International Journal of Engineering Education Vol. 37, No. 6, pp. 1730–1742, 2021
Printed in Great Britain

0949-149X/91 $3.00+0.00

Impact of Blended Learning on Students' Performance, Classification and Satisfaction in a Practical Introductory Engineering Course*

ZHENQIAN SHEN, HUIJUAN ZHAO and ZHEYU LIU
Center for Engineering Internship and Training (National Experimental Teaching Demonstrating Center), Tiangong University, Tianjin 300387, China. E-mail: shenzhenqian@tiangong.edu.cn

HUIJUAN ZHAO
School of Life Sciences, Tiangong University, Tianjin 300387, China. E-mail: 13048860051@163.com

ZHEYU LIU
Faculty of Education, Tianjin Normal University, Tianjin 300387, China. E-mail: zheyuliu@126.com

Blended learning which is an advanced teaching strategy integrating techniques used in Small Private Online Courses (SPOCs) and those in traditional classrooms is increasingly adopted in many courses. The aim of this study is to evaluate whether blended learning in a Practical Introductory Engineering Course can improve students' performance, classification and satisfaction. To do so, a blended learning mode was designed and the blended learning group (182 students) of the academic year 2019–2020 was compared with the traditional learning group (226 students) of the academic year 2018–2019 in terms of the students' performance and classification. Besides, we evaluated the students' satisfaction in blended learning using designed questionnaires. The results show that students in the blended learning group have better performance than those in the traditional group. Regardless of the practical operation scores or the final grades, the interval distribution of scores in blended learning group was about 5 points higher than that of the traditional learning group. We also utilized a classifier based on our proposed deep learning model and verified through a comparative study that the classifier has the best performance among several existing models. The results also reveal that comparing with traditional learning, the accuracy of using the proposed model to classify students in blended learning was improved by 16.45%. As far as the questionnaire survey is concerned, most students had a positive view of employing the blended learning in the course. Overall, these results can serve as reference and guidance for future engineering practice courses.

Keywords: blended learning; students' performance; classification; the deep learning model; satisfaction

1. Introduction

In higher education, traditional face-to-face learning in which teachers are the imparters of knowledge and students are the recipients of knowledge is still the mainstream [1]. Educators strive to provide effective instruction and adopt different teaching strategies to improve students' learning efficiency. However, large sizes of classes, insufficient communication and interaction between teachers and students, and weak ability of practical feedback make it harder for teachers to develop students' potential. Traditional large-class education has difficulty in providing personalized teaching, and its limitations may even have negative effects on students' performance [2–4].

Electrical & Electronical Engineering Practice is an introductory course for students majoring in Electrical Engineering, Electronic Engineering, and Automation. The course is inseparable from theoretical teaching and practical teaching [5]. It is a practical introductory engineering course designed to cultivate students' practical skills. However, due to the large number of students, teachers cannot take into account every student and those students far away from the instructor cannot observe the complete experimental process. Considering that experiments are usually complex, the students may not master some experimental skills after the teacher conducts the experiment. This requires us to introduce a new learning mode for this course, so as to promote teaching efficiency through student-centered learning. The new mode should also help students better connect theory with practice, and provide specific references furthermore for their participation in engineering projects.

The emergence of the Small Private Online Courses (SPOCs) [6–8] brings a wave of reforming classroom teaching. It aims at small-class teaching, which can not only make up for the shortcomings of the Massive Open Online Course (MOOC) [9-10], such as low completion [9], lack of face-to-face communication and incomplete learning experience [10], but also can be combined with offline learning. It also focuses on the centrality of students and transforms passivity into initiative in the learning process so that students can review materials as needed [11] and receive immediate feedback [12].

* Accepted 30 July 2021.

Therefore, a blended Engineering Practice course based on SPOC and traditional classroom was designed. One form called the flipped classroom [13–15] was adopted. It is a creative method promoting active learning in which course materials are provided online before the class.

Students' performance, for instance, the final grades, is the most direct way to know the students' learning progress. It is the main teaching goal of the universities, and the excellent academic achievements will lead to improving the quality of that university. In engineering education, improvement of students' performance in relation to the employment of blended learning is confirmed in the literature, especially in terms of final grades [16–18]. But these courses are based on programming, software operation and so on. There are few studies on blended learning of teaching engineering practices which focus more on practical operation. Generally speaking, educators not only pay attention to the performance of students, but also eager to analyze the daily learning data of students in order to grasp the effect of learning in a timely and accurate manner. Educational Data Mining (EDM) is an application and development of data mining technology in the education field and transform raw educational data into useful information that can significantly improve the efficiency of the learning process [19]. Classification is one of the major research issues in EDM and can be viewed as development of a prediction model [20]. To apply data mining to education, students can receive information about their classmates' performance and teachers can take advantages of EDM to improve the educational environment. On this basis, teachers can also adopt different teaching strategies for students with different learning levels, such as providing opportunities for students with excellent performance to participate in the project, and giving warnings for students with poor performance. To achieve this goal, researchers explored data obtained from traditional universities and online learning and came up with various methods. Most methods used academic features (e.g., grades, quizzes and weekly homework) and non-academic characteristics (e.g., age and gender) as input. The above is from the perspective of educators, while satisfaction is student-centered. Besides improving learning efficiency, another important goal of our education policy is to improve students' satisfaction with the learning environment [21]. We designed questionnaires to get students' feedback on their learning experience. According to the questionnaires, the learning mode is constantly improved so that students can more actively engage in the process of learning.

The contributions of this paper are as follows:

1. We applied blended learning to the engineering practice course, and explored the impact on students' performance, classification and satisfaction. This study provided an example for the design of blended learning and showed the potential of personalized teaching.
2. This paper focuses not only on the paper exam scores, but also on the experimental scores.
3. Machine learning models and deep learning models were compared to study which model is more suitable for classifying students.

2. Related Work

In blended learning, most researchers focus on the impact on students' performance, especially their final grades. The effectiveness of blended learning in terms of students' performance is well established in multiple disciplines, including physiology [22, 23], anatomy [24, 25], nursing [26, 27], physics [28, 29], and mathematics [30, 31]. Moreover, this learning mode has been also shown to improve learning outcomes in engineering education [16–18]. Alkhatib [16] proposed the blended learning method in the form of flipped classrooms for engineering course. The effectiveness of this learning method was verified through a quantitative assessment of program learning outcomes before and after applying the method. And the results showed an average of learning outcomes improved from 3.9 to 4.4 on a scale of 1–5. Martínez et al. [17] used a parallel online group from face-to-face learning to blended learning in an engineering Master's program. There were two learning methods, asynchronous (lecture capture) or synchronous (face-to-face or live broadcast lecture) and students selected one of them. The results demonstrated that the blended learning significantly improved students' average grades. Onofrei et al. [18] confirmed that blended learning can enhance students' learning ability in an undergraduate engineering computer-aided design (CAD) module. Compared with students participating in traditional face-to-face learning, the use of blended learning had a significant impact on the final grades in the CAD module. However, these engineering courses focus on software and are rarely practice-oriented.

Generally, we learn about students' views on the blended learning through questionnaires. Jen-Her *et al.* [26] [32] used a questionnaire survey of 212 participants in a blended e-learning to show that learning climate and performance expectations significantly affect learning satisfaction. Prifti et al. [33] focused on student satisfaction resulting from the introduction of a blended course, which was implemented in 'Management' course and proved that Learning Management System has a positive impact on students' satisfaction. Peng et al. [34] conducted a questionnaire to 960 students who study English as a Foreign Language students, and 10 of them participated in an interview. The results revealed that the learning motivation within a blended learning environment can improve students' English linguistic competence and facilitated their psychological development of English learning.

EDM focuses on the exploit of statistical algorithms, machine learning, and deep learning to analyze educational data, explain educational phenomena, and provide services for educators, learners and managers [35]. De Albuquerque et al. [36] applied artificial neural networks (ANNs) to predict student's performance and achieved high accuracy (85%) by using grades, periods of study and school scores as inputs. Yu et al. [37] applied machine learning methods to predict students' outcome using the click-stream data of MOOCs videos and the K-Nearest Neighbor (KNN) method was used to classify the data. Nespereira et al. [38] utilized Random Forest (RF) and Support Vector Machine (SVM) methods to discover the underlying relationship between students' past course interactions with Learning Management Systems and their tendency to pass/fail.

Recently, deep learning models have been widely used for classification in many fields. In the academic field, deep learning model is used to predict and enhance the student performance [39]. Long short-term memory (LSTM) is a deep learning method, which consists of several non-linear layers that contribute to learning the representations from the input data. Limited studies have used these methods for early prediction of dropouts [40, 41]. Ahmed et al. [42] employed the LSTM network on a set of implicit features to predict learners' weekly performance. Results showed that accuracy of the proposed model was 82%–93% throughout course week. Aljohani et al. [43] proposed a deep LSTM model to classify students' outcome, and achieved the best result with 0.7579 recall score and 0.9346 precision score, and their learning accuracy outperformed the baseline LR and ANNs by 18.48% and 12.31%, respectively. Most of the studies are for either traditional face-to-face learning or online MOOC teaching, and few literatures focuses on blended learning of engineering practice courses. Moreover, the rapid development of deep learning has also provided us with opportunities to explore effective methods for predicting learners' academic performance under blended teaching. It is essential to find a suitable deep learning model to classify students.

3. Methods and Data Collection

The study protocol was approved by the Institutional Review Board Committee at Tiangong University. Blended learning in the form of flipped classroom was introduced in the Electrical & Electronical Engineering Practice course for 182 first-year Communication Engineering students in the 2019–2020 academic year, while 226 first-year students from the same major in the 2018–2019 academic year still adopted traditional learning. The course contained 40 class hours of traditional learning in the academic year (2018–2019), while 8 class hours of online learning and 32 class hours of offline learning in the following academic year (2019–2020).

3.1 Design of Blended Learning

SPOC combines with traditional classrooms to implement the transformation of student-centered teaching methods according to the development of blended learning. Various online and offline activities are designed to achieve a deep combination of online and offline learning, as shown in Fig. 1. These activities included self-paced learning, such as watching videos, doing quizzes etc. The activities marked with * are online learning activities and carried out on the SPOC platform while other activities are mainly offline activities.

In online learning, students mainly learned on the SPOC platform. They must preview the course by watching videos, completing the question and answer (Q&A) in the platform. They can freely choose the time and place to repeatedly review the online course materials, but the latest videos must be completed within 3 hours before class. The teacher checked the results of online learning, and found out the weak links of the students.

In offline learning, the teacher organized the students to discuss the key points and difficulties of this lesson individually or in groups. And students started to do the experiment after understanding the precautions. Finally, the teacher evaluated the scores of the experiment.

After-class activities were designed to help students digest and consolidate what they had learned. They were asked to complete the homework corresponding to the teaching content of each unit deployed on the SPOC platform within the specified time. During this period, students could selectively review the videos and consult relevant materials.

3.2 Design of Questionnaire Survey

We applied a questionnaire survey to collect the satisfaction of the blended learning by the blended learning group. The questionnaire survey was

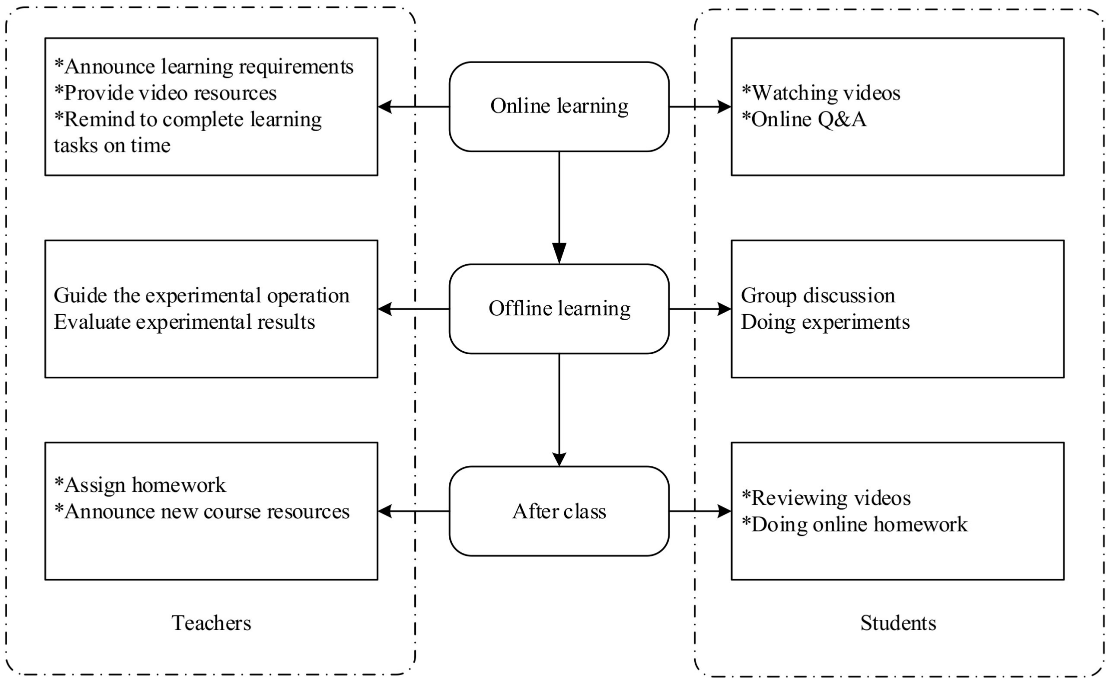


Fig. 1. Flowchart of the blended learning mode.

mainly in four aspects, namely online learning, online homework, Q&A, and learning method to investigate students' satisfaction. Students were required to rank items on a scale from 1 = very dissatisfied to 3 = neutral to 5 = very satisfied. Students answered the questionnaires anonymously.

3.3 Data Collection

In face-to-face learning, the final grade consisted of the following parts. Practical operation and offline homework were worth 55% and 5%, respectively. The rest were a test accounted for 20%, daily performance accounted for 10%, and an experimental report accounted for 10%. In blended learning, videos and the courseware were published on the SPOC platform in advance. Among them, the corresponding score was obtained according to the completion time of each video, and finally all the scores were averaged to obtain the video score, which accounted for 10%. To fulfill the course requirements, students had to take the test, worth 20%. As the assessment in this course, practical operation and online homework were worth 45% and 5%, respectively. Moreover, students were requested to prepare one experimental report, accounting for 10% of their final grade. Daily performance accounts for 10%. We collected all the data of the above students. A total of 182 students in blended learning group were asked to take part in the questionnaire and 155 questionnaires were returned.

4. Data Analysis

4.1 Correlation Analysis

Pearson correlation coefficient is often used to express the linear correlation between dependent variables and independent ones. The greater the absolute value, the stronger the correlation. In blended learning, we studied the correlation of video scores, online homework scores, test scores and practical operation scores, which are shown in Fig. 2. Pearson coefficient between the video scores and the test scores is 0.31, belonging to weak correlation. Correlation between the video scores and the practical operation scores is 0.41, which is medium correlation. It can be seen that video learning has a certain effect on the experimental operation. Compared with the video scores, the online homework scores are weakly correlated with the practical operation scores. Through correlation analysis, teachers may understand which behaviors are correlated with student performance.

From the correlation analysis, it is observed that the video scores are related to the test scores and the practical operation scores, as shown in Fig. 3. The video scores are divided into three categories, namely 40~60 points, 60~80 points and 80~100 points, labeled 0, 1 and 2 respectively. Fig. 3(a) shows that the students whose video scores are in the middle had the best test scores overall. Fig. 3(b) shows that the higher the video scores, the better the practical operation scores.

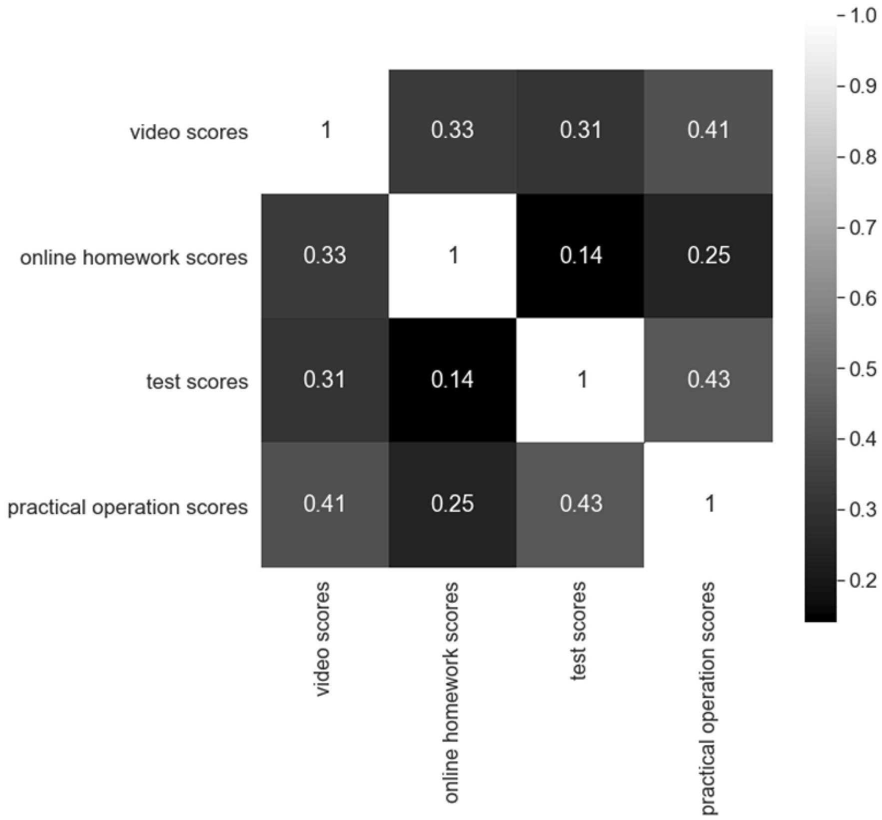


Fig. 2. Pearson coefficient between multiple variables. The bar on the right represents the correlation coefficient, the darker the color, the higher the correlation coefficient value. Each square represents the correlation coefficient between two variables.

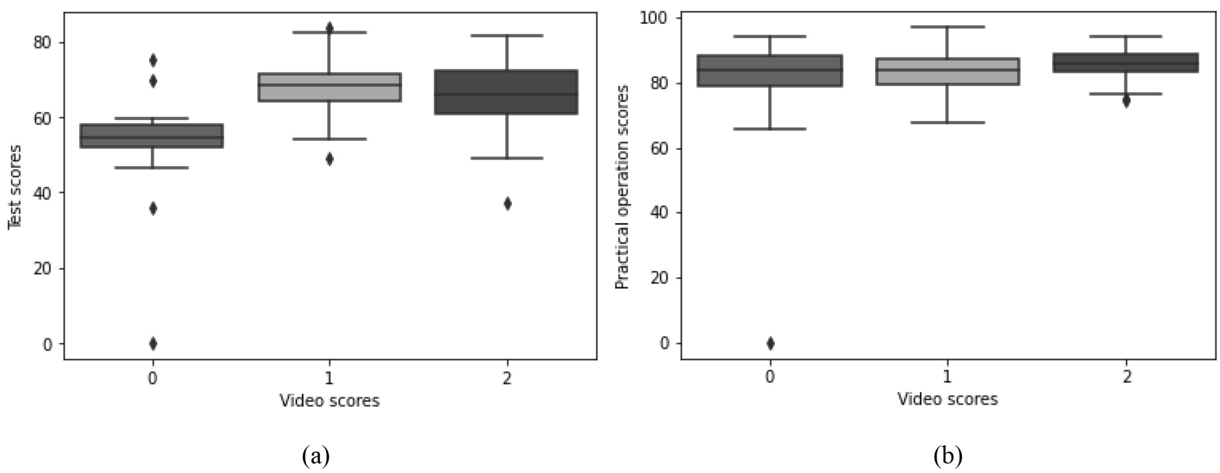


Fig. 3. Distribution of (a) test scores and (b) practical operation scores in three video scores categories. The video scores are divided into three categories, namely 40∼60 points, 60∼80 points and 80∼100 points, labeled 0, 1 and 2 respectively.

4.2 Students' Performance

Fig. 4(a) showed that students achieved better practical operation scores in the blended learning mode, and the scores were mainly from 80 to 90 points. In the face-to-face learning mode, the practical operation scores were mainly between 75 and 85 points. Fig. 4(b) showed that the final grades in the blended learning mode were mainly distributed between 80 and 90 points. In the face-to-face learning mode, the final grades were mainly concentrated on 75∼85 points. The overall score range under blended learning had improved by about 5 points.

4.3 Students' Classification

The proposed model was divided into three stages: data preprocessing, model design and model evaluation. The model framework is shown in Fig. 5.

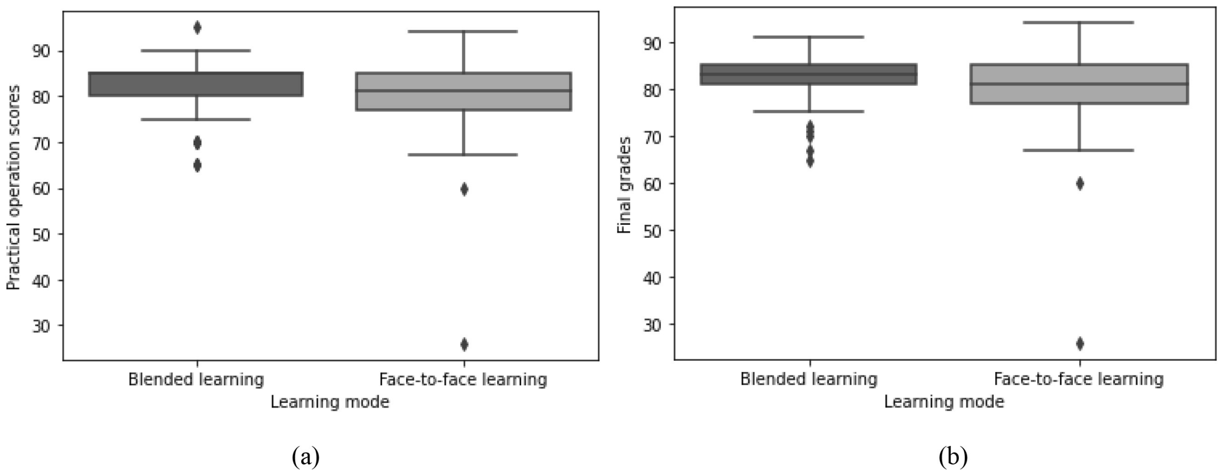


Fig. 4. Distribution of (a) the practical operation scores and (b) the final grades under two learning modes.

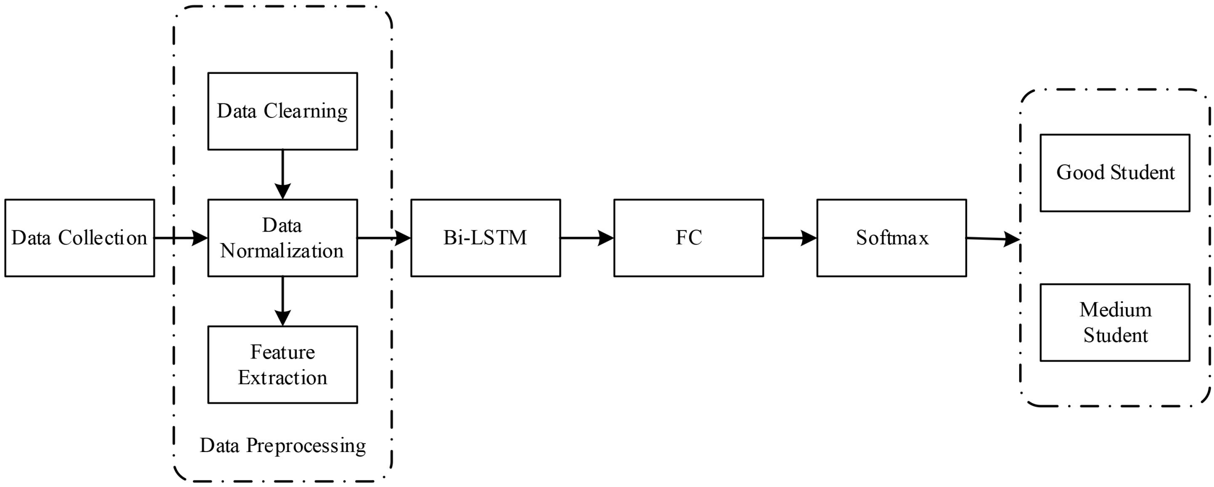


Fig. 5. Student classification based on the Bi-LSTM model.

(1) Data Preprocessing

(1) Data cleaning
In the collected raw data, the missing values and outliers of students' grades are deleted.

(2) Data normalization
The results are normalized to the hundred percentage point system.

(3) Feature extraction and selection

In order to improve the classification efficiency of the model, this study performed the feature extraction. The performance of the classification model depends on the significant features (input variables) that describe student characteristics, and can be used to predict the performance of the students. We extracted five features (X1, X2, X3, X4, and X5) from students' data in traditional face-to-face learning and six features (S1, S2, S3, S4, S5, and S6) from students' data in blended learning, as shown in Table 1.

After the data preprocessing, the data of 182 students were retained under the blended learning, and the data of 226 students were retained under the face-to-face learning. According to the final grades, the students' classification is determined. The students' scores were all above 60, so 60~80 was divided into medium students, the label was set to 0; 80~100 was divided into good students, the label was set to 1. The preprocessing data was split into the ratio of 7:3, i.e., 70% of the data was used to train the model, and the remaining 30% was used to test the proposed model.

(2) Model Selection and Design
LSTM is a type of Recurrent Neural Network (RNN) [44], and it ensures that the entire loop network can proceed more stably. Moreover, LSTM solves the problem of gradient disappearance and gradient explosion of long sequences by selective memory. Through selective memory mechanism, it can ensure the effective use of the information mostly, learn its deep characteristics,

Table 1. List of features used in the study

Features	Description
X1. Practical operation scores	Average of all experimental scores
X2. Experimental report scores	An experimental report submitted at the end of the semester
X3. Offline homework scores	The offline homework at the end of each unit
X4. Daily performance scores	Daily performance is rated based on lateness and absenteeism
X5. Test scores	The final exam at the end of the semester
S1. Practical operation scores	Average of all practical operation scores
S2. Experimental report scores	The same as X2
S3. Online homework scores	The online homework at the end of each unit
S4. Daily performance scores	The same as X4
S5. Test scores	The same as X5
S6. Video scores	Rate according to each video completion

and then make student performance prediction better.

Although LSTM can learn previous information, it can only learn forward information. The bidirectional Long Short-Term Memory (Bi-LSTM) model is an improvement on LSTM, which effectively solves this problem and further improves the learning ability of LSTM. Bi-LSTM structure as shown in Fig. 6. Bi-LSTM combines LSTM with the bidirectional network. Therefore, Bi-LSTM can not only have the advantages of LSTM, but also carry out accurate analysis of sequence data in the reverse direction [45]. This property allows Bi-LSTM to make full use of the information, so that make it possible to do the predictive task effectively.

As illustrated in Fig. 6, the states of forward hidden sequence and the states of backward hidden sequence are calculated by the Bi-LSTM iteratively. The output sequence y from the backward layer and the forward layer then can be updated, where w represents the hidden layer parameters, X_t represents input value, $\vec{h}_t$ and $\overleftarrow{h}_t$ represent the output of the two LSTM layer at time t, $\vec{b}$ denotes bias, and Y_t represents the output value. The formulas of the Bi-LSTM model are shown in the appendix.

In this work, a model based on Bi-LSTM network was proposed to classify students. The proposed model consists of two LSTM layers with 128 and 32 hidden units, respectively. And the dropout layers are set to avoid overfitting and the dropout ratio are set to 0.25. The fully connected layer is followed by a softmax layer to produce a distribution over the 2 (e. g. good and medium) class labels. The binary cross-entropy loss function is employed. In addition, Adam is chosen as the optimizer because of less memory requirements and has the advantages of both AdaGrad to deal with sparse gradients and RMSProp to deal with non-stationary targets.

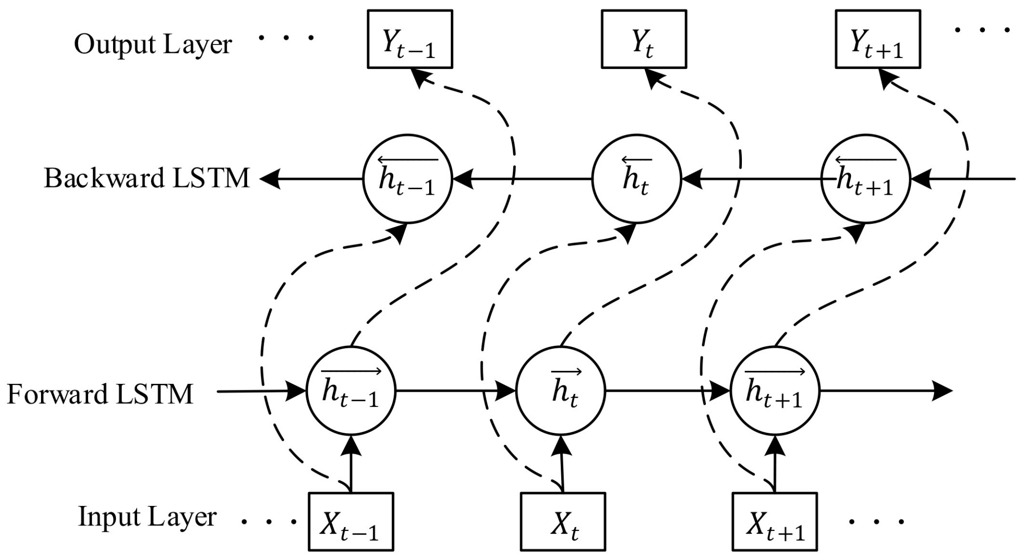
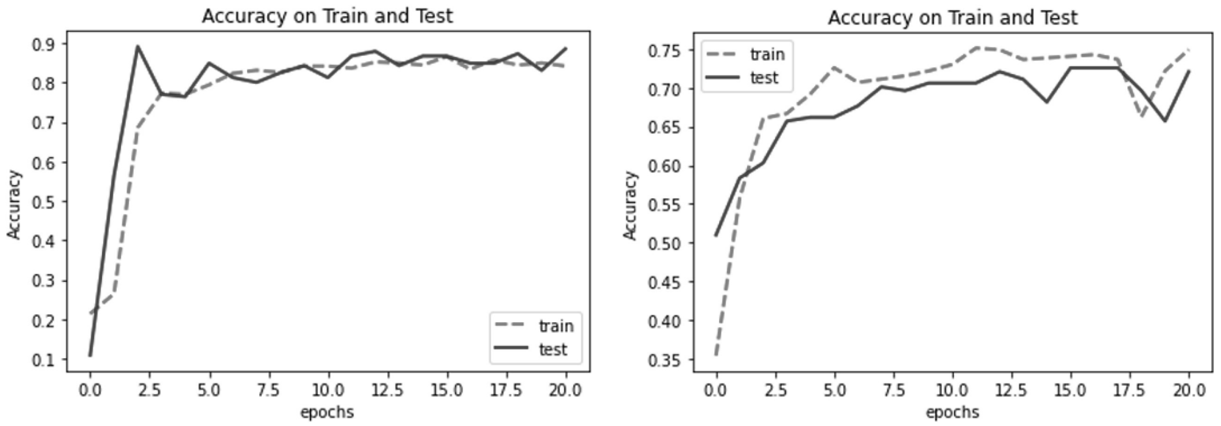


Fig. 6. Structure of the Bi-LSTM network.



(a) (b)

Fig. 7. Classification results of (a) blended learning and (b) face-to-face learning on the final grades. Fig. 7(a). Dotted line: The accuracy curve of the training set. Solid line: The accuracy curve of the testing set. Fig. 7(b). Dotted line: The accuracy curve of the training set. Solid line: The accuracy curve of the testing set.

Table 2. Comparison of classification accuracy of multiple models on the final grades

Model	**Bi-LSTM**	**LSTM**	**RNN**	**ANN**	**SVM**	**LR**	**KNN**	**RF**
Face-to-face learning	72.55%	72.06%	70.59%	67.65%	61.76%	64.71%	64.71%	61.76%
Blended learning	89.09%	83.64%	81.82%	78.18%	81.00%	81.27%	80.63%	81.74%

(3) Classification Model Performance Evaluation
Accuracy is treated as an evaluation metric to evaluate the student classification model. And the higher the accuracy, the better the classification of the model.

The main analysis tool is a curve drawn on a two-dimensional plane, Receiver Operating Characteristic (ROC) curve. The abscissa of the plane is false positive rate (FPR), and the ordinate is true positive rate (TPR). The performance analysis is carried out using the ROC curve. The area under the ROC curve is called the Area Under Curve (AUC). The larger the AUC value, the better the model classification effect.

The following terms are fundamental for understanding the results of model evaluation:

True Positive (TP): The model correctly predicts the class of good students.
False Positive (FP): The model incorrectly predicts the class of good students.
False Negative (FN): The model incorrectly predicts the class of medium students.
True Negative (TN): The model correctly predicts the class of medium student.
TPR measures false negatives against true positives and refers to the ability of the model to identify good students correctly.

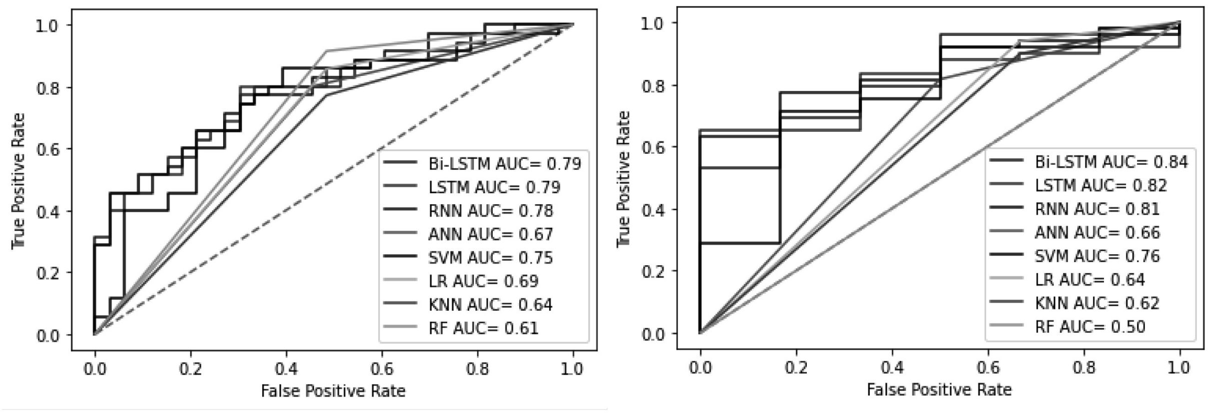
$$TPR = \frac{TP}{TP+FN} \tag{1}$$

FPR measures true negatives against false positives and refers to the ability of the model to identify medium students incorrectly.

$$FPR = \frac{FP}{TN+FP} \tag{2}$$

Fig. 7(a) and Fig. 7(b) show the accuracy plots of the Bi-LSTM model under blended learning and face-to-face learning, highlighting the test accuracy of 89.09% and 72.55%, respectively. It is obviously that the accuracy in blended learning increases steeply from epoch 0 to 5, with minimal changes and gradual improvement from epoch 5 onwards. The experimental results show that the blended learning has better classification effect.

In order to verify the superiority of the proposed model, several deep learning models were selected, such as LSTM model, RNN model, and machine learning models were also used, such as ANN model, SVM model, Logistic Regression (LR) model, KNN model, and the RF model. The experimental results on the final grades are shown in Table 1. The results show that the classification accuracy of the Bi-LSTM model was significantly better than the other models regardless of the learning mode. Obviously, using the same model to classify the students under two learning modes, the classification accuracy of the blended learning was better. In summary, the students' classification based on the Bi-LSTM model had higher accuracy under the blended learning, and the accuracy was



(a) (b)

Fig. 8. ROC curve for (a) face-to-face learning and (b) blended learning. The area under the ROC curve is the value of the Area Under Curve (AUC).

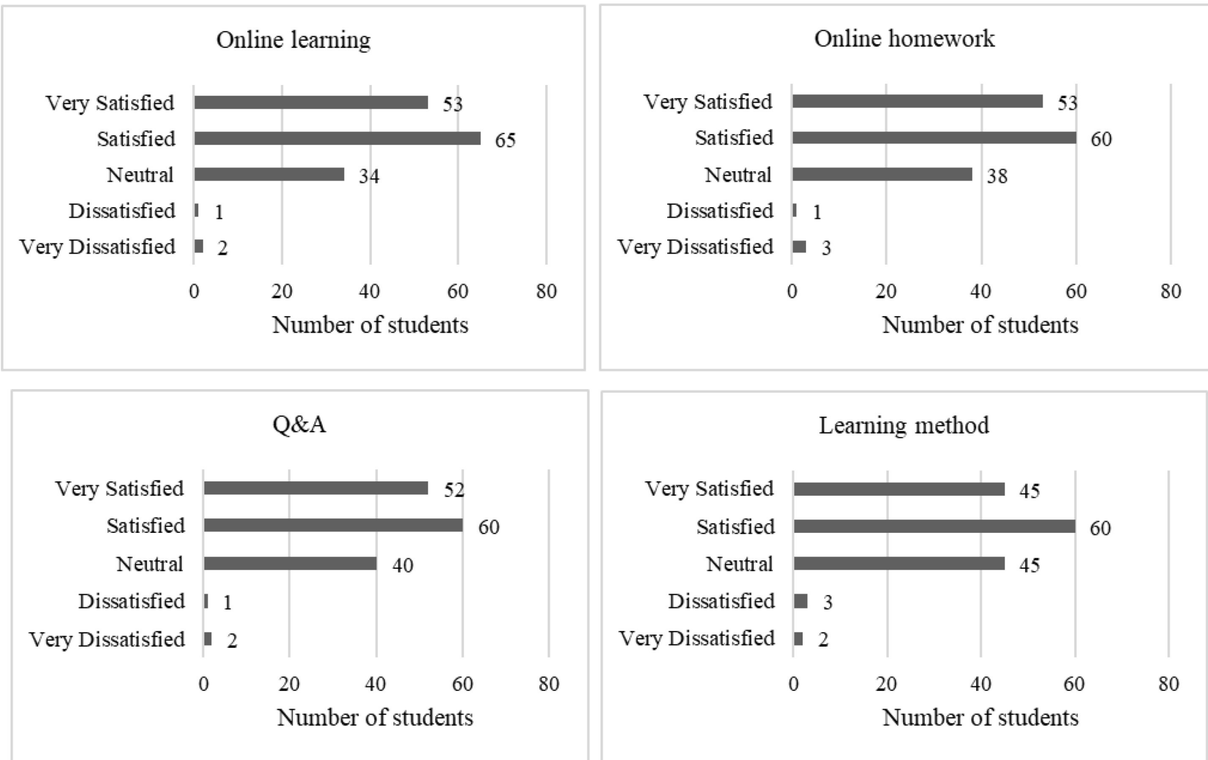


Fig. 9. Students' satisfaction about four aspects of the blended learning: (a) online learning, (b) online homework, (c) Q&A, and (d) learning method.

89.09%, which was at least 5.45% higher than other models.

As revealed in Fig. 8(a), the ROC curve of the Bi-LSTM model had a maximum AUC of 0.79 in face-to-face learning. This also confirms that the Bi-LSTM model had better classification performance. As shown in Fig. 8(b), the ROC curve of the Bi-LSTM model had a maximum AUC of 0.84 in blended learning. It shows that students' classification has better performance on the Bi-LSTM model. In general, compared with face-to-face learning, all models performed better in students' classification under blended learning. And the Bi-LSTM model was better than the other models.

4.4 Students' Satisfaction

Fig. 9 showed the following satisfaction levels in each aspect: online learning was 4.07, online homework was 3.96, Q&A was 4.03, and learning method was 3.92. Most students were satisfied or very satisfied with the blended learning mode in the course.

5. Discussion

This paper verified that blended learning can be successfully implemented in engineering practical education. There are three advantages of the blended learning mode, (i) students arranged their time flexibly according to their learning needs, (ii) online materials could be studied repeatedly, and (iii) they had the opportunity to host group discussions. These activities change the role of students from passive listeners to active learners. They can take the main responsibility for their own learning and at the same time make the learning process more collaborative.

Compared with previous researches, this study not only paid attention to the final grades, but also focused on the practical operation scores. The analysis of the results showed that the blended learning group achieved better performance. This study also contributed to classifying students as good students and medium students through the Bi-LSTM model. The input features of blended learning combined the features of traditional face-to-face learning with online learning. No matter which learning mode was adopted, we compared the proposed model with the baseline model and obtained the best accuracy. And the proposed model had achieved a better classification effect under the blended learning mode. The final questionnaire survey showed subjectively that most students had a positive attitude towards the implementation of blended learning. The improvement in students' performance might be due to the following reasons. First, students selected to pause and re-watch the videos to understand the materials. The correlation analysis also confirmed that the video score affected the practical operation scores. Second, teachers provided more targeted guidance in classroom based on the online answering situation. Third, the Q&A format made students full of energy for learning.

It can be seen that compared with traditional learning, most students prefer blended learning, and this learning mode does improve learning efficiency. However, our research still has some limitations. One is to adopt two learning modes to evaluate teaching effects for two consecutive years separately, and it is in discussion how much the differences between the two groups of students affects the results. In addition, the study is only conducted in this course, so the results may not be applicable to other courses. Thus, our future work would focus on those two problems.

6. Conclusion

This study compared the performance of the blended learning group (182 students) of the academic year (2019–2020) and the traditional learning group (226 students) of the academic year (2018–2019). The blended learning was implemented in this study, combining SPOC and traditional classrooms showed better results regarding students' performance, classification, and satisfaction. Although the introduction of blended learning in engineering education requires meticulous course design and a lot of time for teachers to prepare and provide courses, our implementation of the blended learning model was successful based on students' performance, classification, and satisfaction.

Acknowledgements – This paper was supported by the National Natural Science Foundation of China (NSFC): 61907032 and the Center for Engineering Internship and Training at Tiangong University. The authors appreciate the teachers and students involved with this project.

References

1. Z. J. Xu, H. Yuan and Q. S. Liu, Student Performance Prediction Based on Blended Learning, *IEEE Transactions on Education*, **64**(1), pp. 66–73, 2021.
2. M. Dillon, E. C. Kokkelenberg, and S. M. Christy, The effects of class size on student achievement in higher education: Applying an earnings function, *In Proceedings of the 42nd Annual AIR Forum*, Toronto, Canada, p. 29, 2002.
3. J. Monks and R. M. Schmidt, The impact of class size on outcomes in higher education, *The B. E Journal of Economic Analysis & Policy*, **11**(1), p. 62, 2011.
4. B. N. Matta, J. M. Guzman, S. K. Stockly and B. Widner, Class size effects on student performance in a Hispanic-serving institution, *The Review of Blank Political Economy*, **42**(4), pp. 443–457, 2015.
5. W. Xiao, J. F. Chen and J. Wang, Reform of electrical and electronic experiment teaching and the cultivation of students' ability, *Journal of Physics: Conference Series*, **1168**(2), p. 022029, 2019.
6. S. S. Jaggars, Choosing between online and face-to-face courses: Community college student voices, *American Journal of Distance Education*, **28**(1), pp. 27–38, 2014.
7. R. M. Amanda, L. P. Andrea and E. P. Michael, Best practices for use of blended learning, *American Journal of Pharmaceutical Education*, **81**(3), p. 49, 2017.
8. O. J. Alkhatib, An interactive and blended learning model for engineering education, *Journal of Computers in Education*, **5**, pp. 19–48, 2018.
9. C. Alario-Hoyos, I. Estévez-Ayres, C. Delgado Kloos, P. J. Muñoz-Merino, E. Llorente-Pérez and J. Villena-Román, Redesigning a freshman engineering course to promote active learning by flipping the classroom through the reuse of MOOCs, *International Journal of Engineering Education*, **35**(1B), pp. 385–396, 2019.

10. S. Gao, W. Y. Li, J. M. Liu and H. Gao, Application of flipped classroom based on MOOC in bridge engineering CAD course, *Frontiers in Educational Research*, **3**(6), p. 030619, 2020.
11. K. Andersen, G. Geirsdottir, S. E. Thorsteinsson, H. Thorbergsson and K. S. Gudmundsson, Engineering education case studies: engaging students in blended learning, *2018 IEEE International Professional Communication Conference (ProComm)*, Toronto, ON, Canada, 22–25 July 2018, pp. 203–206, 2018.
12. L. S. Brew, The role of student feedback in evaluating and revising a blended learning course, *The Internet and Higher Education*, **11**(2), pp. 98–105, 2008.
13. L. P. Galway, K. K. Corbett, T. K. Takaro, K. Tairyan and E. Frank, A novel integration of online and flipped classroom instructional models in public health higher education, *BMC Medical Education*, **14**(1), p.181, 2014.
14. J. F. Strayer, How learning in an inverted classroom influences cooperation, innovation and task orientation, *Learning Environments Research*, **72**(9), pp. 1048–1057, 2008.
15. K. M. Martin, J. M. Gallimore, Comparing student performance in flipped and non-flipped space mechanics classrooms, *International Journal of Engineering Education*, **36**(5), pp. 1615–1624, 2020.
16. K. M. Whitcomb, Z. Y. Kalender, T. J. Nokes-Malach, C. D. Schunn and C. Singh, Engineering students' performance in foundational courses as a predictor of future academic success, *International Journal of Engineering Education*, **36**(4), pp. 1340–1355, 2020.
17. P. J. Martínez, F. J. Aguilar and M. Ortiz, Transitioning from face-to-face to blended and full online learning engineering master's program, *IEEE Transactions on Education*, **63**(1), pp. 2–9, 2020.
18. G. Onofrei and P. Ferry, Reusable learning objects: a blended learning tool in teaching computer-aided design to engineering undergraduates, *International Journal of Educational Management*, **34**(10), pp. 1559–1575, 2020.
19. C. Romero and S. Ventura, Educational data mining: A survey from 1995 to 2005, *Expert Systems with Applications*, **33**(1), pp. 135–146, 2007.
20. B. Predic, G. Dimic, D. Rancic, P. Strbac, N. Macek and P. Spalevic, Improving final grade prediction accuracy in blended learning environment using voting ensembles, *Computer Applications in Engineering Education*, **26**(6), pp. 2294–2306, 2018.
21. A. S. Qutieshat, M. O. Abusamak, and T. N. Maragha, Impact of Blended Learning on Dental Students' Performance and Satisfaction in Clinical Education, *Journal of Dental Education*, **84**(2), pp. 135–142, 2020.
22. C. Gopalan and M. C. Klann, The effect of flipped teaching combined with modified team-based learning on student performance in physiology, *Advances in Physiology Education*, **41**(3), pp. 363–367, 2017.
23. P. L. Megaw and M. A. Zimanyi, Redesigning first year anatomy and physiology subjects for allied health students: Introducing active learning experiences for physiology in a first semester subject, *International Journal of Innovation in Science and Mathematics Education*, **27**(8), pp. 26–35, 2019.
24. T. R. Fleagle, N. C. Borcherding and D. S. Hoffmann, Application of flipped classroom pedagogy to the human gross anatomy laboratory: Student preferences and learning outcomes, *Anatomical Sciences Education*, **11**, pp. 385–396, 2018.
25. A. El Sadik and W. Al Abdulmonem, Improvement in student performance and perceptions through a flipped anatomy classroom: shifting from passive traditional to active blended learning, *Anatomical Sciences Education*, **14**, pp. 482–490, 2021.
26. A. M. Blissitt, Blended learning versus traditional lecture in introductory nursing pathophysiology courses, *Journal of Nursing Education*, **55**(4), pp. 227–230, 2016.
27. K. A. Berga, E. Vadnais, J. Nelson, S. Johnston, K. Buro, R. Hu and B. Olaiya, Blended learning versus face-to-face learning in an undergraduate nursing health assessment course: A quasi-experimental study, *Nurse Education Today*, **96**, p. 104622, 2021.
28. L. Deslaureiers, E. Schelew and C. Wieman, Improved learning in a large enrollment physics class, *Science*, **332**(6031), pp. 862–864, 2011.
29. J. L. L. Cagande and R. R. Jugar, The flipped classroom and college physics students' motivation and understanding of kinematics graphs, *Issues in Educational Research*, **28**(2), pp. 288–307, 2018.
30. Z. R. Sun, K. Xie and L. H. Anderman, The role of self-regulated learning in students' success in flipped undergraduate math courses, *The Internet and Higher Education*, **36**, pp. 41–53, 2018.
31. Z. R. Sun, and K. Xie, How do students prepare in the pre-class setting of a flipped undergraduate math course? A latent profile analysis of learning behavior and the impact of achievement goals, *The Internet and Higher Education*, **46**(1), p. 100731, 2020.
32. J. H. Wu, R. D. Tennyson and T. L. Hsia, A study of student satisfaction in a blended e-learning system environment, *Computers & Education*, **55**(1), pp. 155–164, 2010.
33. R. Prifti, Self–efficacy and student satisfaction in the context of blended learning courses, *Open Learning: The Journal of Open, Distance and e-Learning*, **6**, pp. 1–15, 2020.
34. R. Peng and R. Fu, The effect of Chinese EFL students' learning motivation on learning outcomes within a blended learning environment, *Australasian Journal of Educational Technology*, pp. 61–74, 2021.
35. C. Romero and S. Ventura, Educational Data Mining: A Review of the State of the Art, *IEEE Transactions on Systems, Man, and Cybernetics*, **40**(6), pp. 601–618, 2010.
36. R. M. de Albuquerque, A. A. Bezerra, D. A. de Souza, L. B. P. do Nascimento, J. J. de Mesquita Sá and J. C. do Nascimento, Using neural networks to predict the future performance of students, *2015 International Symposium on Computers in Education (SIIE)*, Setubal, Portugal, 25–27 November 2015, pp. 109–113, 2015.
37. C. H. Yu, J. Wu and A. C. Liu, Predicting learning outcomes with MOOC clickstreams, *Education Sciences*, **9**(2), p. 104, 2019.
38. C. G. Nespereira, E. Elhariri, N. El-Bendary, A. F. Vilas and R.P.D. Redondo, Machine Learning Based Classification Approach for Predicting Students Performance in Blended Learning, *The 1st International Conference on Advanced Intelligent System and Informatics (AISI2015)*, November 28–30, 2015, Beni Suef, Egypt, **407**, pp. 47–56, 2015.
39. M. Aniche, E. Maziero, R. Durelli and V. Durelli, The Effectiveness of Supervised Machine Learning Algorithms in Predicting Software Refactoring, arXiv preprint arXiv:2001.03338, 2020.
40. M. Aniche, E. Maziero, R. Durelli and V. Durelli, The Effectiveness of Supervised Machine Learning Algorithms in Predicting Software Refactoring, *IEEE Transactions on Software Engineering*, 2020.
41. M. Fei and D. Yeung, Temporal Models for Predicting Student Dropout in Massive Open Online Courses, *2015 IEEE International Conference on Data Mining Workshop (ICDMW)*, Atlantic City, NJ, USA, 14–17 November 2015, pp. 256–263, 2015.

42. S. Hassan, H. Waheed, N. R. Aljohani, M. Ali, S. Ventura and F. Herrera, Virtual learning environment to predict withdrawal by leveraging deep learning, *International Journal of Intelligent Systems*, **34**(8), pp. 1935–1952, 2019.
43. A. A. Mubarak, H. Cao and S. A. Ahmed, Predictive learning analytics using deep learning model in MOOCs' courses videos, *Education and Information Technologies*, **26**, pp. 371–392, 2021.
44. N. R. Aljohani, A. Fayoumi and S. U. Hassan, Predicting at-risk students using clickstream data in the virtual learning environment, *Sustainability*, **11**(24), p. 7238, 2019.
45. J. Yang, X. Huang and X. Wu, EEG-based emotion classification based on Bidirectional Long Short-Term Memory Network, *Procedia Computer Science*, **174**, pp. 491–504, 2020.
46. S. X. Wang, X. Wang, S. M. Wang and D. Wang, Bi-directional long short-term memory method based on attention mechanism and rolling update for short-term load forecasting, *International Journal of Electrical Power & Energy Systems*, **109**, pp. 470–479, 2019.

Appendix

Abbreviations

SPOC: Small Private Online Course.
MOOC: Massive Open Online Course.
EDM: Educational Data Mining.
CAD: Computer-aided design.
ANNs: artificial neural networks.
KNN: K-Nearest Neighbor.
RF: Random Forest.
SVM: Support Vector Machine.
LSTM: Long short-term memory.
Q&A: Online question and answer area.
RNN: Recurrent Neural Network.
Bi-LSTM: Bidirectional Long Short-Term Memory.
ROC: Receiver Operating Characteristic.
FPR: False Positive Rate.
TPR: True Positive Rate.
AUC: Area Under Curve.
TP: True Positive.
FP: False Positive.
FN: False Negative.
TN: True Negative.
LR: Logistic Regression.

Students' classification – Model Selection and Design

(1) Using input x_t and the previous hidden state h_{t-1}, the forget gate decides what to keep or forget from the previous states.

$$f_t = \sigma\left(W_f * [h_{t-1}, x_t] + b_f\right) \tag{1}$$

(2) The input gate determines what new information will be stored in the cell. First, the cell calculates a memory cell candidate $\tilde{c}_t$. Next, the current state c_t depends on the result of the previous forget gate and the input gate.

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{c}_t = \tanh(W_c * [h_{t-1}, x_t] + b_c) \tag{3}$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{4}$$

(3) The output gate $\mathrm{o_t}$ decides how much information will be transferred into the next cell.

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

where W denotes weight matrices, b denotes biases, σ is the logistic function.

The original signal is fed into the information directly into the Bi-LSTM network through the input layer. The sample signal is calculated by the forward LSTM to get a value, and the reverse LSTM calculation obtains a value. The value of the incoming hidden layer is determined by those two values. The formulas are as follows:

$$\overrightarrow{h_t} = f\left(\vec{w} * X_t + \vec{w} * \vec{h}_{t-1} + \vec{b}\right) \tag{7}$$

$$\overleftarrow{h_t} = f\left(\overleftarrow{w} * X_t + \overleftarrow{w} * \overleftarrow{h}_{t-1} + \overleftarrow{b}\right) \tag{8}$$

$$Y_t = g\left(U * \left[\vec{h}_t; \overleftarrow{h}_t\right] + c\right) \tag{9}$$

where w represents the hidden layer parameters, X_t represents input value, $\vec{h}_t$ and $\overleftarrow{h}_t$ represent the output of the two LSTM layer at time t, $\vec{b}$ denotes bias, and Y_t represents the output value.

Zhenqian Shen is an Associate Professor in the Center for Engineering Internship and Training, Tiangong University. He teaches Electrical & Electronical Engineering Practice. He completed his PhD in Tiangong University. His research interests in electronic technology and embedded system development. He is currently the Director of the Electrical and Electronic Practice Teaching Department.

Huijuan Zhao is a graduate student majoring in School of Life Sciences in Tiangong University. She has focused on several research initiatives about education, specifically in areas related to SPOCs (Small Private Online Courses), and the analysis of students' interaction with them. Her skills and interests include data mining and machine learning.

Zheyu Liu is an associate professor in the Department of Educational Technology at the Faculty of Education at Tianjin Normal University. Her research interests include educational technology, learning sciences and deep learning.