, online teaching has become a common teaching mode for students to obtain better teaching resources. The cultivation of students' core literacy needs to take Deep Learning (DL) as the goal, and teachers need to create learning situations to realize students' DL. The process of DL emphasizes students' deep understanding of core curriculum knowledge and their ability to apply this knowledge to real problems and situations. It also emphasizes whether learners can transfer and apply in similar situations or in new situations. In recent years, curriculum teaching in various disciplines has been actively exploring how to implement the core quality of students' development, and research results have emerged in endlessly [1, 2, 12]. Different countries have different expressions of the core literacy content of sports discipline. But the constituent elements are basically the same, including health education, personality development, sports ability and social adaptation. In the existing literature research, most of them are about the strategy research of the creation of sports in-depth learning situation. And in practice, there are many materials for the creation of in-depth sports learning situations, such as the problem situation, real learning situation, classic historical event situation, and successful experience situation. However, it is relatively scattered and has not formed a theory, which requires comprehensive, detailed and in-depth research and refinement. At the same time, Long Short-Term Memory Network (LSTM) and Particle Swarm Optimization (PSO), as common classification algorithms, have been widely used in education, finance and other industries, and have achieved outstanding results [10, 14]. Based on this, a Chinese ECM combined with multiple classification algorithms is proposed to classify the content of online teaching evaluation of sports technical courses. The purpose is to complete the physical education classroom teaching with a teaching scheme suitable for their own in-depth learning situation.

*School of Culture and Tourism, Luzhou Vocational and Technical College, Luzhou 646000, China (fangyu05li@outlook.com)

2. Related works. Scenarios emphasize more on various objective scenes, things and events that can stimulate students to actively learn. It is divided into two types: passive and mechanical. They have no substantive connection with the learning theme and lack certain depth and breadth. Haerens L and other researchers believe that situational teaching is a combination of vivid intuition and language description. They create a typical scene to stimulate children's enthusiasm for learning and thus promote their active participation in the teaching process. This model has been widely used in the actual teaching process [15]. Lentillon-Kaestner V et al. revealed the connotation of the learning situation of the core quality of the discipline. It includes four aspects: context-based learning, emphasizing students' interaction and participation, paying attention to students' experience and exploration spirit, and paying attention to the leading and guiding role of physical education teachers [16]. Roure C and other researchers created "combination exercises", "game games", "problem tasks" and "group cooperation" situations to promote students to achieve DL and develop students' core quality of sports discipline. Situational teaching is not limited to the middle and lower grades of primary school. As long as the design is reasonable, it is also applicable to senior high school students and college students. Situational teaching includes game competition, imitation and music accompaniment [17]. When physical education network teaching evaluating, the methods based on emotion dictionary and machine learning have some shortcomings. In this regard, Sun Z and other researchers used the Laplacian smoothing algorithm of mutual information of emotional inclination points to expand the dictionary. At the same time, they analyzed the positive and negative effects of different sentence patterns on sentence emotion [18].

Jingchao H et al. found that judging the students' listening state in the classroom is a more difficult problem, and the current intelligent models to recognize the students' state in the classroom are not accurate, to address this problem, the research team proposes a two-stage state detection framework based on deep learning and HMM feature recognition algorithms, which is capable of recognizing the facial expressions of students in the classroom, and judging their listening the research results show that the proposed model has a relatively good performance in classroom student state feature recognition [19]. At present, there is a strong subjectivity problem in online courses teaching evaluation. In this regard, scholars He H have built the most basic Chinese emotion dictionary by using English seed dictionary and machine translation technology. However, the coverage of emotional words is low, which cannot be transferred in combination with the context, which is easy to lead to ambiguity [20]. To realize the improvement of teaching methods in the network teaching process of sports technical courses, Reckhow S scholars and other scholars have expanded Hownet in Chinese. On this basis, they proposed a method based on semantic similarity and a method based on semantic correlation field. The experiment can achieve more than 80% accuracy in the common word set [21]. To evaluate the current common network teaching evaluation methods, Lau E T team selected support vector machine as the basis and compared the bagging method, lifting method and random subspace method. The experiment shows that the integrated learning model has better effect [22]. Peng W et al. designed a model based on three classifiers: the first two are naive Bayesian and maximum entropy models based on statistics. And the last is a knowledge-based tool that can conduct in-depth analysis of natural language sentences. This model has higher practicability and feasibility, and can realize online teaching evaluation [23]. To obtain an objective analysis method for online teaching evaluation, Yang C scholars used two-way LSTM combined with attention model to encode and express the micro-blog text and its emoticons. The model performs better than the known model on multiple tasks [24]. Wang X and other researchers have established a keyword thesaurus based on LSTM, which can further explore the potential information in the depth of the text and improve the judgment ability of emotional orientation. The constructed keyword thesaurus is helpful to objectively and fairly evaluate the text content of online evaluation [25].

DL situation has become an important way and learning method to implement students' core literacy development. And it involves the creation of different situations in primary school, junior high school and senior high school, as well as in the network teaching of sports technical courses. In summary, many scholars have already had research in this field, through similar semantics and LSTM and other methods of learning scenarios construction and evaluation to detect the quality of learning, the experimental results show that the proposed methods can basically achieve the expected results, but there is also a large space for improvement. This study in the sports deep learning scenarios created after the introduction of physical education professional arts course network teaching to build a In this study, we constructed a new online teaching model for sports

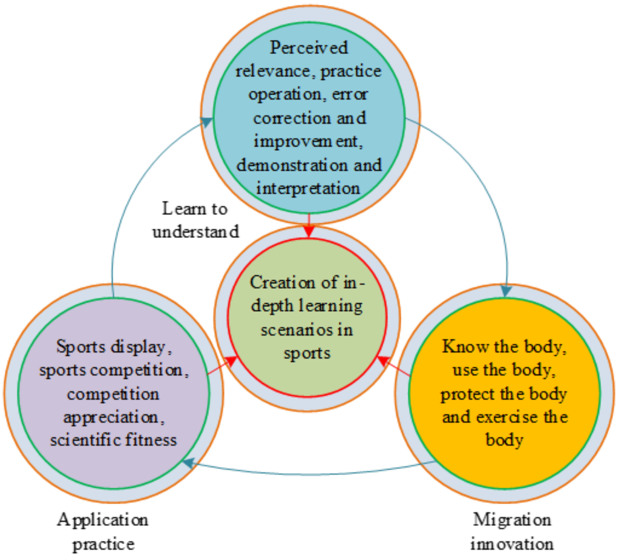


Fig. 3.1: Creation of physical education DL scene in the network teaching

professional arts courses after introducing sports deep learning scenario creation into the online teaching of sports professional arts courses, and constructed PSO-Attention-LSTM Chinese emotion classification model to classify the online evaluation text in order to realize the evaluation of online teaching. This experiment is a cross-section of the basic theoretical research on deep learning contexts and the creation of deep learning contexts in different disciplines at home and abroad, aiming to provide ideas and references for subsequent research.

3. The creation of sports depth LS in the network teaching of sports technical courses.

3.1. Sports depth LS creation. International research focuses on the use of different methods to study the connotation, structure, formation, development and evaluation of the core literacy of sports discipline. It puts forward the understanding and requirements of sports core literacy. The creation of sports DL situation is to make students' sports ability, healthy behavior and sports morality developed. It is a meaningful learning activity created by linking the teaching content of physical education and health with students' learning, life reality and social practice. It has distinct characteristics of subjectivity, inquiry, guidance and openness. Figure 1 refers to the process of creating sports depth LS in the network teaching of sports technical courses [26]. The creation of sports depth LS is based on three dimensions: the cognitive style, activity experience and cognitive level of sports and health discipline. It includes three learning stages: learning understanding, application practice and transfer innovation. Subject knowledge needs to go through learning and understanding, application practice, migration and innovation and other key ability activities to complete the external orientation, independent operation and conscious internalization from specific knowledge to cognitive methods. Learning and understanding is the ability of students to input, store, process, relate and systematize subject knowledge. It is embodied in the ability to complete DL tasks such as recall and extraction, identification and confirmation, generalization and correlation, explanation and demonstration in the cognitive process. Only through DL can students form core literacy, and creating sports DL context is the necessary path to develop students' core literacy. Learning and understanding includes perception and relevance, practice and operation, error correction and improvement, and demonstration and interpretation. Application practice mainly includes sports display, sports competition, competition appreciation and scientific fitness. Migration innovation mainly includes understanding the body, using the body, protecting the body and exercising the body.

Lewin's action model is adopted for the specific action research of the network teaching of sports profes-

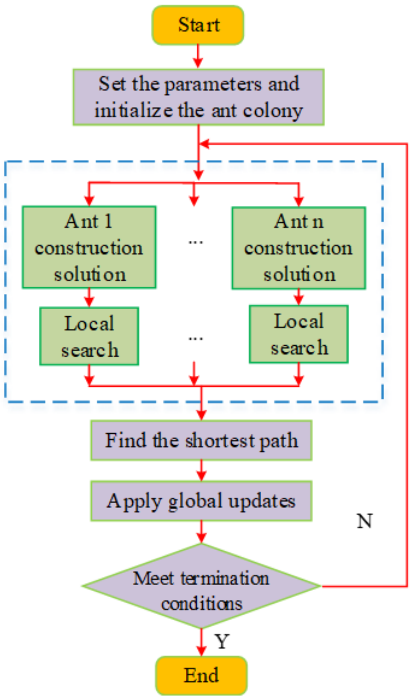


Fig. 3.2: The principle of ant colony optimization algorithm.

sional technical courses, which is the most representative and operational research model and starts from the problem [3]. The experiment plans to carry out two rounds of action research, and carry out the first round of action research according to the relevant theoretical content of the creation of sports DL situation. Observation and reflection are made based on students' classroom performance and feedback, and the quality of students' homework after class. On this basis, the students' homework materials are modified and improved, and the typical cases of the creation of sports DL situations with relatively high quality are selected. The ideas and methods of the creation of sports DL situations are initially condensed. The second round of action research reflects and summarizes the first round of action research, improved the deficiencies, and focuses on how students create the sports DL situation. The first round of action research includes three classes. In the first class, the teacher tells the theoretical knowledge about the creation of sports DL situation, and arranges the homework after class according to the knowledge content in the class. And the experiment allows students to create a sports DL situation based on learning understanding, application practice, and transfer innovation, correct their homework, and screen out excellent homework. In the second class, students rating as excellent homework are selected to share their homework after class and how they created the sports DL situation. Other students and teachers make comments to revise and improve the homework materials. For the third class, students go to the stage to exchange and share the revised and improved homework materials, and other students and teachers comment again to enrich the case materials. The typical cases of creating high quality sports DL situations are screened, and the ideas and methods of creating sports DL situations are initially condensed.

3.2. Improvement of PSO and LSTM algorithm. As an intelligent bionic algorithm, PSO has many advantages, such as heuristic search, strong robustness, positive information feedback, self-organization, distributed computing, and so on. It is often used to find the best path [4]. Figure 3.2shows the principle of PSO. PSO actually imitates the ability of ants to find the shortest foraging path through information exchange. Ants secrete pheromones during foraging, and pheromones complete information exchange between ant groups. The shorter the path length, the higher the ranking order of the ants and the larger the weight value. The pheromone update of the top ants is required, and formula 3.1 is the calculation [5].

$$\tau_i j(t+1) = (1-\rho)\tau_i j + \sum_{k=2}^{w} \Delta\tau_{ij}^k(t) + \Delta\tau_{ij}^*(t)) \tag{3.1}$$

In formula 3.1, the initial pheromone volatilization factor is , and its value range is (0,1). The pheromone update of the second to w ants is $\sum_{k=2}^{w} \Delta\tau_{ij}^k$, and the pheromone update of the best ants is $\Delta\tau_{ij}^*(t)$. PSO can solve many linear and nonlinear problems with good convergence speed. But basic PSO is prone to local optimum when particle searching, which reduces the diversity of particles. To solve this problem, an improved algorithm based on PSO is proposed to make particle population's diversity improved and avoid local optimization [6, 7, 8]. In the M-dimensional target search space, a population including n_2 particles can be obtained randomly. In search space, V refers to the speed of the particles, and U represents particles position. The corresponding fitness value can be calculated through the objective function. $P_I = P_{i1}, P_{i2}, ...P_{iM}, P_g = P_{g1}, P_{g2}......P_{gM}$ represent individual extremum and group extremum respectively. During each iteration, the particle updates its speed and position by comparing the fitness value of the new particle with the fitness value of the current individual extreme value and the population extreme value [9, 10]. The particle speed depends on the position information of the current particle and the particle in the last iteration. Formula 3.2is the update equation.

$$V_{im}^{k+1} = wV_{im}^k + c_1 r_1 (P_{im}^k - (1+\beta_1 U_{im}^{k-1)} + \beta_1 U_{im}^k) + c_2 r_2 (P_{gm}^k - (1+\beta_2) U_{im}^k + \beta_2 U_{im}^{k-i}) \tag{3.2}$$

In equation 3.2, $m = 1, 2.....M, i = 1, 2.....n_2$. k is the current number of iterations. $c_1, c_2 > 0$ are the acceleration factors. r_1, r_2 are random number between 0-1, and w is the inertia weight coefficient. When iterations number k increasing, the non-linearity decreases [11]. Formula 3.3 is its expression.

$$w = w_{ini} - (w_{ini} - w_{end}) \left(\frac{k}{k_{max}} \right)^2 \tag{3.3}$$

w_{ini} and w_{end} are the initial and ending values of w in formula 3.3. $\beta_i < \frac{\sqrt[2]{c_i-1}}{ci}, i = 1, 2, ...n_2$ in the early stage $\beta_i \geq \frac{\sqrt[2]{ci-1}}{c_i}, i = 1, 2......n_2$ in the later stage is to make global search ability enhanced in the early stage. Optimization ability's improving purpose in the later stage is to achieve detailed search. The principle of particle position update is formula 3.4.

$$U_{im}^{k+1} = \begin{cases} U_{im}^k + V_{im}^{k+1}, 2d^k, \sum_{i\neq j, j=1}^n \left\| u_{im}^k - u_{jm}^k \right\| < d^k \\ U_{im}^k + V_{im}^{k+1}, \sum_{i\neq j, j\neq 1}^n \left\| u_{im}^k - u_{jm}^k \right\| \geq d^k \end{cases} \tag{3.4}$$

$d^k = d_{ini} - (d_{ini} - d_{end}) \left(\frac{k}{k_{max}} \right)^2$ is the minimum distance allowed between particles in formula 3.4. $d_i ni$,d_{end} and d^k are the initial value and the end value respectively. Figure 3.3 is LSTM structure. The specific steps includes following : first, determine the information forgotten by neurons. At time , it is assumed that samples number is n,batch data X_t of x is the vector, h and H_t are hidden layer's length and state. H_t at previous time is represented by H_{t-1} . Equation 3.5 is the expression of forgetting gate at time t.

$$f_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f) \tag{3.5}$$

σ is sigmoid function. W_f and b_f are learnable weight and offset vector in formula 3.5. Secondly, it determines the neural unit information. And it uses sigmoid function to obtain updated value in network layer in formula 3.6

$$i_t = \sigma(X_t W_{xi} + H_{t_1} W_{hi} + b_t) \tag{3.6}$$

In formula 3.6, W_i is update door weight. b_t is update door offset. It uses hyperbolic tangent function to obtain candidate value in tach layer in formula 3.7.

$$\overline{C_t} = tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c) \tag{3.7}$$

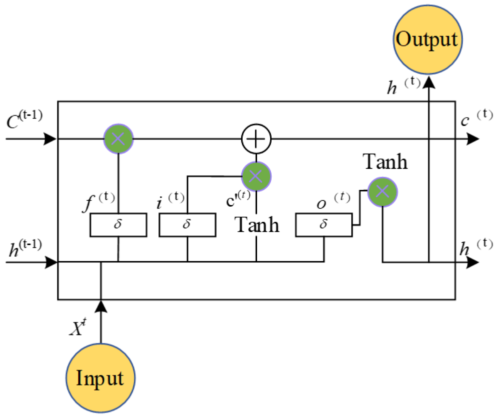


Fig. 3.3: Schematic diagram of LSTM neural network structure

Then, the memory state was updated. The state is updated by point multiplication. Information flow is controlled by output and forgetting gate. Finally it can get updated state in formula 3.8.

$$C_t = f_t \Theta tanh(C_t) \tag{3.8}$$

When the forgetting door is close to 1 and the input door is close to 0, old state memory unit can be recorded to current time in formula 3.9. LSTM can alleviate circulatory nerve's gradient disappearance. Finally, output state memory unit can be got.

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o) \tag{3.9}$$

In formula 3.9, W_o and b_0 are output gate weight and offset. Equation 3.10 is hidden layer state H_t 's calculation at time t .

$$H_t = O_t \Theta tanh(C_t) \tag{3.10}$$

3.3. Chinese ECM of PSO-Attention-LSTM. To realize the evaluation of the network teaching of sports professional technical courses under the creation of sports depth LS, the selection method PSO-Attention-LSTM Chinese ECM is studied. The model has short construction time and memory function, and has good practical value in the actual process. In view of the long distance dependence problem of attention mechanism and the shortcomings of recurrent neural network, we study the use of self-attention mechanism. This mechanism can effectively extract features and get the correlation of words in sentences. It can make long-distance dependence issue solved, carry out parallel operations, reduce the computational difficulty of each layer, and optimize model performance. Self-attention mechanism is mainly divided into Multi-Head Attention and Scaled Dot-Product Attention, as shown in Figure 3.4.

As can be seen in Figure 3.4, the structure consists of multiple attention heads, each with the same structure. In each attention header, the input is divided into three parts: query (Q), key (K) and value (V). These three parts transform the input into different representations by means of linear transformations. Attention weights are then assigned to the different values by computing the dot-product attention scores of the query with respect to the keys. The attention weights indicate the correlation between the query and the key, where higher weights indicate more important information. The attention weights computed by each attention head are multiplied with the corresponding values and these products are summed to get the final attention output. Finally, the outputs of all the attention heads are concatenated together for final transformation by another linear transformation. The computation process of Scaled Dot-Product Attention starts with the inputs consisting of query vectors (Q), key vectors (K) and value vectors (V). The dot product between the query vector and the key vector is computed to get the attention score. The result of dot product indicates

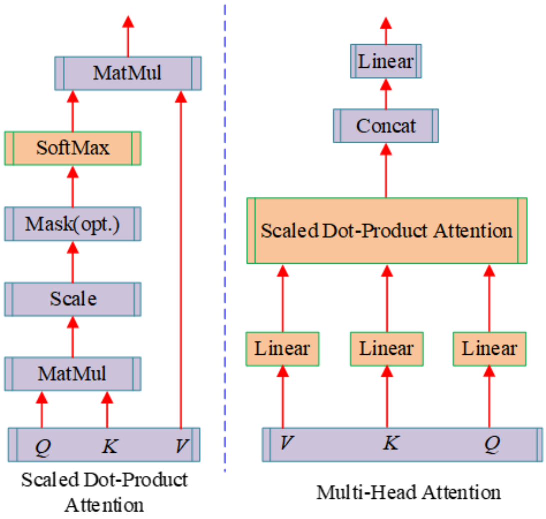


Fig. 3.4: Structure of self-attention mechanism

the similarity between the query vector and the key vector. Then, a scaling operation is performed on the attention score to avoid the value of the dot product being too large. The scaling factor is generally taken as the square root of the inverse of the dimension of the query vector. Next, the attention weights are obtained by normalizing the scaled attention scores by the Softmax function. Finally, the attention weights are applied to the value vectors to obtain the weighted value vectors. In the left part of Figure 3.4, v represents value, K represents key, and Q represents query. The three vectors represent the sentence itself in the algorithm. In the coding, they are obtained by multiplying the input vector X and the weight matrix, as shown in formula 3.11.

$$\begin{cases} Q = W^Q X \\ K = W^K X \\ V = W^V X \end{cases} \tag{3.11}$$

After obtaining the values of the three vectors, the Scaled Dot-Product Attention is calculated by formula 3.12.

$$Attention(Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{d_k}}\right)V \tag{3.12}$$

d_k represents the word vector dimension of k and Q in formula 3.12. $\frac{1}{\sqrt{d_k}}$ plays a regulating role to avoid excessive internal product of K and Q . The probability distribution is normalized by softmax, and the weight relative to V is obtained. The weighted sum is the result of multiplying by V . In the structure shown in the right part of Figure 3.4, it is necessary to project V , K and Q linearly for h times, and then calculate the h times through equation 3.13 to obtain the Multi-Head Attention mechanism, as shown in equation 3.13

$$\begin{cases} MultiHead = Concat(head_1, head_2, ...head_n)W^o \\ \quad headi = Attention(QW_i^Q, KW_i^k, VW_i^v) \end{cases} \tag{3.13}$$

The vector dimensions of model words are $W_i^Q \epsilon R^{dm\times dk}, W_i^k \epsilon R^{dm\times d_k}, W_i^v \epsilon R^{dm\times dv}, W^o \epsilon R^h d_v \times d_m$ and $d_m in$ Equation 3.13. By using softmax function, it can get attention distribution vector, which is ‘s weight, as shown in Equation 3.14.

$$e_i j = \alpha(s_i - 1, 0_j) = v^T tanh(w_s s_i - 1 + w_0 O_j) \tag{3.14}$$

Figure 3.5 is the schematic diagram of the Chinese ECM of PSO-Attention-LSTM. The model consists of four parts. First, it is the preprocessing of text, including sorting and loading text, text cleaning and word

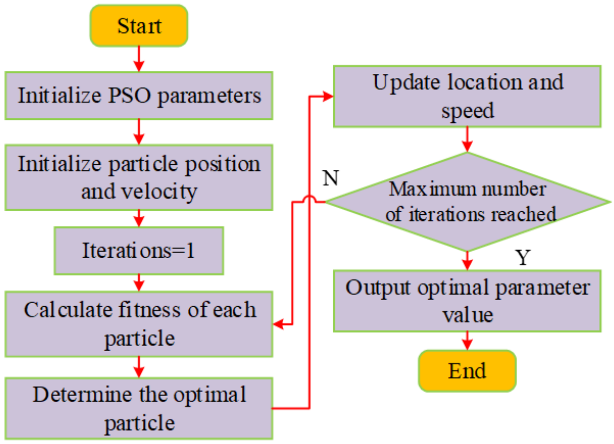


Fig. 3.5: Schematic diagram of Chinese ECM of PSO-Attention-LSTM

segmentation, text standardization and converting text into word vector representation. Then there is the hierarchical structure of the model, which consists of four parts, namely input layer, LSTM layer and attention layer, namely the fully connected softmax layer. The improved PSO is applied to the whole neural network model for parameter optimization. First, the original Chinese comment anticipation in the online teaching process of sports professional technical courses is obtained, and the text preprocessing operations such as word segmentation are carried out. Secondly, the sentence is mapped to the corresponding word embedding vector according to the word vector model, and it is referred to by the word vector of the input layer. Thirdly, the improved PSO is initialized. The parameters include random number, learning factor, inertia weight, fitness function, etc. Thirdly, the optimized object of the improved PSO is set to initialize the speed and position of particles. Fourth, the fitness of particles is calculated according to iterations number, and particles' speed and position at the current time are continuously updated. Fifthly, the improved PSO's iteration is ended, and optimal parameter value is determined. The value is used for model training, and finally the emotional classification of the evaluation text is obtained. Students of a school were selected for this study and the survey was conducted by randomly distributing questionnaires. The data collected from the survey was subjected to data preprocessing, a process designed to screen out data from the raw data that do not fit into the model and to correct the data or eliminate useless data. Such as gender, height, weight, etc.In the questionnaire, there is a large amount of personal information, and if not handled properly, it is highly likely to lead to the leakage of personal privacy. Based on the content of this study, eliminate significantly unrelated information such as blood type, height, weight, etc.

4. The application effect of the creation of sports depth LS in the network teaching of sports technical courses. The system required for the experiment is Windows 10, the processor is Inter (R) Core (TM) i7-6700, the memory is 4.00G, the application software version is MATLAB R2022, the selected experimental data is 10000 groups, and the ratio of training set and test set is 9:1. Table 4.1 refers to the parameter settings of Chinese ECM.

The research first analyzes the model test results of PSO. Figure 4.2 (a) and (b) refer to the sum of error squares before and after the improvement. From Figure 4.2 (a), the sum of squares of the minimum error squares of the PSO indicates a high convergence rate before the number of iterations is 10. However, the convergence rate gradually slows down when iterations number is 10-20, and finally tends to converge when iterations number is 20. Its stable value of the sum of squares of errors is about 0.9. The convergence speed of the improved PSO is faster. When iterations number is about 6, convergence occurs. The convergence value of the sum of squares of errors is 0.21, the convergence speed is increased by 75%, and the average sum of squares

Table 4.1: Parameter setting of Chinese ECM

Parameter	Value
LSTM Batch	30 pieces
LSTM Maximum Iterations	200 pieces
LSTM learning rate	0.001
optimizer	Adam

Parameter	Value
PSO inertia weight	0.68
PSO random number	0.6, 0.3
PSO learning factor	1.7, 1.7
Dropout	0.5

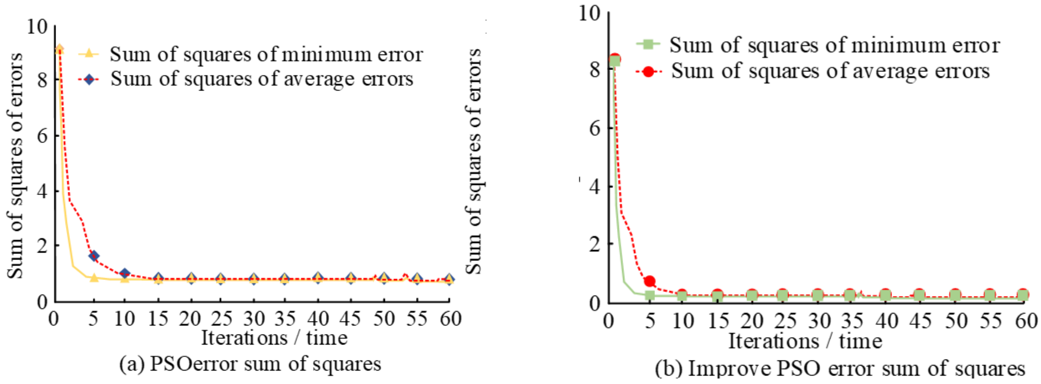
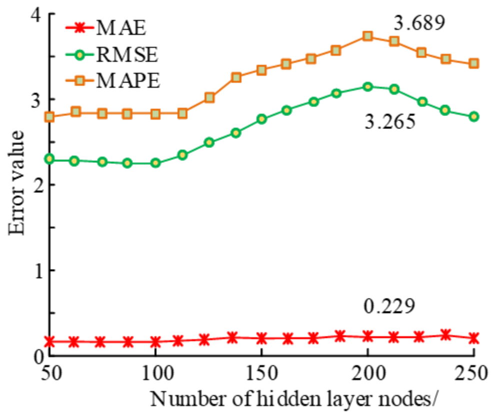


Fig. 4.1: Sum of square errors of GA-BP and AGA-BP neural network algorithms

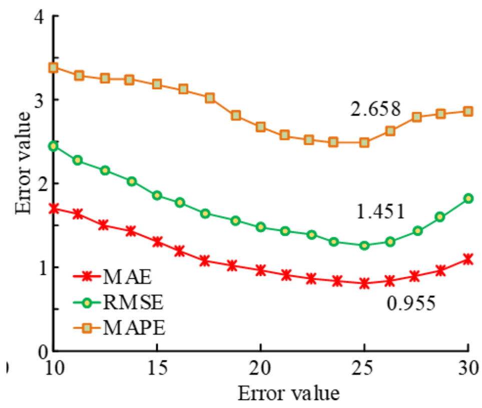
of errors is reduced by 80%.

The research first determines the optimal model parameters of the proposed LSTM model. The loss of the model is calculated using three indicators: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The loss value of the model under different number of hidden layer nodes is shown in Figure 4.4 (a). When hidden layer nodes number is less than 100, the values of MAE, RMSE and MAPE are larger. When the number of nodes exceeds 100, the values of the three indicators gradually increase. When the value exceeds 200, the values of the three indicators gradually decrease. Therefore, the optimal number of hidden layer nodes is about 100, and the error values of MAE, RMSE and MAPE are 0.229, 3.265 and 3.689 respectively. Figure 4.4 (b) refers to the error values under different batch processing data scales., The optimal data size for batch processing is 25. First the three error indicators decrease. Then they increase gradually with the

The research applies the proposed model to the evaluation of the network teaching content of the technical courses of physical education specialty. It sets 956 teaching evaluation contents, and the teaching score is 0-100 points. The teaching effect level is low, medium and high, and the corresponding score is less than 30 points, [30, 70] points and more than 70 points. Figure 4.5 is the result of the evaluation of the network teaching content of the technical courses of physical education. Of the 956 teaching content evaluations, 265, 348 and 343 are rated as low, medium and high, with an average teaching score of (69.68 ± 7.56) points. Therefore, the vast majority of teaching evaluations believe that the network teaching of sports professional technical courses has achieved the ideal teaching effect. Figure 4.6(a) refers to the level of teaching evaluation content of teachers of different genders in sports professional technical courses. From Figure 9 (a), the teaching evaluation effect of male teachers of network teaching in the technical courses of physical education is better than that of female teachers. The average teaching scores of male and female teachers of network teaching in the technical courses of mathematics and physical education are (72.36 ± 7.89) points and (64.26 ± 5.86) points. Figure 4.6(b) refers to the teaching evaluation level of network teaching teachers of different levels of sports professional skills courses. The teaching evaluation effect of senior teachers is better than that of ordinary teachers. The average teaching score of network teaching teachers of ordinary and senior sports professional technical courses is (64.26



(a) No of Hidden Layer Nodes



(b) Error Value

Fig. 4.2: Performance of LSTM model

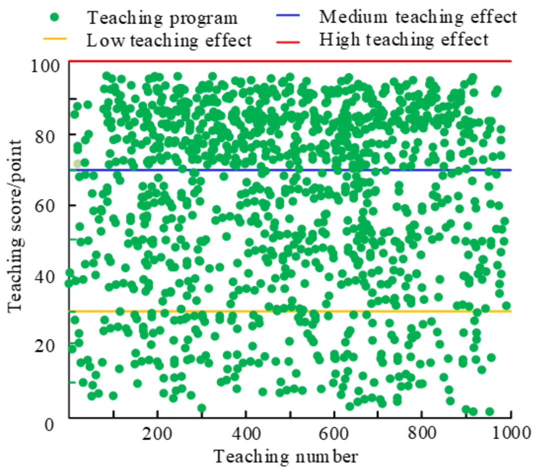


Fig. 4.3: Results of the evaluation of the network teaching content of the technical courses of physical education

± 5.36) points and (76.25 ± 6.35) points.

The research compares the results obtained with the evaluation results of teaching experts. Figure 4.7shows the error rate of different types of teaching grade evaluation. In terms of gender, the overall error rate of male teachers of network teaching in the three teaching evaluations is higher than that of female teachers, with the error rate of 5.3% and 4.8% respectively, and the overall error rate of 10.1%. For the position, the overall error rate of the network teaching teachers of the general physical education professional technical courses in the three teaching evaluations is higher than that of the senior teachers. Its error rate is 7.0% and 5.8% respectively, and the overall error rate is 12.8%. The experiment further verified the application effect of the creation of sports depth LS in the network teaching of sports technical courses. The research sets up a comparison algorithm for verification. The results of regional convolutional neural network (R-CNN), YOLO (You Only Look Once) are shown in Figure 4.9. Figure 4.9 (a) and (b) refer to the receiver operating characteristic curve (ROC)

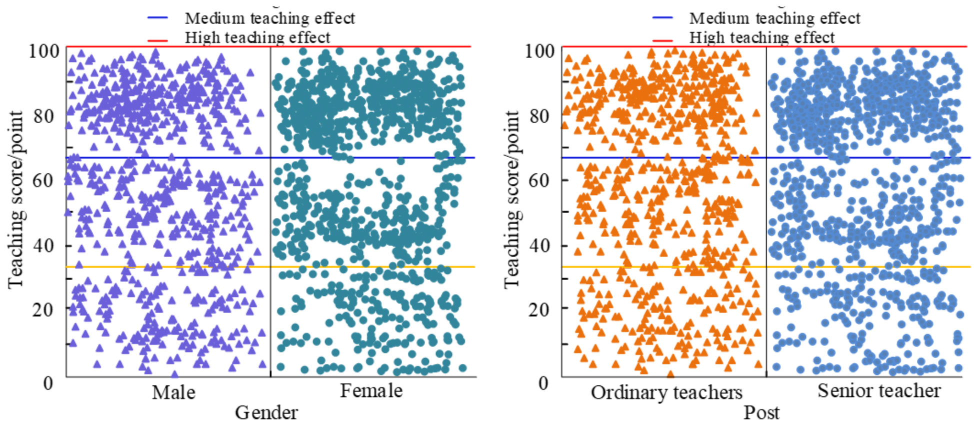


Fig. 4.4: The grade of teaching evaluation content of teachers of different genders in physical education

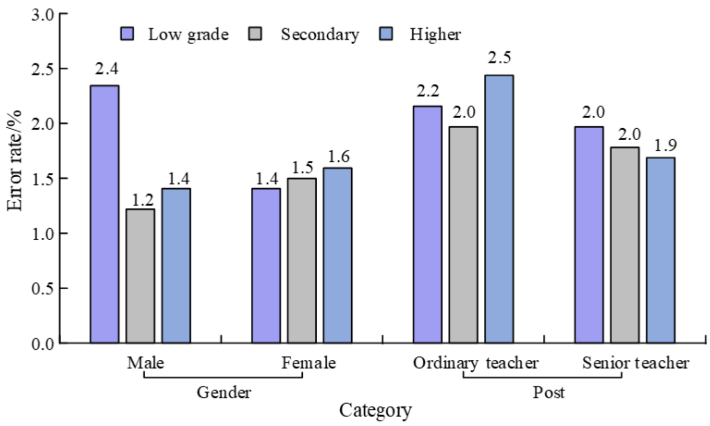


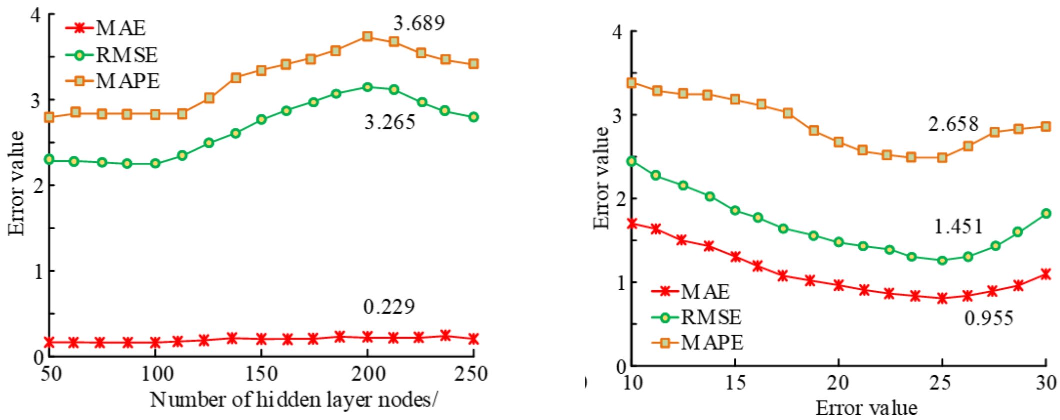
Fig. 4.5: Error rate of evaluation of different teaching levels

with classification threshold of 0.6 and 0.8 respectively. The area under curve (AUC) of the ROC curve of the PSO-Attention-LSTM Chinese ECM is the largest. When the classification threshold is 0.6 and 0.8, the AUC is 0.821 and 0.809 respectively. PSO-Attention-LSTM Chinese ECM performs better than other classification models of the same type.

In order to further verify the performance of the hybrid model, three models were selected to compare their F1 values and recall values, as shown in Figure 4.11. From Figure 4.11, it can be seen that the F1 values and recall of the PSO-Attention LSTM model are relatively high compared to other models, and tend to stabilize at a dataset size of around 6000. The experimental results indicate that the PSO Attention LSTM model performs better than other models.

The common deep learning models used for sentiment analysis and text categorization tasks are LSTM and Attention-LSTM, and the two models are analyzed and compared with PSO-Attention-LSTM to compare their performance. The results are shown in Fig. 4.12. From Fig. 4.12, it can be seen that the accuracy of the three deep learning models increases as the dataset increases, among which, the accuracy of this proposed model is the highest and stabilizes at a dataset size of 700.

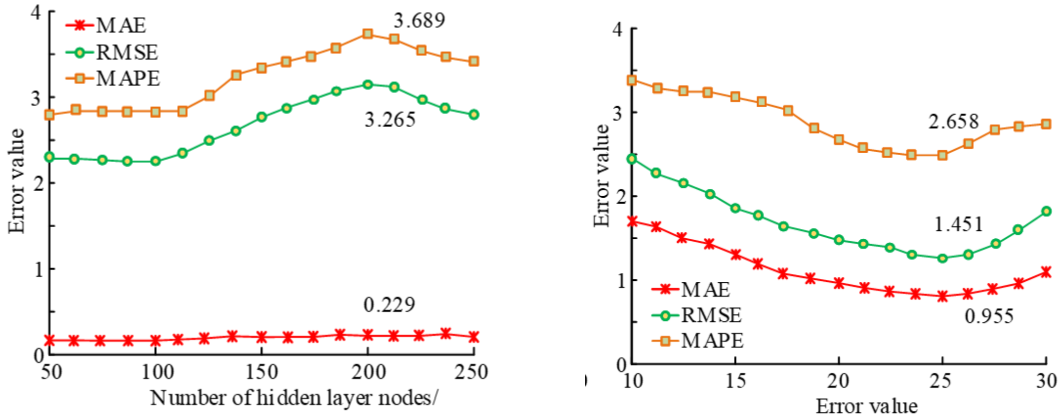
Randomly select 10 students from 3 groups and 10 teachers from 3 groups, and collect their evaluation results on the model as shown in Table 2. From Table 2, it can be seen that teacher 1, teacher 2, teacher 3,



(a) Classification threshold 0.6

(b) Classification threshold 0.8

Fig. 4.6: Performance comparison of PSO-Attention-LSTM Chinese ECM



(a) F1 values of different algorithms model

(b) Recall values of different algorithms model

Fig. 4.7: F1 values and recall rates under four models

and student 1, student 2, and student 3 have PSO-Attention LSTM scores of 8.7, 9.2, 8.9, 9.7, 9.5, 9.3, and the average evaluation scores for the four different models are 9.22, 8.40, 8.22, and 7.73, respectively. The experimental results indicate that the proposed PSO Attention LSTM is more highly praised by users.

5. Conclusions. To explore the application effect of sports depth LS creation in online teaching, a PSO-Attention-LSTM Chinese ECM is proposed to classify the platform comment text. The PSO finally converges when iterations number is 20, and the sum of squares of errors is stable of 0.9. The improved PSO converges faster, and converges when iterations number is about 6. The sum of error squares' convergence value is 0.21, and the convergence speed is increased by 75%. The optimal number of hidden layer nodes is about 100, and the error values of MAE, RMSE and MAPE are 0.229, 3.265 and 3.689 respectively. The optimal batch processing data size is 25, and the corresponding three error values are 0.955, 1.451 and 2.658 respectively. Of the 956

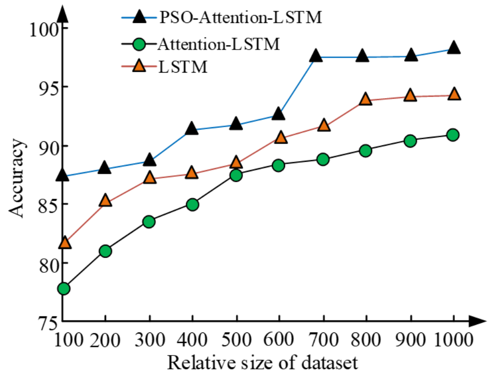


Fig. 4.8: Performance comparison of the three models

teaching content evaluations, 265, 348 and 343 are rated as low, medium and high, with an average teaching score of (69.68 ± 7.56) points. In the three teaching evaluations of professional sports courses, the overall error rate of male teachers of network teaching is higher than that of female teachers, with the error rate of 5.3% and 4.8% respectively. In the three teaching evaluations of the technical courses of general physical education, the overall error rate of the network teaching teachers is higher than that of senior teachers, with the error rate of 7.0% and 5.8% respectively. PSO-Attention-LSTM Chinese ECM performs better than other classification models of the same type. PSO-Attention-LSTM model can effectively classify the evaluation text, and has practical significance in providing teaching feedback for users of online education platform.Haerens L and other researchers believe that situational teaching is a combination of vivid intuition and language description, and have proposed a model. Compared to the research of other scholars, the method model proposed in this study has higher performance. However, there are also shortcomings in the research. Later, more scientific and accurate evaluation can be carried out from the perspective of sentence level of online evaluation text. Moreover, the PSO-Attention-LSTM model has a long training time, which is not advantageous in terms of time, and reducing the training time is a subsequent problem that needs to be investigated, and at the same time, this study was conducted in a laboratory environment, and if its performance can be tested in a real environment, it will be able to show the superiority of the proposed method. The proposed method can be applied not only in physical education, but can be generalized to all online teaching after improving the model, by evaluating the level of learning of students in other teaching for the subject and evaluating the teaching.

REFERENCES

[1] Farias, C., Harvey, S., Hastie, P. & Mesquita, I. Effects of situational constraints on students' game-play development over three consecutive Sport Education seasons of invasion games. *Physical Education And Sport Pedagogy.* **24**, 267-286 (2019)
[2] Casey, A. & Quennerstedt, M. Cooperative learning in physical education encountering Dewey's educational theory. *European Physical Education Review.* **26**, 1023-1037 (2020)
[3] Maia, M. Lapo L V . *Articipatory Action Research For Global Antibiotic Stewardship Network In CPLP: Mixed-method Study.* **29**, 187-192 (2019)
[4] Shou, Z., Lu, X., Wu, Z., Lai, J. & Chen, P. Learning path planning algorithm based on kl divergence and d-value matrix similarity. *ICIC Express Letters.* **15**, 49-56 (2021)
[5] Li, D., Yin, W., Wong, W., Jian, M. & Chau, M. Quality-oriented hybrid path planning based on a* and q-learning for unmanned aerial vehicle. *IEEE Access.* **10** pp. 7664-7674 (2021)
[6] Xiong, S., Zhang, Y., Wu, C., Chen, Z., Peng, J. & Zhang, M. Energy management strategy of intelligent plug-in split hybrid electric vehicle based on deep reinforcement learning with optimized path planning algorithm. *Proceedings Of The Institution Of Mechanical Engineers.* pp. 3287-3298 (2021)
[7] Low, E., Ong, P. & Cheah, K. Solving the optimal path planning of a mobile robot using improved Q-learning. *Robotics And Autonomous Systems.* **115** pp. 143-161 (2019)
[8] Wang, J., Hirota, K., Wu, X., Dai, Y. & Jia, Z. Hybrid bidirectional rapidly exploring random tree path planning algorithm with reinforcement learning. *Journal Of Advanced Computational Intelligence And Intelligent Informatics.* **25**, 121-129

(2021)
[9] Pan, Y., Yang, Y. & Li, W. A deep learning trained by genetic algorithm to improve the efficiency of path planning for data collection with multi-UAV. *Ieee Access.* **9** pp. 7994-8005 (2021)
[10] Xu, X., Cai, P., Ahmed, Z., Yellapu, V. & Zhang, W. Path planning and dynamic collision avoidance algorithm under COLREGs via deep reinforcement learning. *Neurocomputing.* **468** pp. 181-197 (2022)
[11] Chen, P., Pei, J., Lu, W. & Li, M. A deep reinforcement learning based method for real-time path planning and dynamic obstacle avoidance. *Neurocomputing.* **497** pp. 64-75 (2022)
[12] Roure, C., Méard, J., Lentillon-Kaestner, V., Flamme, X., Devillers, Y. & Dupont, J. The effects of video feedback on students' situational interest in gymnastics. *Technology, Pedagogy And Education.* **28**, 563-574 (2019)
[13] Xu, X., Li, D., Sun, M., Yang, S., Yu, S. & Manogaran, G. ... & Mavromoustakis, C. *X. Research On Key Technologies Of Smart Campus Teaching Platform Based On.* **5** pp. 20664-20675 (2019)
[14] Jiang, J., Chen, M. & Fan, J. Deep neural networks for the evaluation and design of photonic devices. *Nature Reviews Materials.* **6**, 679-700 (2021)
[15] Haerens, L., Krijgsman, C., Mouratidis, A., Borghouts, L., Cardon, G. & Aelterman, N. How does knowledge about the criteria for an upcoming test relate to adolescents' situational motivation in physical education?. *A Self-determination Theory Approach.* **25**, 983-1001 (2019)
[16] Lentillon-Kaestner, V. & Roure, C. Coeducational and single-sex physical education: students' situational interest in learning tasks centred on technical skills. *Physical Education And Sport Pedagogy.* **24**, 287-300 (2019)
[17] Roure, C., Méard, J., Lentillon-Kaestner, V., Flamme, X., Devillers, Y. & Dupont, J. The effects of video feedback on students' situational interest in gymnastics. *Technology, Pedagogy And Education.* **28**, 563-574 (2019)
[18] Sun, Z., Anbarasan, M. & Praveen Kumar, D. Design of online intelligent English teaching platform based on artificial intelligence techniques. *Computational Intelligence.* **37**, 1166-1180 (2021)
[19] Jingchao, H. & Zhang, H. Recognition of classroom student state features based on deep learning algorithms and machine learning. *Journal Of Intelligent And Fuzzy Systems.* **40**, 2361-2372 (2021)
[20] He, H., Yan, H. & Liu, W. Intelligent teaching ability of contemporary college talents based on BP neural network and fuzzy mathematical model. *Journal of Intelligent & Fuzzy Systems.* **39**, 4913-4923 (2020)
[21] Reckhow, S., Tompkins-Stange, M. & Galey-Horn, S. How the political economy of knowledge production shapes education policy: The case of teacher evaluation in federal policy discourse. *Educational Evaluation And Policy Analysis.* **43**, 472-494 (2021)
[22] Lau, E., Sun, L. & Yang, Q. Modelling, prediction and classification of student academic performance using artificial neural networks. *SN Applied Sciences.* **1** pp. 1-10 (2019)
[23] Peng, W. Construction and application of accounting computerization skills teaching resource database under the background of. *Curriculum And Teaching Methodology.* **2**, 1-4 (2019)
[24] Yang, C., Xie, L., Qiao, S. & Yuille, A. July). *Training Deep Neural Networks In Generations: A More Tolerant Teacher Educates Better Students.* pp. 5628-5635 (0)
[25] Wang, X., Lin, X. & Dang, X. Supervised learning in spiking neural networks: A review of algorithms and evaluations. *Neural Networks.* **125** pp. 258-280 (2020)
[26] Konar, A., Chakraborty, I., Singh, S., Jain, L. & Nagar, A. A deterministic improved Q-learning for path planning of a mobile robot. *IEEE Transactions On Systems, Man, And Cybernetics: Systems.* **43**, 1141-1153 (2013)

Edited by: Mudasir Mohd
Special issue on: Scalable Computing in Online and Blended Learning Environments: Challenges and Solutions
Received: May 16, 2023
Accepted: Sep 1, 2023