J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 6785--6803

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Design and mental health enhancement strategies of students' emotional intervention model in physical education supported by intelligent algorithms

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ABSTRACT
Appropriate use of emotions as a means to intervene in students' sports behaviors in physical education can promote individuals to form correct concepts of sports and physical exercise. In this paper, in order to construct an emotion intervention model, a cross-temporal adaptive graph convolution network (CST-AGCN) model for whole-body limb emotion recognition is proposed by using the method of spatio-temporal graph convolution. The model was applied to the first stage of negative emotion intervention, after which the appropriate intervention strategy was selected from the intervention strategy library. Then the system was used to assist the teacher in completing some of the intervention initiatives. Finally, based on the empirical study and the system, the learners' classroom status after the intervention was analyzed again. In addition the study also designed strategies related to enhancement of students' mental health to further promote students' physical and mental health. After applying the emotional intervention model and mental health enhancement strategies to the second year (1) class of Secondary School S, this group of students showed significant differences in subjective experience, emotional vitality, body value, interpersonal perception, and dilemma coping, and their mental health was significantly improved. Physical education scores were 7.96 points higher compared to the traditional teaching class, and anxiety decreased significantly. It indicates that the intervention model and mental health enhancement strategies in this study can reduce students' anxiety behavior and have a more significant relief of students' negative emotional symptoms such as anxiety and depression, thus promoting the quality of physical education teaching.

Keywords: Emotion intervention model; spatio-temporal graph convolution; physical emotion recognition; physical education teaching

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Received 15 January 2024; Revised 10 February 2024; Accepted 30 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-371

1. Introduction

Into the 21st century, with the rapid development of the economy, people's value orientation is becoming more and more diversified, leading to an increase in the uncertainty factor of people's choice of society, the transformation of values from single to diverse, from closed to open, and from traditional to modern, which triggers a fierce conflict between different values, and a continuous increase in the choice of psychological contradiction in value orientation, which leads to the corresponding psychological problems as well as the manifestations for a series of somatic diseases [1-4]. Therefore, mental health is particularly important. In addition, the competition for talents is the theme of global competition after entering the 21st century. Social reality and future development have put forward higher requirements for students' psychological quality structure and social adaptability, and psychological quality is the foundation of talent quality, while talent is the key to national construction [5-7]. Students are related to the future of the country and the nation, and their mental health is an important public health problem, which has triggered a high degree of concern in the whole society.

In recent years, students' psychological and behavioral deviations due to psychological problems, which in turn lead to delinquency and crime, have occurred from time to time, making students' mental health problems gradually become a prominent social problem, about 30-70% of students have different degrees of psychological problems, and depression, anxiety, and mental disorders account for about 20%, 45%, and 22%, respectively [8-11]. Students' mental health will have a significant impact on their later life, including various aspects of the situation of academics, family, interpersonal communication, life attitude, future work, etc. Meanwhile, academic pressure, employment pressure, family environment, social adaptability, interpersonal communication, Internet addiction, political unrest, etc., are all the causes of students' psychological problems [12-15]. Moreover, students' mental health problems are becoming more and more prominent, gradually showing a trend of lower age [16]. Therefore, to cultivate the comprehensive development of talents, it is necessary to pay attention to students' mental health problems.

In view of the students' unpromising mental health problems, there are still obvious problems in students' mental health education at this stage, and the traditional education concept advocates the use of moral education to replace mental health education, which summarizes the mental health aspects of students' problems as ideological and moral problems [17-18]. When students have psychological problems they cannot use scientific psychological knowledge to solve them, but use ideological and moral education methods to replace the solution of mental health problems, and therefore cannot better solve the actual psychological problems of students. These problems arising from psychological conflicts are often treated as ideological and moral problems, which adds to the psychological distress of students and makes simple psychological problems serious. Physical activity has been proved by most scholars to directly bring pleasure, enhance interpersonal communication among students, and reduce tension and uneasiness, catharsis and transfer of undesirable emotions, thus regulating human emotions, improving mental health, and enabling students' psychology to be adjusted and restored to a healthy state [19-22]. Exercisers who regularly engage in moderate-intensity (60-75% of maximum heart rate) activities for 20-30 minutes at a time are favorable for mood improvement.

However, in physical education, there are still two levels at which physical activity improves and enhances students' mental health. At the teaching level, physical education courses are uniformly designed, ignoring the individual emotional and physical needs of students, and the psychological identification mechanism in schools is backward, often using only physiological changes such as heart rate and scale tools to discriminate, the psychological dynamics of students did not pay attention to the students, students are strongly subjective, and the identification of the results of the bias is large [23-25]. At the teacher level, it is difficult for teachers to pay comprehensive attention to students' problems in group lessons, while some teachers do not pay enough attention to psychological problems and are not skilled in school psychological interventions [26]. Therefore, it is necessary to study the strategies of students' emotional intervention and psychological well-being enhancement in physical education, in order to promote the all-round development of physical education and help students' psychological well-being development.

Kliziene et al [27] conducted an 8-month physical education program intervention that was effective in reducing students' adverse emotions such as anxiety, depression, and aggression, while promoting physical well-being. Malinauskas and Malinauskiene [28] set up a socio-emotional skills training program for intervening in the socio-emotional aspects of physical education students in the areas of empathy, cooperation, self-expression, self-control, optimism, and the ability to understand emotions, and the results of the intervention were positive and effective. Lindell-Postigo et al [29] reduced aggression, a maladaptive emotional behavior, in students with a judo intervention in physical education, while increasing emotional intelligence and self-concept and facilitating mood improvement. Cheon et al [30] utilized autonomous supportive teaching style interventions based on the participation of physical education teachers, which not only met the psychological needs of students, enhanced the classroom atmosphere, but also reduced students' antisocial behaviors. Ma [31] reported to the teaching of physical education dance under the Embodied Cognitive Teaching Mode, the level of psychological well-being of the students were all enhanced, mainly by reducing the symptoms of depression and aggressiveness. It can be seen that the current interventions in physical education teaching only a small number of students' adverse emotions have an intervention effect, and did not specifically put forward relevant measures to improve the level of students' psychological well-being, only in the teaching mode to make adjustments for the physical education teaching of students' emotional interventions and psychological well-being to enhance the strategy of the research is less.

With the development of artificial intelligence technology, the development of physical education has been promoted, while the identification, prediction and intervention of psychological problems, as well as the enhancement of psychological well-being has been developed by leaps and bounds. For example, Liang et al [32] described the usefulness of big data and artificial intelligence in mental health education under the physical education program and the fact that it can be used to assess students' psychological well-being issues. Huang et al [33] combined the decision tree algorithm and Kendall's correlation analysis to analyze students' psychological well-being questionnaire data and construct a prediction model of students' psychological well-being problems from an objective perspective, which realized the detection of students' early psychological problems. Xu et al [34] introduced deep learning algorithms for multimodal emotion recognition in students with the application of psychometric scale tools, which can cope with large-scale, standardized psychological well-being assessments. Jia [35] used a differential evolutionary algorithm to modify the harmony search algorithm and used the improved algorithm to optimize the back-propagation neural network to construct a psychological crisis early warning model and physical education intervention with the optimized neural network. These examples show that the application of intelligent algorithms to psychological well-being problems has brought a new turn to the emotional intervention and psychological well-being enhancement of students in physical education.

The study first utilizes graph neural networks to construct a spatio-temporal map of bones, and realizes the recognition of limb movements through a cross-temporal adaptive graph convolution network (CST-AGCN) model. Then, the method is used to recognize students' emotions in the physical education classroom, select the appropriate intervention strategies according to the recognition results, and then carry out the recognition of body movements again after the completion of the intervention. The cycle is repeated to realize the intervention of students' emotions in physical education. In addition, the study improves the quality of physical education teaching by adjusting teaching strategies, and enhances students' mental health by stimulating students' motivation to learn, improving teachers' level, and teaching students according to their abilities. Finally, the practicability of the above methods is verified through model testing and teaching practice.

2. Designing emotional interventions for students in physical education

General psychology considers emotions to be attitudes toward external things that accompany cognitive and conscious processes and are responses to the relationship between objective things and the subject's needs. It is a psychological activity mediated by the individual's wants and needs. Emotions contain complex components of emotional experience, emotional behavior, emotional arousal, and perception of stimuli." Emotions are the body's evaluation and experience of the likelihood or even inevitability of the success of a behavior in terms of physiological responses, including the seven types of joy, anger, sadness, thought, grief, fear, and surprise. Behavior in the body action on the performance of the stronger it shows that the stronger the emotion, such as joy will be dancing, anger will be gritting teeth, worry will be tea and rice, sadness will be heartbreaking and so on is the emotional reaction in the body action. Emotions are a part of confidence as a whole, which has a coordinated consistency with outward cognition and outward consciousness in confidence, and is a temporary and more intense physiological evaluation and experience of confidence in the body [36]. It follows that emotions involve changes in the body, and these changes are forms of expression of emotions. Emotions are a preparatory stage for action, which may be linked to actual behavior. Emotions involve conscious experience. Emotions contain a cognitive component that involves the evaluation of external things.

Therefore, in the process of sports teaching, the use of emotional intervention on sports learning interests, hobbies and motivation is not clear as well as behavioral laziness of sports disadvantaged groups behavior, so that it is in the best emotional state, and then mobilize the enthusiasm of the students' sports learning, and ultimately to achieve the promotion of sports disadvantaged groups of students the purpose of the physical and mental health of the development of students.

2.1. Limb Emotion Recognition Based on Graph Convolutional Networks

2.1.1. Skeletal spatio-temporal map construction. Skeletal sequences are usually represented by the 2D or 3D coordinates of each joint in each frame, but since the number of frames varies in each emotionally expressed video, which leads to different frame lengths of the skeletal sequences, the frame lengths are artificially specified in order to ensure the uniformity of the sequence lengths, with repetitive padding for the shorter sequences and truncation for the longer ones. The human skeletal structure naturally constitutes a graph structure data, but such a graph structure has only spatial information and lacks temporal information, therefore, a spatio-temporal graph structure constructed by (Benchmark Model Spatio-Temporal Graph Convolutional Networks) ST-GCN was used for the representation of the temporal and spatial dimensions of the skeletal data [37]. An undirected spatio-temporal graph $G=(V,E)$ is constructed over a sequence of skeletons with T frames and N joints, with both joint connection and time frame connection information maintained on the graph structure.

In the spatio-temporal graph, the point set $V=\{v_{ti} \mid t=1,\cdots,T, i=1,\cdots,N\}$ includes all the data in the skeleton sequence, which adequately records the information of the joints in the spatio-temporal dimension and retains the static and dynamic features of the movement, all of which help to recognize emotions. The spatio-temporal structure of the skeleton is shown in Fig. 1, where each node represents a joint of the human structure, the solid lines represent the natural connections between human joints, and the dashed lines represent the trajectories over time. Formally, the edge set E consists of two subsets, the first subset describes the joint skeletal connection mode within each frame, denoted by $E_s=\{v_{ti}v_{tj} \mid (i,j)\in H\}$, where H denotes the natural connection of the human body's joints; the second subset describes the inter-frame connectivity, i.e., spatial connection information of the same joints in consecutive frames, denoted by $E_F=\{v_{ti}v_{(t+1)i}\}$. These two subsets provide a complete description of the natural structure of the human skeleton and the trajectories of the same joints as they move over time.

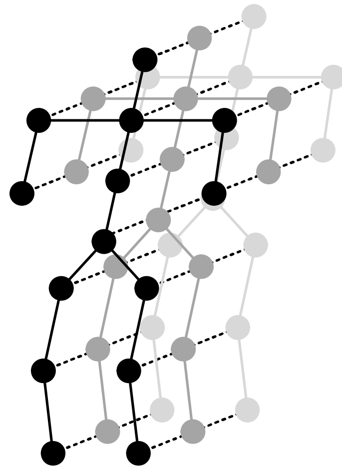


Fig. 1. Skeletal structure

2.1.2. Implementation of spatio-temporal map convolution. For the skeletal spatio-temporal graph defined above, a multilayer spatio-temporal graph convolution operation is applied to the graph to extract high-level features, as in a traditional convolutional network. A global average pooling layer and a softmax classifier are then used to predict emotion categories based on the extracted features. In the spatial dimension, the graph convolution formula for node v_{ti} is defined as follows:

$$f_{out}(v_{ti}) = \sum_{v_{tj} \in B(v_{ti})} \frac{1}{Z_{ti}(v_{tj})} f_{in}(v_{tj}) \cdot W(l_{ti}(v_{tj})) \tag{1}$$

where f represents the feature mapping, v_{ti} and v_{tj} represent the nodes of the graph, $B(v_{ti})$ denotes the sampling area of the convolution of the node v_{ti}, and $B(v_{ti})$ is defined as the set of 1-hop neighboring nodes of the target node v_{ti}. w is analogous to a weighting function in a convolution operation, which provides a vector of weights based on a given input. Where $Z_{ti}(v_{tj})$ is the number of neighboring nodes of node v_{ti}, which is used to balance the contribution of each neighboring node v_{ti} of node v_{tj} to the output. l_{ti} denotes the shortest path length between a node v_{ti} and its neighbor node v_{tj}.

The actual input to the spatio-temporal graph convolutional network is a vector of X as T × N × C, where T represents the length of the time series, N represents the number of nodes, and C represents the number of channels. To realize spatial dimensional graph convolution, Eq. (1) is transformed into:

$$X_t^{l+1} = \sigma(D^{-\frac{1}{2}} A D^{\frac{1}{2}} X_t^l W^l) \tag{2}$$

X_t^l is the eigenvector of the input of layer l at the moment t, A is the N×N adjacency matrix, D is the degree matrix of the adjacency matrix, σ is the activation function, and W is the function of $C_{in} \times C_{out} \times A_{ij} = \begin{cases} 1 & if \quad d(v_i, v_j) = 1 \\ 1 & if \quad i = j \\ 0 & others \end{cases} \quad 1$ weight vector.

The role of the adjacency matrix is mainly used to extract the spatial features of the sample. The construction rule of the adjacency matrix A is as follows:

$$A_{ij} = \begin{cases} 1 & if \quad d(v_i, v_j) = 1 \\ 1 & if \quad i = j \\ 0 & others \end{cases} \tag{3}$$

where $d(v_i, v_j)$ is the shortest path between nodes v_i and v_j.

For convolution in the time dimension, it is simple to use a time graph convolution similar to the classical convolution operation since the number of neighboring nodes per vertex is 2 (the corresponding joints in two consecutive frames). Specifically, the output feature graph computed by Eq. (2) is convolved with $K_t \times 1$ in the time dimension, where K_t is the size of the convolution kernel in the time dimension.

2.1.3. The CST-AGCN model. The key to emotion recognition of students' body movements in physical education lies in how to deeply model the body behaviors expressed by different emotions, and also how the model can aggregate the contextual information to get the feature vectors mapped by body movements under different emotions. To address these key issues, this paper proposes a cross-temporal adaptive graph convolution network (CST-AGCN) model [38], the model architecture is shown in Fig. 2. It mainly consists of an adaptive graph convolution layer and a cross-temporal information interaction layer.

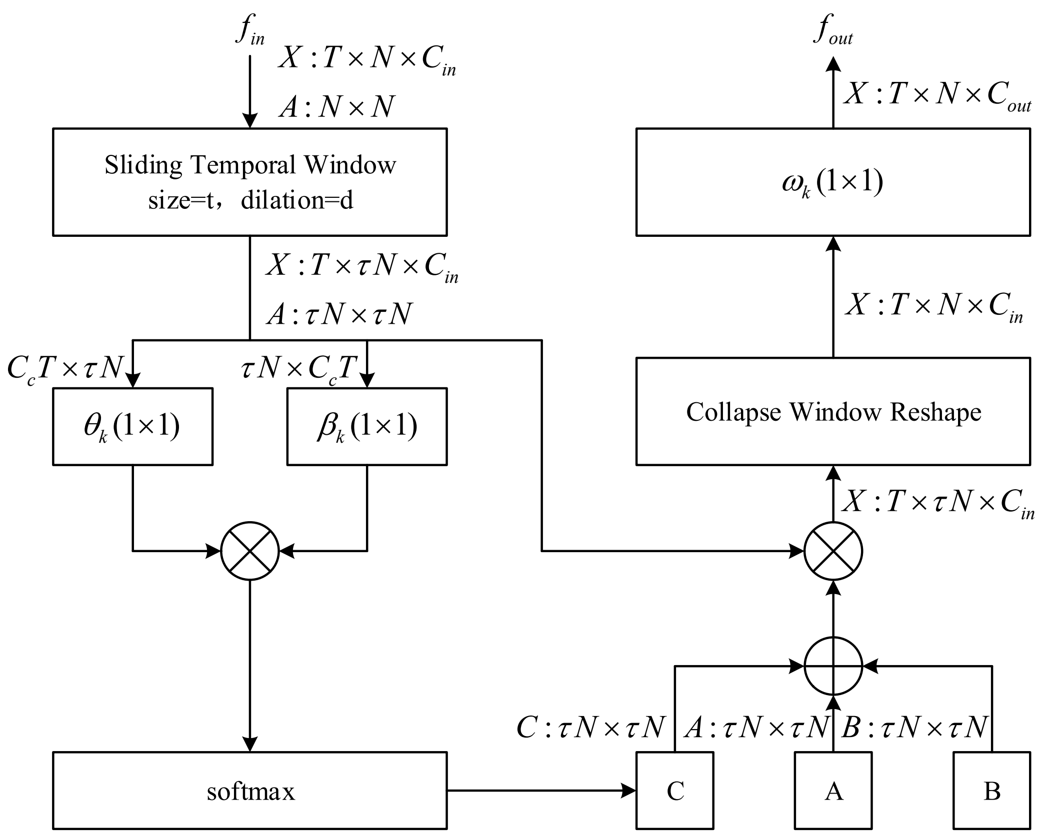


Fig. 2. Cross-spacetime adaptive graph convolutional layer

1) Adaptive graph convolution layer. The hand and foot nodes are not explicitly connected in the original skeletal graph of the human body, which can make the information from the hand not directly transfer to the leg during the node information transfer process. To solve this problem, an adaptive graph convolution approach is used in this paper. It optimizes the topology of the graph along with other parameters of the network in an end-to-end learning manner. The formula for learning implicitly connected adaptive graph convolution in the human skeleton suitable for the task of limb emotion recognition is as follows:

$$X_t^{l+1} = \sigma\left[D^{-\frac{1}{2}}(A + B_l + C_l) D^{\frac{1}{2}} X_t^l W^l \right] \tag{4}$$

The A matrix is the same as the previous one of Eq. (2), who represents the natural explicit connections of the nodes in the body structure.

The B_l matrix is also an N × N adjacency matrix. Each element of the B_l matrix is a learnable parameter, and the initial value of each element of the matrix is set to 10^{-6}. The training of each element in the B_l matrix is shown in Equation (5). Where L is the loss function and α is the learning rate of the network:

$$[B_l]_{ij'} = [B_l]_{ij} - \alpha \frac{\partial L}{\partial [B_l]_{ij}} \tag{5}$$

The C_l matrix is a data correlation graph that is different for different samples with different layers. It learns the unique graph structure for each sample. In this paper, we believe that different emotion samples should have different characteristics, and the model should be able to learn the individual graph structure of different emotion samples.

2) Layer of inter-temporal information interaction. The nature of actions is not just a collection of static frames, but presents an evolution and coherence in time. The temporal sequence of actions is realized through the association and dependency between the previous and previous frames in the action sequence. Each frame carries a portion of the action's information and interacts with the preceding and following frames to form a complete representation of the action. Networks are designed in such a way that nodes should not only be able to access the information of the current frame. Therefore, in this paper, a sliding time window of size τ is set on the input graph sequence, and each slide of the sliding window acquires a temporal subgraph $G_{(\tau)} = (V_\tau, E_\tau)$. The subgraph $G_{(\tau)}$ contains information about the joint points of consecutive τ frames. Therefore, the corresponding adjacency matrix A_τ can be constructed.

The construction rule of A_τ is shown in equation (6):

$$A_\tau = \begin{bmatrix} A & \cdots & A \\ \vdots & \ddots & \vdots \\ A & \cdots & A \end{bmatrix} \in R^{\tau N \times \tau N} \tag{6}$$

By constructing such an adjacency matrix, the spatial connectivity of the nodes will be generalized to the time domain. Each node within the subgraph G_τ is tightly connected to itself and its 1-hop spatial neighbors on all adjacent τ frames. One can easily obtain $X_\tau \in R^{T \times \tau N \times C}$, along with the graph convolution for the tth time window:

$$\left[X_{(\tau)}^{(l+1)}\right]_t = \sigma\left[D_{(\tau)}^{-\frac{1}{2}}(A_{(\tau)} + B_{(\tau)}^{(l)} + C_{(\tau)}^{(l)})D_{(\tau)}^{\frac{1}{2}}[X_\tau^l]_t W^l\right] \tag{7}$$

The inter-temporal strategy enables the flow of node information to be generalized from the small current frame to the entire temporal neighborhood.

2.1.4. Cross-temporal adaptive graphical convolutional networks. The structure of the inter-temporal adaptive graph convolution network is shown in Fig. 3. The input to the inter-temporal adaptive graph convolutional network is a sequence of graphs of length T. The network structure consists of a stack of multiple inter-temporal adaptive graph convolutional basis blocks, each with 64, 64, 128, and 256 output channels. A Batch Normalization layer is added at the beginning to normalize the input data, and the deep features of the samples are extracted after multiple inter-temporal adaptive graph convolution modules. Finally, it goes to the Global Mean Pooling Layer (GMP), which pools the feature maps of different samples equally. The final output is sent to the softmax classifier to obtain predictions.

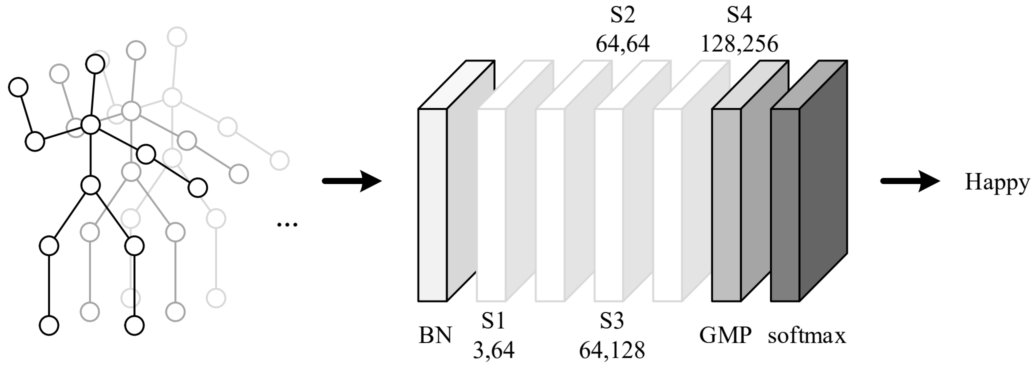


Fig. 3. CST-AGCN structure diagram

2.1.5. Label Smoothing Loss Function. Due to the fact that the total amount of the dataset is too small, in order to alleviate the overfitting problem of the model to some extent, this paper uses the label smoothing technique proposed in the literature. The label smoothing technique is a mechanism that drives the model to reduce the confidence level, which can make the model more generalizable. Specifically, u_k is used to denote the distribution of labels independent of the training samples. ξ denotes the smoothing parameter. For a sample x with label y its original labeling distribution is denoted as $q(k \mid x) = \delta_{k,y}$, and the new labeling distribution $q^{'}(k \mid x)$ is used in place of the original labeling distribution:

$$q^{'}(k \mid x) = (1-\xi)\delta_{k,y} + \xi u_k \tag{8}$$

In this paper, u_k in the experiments uses a uniform distribution instead, i.e., $u_k = \frac{1}{K}$.

In the experiments ξ is taken as 0.001. The label smoothed distribution is equivalent to adding noise to the true distribution to avoid the model being overconfident about the correct label. The effect of preventing the maximum unnormalized log probability from being much larger than all other unnormalized log probabilities is achieved. Remember that the commonly used cross-entropy loss function is:

$$H(q,p) = -\frac{1}{N}\sum_{i}\sum_{c=1}^{K} p_i log q_i \tag{9}$$

Then the loss function after label smoothing is:

$$H(q^{'},p) = (1-\xi)H(q,p) + \xi H(u,p) \tag{10}$$

The loss after label smoothing uses a pair of losses: $H(q,p), H(u,p)$ instead of the original loss $H(q,p)$, and the relative weights $\frac{\xi}{1-\xi}$ are used to penalize the deviation of the predicted labeled p distribution from the prior distribution u.

2.2. Modeling of Negative Emotions Intervention

A physical emotion recognition model was constructed based on graph convolutional network above, and this chapter constructs a negative emotion intervention model with the support of this model. The model first identifies students with negative emotions in physical education through the CST-AGCN model. Then it selects the corresponding combination of intervention strategies from the intervention strategy library, and specifies the intervention strategy, scope, and intensity. After that, the system was borrowed to assist teachers to complete some of the intervention initiatives. Finally, based on the empirical study and the system, the classroom status of the learners after the intervention is analyzed again. The design of the negative emotion intervention model is shown in Figure 4.

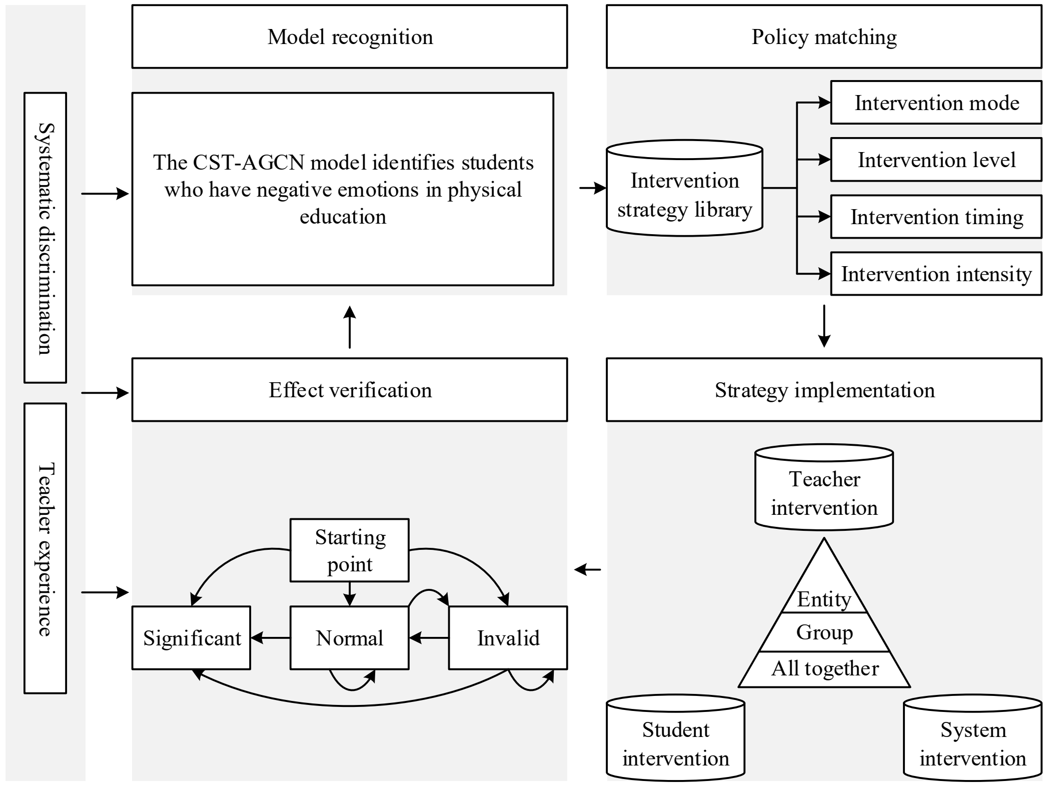


Fig. 4. Negative emotion intervention model

One of the intervention strategies for negative emotions is the focus of the intervention modeling construct. The regulation of negative emotions occurs through intervention strategies, and the choice of intervention strategies is appropriately adapted to the learner's learning state. This study synthesizes existing strategies and designs an intervention strategy library. The strategy library contains three major categories and nine subcategories, the three major categories are teacher intervention, student intervention, and system intervention, and the nine subcategories include pedagogical regulation, atmosphere regulation, and conversation interview in teacher intervention, communication and cooperation, mutual evaluation, and reflection and summarization in student intervention, and supervisory presence, visual presentation, and early warning prompts in system intervention, and each strategy contains a specific intervention method. In the actual intervention process, specific intervention strategies are given comprehensively for the learners' learning status, and the combination of each intervention mode is combined with the intervention level, intervention timing, and intervention intensity in order to realize the comprehensive intervention effect [39].

3. Mental health promotion strategies

In this paper, for the teaching of sports disadvantaged groups, on the one hand, based on the negative emotion intervention model constructed in the previous paper to adjust the students' classroom status in a timely manner, and on the other hand, mainly from the aspect of students' mental health, to improve the quality of physical education teaching by adjusting the teaching strategy.

3.1. Stimulate self-motivation in physical education learning

Research has proved that students' cognitive level of sports directly affects their sports attitudes and sports behaviors. Therefore, teachers should pay attention to strengthening the teaching of students' sports knowledge and try to improve the cognitive level of disadvantaged students. At the same time, they should find ways to stimulate their motivation and enthusiasm for learning, and use more motivational and expectant language and behavior to infect disadvantaged students. In addition, some teaching scenarios can be set up to sharpen their will and gradually guide them into active learning. At the same time, teachers should strengthen ideological education with vivid examples and scientific knowledge, and pay attention to observing and understanding their psychological characteristics, combining awareness-raising and cultivating interest.

3.2. Improvement of teaching standards and educational guidance

Physical education teachers should strengthen their studies, update their knowledge and concepts, improve their teacher ethics, and sensitize the sports disadvantaged with their noble thoughts, profound business and good behaviors. Physical education teachers should be full of confidence in the face of disadvantaged groups and migrate this confidence to students, stimulate the sports disadvantaged, improve their physical and mental qualities, and strengthen the ideological education of disadvantaged students, improve their level of understanding of sports learning and exercise, eliminate their prejudice against sports, help them to correct their learning attitudes, and at the same time, let them under the constraints of certain rules and regulations, gradually develop the habit of exercise, improve their own quality and realize their value in physical education class.

3.3. Tailor-made teaching to stimulate interest in physical education learning

Different sports disadvantaged groups have different psychological characteristics that govern their performance. Therefore, different sports disadvantaged groups should be taught in different ways, not uniform. Poor physical quality of students, can appropriately reduce the difficulty of the exercise and requirements, so that in the frequent frustration, failure and “pain”, taste the joy of progress and success, thus stimulating their interest and confidence. For timid students, we can use funny and witty language, vivid image of the metaphor, to eliminate their nervousness. For students with special body types, we can choose some exercises that meet their physical conditions, give full play to their respective strengths, complement their strengths, and gradually develop their physical qualities. In short, to help them formulate and achieve their own learning goals within their reach, to turn disadvantages into advantages, to change their inferiority self-understanding, and gradually establish self-esteem and self-confidence.

4. Empirical analysis

In this chapter, the emotion recognition method constructed in the previous paper was experimentally tested, and after verifying that the method could be put into use, it was applied to the negative emotion intervention model and combined with the mental health enhancement strategy designed in this paper to reform the physical education teaching in the second semester of 2024 for the second year (1) class (experimental class) of S Middle School. The effectiveness of the emotion intervention model and mental health enhancement strategies designed in this paper was verified by comparing the physical education scores and anxiety tests with the (2) class (control class) that did not implement the emotion intervention.

4.1. Model detection

4.1.1. Data sets. This algorithm uses the latest Emotion-Gait dataset, including the classical datasets BML, Human3.6M, ICT, CMU-MoCap, as well as newly collected limb movement data.Emotion-Gait fully processes all kinds of limb movement data, transforming both video, picture, and graph-sequence limb movement data into graph-sequence limb movement data. The dataset has a total of 1835 body movements, of which 10 annotators provide emotion labels. In the labeled data, 56%, 32%, 23%, and 14% of the body movements were happy emotion, sad emotion, angry emotion, and neutral emotion, respectively.

4.1.2. Comparison and analysis of experimental results. In this paper, we will compare the performance of seven algorithms on the limb emotion dataset, all methods are demonstrated based on the Emotion-Gait dataset.The seven algorithms are:
1) LSTM: Combines Long Short-Term Memory (LSTM) with limb movement emotion recognition, using limb movement joint spatial location data as inputs, which are converted into vectors for classification tasks.
2) STEP: A spatio-temporal graph convolutional network is used as the basic network, and limb pose data is used as input to train the network. Meanwhile, a variational self-encoder based on spatio-temporal graph convolutional network is constructed and the performance is improved by fine-tuning the parameters of the spatio-temporal graph convolutional network.
3) HAP: Semi-supervised learning based on self-encoder is used, and the input is 4-dimensional data, including 3-dimensional spatial motion data and 1-dimensional joint rotation data. In the encoder, the joint motion data are hierarchically aggregated from bottom-up; the decoder reconstructs the joint motion from potential embeddings from top-down at each time step. The classifier is trained to map the embedding data to sentiment labels.
4) ST-GCN: Propose a layered strategy to compute the graph convolution of each joint point based on the 3D skeleton structure, compute the temporal neighborhood based on instances of the same joint point at different time steps, and perform the convolution operation.
5) DGNN: Calculates the directed acyclic graph of the bone structure based on the kinematic dependencies, updates the node features using graph neural networks and random wandering methods, and trains the DGNN network using input human pose space feature data.
6) MS-G3D: Performs multi-scale graph convolution in the spatial dimension and adds jump connections in the temporal dimension to learn the long-range dependencies of various actions.
7) MST-GCN: divides the input 3D spatial pose data into multiple channel dimension features, performs batch processing by stacking spatio-temporal graph convolution networks, and learns long-range features between graph nodes.

The comparison results of CST-AGCN with other methods are shown in Fig. 5. The accuracy of this paper's method on happy, sad, angry and normal categories is improved by 0.1%, 2.6%, 10.7% and 10% respectively relative to the better performing method of Hierarchical Attention Pooling (HAP). CST-AGCN improves the recognition performance of all the emotion categories, with smaller improvement in the recognition accuracy for the happy and sad emotions, and larger improvement for the angry and normal emotions.

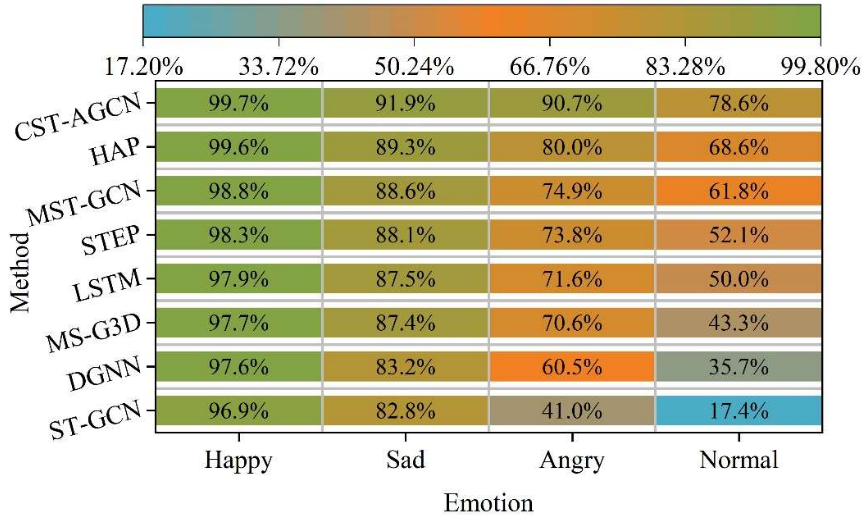
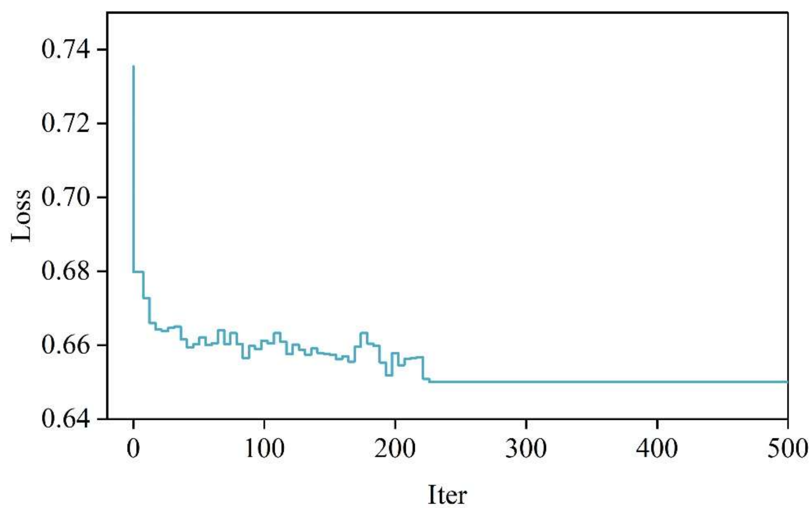
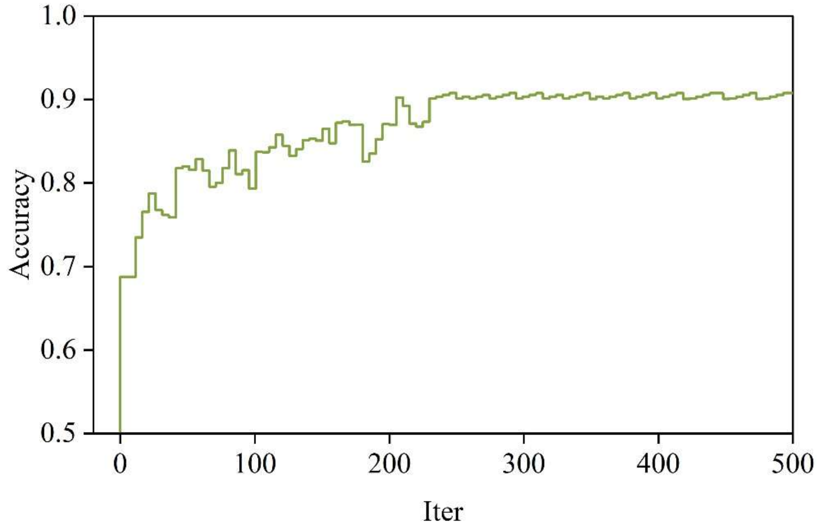


Fig. 5. Emotional recognition performance contrast

The variation of the accuracy loss value of the CST-AGCN network is shown in Fig. 6. (a) and (b) represent the change of network loss value and the change of recognition average accuracy, respectively. From Fig. 6(a), it can be seen that when the number of iterations reaches 230, the network loss value also no longer changes, indicating that the network has good robustness. And from Fig. 6(b), it can be seen that as the number of iterations increases, the recognition accuracy of the network gradually improves and stabilizes when the number of iterations reaches 230, and the recognition rate also remains at 90%.



(a) Network loss value variation



(b) Identify average accuracy variation

Fig. 6. Changes in the value of network precision

The variation of the network's recognition accuracy for the four emotions is shown in Figure 7. After several rounds of iterations, the network's recognition rate for happy emotions exceeds 90%, which is due to the fact that the number of happy emotion samples in the dataset is more than 50%, and also indicates the network's effectiveness in recognizing physical emotions. The network's accuracy for sad emotions improves more slowly, and when the number of iterations reaches 350, the recognition rate stabilizes and reaches 91.9%. The network's accuracy for angry emotions improves more slowly, and when the recognition accuracy reaches 80%, the recognition accuracy fluctuates more, indicating that the network is more inclined to macro features and global features. When the number of iterations reaches 350, the recognition accuracy stabilizes, indicating that the network effectively extracts local features and fuses them into global features. For usual emotions, the recognition accuracy fluctuates more at first, which is because usual emotions have the smallest number of samples, and the network prefers to fit categories with a larger number of samples. Another part of the reason is that the feature changes of the usual emotions are not obvious, the human body posture is not strongly connected at each position, and more human body local position changes. When the number of iterations reaches 300, the network effectively extracts local features and the recognition of usual emotions stabilizes to 78.6%.

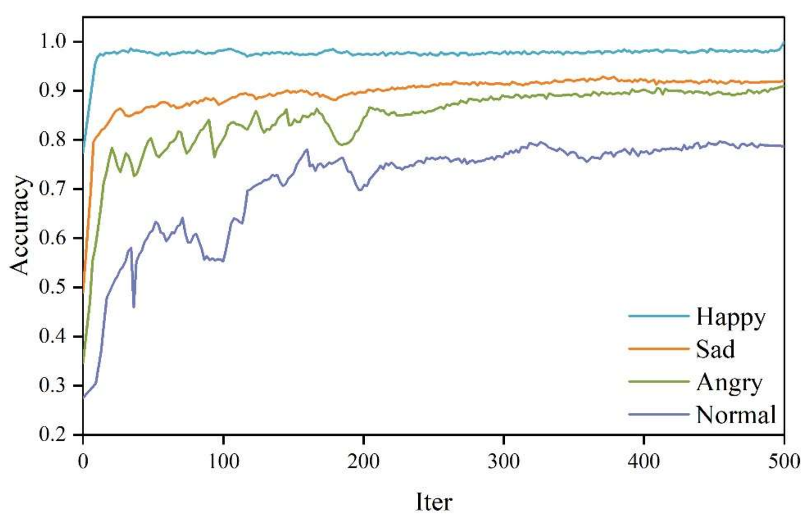


Fig. 7. Four kinds of identification precision changes

The emotion recognition method based on students' body movements designed in this paper was experimented on the Emotion-Gate dataset, which verified the validity of the method and could be applied to the negative emotion intervention model for subsequent teaching practice.

4.2. Comparison of Physical Education Achievement

Based on the literature of relevant research results in psychology, the psychological benefits of exercise questionnaire was selected, and five dimensions (subjective experience, emotional vitality, physical value, interpersonal perception, and dilemma coping) were identified for the evaluation of physical exercise feelings. On this basis, 20 entries consistent with the psychology of physical exercise were collected. Before and after the experiment, the subjects were asked to answer the Likert-5 point scale, which ranges from 1 for “not at all in line with me” to 5 for “completely in line with me”. The reliability of the questionnaire was found to be good.

The test of difference between the pre and post evaluation dimensions of the experimental class is shown in Table 1. The scores of subjective experience, emotional vitality, body value, and dilemma coping of the experimental class had very significant changes after the experiment ($p<0.05$), especially in the scores of interpersonal perception after the experiment, and the experimental class had a significant improvement in all other aspects after the emotional intervention.

Table 1. Evaluate the difference of dimensional changes

Dimension	Preexperiment	After the experiment	T	Sig.
Subjective experience	10.36±3.62	11.63±3.63	-2.632	0.013
Emotional energy	112.63±3.62	115.23±2.63	-2.634	0.036
Physical value	11.96±2.63	13.77±3.36	-3.624	0.011
Interpersonal perception	113.62±3.63	116.52±2.63	-3.242	0.001
Dilemma	99.63±3.21	116.32±2.63	-2.634	0.029

The scores and number of students in the experimental class and the control class of the final overall assessment scores (physical fitness test scores, dribbling and shooting scores, fixed-point shooting scores, sunshine long-distance running scores, and usual performance scores) of each index are data statistics in Excel.

The test analysis of the final overall assessment scores of students in the experimental class and the control class is shown in Figure 8. The final average score of the experimental class in physical education is 7.96 points higher than that of the control class, judging that the emotional intervention method is better than the traditional teaching method and can promote the improvement of students' performance. The use of independent samples t-test on the difference between the final overall assessment scores of students in the experimental class and the control class also further proves that there is a significant difference between the old and new teaching methods.

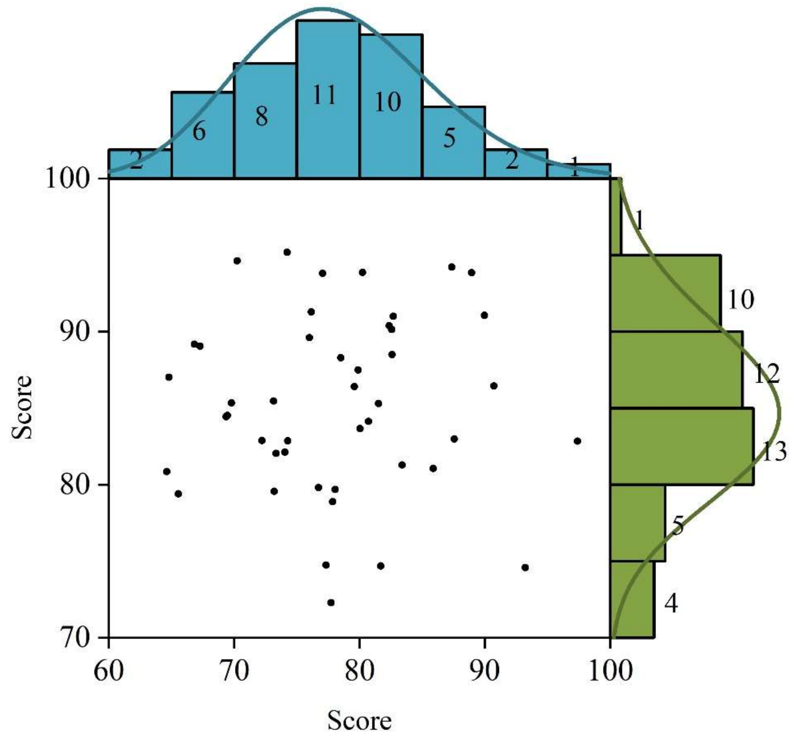


Fig. 8. The test analysis of the final evaluation of the students

4.3. Comparison of Anxiety Detection

Self-Assessment Scale of Anxiety (SAS) [40] and Hamilton Anxiety Scale (HAMA) [41] were used in order to assess the changes in the mental health of the students in both classes. The cut-off value of the standardized score of the SAS is 50, where mild anxiety ranges from 50 to 59 points, moderate anxiety ranges from 60 to 69 points, and a score of 70 or more is considered to be severe anxiety. The HAMA consists of 14 items each rated on a five-point scale. A total score of more than 29 is likely to be severe anxiety. Above 21 points, there is definitely significant anxiety. Over 14 points, definitely have anxiety. More than 7 points, possible anxiety. Less than 7 points, no anxiety. 14 points is generally taken as the cut-off value for anxiety.

The differences in SAS and HAMA scores between the two classes were assessed before and after the teaching practice, respectively.

1) Comparison of SAS scores between the two classes before and after the teaching practice. The comparison of SAS scores before and after teaching practice in the two classes is shown in Table 2. The difference in SAS scores between the experimental class before and after the teaching practice was significant, while there was no significant change in the control class. In particular, the SAS scores of the experimental class after teaching practice were significantly lower than those of the control class, and the difference between the two classes was significant ($P<0.05$).

Table 2. SAS score comparison

Class	N	Prepractice	After teaching practice	T	P
Laboratory class	50	61.53±7.96	34.52±5.10	12.631	<0.05
Cross-reference class	50	62.03±7.41	61.63±7.42	6.354	>0.05
T	-	1.365	10.364	-	-
P	-	>0.05	<0.05	-	-

2) Comparison of HAMA scores before and after teaching practice in two classes. The comparison of HAMA scores before and after teaching practice in the two classes is shown in Table 3. The difference in HAMA scores between the experimental class before and after teaching practice was significant, and there was no significant change in the control class. The HAMA scores of the experimental class after teaching practice were significantly lower than those of the control class, and the difference between the two classes was significant ($P<0.05$).

Table 3. HAMA score comparison

Class	N	Prepractice	After teaching practice	T	P
Laboratory class	50	18.55±4.32	6.53±1.96	9.668	<0.05
Cross-reference class	50	18.44±4.37	17.92±2.55	6.452	>0.05
T	-	1.236	6.851	-	-
P	-	>0.05	<0.05	-	-

Model testing and teaching practice verified that the CST-AGCN can support the construction of an emotional intervention model for students in physical education, and that students' physical education performance increased and anxiety decreased significantly after the application of the emotional intervention model and mental health enhancement strategies.

5. Conclusion

In this paper, a cross-temporal adaptive graph convolutional network (CST-AGCN) model is proposed for the emotion recognition stage of an emotion intervention model in physical education. The model has good recognition accuracy for happy emotion, sad emotion, angry emotion, and neutral emotion, and can be applied to the initial stage of the emotion intervention model.

Applying the emotion intervention model and mental health enhancement strategies to the experimental class for teaching, the independent samples t-test proved that there was a significant difference between the old and new teaching methods. Comparison of SAS scores and HAMA scores before and after teaching practice showed statistically significant differences in anxiety in both classes ($p<0.05$).

The emotional intervention model and mental health enhancement strategies designed in this paper are more effective in improving the physical self-esteem level of students from disadvantaged groups in sports, effectively promoting the mental health status of students, and promoting members of disadvantaged groups to generate positive sports emotions, maintain a good state of mind, and alleviate the emotional state of tension, anger, and depression due to sports disadvantages.

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