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Blended Teaching Evaluation Index System Based on AI Emotion Recognition

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Abstract: With the continuous development of information technology, the teaching method is not limited to offline teaching. Online teaching is on the rise, and more and more teachers use a blended teaching evaluation system that combines online and offline to carry out classroom teaching. However, during online teaching, teachers cannot remind students when students are not paying attention, resulting in low classroom quality. This paper applied artificial intelligence (AI) emotion recognition technology to the blended teaching evaluation index system. When students are studying in the course, the emotion recognition is carried out on the students; when the students are not concentrating, the students are reminded to ensure the quality of the students' learning. Through testing different classes it was found that: the application of AI emotion recognition technology to the blended teaching evaluation system can improve the quality of classrooms, and improve students' learning status and student performance. Student satisfaction had increased by 9.7%, and AI emotion recognition technology can optimize the evaluation index system of blended teaching.

1. Introduction

Blended teaching is a new teaching mode that integrates online and offline teaching. Online teaching and offline teaching are carried out at the same time, which can improve the depth of students' learning. The application of the blended teaching evaluation system to the current teaching mode is of great significance for promoting the development of education.

Many scholars have conducted research on blended teaching. Wang Y studied the effectiveness of a blended teaching intervention using internet-based tutorials combined with traditional lectures in the introduction of undergraduate nursing courses, and compared the effects of the intervention with three outcomes from traditional face-to-face classroom teaching. The results showed that the blended teaching method was more suitable for students [1]. Gupta R discussed the application effect of blended teaching method in the translation of English sentences for vocational high school students. Through the analysis of the learning attitude questionnaire, learning satisfaction questionnaire, interviews, pre-tests and post-tests, and student records before and after teaching, it was found that there was a significant effect in the mixed teaching group [2]. Xue Y took the moodle-based blended teaching mode as the research object, and expounded the basic process and precautions [3]. Han X conducted a comparative assessment of blended learning course design and traditional classroom design in a campus-based university setting. The results showed that the blended learning curriculum design was more suitable for students to learn [4]. The blended English university teaching method based on the online learning platform proposed by Jungang L enhanced the learning content and was conducive to cultivating students' learning interest and autonomous learning ability. It had made a significant contribution to improving the effectiveness of English university education [5]. These studies have suggested that blended instruction is more suitable for students, but do not explain how to implement blended instruction.

AI emotion recognition can intelligently recognize people's emotions. Adom proposed a speech emotion recognition system to collect emotional speech corpora from different topics and speaking different languages [6]. Jiang X developed a fuzzy-coarse emotion recognition method based on sparse Electroencephalogram sensing in biosensor networks, which can help monitor emotional health in specific environments. Experimental results showed that the framework achieved fast and reliable emotion recognition in a wearable network sensing environment, which provided a solution for the initial diagnosis of emotional health [7]. The algorithm proposed by Dong Y C created sequential models of emotional movements based on low-level features inferred from the spatial positions and joint orientations within the tracked bones, and it employed and compared different deep neural networks to identify the emotional states of the acquired movement sequences [8] . Zheng J proposed a semi-supervised learning-based approach for emotion recognition that leverages a modest amount of unlabeled datasets in parallel while minimizing the use of labeled datasets that require high training costs [9]. Demircan S focused on classifying sentiment and applying statistical methods to identify similarities between different features. Statistical tools were used for preprocessing and feature identification, and results were analyzed by identifying similarities using cosine and related similarity measures [10]. These studies have shown that AI emotion recognition can comprehensively analyze people's emotions, but with the continuous improvement of technology, new problems have emerged.

This paper improved the evaluation index system of blended teaching based on AI emotion recognition technology. AI emotion recognition technology can identify students' emotions during class. By analyzing students' emotions, teachers can real-time understand students' learning status in class, so as to improve classroom quality and students' academic performance.

2. Blended Teaching Evaluation Index System

(1) Overview of the blended teaching model

The blended teaching model has "one center, two cores, two platforms, and four focuses". That is, the learning content is the center, and teachers and students are the core; the classroom and the network are the platform, and the needs, motivations, teaching objectives and teaching methods are the key points [11]. The specific content is shown in Figure 1.

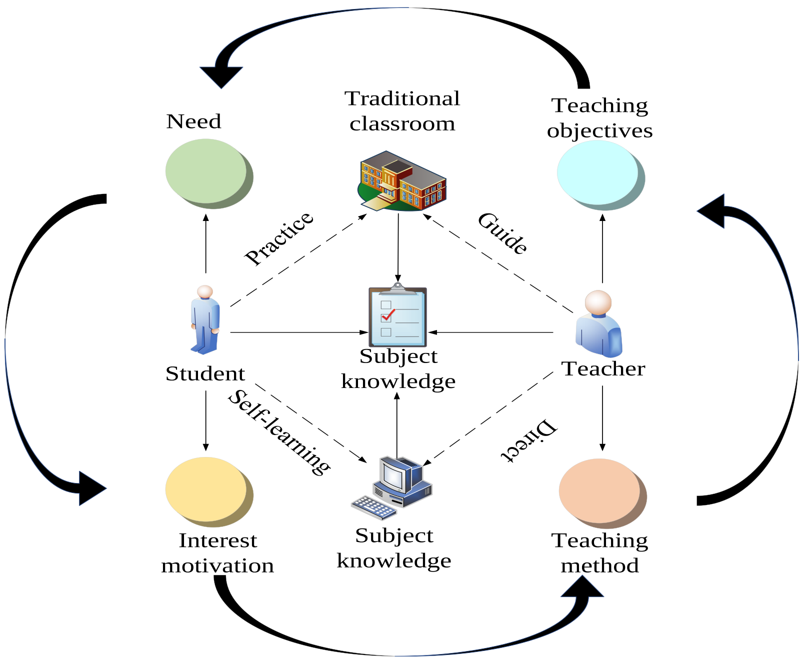

Figure 1. Blended teaching model diagram

The knowledge module of the online course content is mainly the teaching content. It selects some knowledge that students need to master or are interested in according to the course content needs of the offline classroom. By refining the knowledge points and combining with the actual situation of the students, the difficulty is adjusted. In the process of instructional design, teachers deeply understand and fully consider the interests of students. They extensively collects vivid materials and recorded them into micro-lectures, which are then presented by means of information technology. Online assignments and online activities are also designed from the perspective of students, striving to be inspiring and practical. In the online learning period of blended teaching, when students are learning online, teachers are also online at the same time. On the one hand, it can guide students and answer questions in a timely manner; on the other hand, it can also understand students' knowledge and carry out corresponding online interactions.

(2) Blended teaching situation

Students in blended teaching are the main body of teaching organization activities. It is necessary to analyze whether the learning content and learning methods in the learning process really meet the needs of students. First, primary competencies refer to the knowledge and skills that students acquire. Teachers can help improve students' ability to understand knowledge by analyzing students' primary abilities and applying them to the teaching process. Second, from a psychological point of view, learning behavior can be understood as students' emotional responses to different educational environments. Third, learning characteristics can be understood as demographic variables, including learners' age, learning expectations, personal influence, and learning background. The analysis process is shown in Figure 2.

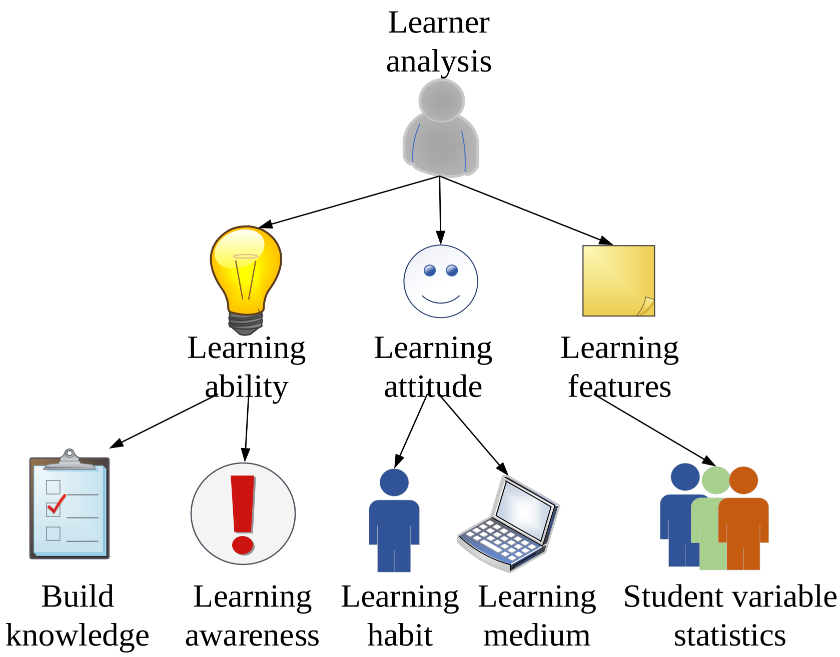

Figure 2. Analysis of blended teaching learning situation

(3) Overall model design of blended teaching evaluation

Teaching assessment runs through the blended learning process of IT services. By analyzing the whole process framework of the project, the "process evaluation" factor of the blended teaching evaluation index system is defined as three sub-indicators "before class, during class and after class". The purpose is to show students the importance of active participation in learning, active participation in classroom preparation and collaboration. When the quality of students' evaluation is not high, the students are warned in time. The specific process is shown in Figure 3.

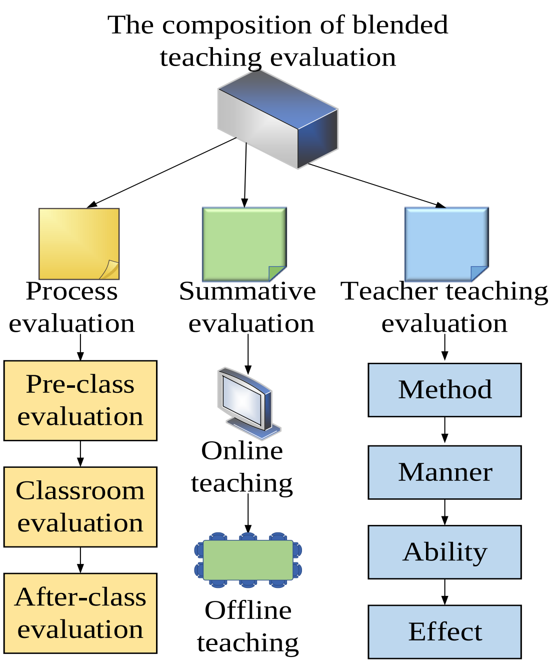

Figure 3. Overall model of blended teaching evaluation

This paper starts from three aspects: process evaluation, summative evaluation and teacher teaching evaluation. Among them, in the division of process evaluation indicators, the principle of before, during and after the project is adopted, and there are three evaluations: "before class", "during class" and "after class". The summative evaluation index distribution system is based on the "two-factor evaluation model", which is mainly divided into the following two indicators, "online education" and "offline education". The distribution of teachers' teaching evaluation indicators is divided into four indicators "teaching method", "teaching behavior", "teaching ability" and "teaching effect" by analysis method, which shows that in the case of students and teachers as the main body, the multi-level analysis and study of the learning effect in the context of blended teaching is carried out.

(4) AI emotion recognition

Facial expressions are important non-verbal information reflecting the emotional changes of students and teachers. Humans have six basic expressions. The sum of emotional information included 7% language, 38% voice and 55% facial expressions. The facial expressions of students while listening to class can indicate the current learning status of students. Facial recognition is a technology that uses computer intelligence to detect changes in facial expressions. The face recognition process is mainly divided into three steps: image preprocessing, feature extraction and classification [12], as shown in Figure 4.

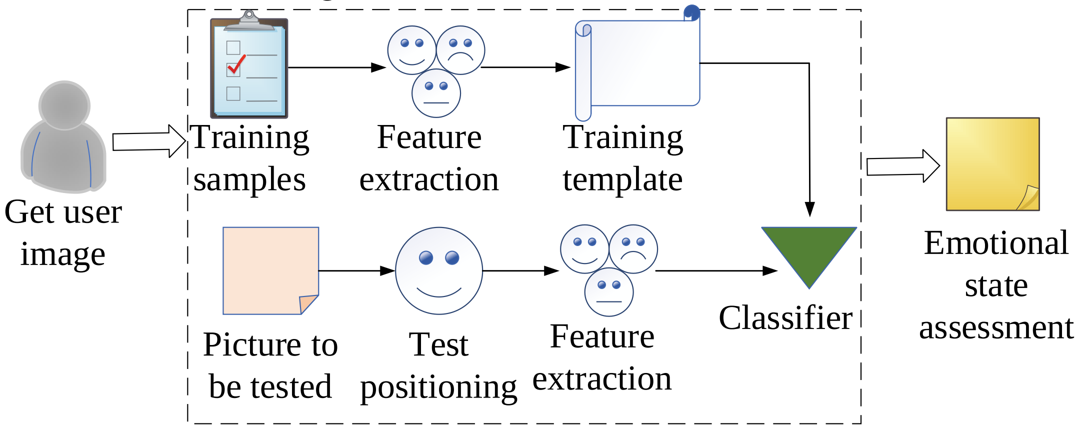

Figure 4. AI emotion recognition

Face recognition is mainly static image recognition and dynamic image recognition. After an image is captured by a device such as a camera, it must first be processed, and the image would be affected by light, background, position, contrast, etc. Exposure detection requires that test images and training images be kept in the same condition to eliminate the influence of extraneous factors as much as possible. The required visual information is obtained through a variety of methods, including face and position detection, scale correction, and grayscale correction. Through image preprocessing, the influence of interference factors on subsequent feature extraction and classification can be eliminated, and the recognition accuracy and efficiency can be improved.

3. AI Emotion Recognition Mathematical Model

(1) Face detection with Haar-like cascade classifier

Haar-like features are features that represent changes in different regions in an image, which show the change information of face regions and the spatial distribution relationship between facial features [13-14]. Figure 5 shows Haar-like features, which are invariant to rotation and scaling, and can detect similar features of different sizes in the image.

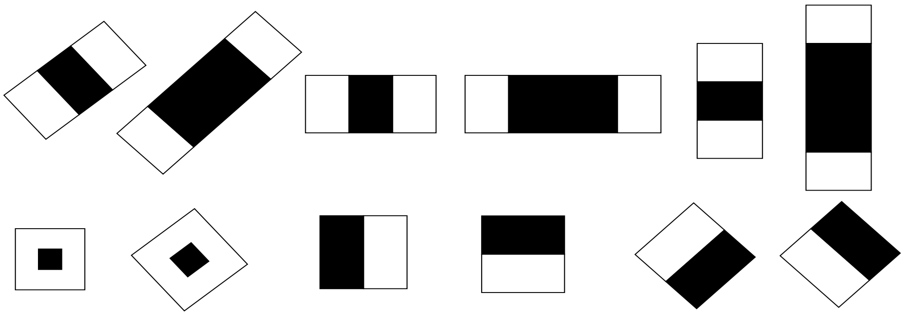

Figure 5. Haar-like features

The Haar-like feature of p(m,n) space is obtained by calculating the grayscale difference of pixels in different color regions in the image. In order to improve the calculation speed, the gray integral method is used. If the gray value of a pixel in the image is p(m,n), where m and n are the coordinate values of the pixel, then the corresponding average gray value is calculated as Formula (1):

$$I(m,n) = \sum_{m' < m, n' < n} p(m', n') \quad (1)$$

The gray value of the pixel point is calculated by Formula (2):

$$G_D = I_d + I_a - I_b - I_c \quad (2)$$

Among them, I_d is the gray value in the area space, and $I_d = G_a + G_b + G_c + G_d$. I_a, I_b and I_c are the gray value of the pixel in the area, and $I_a = G_a$; $I_b = G_a + G_b$; $I_c = G_a + G_c$.

(2) Automatic extraction of face area

The modeling and analysis of the face have been widely used in face detection, motion analysis, expression recognition and other fields, and most shape- and appearance-based facial motion analysis and tracking systems use the Active Shape Model (ASM) [15].

$$m = (m_1, ..., m_y, n_1, ..., n_y)^T \quad (3)$$

It is assumed that there are x training image samples to form a training feature set M, then:

$$M = (m_1, ... m_x) \quad (4)$$

The eigenvalues and eigenvectors of the Eigen covariance matrix are computed by rotating, measuring, and translating, and the first eigenvectors corresponding to these values are retained. ASM is generated; computation speed is increased; storage capacity is increased. The resulting model for reduced storage is:

$$m = \overline{m} + Pb \quad (5)$$

Among them, $\overline{m}$ is the average shape of the sample set. b is the prior eigenvalue of the covariance matrix m, and P is the corresponding eigenvector.

The shape vector of the sample feature points in the training set is defined as:

$$M = T_{M_t, N_t, s, \theta}(\overline{M} + Pb) \quad (6)$$

Among them, $T_{M_t, N_t, s, \theta}$ represents rotation θ. Scale s and translation coordinates (M_t, N_t) use function $T_{M_t,N_t,s,\theta}$ to calculate feature points (m, n), and the calculation expression is:

$$T_{M_t,N_t,s,\theta}\begin{pmatrix} m \\ n \end{pmatrix} = \begin{pmatrix} M_t \\ Y_t \end{pmatrix} + \begin{pmatrix} s\cos\theta & -s\sin\theta \\ s\sin\theta & s\cos\theta \end{pmatrix}\begin{pmatrix} m \\ n \end{pmatrix} \tag{7}$$

When a new image sample N is input, its objective function is to find the corresponding model value. By calculating P and b, the squared distance between the shape vector of the model and the corresponding feature points in the input image is minimized. The calculation formula is:

$$\left| N - T_{M_t,N_t,s,\theta}(\overline{M} + Pb) \right|^2 \tag{8}$$

(3) Local Binary Pattern (LBP) characterization

Feature extraction achieves facial expression classification by evaluating the texture or shape changes of facial expression regions to generate features [16], and feature extraction plays an important role in facial expression recognition. The LBP operator calculates the gray value difference between the center of the region and the surrounding pixels. The binary weights are calculated according to the positive and negative, and the binary pattern of the domain is calculated to describe the change of the image texture [17]. The representation of the local area of the image can be described by the average distribution of gray values, as shown in Formula (9):

$$T = t(f_c, f_0, ..., f_{P-1}) \tag{9}$$

Among them, f_c represents the gray value of the pixel point in the center of the surrounding area, and $f_0, ..., f_{P-1}$ represents the gray value of the pixel point in the circle f_c. In the case of preserving the texture information, the gray value of f_c in the center is subtracted from the gray value of the pixel to obtain:

$$T = t(f_c, f_0 - f_c, ..., f_{P-1} - f_c) \tag{10}$$

It is assumed that 1 and the grayscale difference of the pixels in this area are distributed independently of each other, then it can be obtained:

$$T \approx t(f_c)t(f_0 - f_c, ..., f_{P-1} - f_c) \tag{11}$$

Among them, $t(f_c)$ shows the general illumination distribution of the image, which has little relationship with the local texture of the image and cannot provide effective evaluation and analysis information. Therefore, the common distribution of the differences shown is:

$$T \approx t(f_0 - f_c, ..., f_{P-1} - f_c) \tag{12}$$

According to Formula (12), the difference sign is independent of the variation of the average brightness, and it can be obtained:

$$T \approx t(s(f_0 - f_c), s(f_1 - f_c)..., s(f_{P-1} - f_c)) \tag{13}$$

When $s(m) \geq 0$, $2^{i-1}(i = 1,...P)$ is used to sum the weights according to the pixel position, and the LBP operator is:

$$LBP_{(P,R)}=\sum_{i=1}^{P}s(f_0,f_i)2^{i-1},s(f_0,f_i)=\begin{cases}1,if\ \ f_i\geq f_0\\0,if\ \ f_i\leq f_0\end{cases}\tag{14}$$

(4) Improved LBP operator

The LBP operator generally uses a spherical image area, so there is no guarantee that all pixels fall exactly within the integer coordinate values of the image coordinate system [18]. Therefore, the bilinear interpolation algorithm is used to calculate the image pixel and gray value, and the coordinate position is:

$$(x_{g_p},y_{g_p})=(-R\sin(2\pi p/P),R\cos(2\pi p/P))\tag{15}$$

In the circular motion domain, the number of transitions from 0 to 1 or 1 to 0 between two adjacent grayscale difference points is at most 2. LBP units that do not meet this condition are defined as LBP patterns, and there are P(P-1)+3 types of such patterns. The definition is shown in Formula (16):

$$LBP_{P,R}^{u2}=\begin{cases}\sum_{p=0}^{P-1}s(f_p-f_0),if\ U\ (LBP_{P,R}\leq 2)\\P+1,\qquad otherwise\end{cases}\tag{16}$$

Among them,

$$U(LBP_{P,R})=\left|s(f_{P-1}-f_c)-s(f_0-f_c)\right|+\sum_{p=1}^{P-1}\left|s(f_p-f_c)-s(f_{p-1}-g_c)\right|\tag{17}$$

(5) The nearest neighbor classifier

Expression recognition is done by the nearest neighbor classifier (The nearest neighborhood, NN), which is a special nonparametric classification method. It judges the category of the pattern according to the difference between the input pattern and existing patterns, and is widely used in pattern recognition and machine learning [19-20]. It is assumed that there are c classes called $w_1,w_2,...,w_c$ in a data set, and the number of samples in each class is $N_i(i=1,2,...,c)$, then the judgment function is:

$$f_i(m)=\min_k\left\|m-m_i^k\right\|\tag{18}$$

Among them, $k=1,2,...,N_i$. In Formula (18), the upper corner of m_i^k is marked as the k-th sample in sample set w_i, and the lower corner is marked as class w_i. According to the principle of the nearest neighbor algorithm, its decision function is:

$$f_j(m)=\min_i\ f_i(m)\tag{19}$$

Then the sample m is judged as a class w_j, where i=1,2,...,c.

4. Construction of the Evaluation Index System of Blended Teaching

(1) Experimental process

In a school, 4 classes were randomly selected for teaching evaluation test. Classes 1 and 2 used the traditional blended teaching method for course learning, and classes 3 and 4 used the blended teaching method based on AI emotion recognition for course learning. Classroom quality evaluation test, student learning status test, student achievement test, and student satisfaction test were conducted for 4 classes respectively. After the test was complete, the test results were recorded and how the results differ for each class using the different teaching modes was observed.

(2) Experimental data

The four classes in the experiment are all sophomores, and the specific data of the four classes are shown in Table 1.

Table 1. Experimental data

	Specialized	Number of people	Male to female ratio	Average age
Class 1	English major	65	2:3	20
Class 2	English major	66	4:7	19
Class 3	English major	67	20:47	20
Class 4	English major	64	1:1	20

5. Impact of AI Emotion Recognition on Blended Teaching Evaluation

(1) Classroom quality evaluation test

Classroom quality can be used to evaluate the quality of a class. Students in 4 classes were asked to evaluate the quality of the classroom, and the evaluation grades were divided into 4 grades: poor, generally, good, and excellent. It was observed how the classroom quality of Class 3 and Class 4 using AI emotion recognition blended teaching is improved compared to Class 1 and Class 2 using traditional blended teaching, and the results were recorded and analyzed. The results of the classroom quality evaluation of the four classes are shown in Figure 6.

Figure 6. Classroom quality assessment test results

It can be seen from Figure 6 that the evaluation results of class 1 and 2 were similar, and the evaluation results of class 3 and 4were similar. Among them, when students in class 1 evaluated the quality of the classroom, there were at most 32 students who thought the quality of the classroom was average; 18 students thought the quality of the classroom was good; 13 students thought the quality of the classroom was poor; a small number of students thought that the quality of the classroom was excellent, only 2. The evaluation results of students in Class 2 were similar to those in Class 1. There were 29 students who thought the class quality was average; 19 students thought the class quality was good; 15 students thought the class quality was poor; only 3 students thought the class quality was good. In Class 3 and Class 4 using the AI emotion recognition blended teaching model, no students thought that the quality of the classroom was poor. 19 students in class 3 thought the class quality was average, and 18 students in class 4 thought the class quality was average; 25 students in class 3 thought the class quality was good, and 22 students in class 4 thought the class quality was good; 23 students in class 3 thought the class quality was excellent, and 24 students in class 4 thought the class quality was excellent.

(2) Student learning status test

The student's learning status affects the final learning outcome and affects the student's course achievement. The better the learning status of the students, the higher the quality of the classroom and the more knowledge the students acquire. The use of AI emotion recognition technology can observe the emotional state of students in real time and better control the learning state of students. In order to prove that AI emotion recognition technology has an optimal impact on students' learning status, a student learning status test was conducted. The learning status was divided into four levels: poor, average, good, and excellent. The test results are shown in Figure 7.

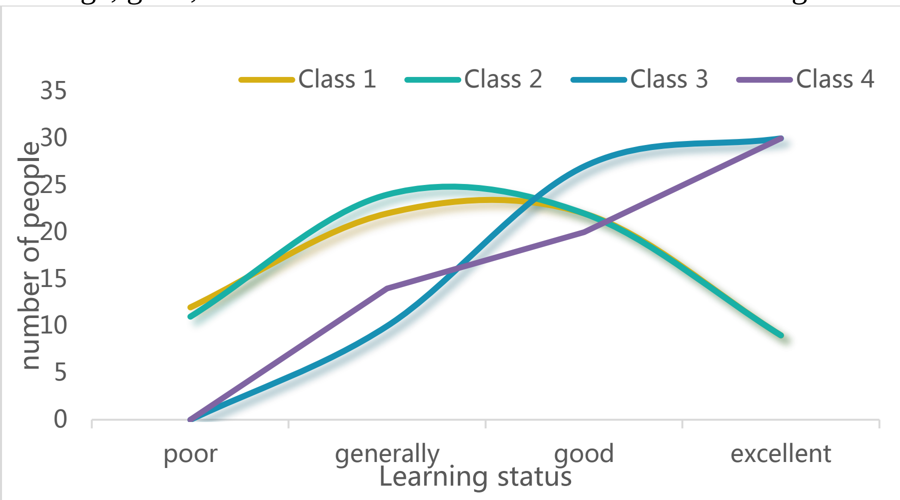

Figure 7. Student learning status test

It can be seen from Figure 7 that the learning status of students in class 3 and 4 was significantly better than that of students in class 1 and 2. The students in Class 1 and Class 2 that did not use AI emotion recognition had the highest learning status, followed by good, and the least was excellent. The students in Class 3 and Class 4 using AI emotion recognition were the most excellent, followed by good, and the least was poor. To sum up, the traditional blended teaching evaluation system could not keep students in a good state of learning, and only a very small number of students had an excellent learning state. The blended teaching evaluation system based on AI emotion recognition could keep students in a good learning state, and the number of students with poor learning state was 0. Therefore, AI emotion recognition can improve students' learning status.

(3) Student achievement test

A student's academic performance is a testament to whether a student is studying hard. The better the students are in class, and the harder they usually study, the better the students' academic performance. The 4 classes were tested for academic performance, and the test grades were divided into A, B, C, and D. Among them, A was excellent (85 points-100 points), and B was good (75 points-85 points); C was average (60 points-75 points), and D was failing (<60 points). The students' grades in each class were recorded and analyzed, and the results are shown in Figure 8.

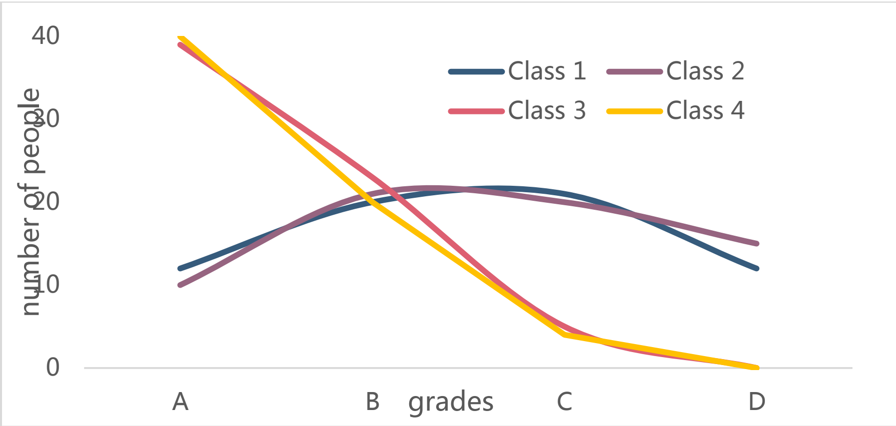

Figure 8. Student achievement test

It can be seen from Figure 8 that the grades of students in classes 3 and 4 were significantly better than those in classes 1 and 2. Among the outstanding students, 12 were in class 1, and 10 were in class 2; 39 were in class 3, and 40 were in class 4. Of the students with good grades, 20 were in class 1, and 21 were in class 2; 23 were in class 3, and 20 were in class 4. For average students, 21 students were in class 1, and 20 students were in class 2; 5 students were in class 3, and 4 students were in class 4. Of the students with failing grades, 12 were in Class 1, and 15 were in Class 2; none in Class 3 and 4. To sum up, the grades of Class 1 and Class 2 students were mostly good and average, and a small number of students were failing and excellent. The blended teaching evaluation system of AI emotion recognition can improve students' performance.

(4) Student satisfaction test

5 students were randomly selected in each of 4 classes to perform a satisfaction score test on the AI emotion recognition blended teaching and the traditional blended teaching evaluation mode, with a full score of 10 points. Differences in student ratings across the 4 classes were observed, and the results were recorded and analyzed. The results are shown in Figure 9.

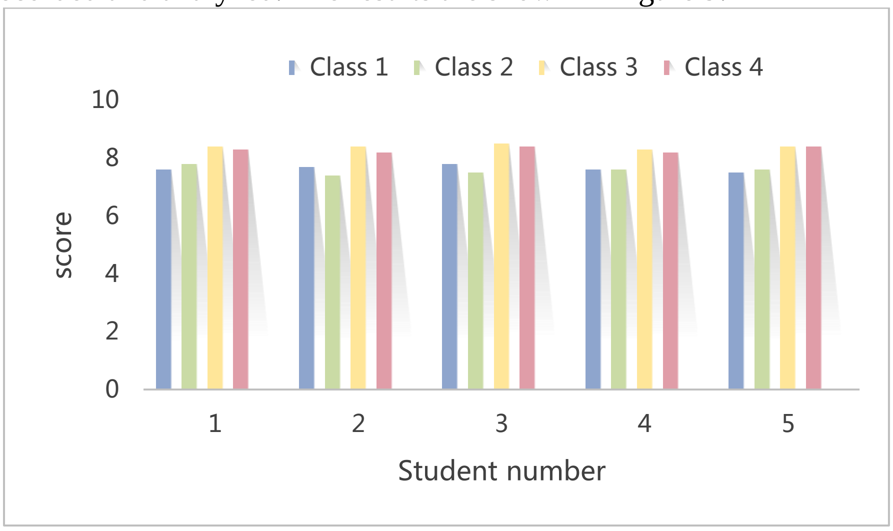

Figure 9. Student satisfaction test

It can be seen from Figure 9 that the student satisfaction scores of classes 3 and 4 were significantly higher than those of class 1 and 2. The average satisfaction score of class 1 was 7.64, and the average satisfaction score of class 2 was 7.58; the average satisfaction score of class 3 was 8.4, and the average satisfaction score of class 4 was 8.3. To sum up, the average satisfaction score of the class using the traditional blended teaching rating model was 7.61, and the average satisfaction score of the class using the AI emotion recognition blended teaching evaluation model was 8.35. The application of AI emotion recognition increased student satisfaction by 9.7%, promoting better education development.

6. Conclusion

The traditional evaluation methods of education and teaching are too backward and cannot improve students' interest in learning and teachers' interest in teaching, thus affecting the quality of the classroom. In this paper, the mixed teaching evaluation index system of AI emotion recognition can identify students' emotions and emotions in real time, so that students can better integrate into the classroom. Through experimental tests on different classes, it was found that the application of AI emotion recognition technology to the blended teaching evaluation system had improved students' learning status and classroom quality. At the same time, students' academic performance had improved, and students were more satisfied with the blended teaching evaluation index system of AI emotion recognition.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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