Effective teaching behavior in physical education has an important impact on the quality of classroom teaching. To overcome the shortcomings in the existing university teaching quality assessment procedure, this paper designs an evaluation model for physical education departments based on long short-term memory networks (LSTM) with the improved particle swarm optimization (PSO). The model is constructed by analyzing the connotation and index system of teacher education teaching quality and constructing a fan-leaf structure model of teacher education teaching quality. Then, an improved PSO-LSTM model is proposed to train the teaching samples. The evaluation model applies the improved LSTM model and optimizes the network structure by dynamically adjusting the learning rate. The model is then optimized for the number of neurons and iterations of the network using the improved PSO. The results of the experiment indicate that the proposed model is effective in evaluating the quality of physical education. Moreover, the model analysis' accuracy has greatly improved. This helps teachers have a comprehensive understanding of classroom dynamics and improve their professional competence and classroom teaching quality.

1. Introduction

As the number of university students continues to increase, the quality of teaching is becoming more and more evident in the quality of university education. The performance of physical education instruction is measured in part by the quality of teaching. Furthermore, as an important element of educational management, the assessment of educational effectiveness is at the heart of educational evaluation in physical institutions [1, 2]. In a university, there are quite a lot of disciplines and there is a certain crossover between them. The flexibility and variety of teaching methods make the assessment of teaching quality in universities quite complex and a challenging issue [3].

There are two types of methods for evaluating the teachers’ performance in higher education institutions: qualitative analysis and quantitative analysis. Qualitative analysis methods mainly include expert systems, association rules, etc. They only grasp the teaching quality of universities as a whole and analyze the overall trend of changes [4–6].
experts’ vast experience and knowledge in analyzing the teaching effectiveness [9, 10]. In practical applications, problems like the parameter optimization of BP networks and extreme learning machine’s structure determination have not been effectively solved, which directly affects the results of university teaching quality assessment [11, 12].

Deep learning models provide an effective solution for the evaluation of teaching models [13]. The authors of literature [14] combined extreme gradient boosting (XGBoost) and ResNet to build a teaching quality evaluation model for early toddler teachers. The authors of literature [15] combined speech and expression to achieve English teaching analysis using deep learning models. The authors of literature [16] proposed a teaching effectiveness evaluation method based on LSTM networks, which solved the problems such as the poor teaching effectiveness of traditional methods. To improve the performance of deep learning models, optimization algorithms are often used to optimize the models, such as ant colony algorithms and particle swarm algorithms [17, 18]. The authors of literature [19] proposed a particle swarm optimization LSTM model for educational data. This method optimizes multiple parameters of LSTM based on PSO, but PSO is easy to fall into local optimization, resulting in a poor optimization effect. Therefore, this paper draws on the ideas of the article in improving PSO using adaptive inertia weights and learning factors, and then adjusting the learning step size of the LSTM using dynamic learning factors, with the goal of improving the overall performance of the LSTM in teaching quality evaluation models.

To address the problem of low performance of current models in assessing the teaching quality of physical education departments, and optimizing LSTM networks with improved PSO for the instruction. Effective assessment model of PE is proposed. The results demonstrate that the proposed assessment model outperforms the existing methods in terms of performance.

The innovations and contributions of this paper are as follows.

1. This paper constructs a fan-leaf structural model that is consistent with the quality of teacher education and teaching in physical education departments.

2. Dynamic adjustment of PSO’s inertia weights and learning factors are based on an adaptive strategy. The global search capability of PSO algorithm improved by adding perturbation factors.

3. The structure of LSTM network is optimized by dynamically adjusting the learning rate, the number of hidden layers, and the number of iterations.

This paper consists of four main parts: the first part is the introduction, the second part is the methodology, the third part is the result analysis and discussion, and the fourth part is the conclusion.

2. Methodology

2.1. Teacher Education and Teaching Quality Model Construction. A model is a form of thinking that reproduces the structure, function, properties, relationships, processes, and other essential features of a prototypical object under certain assumptions based on a specific purpose of research. Academic research is an effective way of understanding things through the representation of knowledge through the construction of models. It expresses the interrelationship between the variables of the research object and makes abstract, complex, and profound scientific concepts and theoretical issues intuitive and concise so that the public can deepen their knowledge and understanding of the scientific laws they express. Based on the connotation and index system of teacher education and teaching quality, this paper constructs a fan-leaf structure model of teacher education and teaching quality (as shown in Figure 1). The model emphasizes its content validity and it consists of two parts: the connotation of teaching quality and the indicator system. The connotation of quality reveals the essential attributes of the teaching quality and constitutes the concentric circle structure of the model. The system of indicators systematically depicts and enhances the quality of teacher education and constitutes the dynamic structure of the teacher education and teaching quality model.

Figure 1 shows that the teacher education quality model first presents a multidimensional representation of the connotation of teaching quality, which gives an expression to the concentric circle structure of teacher education quality with the teacher as the center. The connotation of quality in teacher education includes macro, medium-view, and microdimensions. Among the three connotation levels, the macrolevel expresses the optimization of the structure of teacher education. The meso-level reflects the cultivation of teachers’ qualities of the times. At the microlevel, it is the realization of the morality of teachers. The quantity and quality of physical education teachers’ education, as well as the methods and content of their work, have significantly improved recently. The content and expression of teachers’ growth needs have also become rich and complex and varied. However, at present, the needs of individual teachers’ growth and development continue to be the traditional nature of teachers, involving the cultivation of the qualities of the artisanal spirit of the times. In this regard, the connotation of quality at the meso-level is a specific response and contemporary interpretation of the macrolevel view of quality. At the microlevel, the quality of teacher education and teaching is a specific issue directly related to the professional development of teachers and the realization of the ethical nature of teaching. Teachers’ pursuit of the moral goodness of teaching reflects the esteem and expectation of the state of teaching as it should be, a pursuit of values that is a necessary condition for the realization of truly effective teaching. In other words, if the morality of teaching can be achieved, the quality of teachers will be cultivated and the quality of human resources will be improved. This supports the further optimization of the structure of teacher education. Thus, the realization of ethical teaching as a microlevel connotation of quality is in line with the inherent requirements of craftsmanship. It is a refined implementation of the qualities of the teacher’s time and a concrete guide to the improvement of teaching behavior.
The logical relationship between the three levels of the connotation of quality in PE teacher education is as follows. The connotation of teaching quality at the meso-level is established through the optimization of the macrolevel structure. The connotation of microlevel needs to refine the quality of teachers’ times. This is a prerequisite for the cultivation of teacher quality at the meso-level. At the same time, all three dimensions of quality revolve around the teacher, involving the optimization of structures, the cultivation of contemporary qualities, and the realization of the ethical nature of teaching.

The teacher education and teaching quality model also presents the main elements, logical relationships, and mechanisms of the teacher education and teaching quality indicator system at the work area level, which is embodied in a dynamic structure similar to the fan blades of a windmill. The four key elements of teacher education and teaching quality are portrayed from different perspectives, from the perspective of the specifications of teacher training, and the development of teacher education and teaching work.

Professional beliefs are the systematic understanding, stable emotional experience, and committed behavior of teachers towards the teaching profession. It helps teachers to build on their own good character by providing them with the inner motivation to find their professional home and to take the initiative in teaching. It provides effective traction for the development of education and teaching in compliance with profession-specific rules and regulations and identifies the fundamentals of the quality of teachers’ education and teaching. It is measured through three secondary indicators: professional ideals and beliefs, professional moral sentiment, and professional benevolence, which are broken down into six tertiary indicators and a number of measurement indicators (as illustrated in Figure 2).

Knowledge teaching is the main form of teachers’ educational and teaching activities, and its realization is the most basic requirement and provision of the teaching profession, providing the main basis for teachers to be qualified as teachers with knowledge. In this sense, knowledge teaching identifies the basis of the quality of teachers’ education and teaching, involving four secondary indicators, such as subject expertise, educational psychology knowledge, pedagogy knowledge, and teaching research knowledge, which are broken down into 11 tertiary indicators and a number of measurement indicators (as illustrated in Figure 3).
Methodological training is the practice of teacher educators in guiding teachers to better guide student learning in their educational work. It helps teachers to acquire the skills and techniques necessary to carry out their teaching activities and solve related teaching problems. It enhances the pedagogical rationale for future work in education and opens up the link between theory and practice. Methodological training marks the quality of teachers' education and teaching. It includes four secondary indicators: teaching scheme design method, classroom observation and reflection methods, subject teaching methods, and teaching research methods. These secondary indicators are broken down into 10 tertiary indicators and several measurement indicators (as shown in Figure 4).

Competency development refers to the qualities of literacy that teachers need in order to guide students in their educational and teaching activities that lead to the acquisition of knowledge and skills and to their physical and mental development. Knowledge, literacy, and skills in education and teaching need to be transformed into educational and pedagogical competencies for future teaching. By recognizing the ethical nature of teaching, teachers...
develop the ability to influence the character of their students in their future teaching work, to fulfill the fundamental task of developing moral character. Competence development identifies the quality of teacher education and includes four secondary indicators: teachers’ professional ethical competence, teachers’ situational adaptation competence, knowledge application teaching competence, and teachers’ identity construction competence. The secondary indicators are broken down into nine tertiary indicators and a number of measurement indicators (as shown in Figure 5).

The arrows between the indicators briefly indicate the logical linkages and mechanisms of action of the indicators of the quality of teacher education and teaching. Specifically, professional beliefs are fundamental to teachers’ professional aspirations and wellbeing and can motivate teachers to engage in teaching and learning. It can effectively guide teachers in the teaching of knowledge, the training of methods, and ultimately the development of their competencies. Knowledge teaching demonstrates the need for teachers to acquire the necessary subject expertise and educational theories to fundamentally establish their framework of understanding of education and thus effectively enhance the rational support for professional beliefs, methodological training, and competency development. Only by applying the subject knowledge and educational knowledge acquired through knowledge teaching to educational teaching situations can teachers train their educational teaching skills. They can also develop competencies, validate knowledge, and construct beliefs through repeated training. Competence development is the ultimate goal of teacher education and teaching. Guided by their professional beliefs, teachers construct their personalized system of teacher education and teaching competencies through a series of knowledge teaching and methodological training sessions. In this way, the four elements of quality are logically parallel and indispensable, assessing the quality of teacher education and teaching in a comprehensive and integrated way from four perspectives: fundamental, basic, protective, and purposeful. They are also closely linked and progressive, leading the work of teacher education and teaching to unfold following the sequence of these four aspects. Hence, they become a system of teacher education and teaching quality indicators that integrate both evaluative and guiding functions.

The quality of teacher education and teaching is a driver and contributor to the professional development of teachers and a prerequisite for the quality and balanced development of education. The teacher education quality model as a whole is a powerful model with a fan-leaf structure, which has important functions and values. The operation of the power system provides the impetus for the rotation of the concentric circles of teacher education and teaching quality. It not only further regulates the teaching and learning process of teachers, thus improving the quality of teacher training, but also provides guidance for the improvement of teachers’ teaching philosophy and behavior, thus promoting the healthy development of teacher education.

The assessment of the quality of physical education teaching in higher education should take into account the quality of students’ learning and practice as a basic indicator for assessing their ability to apply their learning and the level of their physical education development. In addition, the assessment of the quality of PE teaching should focus on the teaching process and the students’ original foundations, taking the students’ acquisition and application of PE knowledge at a later stage as the outcome of the assessment, and using the results to feedback the teaching process.
2.2. Data Sources. According to the 4 primary indicators, 15 secondary indicators, and 36 tertiary indicators subdivided in the index system, a questionnaire was developed, distributed, scored by students, using a percentage system, and collected to obtain the experimental data. Second, the scoring data \([0, 100]\) were standardized to between \([0, 1]\), and the standardization method was calculated as shown in formula (1).

\[
i = \frac{j - j_{\text{min}}}{j_{\text{max}} - j_{\text{min}}},
\]

where \(i\) is the normalized score and \(j\) is the untreated score.

After screening, 400 sets of valid experimental data were identified, of which 360 sets were used to train the model so that an optimal LSTM neural network structure could be obtained, and the remaining 40 sets of data were utilized for testing and evaluating the model’s performance. The processed student evaluation sample data had 36 input datasets and 1 training output datasets for each group.

2.3. Optimized LSTM Model. LSTM neural networks are an improvement on recurrent neural networks (RNNs), with the same external cycles as RNNs, but also with self-cycling between their nodes, improving the problem of long term dependence of RNNs leading to gradient disappearance and gradient explosion.

Neural networks cannot be updated without gradient descent. The traditional gradient descent method is shown in formula (2), where \(V_z\) is the weight at the \(z\)th iteration, \(\gamma\) is the learning rate, and \(L_z\) is the value of the loss function. In this paper, MAE and MAPE are chosen as the loss functions of the LSTM model.

\[
V_{z+1} = V_z - \gamma \frac{\partial L_z}{\partial V_z},
\]

The learning rate \(\gamma\), which is an important factor in determining the effectiveness of network training, can be too large and lead to the oscillation of the loss function, making it difficult for the network to converge. Too small a value will lead to poor training efficiency and slow convergence of the network. To solve this problem, the learning rate is dynamically adjusted in each training round, which is calculated as shown in formula (3).

\[
y_{z+1} = \begin{cases} 
\frac{y_z}{1 + (\Delta L_z)^2 + y_z^2}, & \Delta L_z > 0, \\
\frac{y_z}{1 - 0.1 \times (\Delta L_z)^2 + 0.01 \times y_z}, & \Delta L_z \leq 0.
\end{cases}
\]

where \(\Delta L_z\) denotes the gradient of the current loss function, which is defined as follows:

\[
\Delta L_z = \frac{\Delta L_z - \Delta L_{z-1}}{2}.
\]

As the number of training rounds increases, the dynamic learning rate gets smaller and smaller to prevent crossing the optimal solution, but when \(\Delta L_z \leq 0\), i.e., when the network has not yet shown a convergence trend, the dynamic learning rate decreases slower to keep the network training efficient. It should be noted that when the network learning rate is too low, it can cause the gradient disappearance problem, so \(y_{z+1}\) will not be less than 0.01.

2.4. Improved PSO. See literature [18] for a definition of the particle swarm optimization algorithm. As an evolutionary computational technique, the optimal solution is obtained through collaboration between individuals in a population and information transfer between them, allowing the
population solution space to be continuously updated. The particle convergence rate mainly depends on three factors: the global optimum, the individual historical optimum, and particle velocity. Considering that the inertia weight $G$ and the learning factor $\eta$ are the main parameters affecting the performance of the particle swarm optimization algorithm, literature [20, 21] dynamically adjust the inertia weight $G$ between linear and nonlinear using the Sigmoid function and the dynamic multigroup particle optimizer, respectively, which improves the performance of the PSO algorithm. The authors of literature [22] used a dynamic change strategy with dynamic acceleration constants as the learning factor to improve the convergence accuracy in the latter stages while ensuring the exploration capability of the particles in the early stages. The methods proposed in the above literature all enhance the search capability of the algorithm to varying degrees and reduce the premature convergence of the algorithm.

2.4.1. Adaptive Inertia Weights. To improve the global search capability and convergence speed of the algorithm, this paper proposes an adaptive optimization strategy that can dynamically adjust the learning factors and inertia weights $G$ in the update formula during the algorithm search process, achieving a balance between global and local search.

The inertia weight $G$ of the improved algorithm is updated in the following way.

$$G = G_{\min} + \frac{(G_{\max} - G_{\min})}{1 + \exp(\lambda (2n/N) - 1)}, \quad (5)$$

where $G_{\min}$ denotes the preset minimum value of inertia weight and $G_{\max}$ denotes the preset maximum value of inertia weight, which is taken as 0.4 and 0.7 in this paper. $\lambda$ is the control parameter, which is taken as 10 in this paper. $n$ represents the number of current iteration and $T$ represents the maximum iteration.

Figure 6 shows the nonlinear variation curve of the inertia weight. In the early stages of the PSO, $G$ can maintain a relatively smooth state, allowing the particles to maintain a relatively large update rate and population diversity during this period, ensuring that the algorithm has good global search capability. The value of $G$ is forced to fall rapidly, which allows the particles to be updated in smaller steps in the later stages, enabling a more refined search and improving the convergence capability of the algorithm.

2.4.2. Adaptive Learning Factors. This paper also introduces an adaptive learning factor, which is used to regulate the balance between global and local search by dynamically adjusting the learning factor in a way that selects the appropriate parameters. The learning factor $\eta$ update formula is as follows.

$$\eta = \eta_{\min} + (\eta_{\max} - \eta_{\min}) \left(\frac{f(n)}{f_{\max}}\right)^{\lambda}, \quad (6)$$

where $\eta_{\min}$ and $\eta_{\max}$ denote the minimum and maximum values of the learning factor, respectively, which are taken as 0.5 and 2; in this paper, $f(n)$ and $f_{\max}$ are the fitness of the current individual particle and the maximum fitness in the particle swarm, respectively.

The trend of the learning factor values is shown in Figure 7. In the proposed strategy, the size of the learning factor determines the degree of particle learning. At the beginning of the algorithm, the learning factor is small and tends to increase slowly, so that few particles participate in the learning process, which ensures the global search capability of the algorithm. In the later stages of the algorithm, the learning factor increases considerably, which causes more particles to participate in learning process, and enhances the local search capability of the PSO.

2.4.3. Extreme Value Perturbations. Furthermore, the analysis of the principles of PSO reveals that the updated state of an individual particle is attracted to both the current population optimum and the individual optimum. This drives the particle towards the sector formed by the individual’s current position, the individual’s historical optimal position, and the group’s current optimal position. The search range is not spread and the particles become “premature”. To avoid the “premature” situation, this paper perturbs the population optimum, and the perturbation formula is as follows:

$$D_{ay}(z) = d_{ay}(z) + \varepsilon, \quad (7)$$

where $\varepsilon$ is the random perturbation, denoting the product of the average value of the particle at the current iteration and a random number. $d_{ay}(z)$ is the global extremum of the $y$th component in $z$ iterations, and $D_{ay}(z)$ is the global extremum after the perturbation.

2.5. Teaching Quality Evaluation Model. The proposed model utilizes an improved LSTM model to construct the evaluation model, which is used to overcome the shortcomings in the current method and to improve the accuracy of teaching quality. In addition, to better match the evaluation model with the characteristics of the PE department evaluation data, the mean absolute percentage error of the
The prediction results was utilized as the fitness function $f$. The improved PSO was applied to optimize the LSTM model to obtain a better combination of parameters.

$$f(n) = \sum_{y=1}^{Y} \frac{|\bar{K}^1_y - K^1_y|}{K^1_y} + \sum_{z=1}^{Z} \frac{|\bar{K}^2_z - K^2_z|}{K^2_z},$$

where $\bar{K}^1_y$ and $\bar{K}^2_z$ are the training sample expected output and the validation sample expected output, respectively.

The flow of the proposed evaluation model is shown in Figure 8.

### 3. Result Analysis and Discussion

**3.1. Simulation Conditions.** The algorithm was tested in a Python 3.6 environment; the PSO calculation program was written in Python language and four prediction models were constructed using the Keras deep learning library: BP neural network model (BPNN), LSTM model, standard PSO optimized LSTM model, and the proposed model. Because most current teaching quality evaluation models use BP models, this paper chooses BPNN as the comparison model in order to illustrate the advantages of LSTM.

The BPNN uses an $m - 2m + 1 - 1$ structure, with $m$ denoting the number of neurons, and the LSTM uses the same structure as the BPNN, with 2 hidden layers. The number of neurons in the input and output layers of the LSTM is 36 and 1, respectively, and the LSTM model is trained 1000 times. The initial number of populations in the LSTM is 36 and 1, respectively, and the LSTM model is optimized with PSO. In standard PSO, inertia weight $G = 0.5$, learning factor $\eta_1 = \eta_2 = 2$. In the improved PSO, the inertia weight $G$ and learning factor $\eta$ are dynamically adjusted with formulas (5) and (6).

The following two metrics were adopted for the error evaluation of the experiments.

$$\text{MAE} = \frac{\sum_{x=1}^{t} |\bar{K}_x - K_x|}{t},$$

$$\text{MAPE} = \frac{100}{t} \sum_{x=1}^{t} \frac{|\bar{K}_x - K_x|}{K_x},$$

where $K_x$ and $\bar{K}_x$ denote the true and predicted values, respectively, and $t$ is the number of predicted samples. MAE and MAPE reflect the degree of coincidence between the predicted value and the real value. The smaller the value, the better the model.

**3.2. Experiments on Improved PSO-Optimized LSTM Networks.** Figure 9 shows the prediction errors of the four models. The MAE and MAPE of the proposed model, PSO-LSTM model, and LSTM model are all smaller than those of BPNN. Compared to the BPNN, the LSTM can improve the prediction accuracy by more than 45%, which is a good illustration of the ability of the LSTM to capture the trend of data changes and thus make accurate predictions.

Compared to the LSTM, optimizing the LSTM using PSO or improved PSO can yield smaller evaluation errors, and PSO-LSTM and the proposed model can improve the accuracy of the LSTM by 52% and 80%, which indicates that PSO can improve the overall performance of the LSTM. The proposed model has the smallest prediction error with MAE of 3.2 and MAPE of 1.60%, which improves the prediction accuracy by 58% over PSO-LSTM, indicating that better parameters are obtained during the iterative process using the proposed improved PSO algorithm, which in turn can lead to better prediction results when optimizing the LSTM network. In addition, the dynamic adjustment of the learning factors in the LSTM model also provides help in evaluating the performance improvement of the model.

Figure 10 represents the change in fitness of the optimized LSTM using PSO. The LSTM model is optimized with PSO or improved PSO parameters to obtain smaller values of fitness. Moreover, the convergence speed of the LSTM model gains an improvement. Among the three compared models, the proposed model is able to converge to the minimum fitness value at the fastest rate, thus demonstrating that the proposed model obtains faster convergence and better global optimization finding capability by optimizing the parameter combinations.

**3.3. Model Comparison Experiments.** The prediction results of the proposed model were compared with the BP [11] model, LSTM [16] model, PCA + BP [18] model, GA + BP [23] model, and adaptive BP [24] model. The prediction results of the different evaluation models for some of the data are given in Table 1, and the absolute error comparison graph is shown in Figure 11.

Table 1 and Figure 11 show that the BP and adaptive BP neural network models of literature [11, 24] have the largest error and the largest error fluctuation, indicating that the models have a large degree of deviation from the prediction results of individual samples and poor model stability. The
The authors of literature [18] and literature [23] used the PCA algorithm and GA algorithm to optimize the BP network, respectively, and were able to achieve high evaluation accuracy in their experiments. The prediction results of the model in literature [16] also have high accuracy and stability, and the performance is better than that of literature [23], but the evaluation results are not as good as that of literature [18]. Compared with several other models, the proposed method establishes a teaching quality evaluation model with higher prediction accuracy, smaller absolute error, more stable sample prediction results, and better performance results than several other evaluation models.

The evaluation results of the different models are given in Figure 12. The average evaluation accuracy for the 40 sets of data based on the BP model and adaptive BP model were 85.28% and 90.52%, respectively. The evaluation accuracy of the two models is low, because the model only makes few modifications to the BP neural network. The average evaluation accuracy of the PCA + BP and GA + BP models were 96.75% and 93.26%, respectively, and the average evaluation accuracy for the LSTM model was 94.55%. In contrast, the average evaluation accuracy of the proposed model was 98.37%, thus demonstrating that the evaluation results of the proposed model were significantly better than those of other methods in the literature and showing that the method is feasible for teaching quality evaluation.
Table 1: Selected data prediction results for different evaluation models.

| Sample number | Actual average | Proposed model | Literature [11] | Literature [16] | Literature [18] | Literature [23] | Literature [24] |
|---------------|----------------|----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1             | 0.89           | 0.8991         | 0.9724          | 0.8412          | 0.8715          | 0.9115          | 0.8112          |
| 2             | 0.61           | 0.6149         | 0.6887          | 0.5638          | 0.6223          | 0.5771          | 0.5438          |
| 3             | 0.73           | 0.7210         | 0.8221          | 0.7529          | 0.7006          | 0.6732          | 0.8029          |
| 4             | 0.79           | 0.7855         | 0.6402          | 0.7432          | 0.8001          | 0.7258          | 0.7032          |
| 5             | 0.91           | 0.9137         | 0.8005          | 0.8429          | 0.9617          | 0.9662          | 0.8229          |
| 6             | 0.93           | 0.9355         | 0.9912          | 0.8634          | 0.9551          | 0.8878          | 0.8434          |
| 7             | 0.86           | 0.8711         | 0.9386          | 0.9028          | 0.8818          | 0.8009          | 0.9128          |
| 8             | 0.77           | 0.7554         | 0.6503          | 0.8228          | 0.7592          | 0.7992          | 0.8528          |
| 9             | 0.52           | 0.5354         | 0.5997          | 0.4773          | 0.4892          | 0.5921          | 0.4473          |
| ...           | ...            | ...            | ...             | ...             | ...             | ...             | ...             |

Figure 11: Absolute errors in the assessment results of different models.

Figure 12: Comparison of performance of evaluation models.
4. Conclusion
This study creates a leaf structure model suitable to the education quality in the department of physical education by drawing on the evaluation index systems of other disciplines in order to improve the teacher performance. Aiming at the shortcomings of the existing evaluation models, an evaluation model of the LSTM with dynamic adjustment of the learning rate of the network is designed for solving the problem of the network falling into local optimum due to the occurrence of the gradient disappearance phenomenon during the training process. The improved PSO is adopted to optimize the hidden layer’s number of neurons and the number of iterations of the LSTM network for the sake of the further improvement of the evaluation model performance. The experimental results demonstrate that the designed evaluation model can objectively and effectively evaluate the teaching quality of the physical education department and the output of the model has important practical guidance value for actual teaching. LSTM performs well in the teaching quality evaluation model, but there are different degrees of differences in the quality evaluation indicators, which will affect the selection of information by LSTM. Therefore, the attention mechanism is introduced into the quality evaluation model to improve the matching between the model and data features.

Data Availability
The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest
The authors declare that there are no conflicts of interest.

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