Data Mining Technology-Based Algorithms for Evaluating English Language Teaching Indicators

Wang Qian(✉), Wang Jiaxin, and Zhou Huixing

Beijing Polytechnic, Beijing 100176, China
stephaniewq@163.com, wangjiaxin@bpi.edu.cn

Abstract. TE is a judgement on the value of teachers' teaching (TT) and students' learning (SL), and has become an important part of the teaching management and teaching process in universities. There are many common TE systems, most of which evaluate the behavioural performance of teachers, while the learning process and effectiveness of students are rarely mentioned. At the same time, the workflow of implementing TE is tedious and often requires the completion of a large number of data calculation tasks. Therefore how to use modern science and technology to establish a sound, objective and feasible classroom TE system and optimise the evaluation process is an important issue that needs to be addressed urgently. The main objective of this paper is to conduct a study on the evaluation algorithm of English teaching indicators based on data mining (DM) technology. Starting from the construction of a learning-centred university TE system, this paper optimises student TE indicators by using data correlation analysis and association rules. At the same time, machine learning algorithms are introduced into the TE process to build TE models and automate the TE process. Through clustering, the experiment can divide all teachers into corresponding categories, analyse the overall characteristics of teachers in each category, and obtain the performance of teachers in different categories in each indicator, and teachers can focus on their lower level indicators according to the performance of each indicator in their respective categories.

Keywords: Data Mining · English Language Teaching · Teaching Indicators · Indicator Evaluation

1 Introduction

Currently, many forms of TAL have emerged in the education sector. Although, with the rapid development of the Internet, online education is becoming more and more popular, traditional classroom teaching still has an important and fundamental position in campus teaching. At the same time, classroom TE, as a necessary part of teaching management, is of great importance to the development of schools. TE mainly studies the value of TT and SL, and its evaluation includes both the evaluation of TT work and the evaluation of SL outcomes [1].

Y. Zhang and N. Shah (Eds.): BigIoT-EDU 2023, LNICST 580, pp. 49–60, 2024.
https://doi.org/10.1007/978-3-031-63130-6_7

In a related study, Evangelia et al. explored the effectiveness of a pedagogical approach using information and communication technology (ICT), based on Van Hiele's level of geometric thinking and Hoffer's skills in describing geometric thinking, for teaching the English alphabet [2]. The results of the study showed that the impact of the intervention on SL of the English alphabet was statistically significant and that this impact varied according to students' skills, which could be attributed to a number of factors.The Sedat study investigated Turkish pre-service English teachers' perceptions on the FCM and LMS platforms Google Classroom [3]. The findings show that service learning teachers have a very positive view of FCM in terms of student motivation, effectiveness, engagement and overall satisfaction. They also found that classes required more time to prepare for lessons, that lesson preparation had a positive impact on motivation, that each participant was given the opportunity to learn at their own pace, and that learning by doing was encouraged through increased practice. It was also noted that participants were satisfied with the teachers' attitude towards the online platform [4].

The integration of the global economy has made English a universal language as early as the early 1990s. The deepening of international scientific, economic, and cultural exchanges has set higher requirements for the college English teaching level of Chinese universities and educators. The country urgently needs to cultivate high-quality practical English talents with solid basic knowledge. The typical problem with English teaching quality evaluation methods has always been that the data is not comprehensive enough and the evaluation is not objective enough [5]. The emergence of data mining technology, and the improvement and maturity of massive data classification and recognition algorithms provide the possibility to solve these problems. Yu Chaoyang pointed out the idea of combining data analysis technology with teaching quality evaluation system in his "AHP-PCA-SVM Evaluation of Higher Mathematics Teaching Quality", Expounded the theoretical significance and practical attempt of teaching evaluation of big data technology application "Chen Liangdi, Yang Bo, and others have made discrete improvements to the kernel function of the SVM model for teaching quality monitoring and evaluation, which can effectively improve the objectivity of teaching quality monitoring. Yang Zhao and other experts proposed applying the Logistic algorithm to the evaluation of English teaching quality, selecting 0.47 as a cross-sectional area, and conducting segmentation experiments to confirm that the accuracy of artificial statistical recognition has greatly improved [6]. Based on previous research experience, due to the Logistic regression model Type is closely related to the parameter values of boundary points, and unreasonable parameter settings can lead to a greater probability of miscalculation. This paper proposes an improved Logistic algorithm and introduces SVM support vector machines to combine with this algorithm to reduce the impact of boundary points on the algorithm, improve the accuracy of classification recognition and feature extraction, in order to improve the level of college English quality teaching in China, Objectively, it provides an objective, scientific, and reasonable evaluation method to solve the problems existing in the process of English teaching evaluation, such as the unreasonable formulation of teaching content, the single teaching method, the uneven level of teachers, and the incomplete teaching evaluation system [7].

DM technology is a product of the rapid development of information technology. The use of DM methods can capture more finely the data of changes at all levels and their complex relationships, helping decision makers to have a clearer grasp of the current situation, monitor TQ more comprehensively, and effectively regulate the factors affecting TQ, so as to achieve the purpose of safeguarding the quality of education. In this work, the SPSS and Weka DM tools are used to conduct an in-depth study and analysis of various data on the current state of the teaching model, to explore the complex relationships behind the data and their value and meaning, and then to propose additional methods and measures on how to effectively use DM to implement TQ monitoring and to explore how to optimize the use of student assessment data in conjunction with the results of the analysis To explore how to conduct [8].The study also explores how the results of the analysis can be used to optimise the use of student assessment data, improve the student academic monitoring and curriculum early warning system, and innovate academic evaluation and career guidance methods, so as to provide meaningful references for the implementation of TQ monitoring.

2 Design Research

2.1 Direction of Evaluation

The Microsoft SQL Server 2000 database can scientifically organize and manage a large amount of data, and can analyze and count these data. And has excellent sharing and manageability. The selection of a database should fully consider the actual needs of the system, not only to meet the needs of system operation, but also to facilitate the user and programming habits of developers. In this system, I have selected the Microsoft sQLserver 2000 database. As a database management system, Microsoft SQL Server 2000 provides stable data storage and management, which is fully suitable for the needs of this system. These functions are sufficient for this system [9]. Microsoft SQL Server 2000 has powerful network processing capabilities, support for data warehouses, and online transaction processing capabilities.

The assessment of the TQ and learning (TAL) is also based solely on the good or bad results of students' examinations or the high or low evaluation of teachers to make a simple assessment, the data collection process is cumbersome, such assessment lacks systematization and comprehensiveness, and in today's complex educational situation, the results are mostly neither practical nor accurate.

Nowadays, the value implied by BD has gradually become the focus of attention in all walks of life, and the processing technology of BD is becoming increasingly mature, ushering in the best development opportunities for education [10]. Using big data (BD) to serve education comprehensively and adopting evidence-based teaching allows students to be more aware of their learning, allowing teachers to adjust their education methods in a timely manner and allowing the education system to be more rationally transformed.

Teaching quality (TQ) is an important criterion for measuring teaching and guiding teaching reform, and can objectively reflect the level of educational attainment and the extent to which educational outcomes are good or bad [11]. The evaluation of TQ can be based on two aspects: firstly, students, who are the most important subject in teaching, can objectively reflect the TQ by analysing their learning effectiveness; secondly, teachers, who are the main source of knowledge for students, can also reflect the TQ by evaluating the TT performance. Past evaluation approaches have also focused on these two aspects, but the drawback is that either the students' perspective or the teachers' perspective is evaluated, and less research has been done to evaluate multiple perspectives together [12].

2.2 Monitoring Content

Based on the many factors that influence the quality of TAL, such as the school environment and conditions, teacher conditions, management levels, educational and teaching activities, and academic quality, it constitutes outcome monitoring and process monitoring. The content of monitoring will be determined as follows [13].

(1) School-level monitoring content

The content of school-level monitoring includes: teachers' classroom teaching plans and teaching processes; SL behaviour and moral quality; subject tests and stage examination results and test paper answers.

(2) District and county level monitoring

The content of monitoring at the district and county levels includes: the completion of the school curriculum plan and curriculum objectives; the structure of teachers; the teaching environment and school management; the teaching process of teachers; the learning behaviour and moral quality of students; and the results of subject tests and stage general examinations and the answers to examination papers.

(3) Construction of the indicator system

The establishment of a system of monitoring indicators is a key element of monitoring. An organic set of indicators and criteria for monitoring at all levels will facilitate quantitative and qualitative analysis of technical quality. The document defines the structure of the monitoring indicator system based on four aspects of monitoring: the quality of school management, the teaching and learning process of teachers, the learning behaviour of students and academic quality [14].

2.3 Steps of G1 Method to Calculate Weights

Step 1: Determine the sequential relationship.

Let the set of assessment indicators be noted as m1,m2,…,mn, the group of experts to compare the importance of these indicators to judge, and in these indicators they think the most important one, recorded as m1; and then in the remaining n−1 indicators selected as long as the most important one, recorded as m2; and so on, in the remaining n–(k−1) indicators in this way selected the most important indicators, respectively level as mk; until the selection, the indicator until only the last indicator remains in the set, which is recorded as mn [15].

After the above calculation steps, the order relationship of this indicator set can be derived as

$$m_1 > m_2 > m_3 > \cdots > m_n \quad (1)$$

Step 2: Determine the relative importance between neighbouring indicators wk-1 and wk. Denoted as

$$q_k = w_{k-1} \big/ w_k, k = n, n-1, n-2, \ldots, 3, 2, 1; \quad (2)$$

This allows the relative importance of each neighbouring indicator to be determined according to the ordinal relationship derived in the first step, and to facilitate comparison we can set the least important indicator qk = 1.

Step 3: Calculate the weight values for each indicator. When the group of experts are all measured objectively, it is clear that there are

$$q_{k-1} \geq q_k, k = n, n-1, n-2, \ldots ,3,2,1; \quad (3)$$

$$\text{w} = \{1 + \sum\nolimits_{k=2}^{n} \prod\nolimits_{i=k}^{n} q_i\}^{-1} \quad (4)$$

$$W_{k-1} = p_k W_{\text{k}}, k = n, n-1, n-2, \ldots, 3,2, 1. \quad (5)$$

3 Experimental Study

3.1 Design and Implementation of the Teaching Evaluation (TE) Module

(1) Overall design of the module

TE system usually includes several modules such as expert evaluation, teachers' mutual evaluation, teachers' self-evaluation and students' evaluation. This paper mainly implements the student evaluation module from the perspective of student learning, and other modules can be evaluated according to their corresponding evaluation indexes, using the same evaluation algorithm to construct models and complete the evaluation.

The student evaluation module implemented in this paper is divided into two parts: the front-end visualization interface and the back-end data processing. The front-end interface includes the collection of data, the display of evaluation results, etc.; the back-end data processing includes the storage of data, the invocation of algorithms, etc.

(2) Main function analysis

The main functions of the student assessment module designed in this paper include: user login and registration, enquiry of assessment records, collection of assessment questionnaire data and application of assessment algorithms, etc.

The main components of the module are shown in Fig. 1 below.

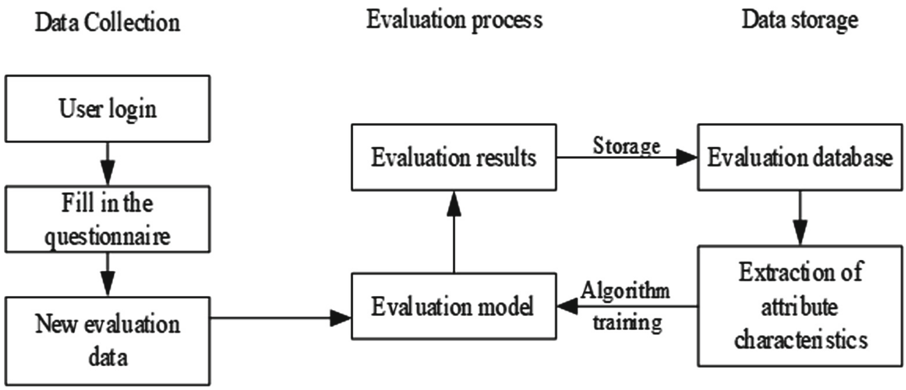

Fig. 1. Components of the Student Assessment Module

(3) Database design

In this paper, MySQL 5.7 is used as the relational database to store data. The two data tables designed in the database are the user information table and the student assessment data table.

Firstly, the basic information data table is shown in Table 1 below.

Table 1. User information table

Field Name	Type	Name	Password
Data Type	Varchar	Varchar	Varchar
Field Length	8	10	10
Description	User type	User name/account number	Password
Remarks	Not null	Primary key	Non-null

Next is the student assessment data table, which records the evaluation subjects, basic information about the evaluator, the results of the 10 evaluation indicators and the overall evaluation value. The specific fields are shown in Table 2 below.

3.2 DM Process

In general, the ABM process can be divided into five phases: preparation phase, data pre-processing and analysis phase, Model training phase (MTP), model validation and evaluation phase, and online development phase.

Table 2. TE data sheet

Field Name	Data Type	Field Length	Description	Remarks
Id	Int	4	Data Number	Primary Key
Course	Varchar	20	Course Name	Non-null
Major	Varchar	20	Major	Non-null
Sex	Varchar	4	Gender	Non-null
Nation	Varchar	8	Ethnicity	Non-null
A	Int	4	Indicator 1	Non-null
B	Int	4	Indicator 2	Non-null
C	Int	4	Indicator 3	Non-null
E	Int	4	Indicator 4	Non-null
F	Int	4	Indicator 5	Non-null
G	Int	4	Indicator 6	Non-null
I	Int	4	Indicator 7	Non-null
J	Int	4	Indicator 8	Non-null
L	Int	4	Indicator 9	Non-null
N	Int	4	Indicator 10	Non-null
P	Int	4	Overall Rating	NULL

(1) Preparation phase.

The DM preparation phase focuses on understanding the project objectives and business and user requirements, defining the problem and initially identifying search and data collection objectives. There are many methods of data collection, such as questionnaires, interviews, observations and discussions. Initial process definition and DM definition. Each method has more or less unique characteristics. One of the main sources of massive data in the Internet industry is log files, which record information about users and different behaviours and activities, or data acquired through technologies like data loggers. The data source for this study was the data produced when students logged into the ELT system for practice and examinations in English, which was stored in a database.

(2) Pre-processing and data analysis stage.

In the pre-processing and data analysis stage, the raw data collected is processed and incomplete, inconsistent and noisy data is processed and integrated using pre-processing techniques and methods to obtain 'clean' data for information extraction; in this stage, information extraction tasks such as classification, regression, etc. are identified. At this stage, information extraction tasks, whether classification, regression, etc., must be identified. Feature extraction methods generate features in the sample data.

(3) MTP.

The MTP involves selecting an appropriate machine learning model to extract and analyse the processed 'clean' data, such as a classification problem, and selecting an appropriate classification algorithm. During the modelling process, parameters are continuously adjusted to achieve optimal results, and the training model often requires a return to the previous phase to reprocess previously trained data and features.

(4) Model validation and evaluation phase.

Once the training of the machine learning model is complete, the final search results need to be analysed and evaluated, which means that the model generated during the training process is tested against the data to validate the results. For example, accuracy and recall can be evaluated for the classification task and mean squared error for the regression task.

(5) Online use phase

At this stage the entire DM process is completed and the resulting model can be used for online development or to solve more complex problems. Figure 2 illustrates the five stages of the DM process.

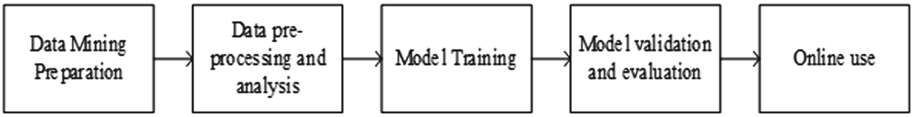

Fig. 2. The five stages of DM

4 Experiment Analysis

4.1 Experimental Comparison and Analysis

A region was selected to conduct an experimental comparative analysis of the performance of all teachers' evaluation data over the last five years, as shown in Table 3.

Table 3. Distributed DM algorithm performance tests

Calculation/Time	2	4	8	10	12
Stand-alone computing	20	30	60	150	230
Distributed Computing	30	45	65	80	115

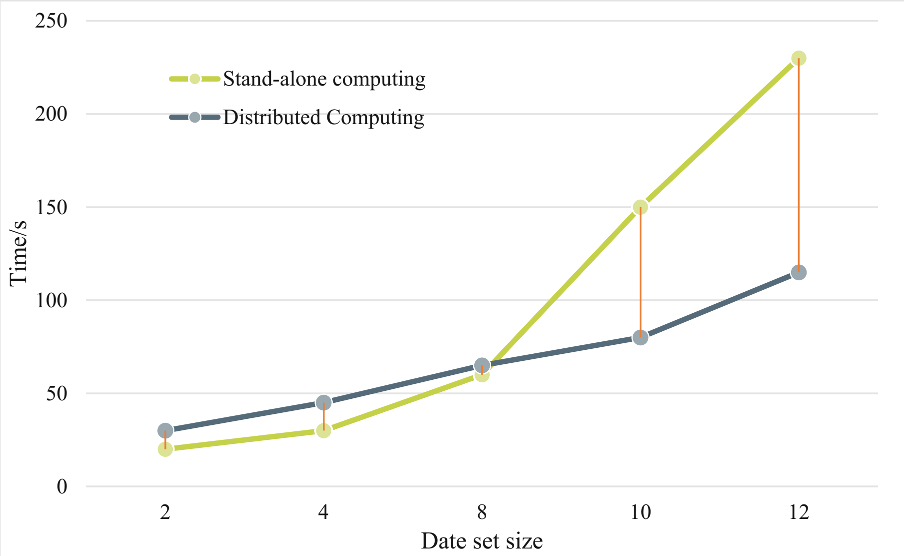

Fig. 3. Performance test chart of distributed DM algorithm

The comparison in Fig. 3 reveals that when distributed-based DM correlation analysis is performed on TT process, when the amount of data is small, the advantage of single-computer computing is more obvious in terms of running speed, and when the amount of data gradually increases, the advantage of the computing rate of distributed starts to be obvious because it is running in parallel on multiple hosts at the same time.

4.2 Clustering Analysis of TE Data

The k-means cluster analysis is used to automatically group professional teachers with the same or similar teaching ability, which is convenient for teaching managers to make grouping arrangements for the subsequent supervisory listening system and to guide teachers to carry out targeted teaching skill enhancement training. As there are many teachers in the college, it is impossible to give feedback on teaching analysis for each teacher. It is necessary to cluster teachers with the same characteristics into one category through clustering and then provide targeted advice measures for each category. The k-means clustering method of the SPSS statistical analysis software was used to cluster the student assessment scores of each teacher, and the number of clusters, K, was specified by the user in the experiment. The K value of 3 is therefore appropriate. The results of the analysis are as follows Table 4.

After the k-means cluster analysis by SPSS, the system will automatically give the category to which each teacher has been assigned. The final clustering centre, the mean of each category of teachers on each indicator and total score, will also be obtained, and the mean performance of teachers in each category on each indicator and total score will be plotted as a visual bar chart, as shown in Fig. 4. The clustering results overall appear to show a large difference in the mean scores of teachers in different

Table 4. Mean values of assessment scores for each category

	Category 1	Category 2	Category 3
Indicator 1	−0.73	0.75	−2.22
Indicator 2	−0.7	0.74	−2.4
Indicator 3	−0.74	0.73	−1.8
Indicator 4	−0.7	0.73	−2.26
Indicator 5	−0.68	0.73	−2.38
Total Assessment Score	−0.73	0.74	−2.28

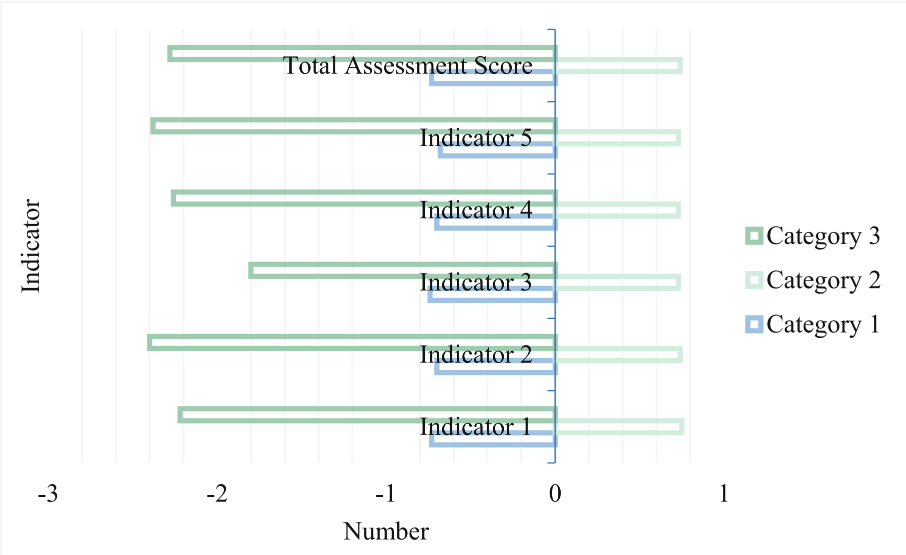

Fig. 4. Analysis of the mean scores for each category of assessment

categories on each indicator, with teachers in category 2 outperforming teachers in all indicators, followed by teachers in category 1, followed by teachers in category 3, who performed the worst. Category 2 teachers scored relatively evenly on all indicators, indicating that good teachers tend to be very demanding in all areas, and reminding teachers that mastering every teaching skill is a must, and that improving their teaching skills in all areas is something that all teachers should strive for. Teachers in categories 1 and 3 had below-average averages in all scores, and their teaching needs to be further improved. In particular, teachers in category 3 scored very low on all indicators, which means that teachers in this category urgently need to adjust their teaching methods, etc. Administrators should also combine student questionnaires and individual teacher interviews to improve the teaching standards of teachers in this category. Teachers in category 3 have the worst scores on indicators 2 and 5, which means that some measures in terms of teaching content, methods and effectiveness would be effective and quick to improve the teaching level of teachers in this category.

Through clustering, all teachers can be divided into categories, and the overall characteristics of teachers in each category can be analysed to obtain the performance of teachers in different categories on each indicator, so that teachers can focus on their own lower level indicators according to their performance in each category. At the same time, teaching managers can use the results to develop different teaching improvement programmes for different categories of teachers, such as organising for teachers in the lower categories to attend the classes of high level teachers.

5 Conclusions

Traditional assessment in the classroom usually includes peer assessment, teacher's peer assessment, teacher's self-assessment and student assessment. However, most of the existing assessment indicators are very general and focus mainly on aspects such as attitudes to teaching and IT. When these indicators are assessed from the students' perspective, they are often formal and do not truly reflect the strengths and weaknesses of teaching effectiveness, nor do they take into account the specific factors that affect teaching effectiveness. At the same time, the analysis of existing teaching outcomes is mainly in the form of statistical reports on teaching effectiveness, which is not only a heavy burden but also makes it difficult to find hidden information in the data base, which is why new data management techniques are needed to solve this problem." The 'Internet + Education' has become a trend that presents new opportunities and challenges for English at university. The use of DM technology to analyse and model student learning data and to explore the relationship between English exams and various TAL tasks through an English learning platform can be very beneficial to student learning and teacher education.

References

1. Chen, H.: A Data mining-based model for evaluating tennis players' training movements [J]. Discrete Dyn. Nat. Soc. (2022)
2. Xin, Y.: Analyzing the quality of business english teaching using multimedia data mining [J]. Mobile Inf. Syst. (2021)
3. Zhou, Q., Jiang, W.: Implementation of openairinterface-based real-world channel measurement for evaluating wireless transmission algorithms [J] (2021)
4. Huang, X., Wang, Q., Lu, S. et al.: Evaluating FFT-based algorithms for strided convolutions on ARMv8 architectures [J]. Performan. Evaluat. (2021) (152-Dec.)
5. Iftikhar, U., Asrar, K., Waqas, M. et al.: Evaluating the performance parameters of cryptographic algorithms for IOT-based devices[J] (2021)
6. Li, Z.: Elliptocyte detection technology based on super-resolution algorithms for a lensless imaging system [J]. Measur. Sci. Technol. **32**(2) (2021)
7. Zhang, A.: Influence of data mining technology in information analysis of human resource management on macroscopic economic management[J]. PLoS ONE **16**(5), e0251483 (2021)
8. Wang, A., Yu, H.: The construction and empirical analysis of the company's financial early warning model based on data mining algorithms [J]. J. Mathematics (2022)

9. Deng, J., Qing, H.: Practice teaching method of electronic commerce major based on data mining algorithm [J]. J. Phys. Conf. Ser. **1852**(2), 022039 (7pp) (2021)
10. Wang, X.: Construction of civil engineering teaching system based on data mining algorithm and big data technology [J]. J. Phys. Conf. Ser. **1852**(3), 032022 (6pp) (2021)
11. Chen, Z.: Using BIG DATA FUZzy K-means clustering and information fusion algorithm in english teaching ability evaluation[J]. Complexity **2021**(5), 1–9 (2021)
12. Han, Y.: Evaluation of English online teaching based on remote supervision algorithms and deep learning[J]. J. Intell. Fuzzy Syst. Appl. Eng. Technol. **4**, 40 (2021)
13. Hong, J., Qin, X.: Signal processing algorithms for SSVEP-based brain computer interface: state-of-the-art and recent developments[J]. J. Intell. Fuzzy Syst. Appl. Eng. Technol. **6**, 40 (2021)
14. Cobian, D.: Comprehensive efficiency analysis of machine learning algorithms for developing hardware-based cybersecurity countermeasures [J] (2022)
15. Du, Y., Zhao, T.: Network teaching technology based on big data mining and information fusion [J]. Secur. Commun. Netw. **2021**(9), 1–9 (2021)