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Emotion Classification for Students with Autism in Mathematics E-learning using Physiological and Facial Expression Measures

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***Abstract*—**Avoiding learning failures in mathematics e-learning environments caused by emotional problems in students with autism has become an important topic for combining of special education with information and communications technology. This study presents an adaptive emotional adjustment model in mathematics e-learning for students with autism, emphasizing the lack of emotional perception in mathematics e-learning systems. In addition, an emotion classification for students with autism was developed by inducing emotions in mathematical learning environments to record changes in the physiological signals and facial expressions of students. Using these methods, 58 emotional features were obtained. These features were then processed using one-way ANOVA and information gain (IG). After reducing the feature dimension, methods of support vector machines (SVM), k-nearest neighbors (KNN), and classification and regression trees (CART) were used to classify four emotional categories: baseline, happy, angry, and anxious. After testing and comparisons, in a situation without feature selection, the accuracy rate of the SVM classification can reach as high as 79.3-%. After using IG to reduce the feature dimension, with only 28 features remaining, SVM still has a classification accuracy of 78.2-%. The results of this research could enhance the effectiveness of eLearning in special education.

***Keywords*—**Emotion classification, Physiological and facial Expression measures, Students with autism, Mathematics e-learning.

I. INTRODUCTION

EDUCATIONAL reform is a global trend for the 21st century. The promotion of educational reform laws in various countries in recent years, along with the support from academia, have all indicated that improving the learning ability in subject areas of students with disabilities is an emphasis of current educational reform. However, because students with disabilities learn differently from ordinary students, a major issue of special education is providing of adaptive education in academic disciplines and developing learning advantages for students with disabilities based on their diverse characteristics.

Recent studies have indicated that primary and secondary school students consider mathematics to be the most difficult subject [1].

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As students advance through the grades, their difficulties with mathematics learning continue to increase, the ratio of those who hate math increases, and learning interest and motivation plummet, thus influencing learning effectiveness. Students with disabilities similarly have the most serious problems in this regard, indicating much room for development in guiding the mathematics learning of students with disabilities.

As the Internet and computer technology develops, a trend has emerged in using new e-learning methods to obtain knowledge and learning. Through the Internet, e-learning can eliminate barriers of time and space, reduce learning costs, and provide adaptive learning services, thereby significantly improving mathematics learning effectiveness. Moreover, among students with disabilities, those with high-functioning autism [2] -- despite their deficiencies in social communication skills and dispositions that are resistant to change -- have excellent spatial concepts and memory. For these students, e-learning environments can fulfill their behavioral and cognitive requirements, stimulating learning motivations and resolving the difficulties they face in mathematical learning.

Because of the interactions of society, culture, family, and the learning characteristics of the students, the factors influencing the difficulties that students face in mathematical learning tend to be complex. The emotional intelligence and ability for emotional self-management of autistic students is weaker than in ordinary students, leading to the frequent influence of internal and external emotional factors in the learning process, such as failures and setbacks during the learning of mathematics. The emotional reactions thus produced are also more intense, easily causing mathematical anxiety or negative attitudes toward mathematics [3, 4]. Despite the considerable benefits that the structured features of digital learning environments for mathematics have provide for students with autism, emotional problems [5, 6] frequently lead to interruptions in study. This influences student learning effectiveness.

The application of the field of special education to mathematics e-learning typically emphasizes cognitive assistance in learning, educational instruction, and content design for teaching materials, thus overlooking the emotional experiences of autistic students during the learning period.

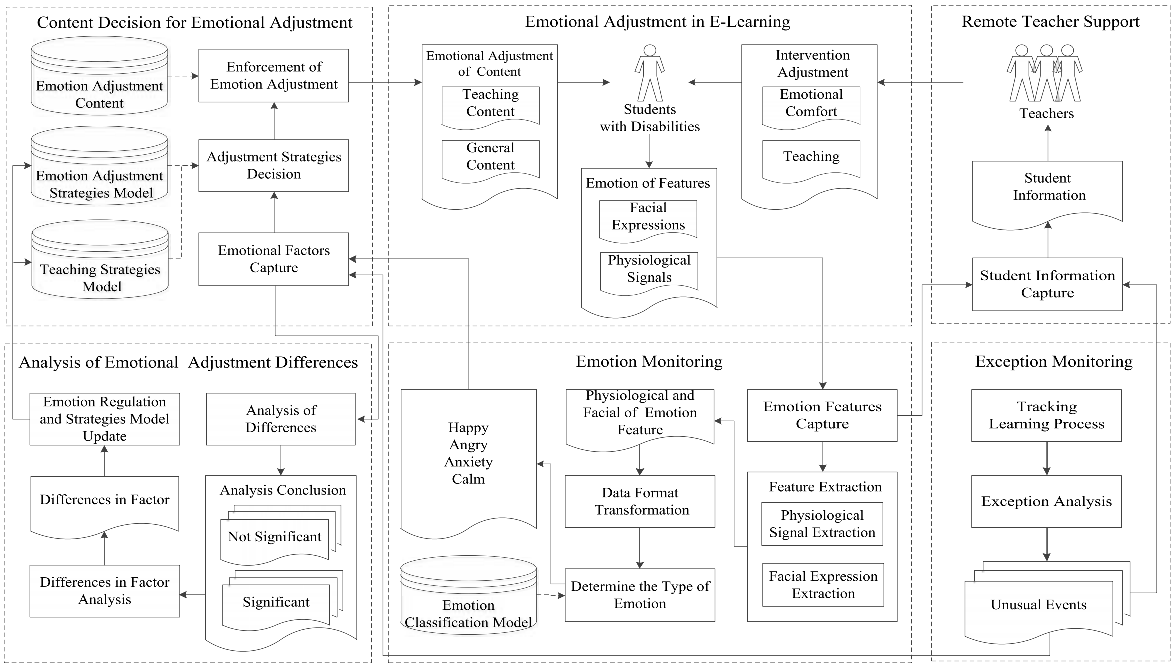

Fig. 1 Adaptive emotional adjustment model in mathematics E-Learning for students with autism

In recent years, emotion detection technology has become increasingly complete. Emotion detection technologies and methods are continuously being updated. The main direction of research is in the identification of emotional features such as physiological signals, facial expressions, speech, and physical postures [7]. If an emotion classification mechanism that enables the system to automatically identify the emotional states of students with autism can be developed, the insufficiencies of conventional mathematics e-learning can be remedied and timely adjustments or changes can be made to course content, resolving emotional problems in learning. Thus, the learning efficiency of students with autism in mathematics e-learning can be further improved.

Human emotional expression adopts numerous forms, such as facial expressions, body language, and voice. Among these, 55 % of emotional information passes through the facial features, such as inferences from changes in the positions of the eyes, eyebrows, nose, and mouth [8]. Therefore, changes in facial expression are extremely important indicators in judging emotion. However, students with autism have severe difficulties in communicating emotions, interacting with society, and presenting their own facial expressions and describing those of others, and their facial expressions change less than those of ordinary people. Thus, a single identification method for facial expression is adopted, which does not classify emotion categories easily and accurately. Another aspect, which indicates changes in physiological signals, is the automatic neural response. In different emotional states, these physiological changes and fluctuations provide extremely useful information in distinguishing emotions in autism [9]. Therefore, this study combines facial expressions with physiological indicators, such as electrocardiograms (ECG), electromyograms (EMG), blood volume pulses (BVP), and skin conductance (SC), using a bimodal method to develop an emotion classification mechanism for students with autism.

This paper is divided into three sections as follows. First, because students with autism cannot autonomously determine emotional states, an adaptive emotional adjustment model for students with autism in mathematics e-learning is presented to resolve the problems of mathematics e-learning systems experienced by autistic students. Subsequently, to accurately classify students' emotional states and support the operation of the model, the emotion classification mechanism is introduced, which uses physiological signals and the extraction of facial expressions to classify emotions into categories. Two types of feature filtering methods, information gain and one-way ANOVA, are used to select distinguishing emotional features. Support vector machines, k-nearest neighbors, and classification and regression trees are then used as methods for training the emotion classification model. Finally, an experiment to elicit the emotions of autistic students in a digital learning environment is conducted to verify the performance of the emotion classification mechanism. The method which identification best result is use as basis for emotional classification. This can assist in future mathematics e-learning systems by recognizing the emotional changes of students with autism and providing timely emotional adjustment.

II. Adaptive Emotional Adjustment Model in Mathematics E-Learning for Students with Autism

By understanding students' emotional states when learning , combined with emotional adjustments, this study designed an adaptive emotional adjustment model for students with autism studying e-learning mathematics, as shown in Fig. 1. The design of this model includes five main modules: emotional monitoring, exception monitoring, content decision for emotional adjustment, analysis of differences in emotional adjustment, and remote teacher support. These are described sequentially below.

A. Emotional Monitoring

In the mathematics e-learning process, the emotion classification mechanism was used with physiological signal sensors and webcams as emotional monitoring devices to obtain the physiological signals and facial expression features of autistic students during their real-time learning states. These serve as data for emotional recognition to identify categories of emotions.

B. Exception Monitoring

This module monitors and follows the unusual events of students during the learning process. If learning stagnates for too long, questions are answered randomly, or mistake rates tend to be high, the module analyzes whether the emotions created are caused by the learning, to provide follow-up content decisions for emotional regulation.

C. Content Decision for Emotional Adjustment

By using emotional monitoring to identify the emotional categories of students and combining this with abnormal events in learning obtained through exception monitoring, preliminary judgment can be made as to whether the causes of the emotions are related to the mathematics e-learning content. The teaching and emotional adaptive strategy model constructed through empirical research and the experiences of expert teachers determine suitable teaching and emotional adaptation strategies. Therefore, emotional adjustment of the content is provided in real time, ensuring effective adaptation of the harmful emotional reactions of students in learning.

D. Analysis of Emotional Adjustment Differences

Before and after engaging in the adjustment of emotional content, information on autistic students obtained through emotional monitoring and learning exception monitoring is used to compare the rate of occurrence of harmful emotions and abnormal events in learning. If the difference lies within a certain threshold, it indicates that there are no significant differences prior to and after emotional adaptation. In contrast, if the difference exceeds a certain threshold, this then indicates that significant differences exist before and after the implementation of emotional adaptation. These results can serve as a basis for adjusting the teaching and emotional adaptation strategy model, thereby improving the effectiveness of decisions for emotional adjustment.

E. Remote Teacher Support

After students receive the emotionally adapted content, when their moods fail to stabilize and if the teaching and emotional adaptive strategy model lacks a suitable resolution, the information obtained through emotion and learning exception monitoring is sent to the remote teachers to serve as a reference for the learning conditions of autistic students. The remote teachers intervene in adjusting the emotional state of the students, providing remedial teaching and assisting the students in continuing with their learning tasks.

An emotion classification mechanism for students with autism was designed to resolve emotional monitoring problems and to ensure smooth operation of the emotional adjustment model previously described.

III. Emotion Classification Mechanism for Students with Autism

The emotion classification mechanism includes physiological signal feature extraction, facial expression feature extraction, and emotion classification model construction. These are explained sequentially below:

A. Physiological Signal Feature Extraction

As shown in Fig. 2, the physiological signals feature extraction process transforms signals and divides them into feature units of different types, producing 41 main physiological signal features for follow-up analysis. This process includes the steps of signal filtering, signal feature extraction, and signal feature normalization. The sequence is explained below:

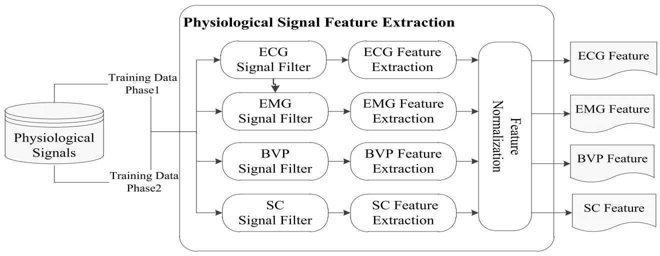

Fig. 2 Physiological Signal Feature Extraction Process

1. Signal Filtering

The process of recording physiological signals through computer sensors often experiences interference from external energies of high frequency, such as noise from the 60 Hz power supply and low-frequency energies produced by human breathing or movement, preventing the signals from being analyzed easily. Thus, prior to signal analysis, signals containing noise must be processed through high-pass and low-pass filters to obtain the original signal without distortion. Table I shows the high-pass and low-pass cut-off frequencies of each signal [10, 11].

TABLE I
CUT-OFF FREQUENCY OF PHYSIOLOGICAL SIGNALS

Physiological Signals	LPF	HPF
ECG	90HZ	0.5HZ
SC	LPF Cut-off Frequency (4 HZ)	
EMG	Moving Average Filter(128 Points)	
BVP	40HZ	1HZ

2. ECG Feature Extraction

ECG feature extraction primarily performs feature calculation on heart rate (HR) and heart rate variability (HRV). The ECG wavelength was used to detect each heartbeat R-peak position [12]. Heart rate was then calculated as in Equation (1), along with variation in RR-interval. The features include the maximum, minimum, mean, variability, standard deviation, and mode of heart rate per unit of time.

$$Heart\ Rate = \left[1/(R\text{-}R\ Interval)\right] Time \tag{1}$$

Where $1/(R\text{-}R\ Interval)$: heart rate per second.
$Time$: time interval.

The calculation indicators used for HRV features per unit of time are time domain features [13], such as the mean RR-interval (MeanRR), standard deviation (SDNN), root mean square (RMSSD), the number of distant differences exceeding 50 ms (NN50), and the ratio of distant differences exceeding 50 ms (PNN50). For the frequency features, the R-R interval is transformed into power spectral density (PSD) via fast Fourier transform (FFT) before performing frequency domain analysis. The frequency domain indices used [14] are high frequency (HF), low frequency (LF), very low frequency (VLF), high- and low-frequency power ratio (LF/HF), and total power (TP).

i. EMG Signal Extraction

EMG signal extraction analyzes the raw EMG signal to obtain indicator parameters, which are then used to estimate the response characteristics of muscular force in different emotional states. In consideration of the complexity and utility of the calculations, frequently used calculation parameters were adopted [15]. The maximum, minimum, mode, integrated EMG (IEMG), electrical activity (EA), root mean square (RMS), variability, and standard deviation of the EMG signal per unit of time were obtained through time domain analysis. After FFT, frequency domain analysis was performed to obtain the median frequency (MDF) and mean power frequency (MPF) of the equalized power spectrum.

ii. BVP Feature Extraction

BVP primarily performs feature extractions on peak amplitude and pulse transit time (PTT). First, the peaks and valleys of periodic waveforms were measured from the BVP signals. Because the peaks and valleys represent the greatest and smallest values of the signal, peak-valley detection [16] was used to obtain the main peak amplitude values of the period signal. The mean and standard deviation of the amplitude per unit of time were calculated and then synchronized to obtain the R-peak position of the ECG. The mean and standard deviation of PTT were calculated according to the different positions of their occurrence during the time period.

iii. SC Feature Extraction

SC feature extraction primarily calculates the SC maximum, minimum, mean, variability, standard deviation, and mode per unit of time. In addition, the features of the SC amplitude were calculated [17], such as the mean and standard deviation of the SC amplitude, and the mean and standard deviation of the differences among the amplitudes.

iv. Signal Feature Normalization

In experiments with multiple people, because of the individual differences among students and the influence of different tests along with inconsistent initial baselines for the signals, baseline normalization was first performed to eliminate these baseline differences. To encourage the physiological signals feature values to fall within a consistent range, feature normalization was performed to allow the range of distribution of the physiological signal features to normalize between zero and one, such as in Equation (2), thus reducing the error rate in the emotion classification model and improving classification performance.

$$\{NX_n\} = \frac{\{X_n\} - Min(\{X\})}{Max(\{X\}) - Min(\{X\})} \tag{2}$$

Where $\{X_n\}$: feature value data collection
$\{NX_n\}$: n^{th} normalized value of data collection
$Max(\{X\})$: maximum value of data collection
$Min(\{X\})$: minimum value of data collection

B. Facial Expression Feature Extraction

The goal of the facial expression feature extraction process, shown in Fig. 3, is to follow changes in the facial expressions of students. Facial feature anchor points were transformed into expression features of different emotional states, producing 17 primary facial features. This process included facial feature tracking, expression feature extraction, and expression feature normalization. These are explained in sequence below:

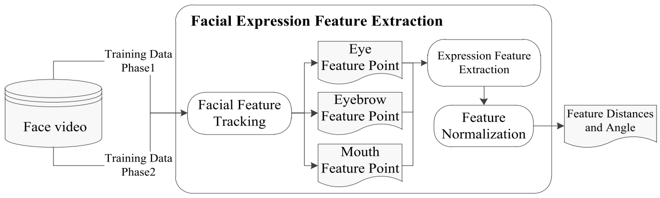

Fig. 3 Facial Expression Feature Extraction Process

3. Facial Feature Tracking

Changes in facial expression are closely related to facial features. Thus, the number and position of the corresponding points of the facial features must be defined to perform subsequent facial feature positioning and tracking. The majority of previous studies considered two-dimensional coordinate positioning on the X and Y axes. The core technology developed in this study, Face API [18], considers the Z axis, using the Cartesian head three-dimensional coordinate positioning method to automatically follow the features in sequences of human face images. This permits the heads to turn +/- 90 ° while preserving excellent tracking effects. Fig. 4 shows the selection of facial feature points, with a total of 21 points. There are five points controlling each of the eyes, three points each for the eyebrows, and four for the mouth.

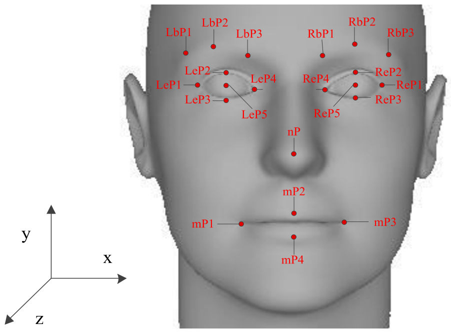

Fig. 4 Facial feature point distribution

4. Expression Feature Extraction

The 21 feature points were acquired. Feature distances and angles judging the facial expressions were defined between each of the points to serve as features of facial expression, as shown in Fig. 5. Twelve feature distances and five feature angles were calculated through the coordinates of the facial feature points, as shown in Equations (3) and (4):

$$D2 = Distance(mP1, mP3) \tag{3}$$

Where $D2$: mouth width.
$mP1$: right mouth angle positioning point.
$mP3$: left mouth angle positioning point.

$$LA12 = \cos^{-1}\left(\frac{v_3 \cdot v_4}{|v_3| \cdot |v_4|}\right) \tag{4}$$

Where $v_3 = mP2 - mP1$
$v_4 = mP4 - mP1$

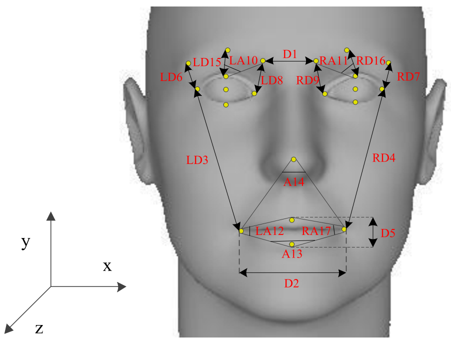

Fig. 5 Facial feature distances and angles

5. Expression Feature Normalization

Because individuals differ, some differences still exist in the distribution of human facial features. Even the facial feature positions of expressionless faces are different. Thus, the facial features of each autistic student when expressionless must be removed according to the results of feature extraction to reduce the disparity caused by differences in individual facial features -- as in Equation (5) -- before performing feature normalization to between zero and one.

$$NF_n^k = F_n^k - FBase_n \tag{5}$$

Where NF_n^k : expression feature values obtained after normalization.
k : each expression type.
n : features included in each expression.
F_n^k : normal feature values of each expression.
$FBase_n$: expressionless feature values.

C. Construction of an Emotion Classification Model

Emotional sample data was divided into two parts. Data from the first part serves as training data and made up 90 % of all data. Referencing the document classification method, emotional features corresponded to the keyword concepts in the document classification. The relative degrees of importance of emotional features were used in the emotion categories to select distinguishing emotional features to serve as training features for the classification model. For the second part of the data, 10 % was obtained to serve as testing data. Finally, the average value was obtained to perform an evaluation of the effectiveness of classification. The primary process includes feature selection, emotion classification model training, and correctness assessment, as shown in Fig. 6. These are sequentially explained below.

6. Feature Selection

- Information Gain (IG): according to information theory, IG is a feature selection method [19], fundamentally defined as “the amount of information prior to testing” subtracted by “the amount of information after testing.” As shown in Equation (6), the amount of information a feature contains is calculated to judge whether the feature is selected. This was used to reduce the original feature sets to feature subsets that are easier to process, thereby reducing the feature dimension. This study uses IG to calculate the amount of information contained in each emotion feature. “The amount of information before testing” corresponds to this study, and represents the calculation of the total amount of information contained by the emotional categories. “The amount of information after testing” indicates the total amount of information contained in certain single emotion features after information S is categorized. Larger IG indicates that the emotional feature contains more information. These emotional features are more important to the classification algorithm.

$$InfoGain(A_j) = Info(S) - Entropy(A_j) \tag{6}$$

Where $Info(S)$: total amount of information contained by emotion categories.
$Entropy(A_j)$: total amount of information contained in a certain emotion feature after information is categorized.
A_j : a certain single emotion feature.

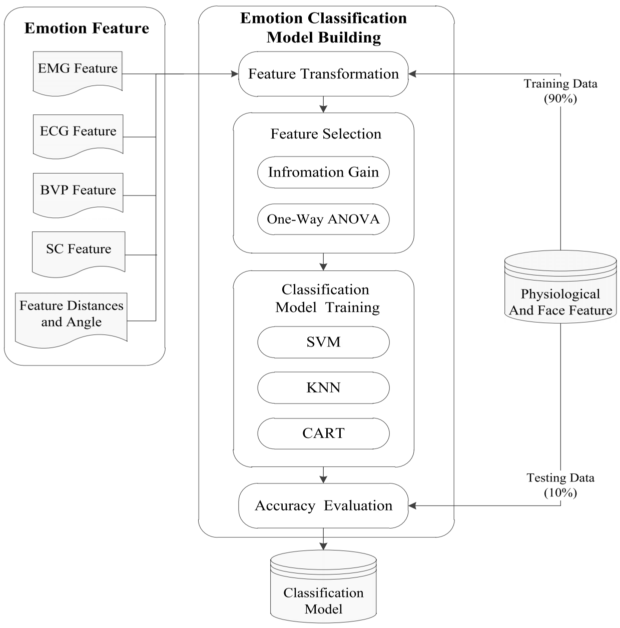

Fig. 6 Emotion classification model construction process

● One-Way ANOVA: One-Way ANOVA primarily analyzes the sources of each variation, thereby comparing the “averages” to distinguish whether significant differences exist among different emotional features. This can serve as a test of emotional features, observing the influence of different emotion categories on features. When the variation ratio between subgroups and within the emotional category subgroups increase, the significance of F values also grow, such as in Equation (7). This indicates that a significant difference exists between emotional features and different emotion categories, and can serve as a basis for feature selection.

$$F = \frac{MSB}{MSE} \tag{7}$$

Where MSB : emotion categories average variation between groups.
MSE : emotion categories average variation within groups.

7. Emotion Classification Model Training

● Support Vector Machines (SVM): SVM is a machine learning method in statistical learning theory. It uses structural risk minimization (SRM) for rules, constructing a separating hyperplane through the learning mechanism and differentiating data from two or more different classes. This study belongs to the multi-class emotion classification problem and is of an inseparable linear type. The radial basis function kernel (RBF) [20] must be used to calculate an equation such as (8) to serve as a kernel function. The feature data is transformed from input space to feature space, and linear classification is then performed on the space.

$$K\ x_i, x_j\ = \exp(-\gamma \| x_i - y_j \|^2), \gamma > 0 \tag{8}$$

RBF can classify nonlinear, high-dimensional data, only requiring the adjustment of cost (C) and gamma (γ). Therefore, finding optimized C and γ is critical. The grid search algorithm [21] was used to seek the optimal combination of parameters (C, γ), training a better SVM emotion classification model.

● K-Nearest Neighbor (KNN): an intuitive classification method comparing the similarities of data from unknown categories with the training data to seek the neighboring points with similarities closest to the prior K position, and calculate the categories of the K sites. In addition, it uses the plurality method to determine the categories of new data. This study used Euclidean distances to calculate the similarity of KNN, as shown in Equation (9). Emotion features of unknown types and the feature distances of known types were used to judge the categories of emotion feature data.

$$Dis(x, y) = \sqrt{\sum_{i=1}^{n} (f_i(x) - f_i(y))^2} \tag{9}$$

Where $f_i(x)$: emotion feature of unknown category in feature space coordinates.
$f_i(y)$: emotion feature of known category in feature space coordinates.

Because of the different K value settings, some of the classification results could be improved. However, no clear conclusion exists regarding the K value settings. Numerous tests must be performed according to the characteristics and number of categories in the data to make this decision. Thus, a standard principle was used to test the K values ranging from 1 to 29 to select the K value with the best classification results to serve as parameter settings.

● Classification and Regression Tree (CART): the segmentation conditions of CART were determined based on the categories and feature attributes of the data. Data with identical attributes were divided into similar emotional categories to train the segmentation rules between the target variable (emotional categories) and the explanatory variable (emotional feature). The CART node selection criteria, using the impurity of each node, were the Gini index of diversity, as in Equation (10). Decreasing node impurity values indicate that identification is increasing and that the node is better able to judge the differences between different categories of emotions. Each node was created to reduce its impurity, also representing a decrease in overall node impurity. When further separation of the nodes was impossible, and the node impurities could be significantly reduced, the construction of the largest trees was complete, and tree pruning was performed to select the classification tree with the lowest error costs to serve as the optimal classification tree.

$$i(t) = \sum_{i \neq j} p(i|t)p(j|t) \tag{10}$$

Where $i(t)$: Impurity of the node.

$p(i\,|\,t)$: ratio of emotions categories in node t and emotion categories of i sample.

$p(j\,|\,t)$: ratio of emotion categories in node t and emotion categories of j sample.

8. Accuracy Estimation

After completing emotion classification model training, precision (P), recall (R), and f-measure were used to estimate the performance of emotion classification, with the equation shown below:

$$precision = \frac{|\ relevant\ emotion\ \cap\ retrieved\ emotion\ |}{|\ retrieved\ emotion\ |} = \frac{TP}{TP+FP} \quad (11)$$

$$Recall = \frac{|\ relevant\ emotion\ \cap\ retrieved\ emotion\ |}{|\ relevant\ emotion\ |} = \frac{TP}{TP+FN} \quad (12)$$

$$F-measure = \frac{2RP}{R+P} \quad (13)$$

Where TP : number of emotion categories classified correctly.
FP : number of emotion categories classified incorrectly.
FN : number belonging to certain emotion categories but classified incorrectly.

IV. Evaluation of the Emotion Classification Mechanism

A. Emotion Evocation Experiment

Emotions are subjective feelings, with the expressions of natural states being the most realistic. However, few emotional category samples can be recorded, and it is difficult to remove the influence of other situational variables on emotion. Therefore, to correctly stimulate the emotions of students with autism and authenticate the collected emotion samples, this study simulated four digital learning environments for mathematics that frequently produced different emotions within autistic students. The same scenarios were used to collect sample emotions. The samples herein referred to are the data on physiological signals and facial expressions collected from students with autism in actual mathematics e-learning situations. The physiological signals were obtained through the ProComp5 [22] device. Four physiological signal sensors were set up on the bodies and limbs of students to detect ECG, EMG, BVP, and SC. In addition, a camera was installed to record changes in facial expression and physical posture in synchronization with the sensors. To avoid external interference when performing the experiment and enable students to integrate into the learning environment in real time, this learning space was an independent testing environment. Fig. 7 shows an overview of the environment of the emotion evocation experiment.

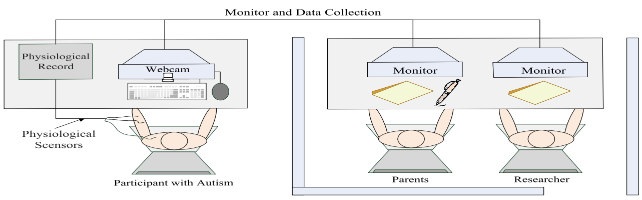

Fig. 7 Emotion evocation experimental environment

B. Subjects

A purposive sampling method was used to select 15 students with highly-functional autism between the ages of 8 and 12. Teachers from elementary school special education classes and civil groups were contacted to seek subjects for this study. This study used mathematics e-learning as the emotional evocation method. All subjects had IQ over than 70, basic mathematical knowledge, language and communication skills, and the ability to use the system interface, operate the keyboard, and move and click the mouse.

C. Emotion Inducing Materials

In the mathematics e-learning environment, specific emotions were collected from the students. Three mathematics e-learning situations and one type of relaxation material were designed for this experiment, aiming at inducing four target emotions: baseline, happy, angry, and anxious.

1. Baseline

Twenty different geometric shapes were used and connected. The shapes were transformed every ten seconds, and the subjects were requested to calculate the total number of changes in shape or color. Because the shapes transformed extremely slowly, this induced baseline emotions.

2. Happy

The game training involved making the subjects operate and observe entertaining mathematics material. The content included Qiaohu e-play mathematics, Hello Kitty fun mathematics games, and anchored instruction videos. The first two game sessions had selections of difficulty, using interesting methods to guide in graphic decomposition, spatial concepts, and logical reasoning. The latter used interactive methods to relate amusing stories, teaching mathematics problems from everyday life. In this phase, students could select the interactive mathematics materials that they preferred to learn. This was done to stimulate happy emotions.

i. Angry

In this phase, a curriculum-based exam was used as the learning material, with a total of 18 questions. The first three questions were calculation problems one level lower than the subjects' current grade level. Following this, the difficulty of the questions was increased to the content expected in the following academic year, and the question type changed to text calculation problems. By continually increasing the difficulty of the problems, this design makes the problems more difficult than the subjects expected, thereby producing emotions of dissatisfaction and stimulating angry emotions.

ii. Anxious

This phase used a time-limited competition method to induce anxiety in the subjects. The content of the competition was taken from the curriculum-based question database. The difficulty of the questions was set to two years below the levels at which the students had currently been studying. This was done to ensure that the subjects were familiar with the content.

There were a total of 50 questions in the competition, and time for response was limited to 10 minutes. Those who answered the most questions correctly could obtain a gift as a reward. This scenario was designed to induce feelings of anxiety among the subjects in their learning situations. Providing students with gifts as an incentive to compete and requiring them to answer questions under a time constraint similar to that of a test, anxious emotions were stimulated.

D. Experimental Procedure

To avoid the appearance of non-targeted emotions induced by a strange environment, the subjects had to participate in two mathematics e-learning exercises. The entire experiment took 50 minutes. The first time was a pre-test, whereas the second was the official experiment. This study took the Latin square design, using partial counterbalancing based on the balance of the subjects to control the sequencing and carry-over effects. The experimental scenario sequence is shown in Table II, and the implementation steps are depicted in Fig. 8. During the emotional evocation period, the researchers and the subjects' guardians were in a monitoring room. The researchers could control the transmission of physiological signals at all times, avoiding abnormal signals caused by equipment problems. The guardians could observe the changes in the subjects' emotions, assisting in marking emotional categories. If the subjects had lost control of their emotions or if unanticipated situations occurred, the guardians could provide timely comfort.

TABLE II
EXPERIMENTAL SCENARIO SEQUENCE OF PARTIAL COUNTERBALANCING

Number	Emotion Induction Sequence
1	Baseline→Happy→Baseline→Anxious→Baseline→Angry
2	Baseline→Angry→Baseline→Happy→Baseline→Anxious
3	Baseline→Anxious→Baseline→Angry→Baseline→Happy

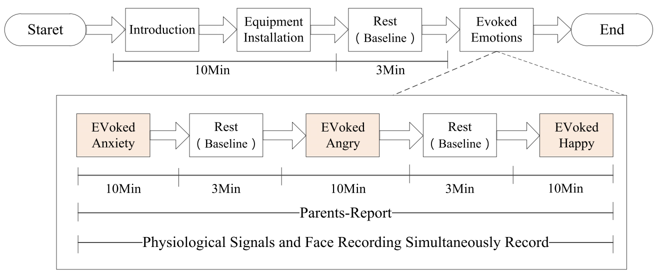

Fig. 8 Experimental Process for evoking emotions

E. Emotion Categories Tagging

Students with autism are weaker than ordinary students in their abilities and experiences with description, having extreme difficulties in describing their moods and psychological states [23, 24]. They commonly have barriers to emotional communication. Therefore, estimating the effectiveness of emotional stimulation among students with autism using conventional emotional assessments is inappropriate. Third parties familiar with the way in which the subjects expressed their emotions were necessary to assist in the tagging of emotional categories, and to confirm the categories of the emotional sample data. Thus, accompanying guardians were the primary collaborators in labeling emotions, participating in the entire experiment.

During the experimentation period, the guardians filled out questionnaires for tagging the emotional categories of the subjects, with synchronized marking being performed in units of 30 seconds. This marking questionnaire had two goals. The first goal was to help the researchers in confirming whether the emotions of the subjects were at baseline during rest times, to prevent the interference of emotions from the previous round on the emotions evoked during subsequent rounds. The second goal was the represent the baseline, happy, anxious, and angry moods using the emotional marker codes A, B, C, and D. Code E represented emotions evoked that were not part of the default emotional categories. In addition to the marking of guardians, this study arranged an expert in the field of autism to confirm the emotions produced by the subjects. This expert reviewed the video and used the same methods to mark the emotional categories produced by the students during the learning process. These were compared with the markings of the guardians, and used in an intersecting way as a basis for emotional sample selection.

F. Emotion Classification Result

From the samples collected by the experiment as described above, 41 physiological signals and 17 facial expressions were obtained, for a total of 58 features. One minute was selected as the length of the time interval. There were a total of 653 emotion samples. The marking results of the guardians and the expert were used in an intersection method to preserve 536 emotion samples to serve as data for emotion classification model training. Table III shows the data distribution of the emotion categories.

TABLE III
EMOTIONAL CATEGORIES DATA DISTRIBUTION

Emotional Type	Baseline	Happy	Anxious	Angry
Quantity	191	99	195	51

After the data were selected according to the emotion samples, the feature selection of IG (Value > 0) and ANOVA (p - Value < 0.05) was performed on the 58 emotion features to select features with clear differences. Table IV reveals the number of features preserved.

TABLE IV
NUMBER OF FEATURES PRESERVED

Feature Selection	Sensors	Feature Quantity
IG	Physiology	20
	Face	8
	Physiology + Face	28
One-Way ANOVA	Physiology	27
	Face	11

Physiology + Face	38

After selection with IG and ANOVA as described above, the feature subsets served as input variables for the classification models of SVM, KNN, and CART. K-fold cross validation [25] was used to divide the samples into ten sections. Nine groups of the data served in turn as training data, whereas the remaining single group of data was the test data. Testing and verification was performed ten times to obtain the final average correct rate. These results were mutually compared with the classification results, with the original number of features as the input variable. The results of these classification model types are explained below in sequence.

3. Support Vector Machines Classification Model

Table V indicates that the original number of features performed best after being classified into four emotional categories by SVM. The accuracy of classification of the physiological signals combined with facial expressions reached 79.29 %. Of these, the individual accuracies of the physiological signals and facial expressions were 75.18 % and 57.08 %, respectively.

TABLE V
SUPPORT VECTOR MACHINES CLASSIFICATION RESULT

Feature Selection	Sensors	TP Rate				Correctly Classified Instances(%)
		Baseline	Happy	Anxious	Angry	
No	Physiology	0.529	0.525	0.723	0.235	57.08
	Face	0.791	0.879	0.846	0	75.18
	Physiology + Face	0.859	0.828	0.841	0.294	79.29
IG	Physiology	0.497	0.485	0.631	0.333	52.79
	Face	0.796	0.808	0.815	0	72.94
	Physiology + Face	0.832	0.859	0.841	0.216	78.17
One-Way ANOVA	Physiology	0.534	0.434	0.79	0.059	56.34
	Face	0.822	0.808	0.831	0	74.44
	Physiology + Face	0.785	0.879	0.779	0.431	76.67

4. K-Nearest Neighbor Classification Model

Table VI indicates that the original number of features of the physiological signals performed best following KNN classification into four emotional categories. Physiological signals combined with facial expressions and facial expressions alone performed best following IG feature selection, with classification accuracies of 70.52 % and 72.94 %, respectively.

TABLE VI
K-NEAREST NEIGHBOR CLASSIFICATION RESULT

Feature Selection	Sensors	TP Rate				Correctly Classified Instances(%)
		Baseline	Happy	Anxious	Angry	
No	Physiology	0.534	0.354	0.764	0.02	53.54
	Face	0.853	0.758	0.749	0.078	72.38
	Physiology + Face	0.738	0.697	0.81	0.176	70.33
IG	Physiology	0.545	0.384	0.656	0.157	51.86
	Face	0.806	0.788	0.815	0	72.94
	Physiology + Face	0.738	0.778	0.8	0.078	70.52
One-Way ANOVA	Physiology	0.461	0.465	0.728	0.078	52.23
	Face	0.827	0.778	0.749	0.039	71.45
	Physiology + Face	0.702	0.747	0.769	0.333	69.96

5. Classification and Regression Tree Classification Model

Table VII indicates that the original number of facial expressions performed best following CART classification into four emotional categories, with a classification accuracy of 69.40 %. For feature selection, a combination of physiological signals and facial expressions, or physiological signals alone, performed best following ANOVA feature selection, with classification accuracies of 68.28 % and 52.61 %, respectively.

TABLE VII
CLASSIFICATION AND REGRESSION TREE CLASSIFICATION RESULT

Feature Selection	Sensors	TP Rate				Correctly Classified Instances(%)
		Baseline	Happy	Anxious	Angry	
No	Physiology	0.309	0.515	0.882	0	52.61
	Face	0.78	0.768	0.697	0.216	69.40
	Physiology + Face	0.754	0.737	0.744	0.078	68.28
IG	Physiology	0.272	0.566	0.887	0	52.42
	Face	0.764	0.768	0.677	0.176	67.72
	Physiology + Face	0.77	0.768	0.682	0.137	67.72
One-Way ANOVA	Physiology	0.33	0.515	0.856	0.02	52.61
	Face	0.759	0.768	0.718	0.137	68.65
	Physiology + Face	0.77	0.778	0.687	0.157	68.28

V. CONCLUSIONS AND FUTURE WORK

This study presents an adaptive emotional adjustment model in mathematics e-learning for students with autism, recording the physiological signals and facial expressions of students in actual mathematical e-learning environments to develop a suitable emotional classification mechanism. Following the results of emotional classification model training, the number of original features in the SVM classification model was most effective. By combining physiological signals with facial expressions, emotion classification accuracy could reach 79.29 %. After IG feature selection on the original number of features, when only 28 features were preserved, emotion classification accuracy could still be maintained at 78.17 %, increasing the operational efficiency of the emotional classification mechanism. Future studies need to develop a superior method for feature selection to seek the most robust features that can accurately classify the emotions of autistic students. Performance could also be increased when improving the efficiency of the mechanism, or other sensory technology can be considered to perform multimode emotion recognition, such as analysis of physical posture or voice, thereby accurately classifying the emotional categories of students. The classification accuracy of anger tends to be low. However, one reason may be the insufficiency of sample data for angry emotions. This result may also be occurred by the low intensity of the anger induced in the test scenarios was insufficient, leading to expressions of this emotion approximating those of anxiety. Therefore, the accuracy of the anger classification was influenced. This result requires further investigation and analysis.

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