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An Improved LSTM Based Early Warning Model for Physical Education Network Teaching Achievements

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Abstract

The development of data mining technology has pushed data-driven decision-making to gradually become the core content of educational data mining. To identify students who are at risk of failing physical education online courses at an early stage, this article uses bidirectional long-short term memory (BiLSTM) neural networks to construct a deep BiLSTM (DBiLSTM) prediction model. The experimental verification of its effectiveness showed that in the full attribute data experiment, the DBiLSTM specificity at Stage 1 was the highest, at 30.8%, and the accuracy rate at Stage 3 was as high as 73.6%. In the best attribute data experiment, compared to the full attribute, the accuracy of all models at Stage 2 increased, except for the SVM model, which had a 61.8% accuracy rate. At Stage 3, the early warning accuracy of DBiLSTM was higher than other algorithms, with a rate of 75.7%. In the experiment after introducing the balanced data method, the accuracy of the DBiLSTM-SMOTE model combined with the Synthetic Minority Oversampling Technique was 72.6%. At this time, the AUC value of DBiLSTM-SMPOTE reached 72.6% in the middle of the semester, significantly superior to other algorithm models. Overall, DBiLSTM is effective in the early warning of students' performance in online sports courses, while DBiLSTM-SMOTE is highly practical in early warning of performance in online sports teaching.

Keywords

DBiLSTM, Early Warning Model, Online Courses, Sports

1. Introduction

The goal of education data mining (EDM) is to analyze unique data generated in the educational environment to solve educational research problems. The emergence of EDM has provided teachers and scientific researchers with the possibility of effectively analyzing and mining education big data, greatly promoting the development of early warning in education. Meanwhile, due to its unique characteristics, deep learning outperforms traditional data mining algorithms in terms of accuracy in data mining. Therefore, the use of deep learning technology can accurately and timely identify students at risk of failing their physical education (PE) studies. Yakubu and Abubakar [1] proposed an early warning method for students' academic performance based on deep learning in response to issues related to student performance in higher education. Freshmen were at risk of dropping out. In response to this problem, Plak et al. [2] collected experimental data to construct an early warning system for student learning achievement consultation. In this context, this paper constructs an early warning model, deep

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bidirectional long-short term memory (DBiLSTM), through BiLSTM and the introduction of Synthetic Minority Oversampling Technique (SMOTE). Moreover, a DBiLSTM-SMOTE model for early warning is proposed. The objective is to implement an effective early warning system for students who fail in online PE courses, with the aim of providing accurate early warning at an early stage and thereby facilitate the delivery of appropriate assistance for actual teaching activities.

2. Related Work

EDM is based on the theories of psychology and learning science, utilizing knowledge in fields such as computer science and data mining to master students' learning processes [3]. The rapid development of educational informatization has also made the collection of educational data easier, and its sources are becoming increasingly widespread [4]. In this background, a large number of scholars have conducted in-depth research on it. Regarding the quality of student curriculum teaching, Mahboob et al. [5] put forward a prediction framework for student academic performance based on EDM technology, which effectively reduces the risk of student learning. To effectively improve the actual quality and efficiency of talent cultivation in universities, Ma and Ding [6] constructed an information system for talent cultivation in universities in line with the requirements of in-depth learning and EDM. Given this, it effectively solved related problems while improving the accuracy of talent cultivation classification. Regarding the correlation between grade point average (GPA) and psychological factors, Khanna et al. [7] conducted a detailed analysis of relevant parameters using educational mining techniques. In this way, the prediction of recent exams was completed while classifying individual performance. For improving the classification accuracy of students' reading scores, Buyukatak and Duygu [8] proposed corresponding classification methods using EDM, which effectively improved the classification accuracy and students' reading scores.

In other words, related to teaching strategies and quality, Quadir et al. [9] used EDM to qualitatively analyze relevant content, thereby assisting in effectively ensuring educational quality. Nuryana [10] proposed relevant prediction model algorithms through EDM, effectively improving the accuracy of student graduation prediction. Kimmons and Rosenberg [11] used educational mining technology to analyze multiple databases, providing a reference for students in the field of educational technology to cope with academic crises.

The numerous studies above prove that there is still little research on the current situation of education in China, and there are still shortcomings in the depth of technology. However, foreign scholars have not done much research on the application of deep learning in EDM, and, international research on student data mining in PE online courses is also less involved. As a result, the research on building an early warning model DBiLSTM and DBiLSTM-SMOTE based on BiLSTM has certain innovations. It can not only assist in the development of online curriculum education but also promote the development of information technology in PE.

3. Analysis of the Early Warning Model of PE Network Teaching Results based on Improved LSTM

3.1 Analysis of Temporal Characteristics of Students' Behaviors

To identify the students who are at risk of failing in the online sports course at an early stage, to correct their learning attitude, and to improve their performance, the study builds a DBiLSTM pre-alarm model based on the BiLSTM neural network. Mobile learning is centered around users and technology, allowing users to apply positive learning methods and achieve autonomous learning based on their actual situation. Due to its learning on mobile terminals, time and location have random and uncertain characteristics. Researchers usually use behavioral data collected by learning systems such as the learning management system (LMS) to describe and analyze students' learning behaviors. The study selects LSTM to select time series data to analyze the behavioral patterns of students' PE online learning.

In addition, time series clustering has been widely used for similarity analysis of business data. It combines automated time series analysis and decomposition by introducing similarity measures. After conducting similarity analysis, the results are explained by combining other basic information data. Therefore, to better distinguish groups of students with different sports online learning behavior patterns, the K-means clustering algorithm with good application effect is selected for clustering analysis of their behavior patterns.

3.2 Construction of DBiLSTM Prediction Model for PE Network Teaching Achievements

Based on the analysis of the temporal characteristics of students' behavior, the research begins to construct an early warning model for PE online teaching performance. For prediction model research, BiLSTM is selected, which can not only obtain long-term historical information like LSTM but also obtain the connection between the future and the current moment. For the prediction model research, the DBiLSTM model under the deep learning model is chosen. The use of BiLSTM can effectively avoid the gradient guarantee problem that often occurs in recurrent neural networks, and secondly, the staggered BiLSTM can deeply mine the value of the dataset and simultaneously learn the contextual relationships between the front and back time directions. The subsequent multi-layer fully connected parts can improve the model's nonlinear expression ability and learning ability. Therefore, multi-layer networks to some extent bring higher complexity to algorithms. The basic structure calculation expression is shown in Eq. (1):

$$g_t = \vec{g}_t \oplus \overleftarrow{g}_t. \tag{1}$$

The g_t in Eq. (1) represents the actual output in the hidden state. $\vec{g}_t$ is the actual state of the forward hidden layer. $\overleftarrow{g}_t$ represents the actual state of the hidden layer. The research and application of traditional deep learning models in education is not deep enough, so improvements have been made for BiLSTM. The DBiLSTM is obtained by introducing a depth characteristic, and the structure of the model is shown in Fig. 1.

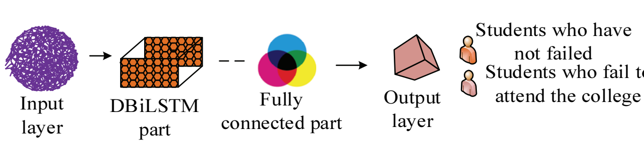

Fig. 1. Structure diagram of DBiLSTM model.

The model in Fig. 1 includes an input layer, a BiLSTM module, a fully connected layer module, and an output layer module. Among them, the BiLSTM part and the fully connected layer part are composed of multi-layer BiLSTM and multi-layer fully connected layers, respectively. It is worth noting that as the hierarchy increases, the complexity and overfitting problems of the model also increase. Therefore, the study addresses these issues by adding a Dropout layer. The mathematical expression is shown in Eq. (2):

$$z = f(\omega \cdot d(x)). \tag{2}$$

In Eq. (2), $f(\cdot)$ represents the activation function. z is the output value. x refers to the input value. ω means weight. The calculation expression of $d(x)$ is shown in Eq. (3):

$$d(x) = \begin{cases} mask * x, h \\ (1-p)x, \quad other \end{cases} \tag{3}$$

$mask$ in Eq. (3) is a binary vector. h represents the training phase. p is the Dropout rate. Based on this, the performance warning process of the DBiLSTM model proposed in the study first preprocesses the data of each stage according to the prediction method in Fig. 1, inputs it into the embedding layer, and initializes the memory state of the neurons. Secondly, parameters such as forget gate and input gate are calculated according to the corresponding formulas. Next, the corresponding formulas are used to calculate the output of the neurons, and these two sets of formulas are repeated until all neurons in BiLSTM learned the dataset. Then, the neural dataset learning of BiLSTM is repeated until the last layer outputs nonlinear data features. After entering the fully connected layer, the nonlinear data features are weighted to calculate the hidden layer output, and an adaptive momentum (Adam) algorithm is introduced to update the model parameters until they are optimal. Finally, the test set is input into the DBiLSTM model, and the actual output value is the student's sports performance warning result.

In the experiment, when validating the DBiLSTM model, the evaluation criteria include mean absolute error (MAE), mean square error (MSE), binary cross entropy loss (BCE Loss), accuracy, specificity, and sensitivity. The calculation expressions of the six indicators are shown in Eqs. (4) to (5).

$$\begin{cases} MAE = \frac{1}{N}\sum_{j'=1}^{N} \left|V_{j'} - P_{j'}\right|, \quad MSE = \frac{1}{N}\sum_{j'=1}^{N} \left(\tilde{V}_{j'} - V_{j'}\right)^2 \\ \text{loss} = -(\delta \log(p') + (1-\delta)\log(1-\delta)) \end{cases}. \tag{4}$$

In Eq. (4), N is the total amount of samples. $V_{j'}$ represents the value of the estimator. $\tilde{V}_{j'}$ refers to the value of the estimated quantity. $P_{j'}$ is the exact value. δ refers to the real label. p' is the probability that the sample is predicted to be positive.

$$\begin{cases} \gamma = \frac{TP}{TP+FN} \\ \vartheta = \frac{TN}{TN+FP} \\ \lambda = \frac{TP+TN}{P'+N'} \end{cases} \tag{5}$$

γ in Eq. (5) represents sensitivity. ϑ is the degree of specificity. λ refers to the accuracy rate. *TP* is the real example. *FN* means false negative example. *TN* is a true negative example. *FP* represents a false positive example. The feature selection method selects chi-square test, Pearson correlation coefficient, L1 and L2 penalty terms, recursive feature elimination, and extreme random trees. In the unbalanced data set, the study selects area under curve (AUC) as the evaluation index, and its calculation expression is Eq. (6):

$$AUC = \frac{1 + TPR - FPR}{2}. \tag{6}$$

TPR in Eq. (6) represents the positive classification rate. *FPR* is the negative category rate.

4. Performance Analysis of DBiLSTM Early Warning Model

To verify the effectiveness of the DBiLSTM model proposed in the study, four grade students from a certain college of a certain university of science and technology are selected as the research subjects. In the experimental simulation environment, the software environment is selected as Python development language, the database management tool is Navicat, the hardware environment is Windows 10 Professional operating system, the processing area is 6-core Intel, and the memory is 8 GB. The research divides the collected data into four stages, namely Stage 1 (before the start of the semester), Stage 2 (at the beginning of the semester), Stage 3 (2 months after the start of the semester), and Stage 4 (5 months after the start of the semester). When determining parameters, the research uses BCE Loss to determine the number of hidden layers in DBiLSTM, and uses implementation to determine the insertion position of Dropout layers. The study uses 10-fold cross-validation to divide the dataset into 10 parts, with nine parts being the training set and one part being the test set. After comprehensive comparison, the number of hidden layers in the DBiLSTM model is set to 3, and Dropout is added after each BiLSTM layer. On this basis, the study introduces classification and regression tree (CART), support vector machine (SVM), and LSTM as comparative models. The sensitivity, specificity, and accuracy comparison results of the four models at four stages are shown in Fig. 2.

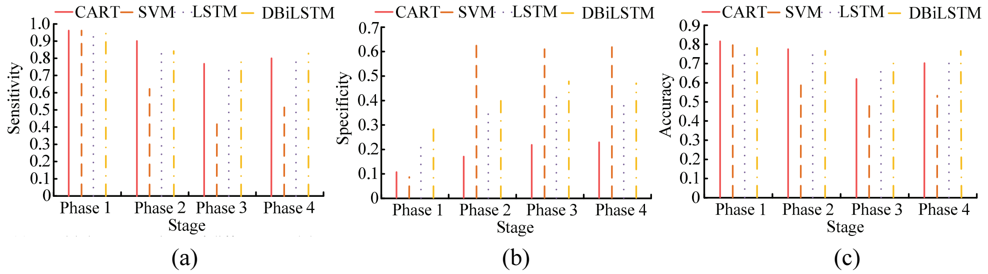

Fig. 2. Comparison results of (a) sensitivity, (b) specificity and (c) accuracy of the four models at four stages.

From Fig. 2, after reaching Stage 3, the DBiLSTM model has the highest sensitivity (79.0%) and the second highest specificity (47.6%) with an accuracy of 73.6%. Overall, the DBiLSTM early warning model proposed in the study shows high performance in the first three stages. Based on the optimal attribute screening, the sensitivity, specificity, and accuracy comparison results of different models at different stages are shown in Fig. 3.

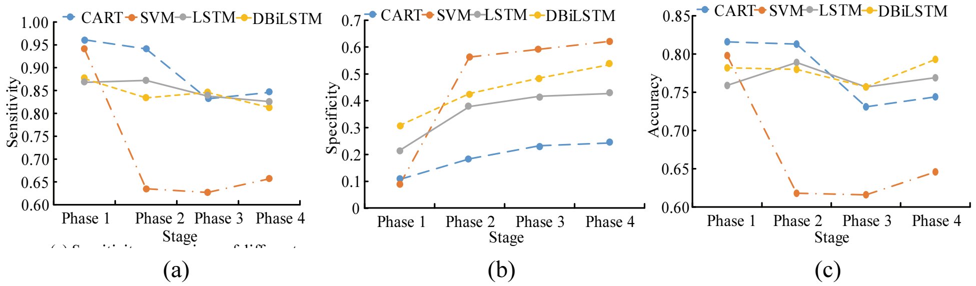

Fig. 3. Comparison results of (a) sensitivity, (b) specificity and (c) accuracy of different models at different stages.

From Fig. 3, in Stage 3, the removal of a large number of attributes results in an increase in the specificity of different models. At this time, the specificity of CART is 23.3%, with 59.2% of SVM, 41.7% of LSTM, and 48.5% of DBiLSTM. This result indicates that the introduction of feature selection methods effectively improves the overall prediction accuracy of the model. Overall, in Stage 3, the warning accuracy of DBiLSTM is higher than other algorithms, at 75.7%. However, the model has a very low recognition rate for failing students and is not sufficient as an early warning model. Therefore, based on the relevant data set after feature selection, the research introduces the methods of random oversampling (ROS), random undersampling (RUS), and SMOTE to balance the research data, to reduce the impact of multi-sample training on the accuracy of model recognition. At this time, the specificity and accuracy results of different models combined with three sampling methods at different stages are shown in Fig. 4.

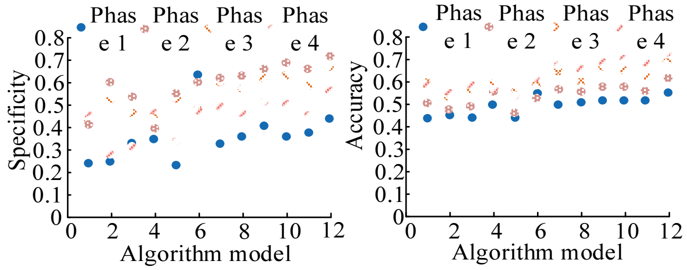

Fig. 4. Results of (a) specificity and (b) accuracy at different stages of different models combined with three sampling methods.

In Fig. 4, "1" to "12" represent: CART-ROS, CART-RUS, CART-SMOTE, SVM-ROS, SVM-RUS, SVM-SMOTE, LSTM-ROS, LSTM-RUS, LSTM-SMOTE, DBiLSTM-ROS, DBiLSTM-RUS, and DBiLSTM-SMOTE. The sensitivity of each model has decreased, but the specificity has improved, indicating a significant improvement in the prediction accuracy of each model for students who fail PE. The combination of DBiLSTM and the three data balancing methods has a high level of specificity at Stage 3, with 63.1%, 58.3%, and 67.0%, respectively. The accuracy rate in Stage 3 is also higher than other models, with 68.9%, 66.9%, and 72.6%, respectively. In Fig. 4, DBiLSTM has high effectiveness in predicting PE failing students, reaching a maximum specificity of 71.8% in Stage 4.

To further verify the advantages of the DBiLSTM-SMOTE model, random forest (RF), gradient boosting decision tree (GBDT), and extreme gradient boosting (XGB) are introduced for comparison. The results are shown in Table 1.

Table 1. Comparison results of different algorithm models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
RF	75.59	87.12	77.37	81.96
GBDT	78.66	87.33	82.13	84.65
XGB	79.85	89.10	81.89	85.34
DBiLSTM-SMOTE	81.39	89.15	84.28	86.65

From Table 1, the accuracy rate of the DBiLSTM-SMOTE model is 81.39%, the precision rate is 89.15%, the recall rate is 84.28%, and the F1 value is 86.65%, all of which are higher than the comparison algorithm model, indicating that it has better effects on student warning in real scenarios.

5. Conclusion

To identify students at risk of failing PE online courses in the early stages, correct their learning attitudes, and improve their grades, a DBiLSTM early warning model was constructed based on the BiLSTM, and its effectiveness was experimentally verified. The experimental results demonstrated that in all data prediction experiments, the sensitivity of the DBiLSTM model reached the highest at Stage 3, reaching 79.0%, and the accuracy was also as high as 73.6%. In addition, the specificity and accuracy of the DBILSIM-SMOTE model in Stage 3 were 67.0% and 72.6%, respectively. Meanwhile, the DBiLSTM model exhibited high advantages in AUC values at different stages, with an accuracy rate of 81.39% and a precision rate of 89.15% compared to other algorithms, both of which are higher than the comparison algorithms. Overall, the DBiLSTM early warning model proposed in the study has high effectiveness in early warning of students' PE online course grades. However, the dataset used in the study essentially only contains over 2,000 students, which is slightly insufficient for the DBiLSTM model proposed in the study. Increasing the number of layers of deep neural networks will cause fitting phenomena, so it is necessary to increase the size of the dataset in the future.

Conflict of Interest

The authors declare that they have no competing interests.

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