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ORIGINAL

Emotion Regulation and Performance Enhancement in College Athletes Based on Emotion Recognition and Deep Learning

Haiqing Li[1]

[1]Shanxi Jinzhong Institute of Technology, College of General Education,Shanxi Jinzhong City, 030600, China

Email: lihh1999@163.com

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Abstract

Different emotions on the field will affect athletes' attention, decision-making and behavior, and exploring the effects of emotion regulation strategies on different emotions will be helpful for athletes to quickly adjust their state on the field and play at their proper competitive level. This paper proposes a novel method for athletes' emotion regulation and performance enhancement based on emotion recognition and deep learning technology. Firstly, a strong attention and residual network model of emotion recognition network is proposed. The model can carry out the whole process of capturing the important features of expressions and form the strong attention function. Specifically, strong attention refers to the capture of expression important features by adding channel and spatial attention mechanism (CBAM) in front of ResNet residual module. The global effective channel attention (G-ECA) is then added to the residual module to enhance the extraction of key features. Finally, CBAM is again embedded into the residual module to play the role of auxiliary extraction to minimize the loss of useful facial information. Secondly, the proposed model is simulated on two public benchmark expression datasets, CK+ and JAFFE, and the experimental results prove the effectiveness of the proposed method. Finally, based on the emotion recognition results, a standardized method for emotion regulation and performance enhancement in college athletes is given.

Keywords. Emotion Regulation, Performance Enhancement, College Athletes, Emotion Recognition, Deep Learning

1. INTRODUCTION

Emotions affect athletes' behavior generation and behavioral decisions.

The situation on the sports field is constantly changing, and in the face of various unexpected situations, athletes need to calmly face and use emotion regulation strategies to adjust their emotional state in time and stabilize their performance (Canal et al., 2022; Chowdary, Nguyen, & Hemanth, 2021). In the experimental task before inducing emotions to make participants in a certain emotional state found that there are differences in individual behavioral control under different emotional states (Gagne, Liew, & Nwadinobi, 2021; Hajal & Paley, 2020). After being affected by emotions, if we can use the corresponding emotion regulation strategies in time to effectively regulate emotions, it will be beneficial to the athletes' behavioral inhibition (Hut et al., 2023; Jain, Shamsolmoali, & Sehdev, 2019) and emotion regulation. Athletes' emotion regulation is not only affected by the factors of the field state, but also by the athletes' personality traits and character. Different goal-oriented athletes have different evaluation standards for achievement events, and there are also differences in the degree of effort. The hypothetical model with motivation, emotion, cognition and behavior as mediating variables about goal orientation and outcome argues that goal orientation affects the individual's behavioral style, and whether different goal orientations have any influence on athletes' emotion regulation and how to influence athletes' emotion regulation is the focus of this paper (Kalanthroff, Cohen, & Henik, 2013; Kim, Lee, & Kang, 2019).

Emotional control is an important part of executive function and an important part of sport psychology research, which helps athletes to inhibit the action that is being or has been issued and to re-engage in behavioral choice to issue a new action. In the arena, athletes can use the effective time is very short, need to pay close attention to eliminate interference, always ready to deal with a variety of changes, which requires athletes to have better behavioral inhibition; In addition, because athletes can refer to the effective information is also very limited, even if it is a very good athlete is difficult to all the incoming ball or all the movements of the opponent to make an accurate and accurate judgment, so when the Therefore, when an athlete realizes that he/she has made a wrong decision, he/she has to quickly adjust his/her dominant movements (Kleibeuker et al., 2013). Behavioral inhibition in high-level athletes can even occur after the movement is made, during which the athlete can quickly stop the current movement and choose a new response based on the environment and information of the court to make the appropriate movement (Lee et al., 2022; Lindström & Bohlin, 2012). In the research related to emotional control, the influencing factors of emotional control is a key issue, and researchers believe that emotional control requires cognitive participation, and individual cognitive resources are limited, and other interfering factors take up individual cognitive resources before the behavioral inhibition task, resulting in slowing down or even failing to inhibit the individual's behavior. What factors influence emotional control? How do the influences work? What kind of role do they play? At what stage of emotional control do they act? These questions are important for understanding the working process of behavioral inhibition and improving emotional control in athletes (Mellouk & Handouzi, 2020).

The study shows that facial expression of human face accounts for

55% of the communication information of college athletes, which is higher than the voice which accounts for 38% and the language which accounts for 7%. Therefore, facial expression is an important feature of college athletes' emotional expression and transmission, and is an important foundation for emotion analysis research, which is of extraordinary importance for solving college athletes' emotional problems and robotic intelligent emotions. Face emotion recognition (Merchán-Clavellino, Alameda-Bailén, Zayas García, & Guil, 2019; Moharamzadeh, Pashaei, & Nagavi, 2019) refers to the characterization of the face in an image or a video frame, specifically facial expressions can be classified into seven categories of basic emotions, i.e., happy, surprised, neutral, sad, disgusted, scared and angry. Based on the category of the input image, it can be categorized into controlled environment (laboratory environment) and uncontrolled environment images, controlled environment images have higher quality and their recognition accuracy is higher as compared to uncontrolled environment images. Whereas, the problems such as head pose changes and occlusion of the face in uncontrolled environment images make face facial expression recognition still a challenging task. In recent years, attention mechanism networks formed by imitating human visual attention have been widely used in the field of deep learning (Nippert & Smith, 2008; Nook, Satpute, & Ochsner, 2021). In the image task, it is reflected in focusing on the important information of the image and reducing the influence of secondary information to improve the performance of the network. For face expression tasks with significant features, such as the upturned corners of the mouth and the eyes squinting feature when smiling, and the mouth opening and eyes widening feature when surprised, it is more beneficial to accurately recognize expressions by combining the attention mechanism with expression recognition and proposing a network model that conforms to the expression task (Walker et al., 2022).

Therefore, the emotion recognition identification task not only has important scientific research value, but also has rich practical application value, which has a positive effect on college athletes' emotion regulation and performance enhancement. The main contributions of this paper are as follows:

(1) In this paper, a novel approach for emotion regulation and performance enhancement of athletes is proposed based on emotion recognition and deep learning techniques, and the effectiveness is demonstrated through simulation experiments.

(2) In this paper, a novel network model for facial expression recognition with strong attention and residual network is proposed. The model can carry out the whole process of capturing the important features of expressions to form the strong attention function. Specifically, strong attention refers to the capture of expression important features by adding the channel and spatial attention mechanism (CBAM) in front of the residual module of ResNet. Global Effective Channel Attention (G-ECA) is then added to the residual module to strengthen the extraction of key features. Finally, CBAM is again embedded after the residual module to play an auxiliary extraction role

and reduce the loss of useful facial information.

2. Related Works

2.1 Emotions and Individual Behavior in College Athletes

Emotions are motivational and perceptual positive forces that organize, maintain, and direct behavior, and different emotions experienced by an athlete before or during a competition can affect the athlete's athletic performance during the competition. Emotions experienced by an individual are expressed in three ways (physiological, cognitive, and behavioral), and through these three responses, emotions can be functional or dysfunctional. On the field of play, if an athlete's emotions are not reasonably released, the athlete's athletic performance or athletic achievement will be affected. Research on the relationship between emotion and behavioral inhibition has mainly explored the relationship between different dimensions of emotion and behavioral inhibition based on the potency-arousal theory. A few scholars believe that the influence of emotion on behavioral inhibition is mainly due to the strength of emotional arousal changing the results of behavioral inhibition, while emotional potency has no effect on individual behavioral inhibition (Prefit, Candea, & Szentagotai-Tătar, 2019). However, more studies have found that emotional valence has a significant effect on behavioral inhibition, but there is still no definite conclusion on how emotional valence affects individual behavioral inhibition. The Go/Nogo research paradigm was used to examine the relationship between emotional valence and behavioral inhibition, and it was found that under the Go stimulus condition, positive emotions facilitated individuals' responses, with shorter response times than those of neutral and negative emotions; under the Nogo condition, positive emotions interfered with individuals' behavioral inhibition, increased the difficulty of the task, and led to more errors and a decrease in the rate of correctness (Preuss, Capito, van Eickels, Zemp, & Kolar, 2021). A number of related studies with children have provided similar evidence. Longitudinal studies have found positive effects of positive emotions on children's behavioral inhibition from childhood to early adulthood, with the effect being more pronounced in early childhood (Sagaspe, Schwartz, & Vuilleumier, 2011). The use of negative emotion pictures as eliciting materials yielded the opposite results, with negative emotions hindering individuals' behavioral inhibitory responses and decreasing correctness (Tamminen et al., 2019). It can be seen that the directionality of the influence of emotions on behavioral inhibition is also influenced by various types of emotional characteristics.

At the same time, some work has focused on the relationship between specific emotions and behavioral inhibition. When horrifying facial pictures were used as threatening stimuli and appeared incidentally and without warning during the experiment, study participants showed significant increases in behavioral inhibition responses (Thomson & Jaque, 2020). However, the study could not well distinguish whether it was because the emotion generated by the threat affected behavioral inhibition or the abruptness of the stimulus. After this a researcher used pictures related to spiders and snakes as threatening materials and obtained the same results, threatening stimuli increased individuals' error rate in a behavioral inhibition task, indicating that threatening stimuli interfere with individuals' behavioral inhibition.

2.2 Emotion Regulation

Emotion regulation is a process by which an individual adapts to changes in the environment by reducing the impact of emotions through conscious or unconscious regulation. Individuals use regulation strategies to change their attitudes, emotional experiences, or to change emotionally triggering events. According to the emotion regulation process model (shown in Figure 1), the emotion regulation used by individuals during the emotion process can be divided into two categories: first, prior attention regulation at the attentional and cognitive levels; and second, reactive attention regulation that occurs in the response phase. Prior attention regulation, which also includes context selection, context modification, attention allocation, and cognitive change, mainly occurs before the activation of emotional responses, and the most commonly used approach is the cognitive reappraisal strategy (Vanderlind, Millgram, Baskin-Sommers, Clark, & Joormann, 2020), which occurs at the stage of giving meaning to emotions, and regulates emotions by reappraising emotional events; response-attention regulation regulates emotions by adjusting the responses, and occurs during the formation of emotions, after the activation of emotional responses, and the most commonly used strategy is called response-attention regulation. After that, the most frequently used strategy is called expression inhibition, in which individuals regulate emotional affect by inhibiting expressive behaviors (facial expressions, body) that are caused by emotions. These two emotion regulation strategies are the most effective and actionable methods, and we find that many athletes spontaneously use emotion regulation strategies on the sports field. For example, if you are nervous about an important game, you may tell yourself that one game does not determine your fate and that you need to relax and focus on the game itself. This is a typical cognitive reappraisal strategy to alleviate the adverse effects of emotions by reevaluating the relationship between winning and losing the game. Some athletes try to suppress their expressions when they do not perform well in a competition, which is an expression suppression strategy.

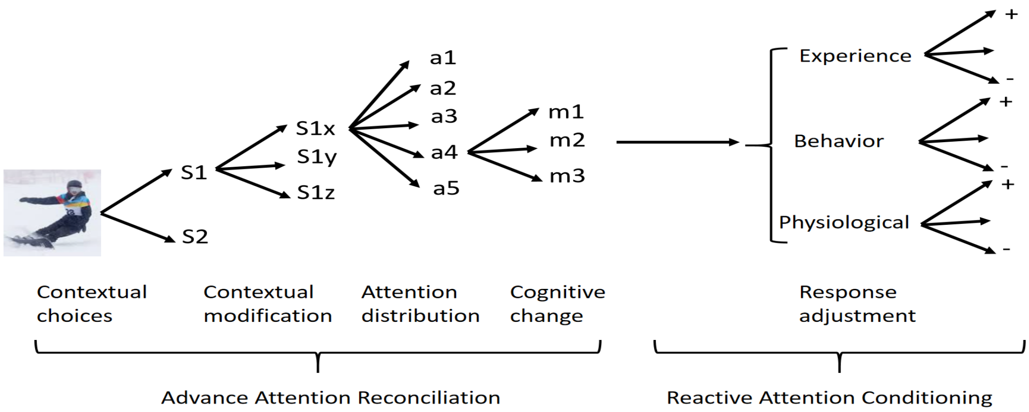


Figure 1. Modeling of emotion regulation processes (Gross, 1998)

Individual college athletes have a greater preference for the use of a particular emotion regulation strategy in their life experiences, and in addition to this more fixed and habitual use of the strategy in the laboratory setting, the use of emotion regulation strategies can be induced by the use of instructional phrases. When viewing negative emotional pictures, subjects were instructed to achieve neutral viewing, suppressed emotional response viewing, and heightened emotional response viewing, which resulted in a significant decrease in LPP amplitude for suppressed viewing.

All of the above studies show that both cognitive reappraisal and expressive inhibition can regulate individuals' emotions to a certain extent and attenuate physiological responses caused by emotions. On this basis, researchers have begun to care about the role of emotion regulation strategies on individual behavior.

Emotion regulation strategies also affect individuals' behavioral inhibition, as evidenced by the use of cognitive reappraisal strategies to effectively promote individuals' behavioral inhibition. Expressive inhibition strategies, on the other hand, resulted in lower rates of correct behavioral inhibition. Emotion regulation strategies primarily affect conflict monitoring sessions, which in turn affects individuals' behavioral inhibition responses (Verbruggen & De Houwer, 2007).

3. Methodology

This research introduces a unique network framework that integrates a robust attention mechanism with a residual network, resulting in a network that consistently attends to expressive features for enhanced performance. The ResNet convolutional neural network is selected as the primary framework owing to its profound capacity to extract features. The utilization of the strong attention mechanism is aimed at improving the extraction of significant facial expression features. This is achieved by incorporating the Channel and Spatial Attention Mechanism (CBAM) both before and after the residual module. Additionally, the proposed Global Effective Channel Attention (G-ECA) is integrated within the residual module of ResNet.

The purpose of G-ECA is to effectively attend to important expression features in the channel dimension, combining both global and local levels of attention. Hence, the framework that has been developed is denoted as CBAM-Global-Efficient Channel Attention-ResNet. In this particular architecture, an additional component is introduced, namely a one-dimensional convolutional global attention mechanism consisting of 11 layers with a convolutional kernel size of 1. Given the constant size of the facial expression image, it can be inferred that the features obtained from 11 layers of 1D convolution will exhibit a higher level of comprehensiveness.

Hence, the process of extracting the fundamental characteristics of face expressions in a comprehensive manner is facilitated. It is important to acknowledge that the information exchange within the One-Dimensional Local Cross-Channel Interactive Convolution (referred to as local attention) in ECA falls under the category of partial channel interaction. This limitation results in inadequate information extraction. To address this issue, the local attention mechanism is combined with the proposed global effective channel attention fusion. In order to conduct a more in-depth investigation of the fusion approach including global and local attention, this study introduces two variations of G-ECA, denoted as G-ECA-1 and G-ECA-2.The distinction between the two is rooted in the disparate methodologies employed for extracting facial expressions, specifically through global and local attention mechanisms. The findings from comparison and ablation investigations demonstrate that the network architecture presented in this study effectively boosts attention towards facial expression features, mitigates information loss during the training process, and enhances the ability to capture crucial features of expressions.

The current study demonstrates an enhanced recognition rate of facial expressions in comparison to previous research. Furthermore, the experimental results pertaining to the visualization of facial expressions on human faces indicate that, among the different combinations of attention mechanisms and ResNet network models, the CBAM-Global-ECA-ResNet18 (C-G-ECA-R18) model, with ResNet18 serving as the backbone network, exhibits a greater ability to concentrate on the discernible crucial attributes of facial expressions, specifically the eyes and mouth.

3.1 Network Framework Architecture

As depicted in Figure 2, the grey module serves as the initial processing stage for the input expression image. This module enhances the network's capacity to acquire knowledge from the expression image during the training phase by applying rotation techniques. The input expression image is cropped to retain solely the facial region. The shallow feature map is created after performing the initial convolution, batch normalization, activation function, and maximum pooling operations. Subsequently, the yellow block employs the channel attention mechanism to concentrate on discerning the significant aspects inside the input image.

Simultaneously, the pink block utilizes the spatial attention mechanism to direct attention towards the specific locations of crucial elements, such as the eyes. The combination of channel and spatial attention results in a Convolutional Block Attention Module (CBAM) that effectively reduces the significance of irrelevant aspects and emphasizes the relevant information within the expression feature map.

This process occurs in both the channel and spatial dimensions, ultimately producing a refined attention feature map. Upon the activation of the residual module, the feature map undergoes an increase in the number of channels and a reduction in its dimensions. The process commences with the initial stage of convolution, followed by bulk normalization and activation function. Subsequently, it proceeds to the subsequent stage of convolution and bulk normalization. The feature map traverses the blue zone and proceeds through the Global Average Pooling (GAP) layer, which serves to decrease the number of parameters in the model and mitigate the occurrence of overfitting.

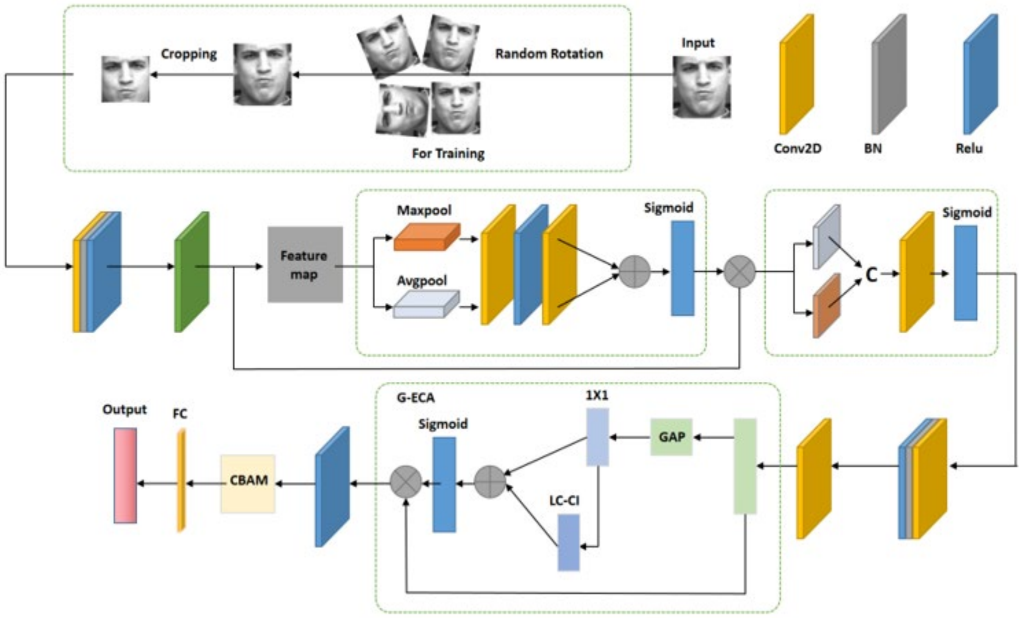


Figure 2. Network Framework Architecture

The initial step of the suggested approach involves enhancing the network's learning capability on expression images with the incorporation of rotation during the training phase. Additionally, the input expression image undergoes a cropping process to retain solely the facial region. Following the initial convolution operation, batch normalization, activation function, and max-pooling, a shallow feature map is generated. Subsequently, the channel attention system directs its attention towards discerning the significant aspects included in the input image, while the spatial attention mechanism concentrates on identifying the precise placement of crucial elements, such as the eyes. The combination of channel and spatial attention results in a Convolutional Block Attention Module (CBAM), which effectively suppresses irrelevant features and highlights the significant information within the expression feature map. This process occurs in both the channel and spatial dimensions, ultimately generating a new attention feature map. Upon the activation of the residual module, the feature map undergoes an increase in the number of channels while simultaneously experiencing a reduction in its dimensions. The initial stage involves the application of convolution, followed by batch normalization and an activation function. Subsequently, the subsequent stage entails another round of convolution and batch normalization. The feature map is subjected to global average pooling, resulting in a reduction in the number of parameters in the model and a decrease in the likelihood of overfitting.

In the initial branch, the feature map undergoes a one-dimensional convolution operation, denoted as Conv(11), utilizing an 11-layer convolution kernel with a size of 1. This convolution operation does not alter the dimensions of the feature map. Its purpose is to extract information from the feature map in a comprehensive and profound manner, resulting in the generation of a global feature map that is represented by the global attention mechanism. In the second branch, the global map undergoes LC-CI, or local attention, which defines the extent to which neighboring channels contribute to attention prediction. While the interaction of neighboring local channels may not ensure information exchange across all channels, it can contribute to reducing the complexity of the model. At this juncture, the integration of global and local attention mechanisms results in the acquisition of a more comprehensive feature map by the summation of relevant items from both the global and local feature maps. The feature map obtained following the use of the residual module is then utilized for enhanced feature extraction through the employment of CBAM. This technique assists in incorporating crucial feature information from both the channel and spatial levels. The resulting feature map is then inputted into the classifier for the purpose of classification.

3.2 Attention Mechanism

The one-dimensional LC-CI exhibits limited information extraction due to the interchange of information between incomplete channels in the feature maps. Hence, the suggested approach involves employing a one-dimensional convolution with a convolution kernel size of 11 layers and a width of 1. This technique aims to extract expressive characteristics thoroughly. Additionally, it incorporates a mechanism of global attention along with local attention to enhance the feature extraction process. This is seen in Figure 3.

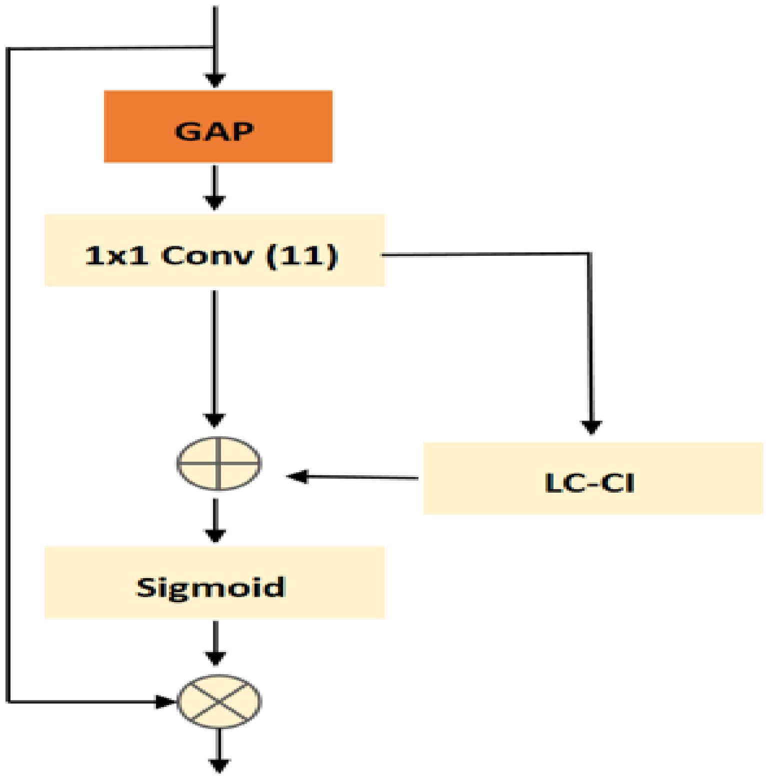


Figure 3. Schematic diagram of the mechanism of attention

The G-ECA in Figure 3 shows that the input weight matrix F is first pooled by the global average, and then the global attention is used to obtain the strong attention weight matrix of the feature map G. The matrix G is fused with the weight matrix L after cross-channel cross-convolution (local attention LC-CI) by summing the corresponding elements of the matrices, and then the weight matrix M is obtained by the Sigmoid function, which is multiplied by the corresponding elements of the input matrix F to get the latest strong attention weight matrix $\widehat{M}$. The purpose of G-ECA is to effectively improve the capture of the key information in the feature map. M is multiplied with the corresponding elements of the input matrix F to obtain the latest strong attention weight matrix $\widehat{M}$. The purpose of G-ECA is to effectively improve the capture of key information in the feature map. The weight matrix M is obtained from the following equation:

$$M = \sigma\left(C1D_k\left(C1D_{11}\big(GAP(F)\big)\right)\right) \quad (1)$$

Multiplying M by the input feature map F, we can get:

$$\hat{M} = F \otimes M \quad (2)$$

The weights of the LC-CI can be realised by a fast one-dimensional convolution, viz:

$$\omega = C1D_k(y) \quad (3)$$

where k is the convolution kernel size that determines the coverage of neighbouring channels. A one-dimensional convolution of size k can be used to generate weights for each feature channel and to obtain the correlation between feature channels. The channel size C can be computed as:

$$C = 2^{\gamma * k - b} \quad (4)$$

where γ and b are set to 2 and 1, respectively, which gives a larger range of interactions for k. The equation for k is as follows:

$$k = \left|\frac{log_2(C)}{\gamma} + \frac{b}{\gamma}\right|_{odd} \quad (5)$$

where odd denotes the selection of the nearest odd number, and different channels C will produce different interaction ranges k.

3.3 Loss function

This section examines the cross-entropy loss function as a means to quantify the disparity between the actual probability distribution and the anticipated probability distribution. A lower cross-entropy value indicates superior model prediction, and the utilization of the cross-entropy loss function mitigates the issue of gradient dispersion, hence enhancing the training speed of the model. This makes it particularly well-suited for facial expression categorization. The loss function formula is as follows:

$$L = -\sum_{i=1}^{N} \hat{y}_i \, log(y_i) \quad (6)$$

where N represents the number of expression categories, $\hat{y}_i$ refers to the variable (0 or 1), which is 1 if the predicted expression category is the same as the sample expression category and 0 otherwise, y_i represents the predicted probability that the observed expression sample belongs to expression category i, and the smaller L is, the closer the predicted college student-athletes' expressions are to the real sample expressions.

3.4 Emotion Regulation and Performance Enhancement in College Athletes

In this paper, the expressions of college athletes on the training field are firstly captured by video equipment, and then input into the proposed neural network recognition model to obtain the emotion recognition results, according to the recognition results, different emotion regulation strategies are used for emotion control, which ultimately assists in promoting the performance enhancement of college athletes, and the flow of the method is shown in Figure 4.

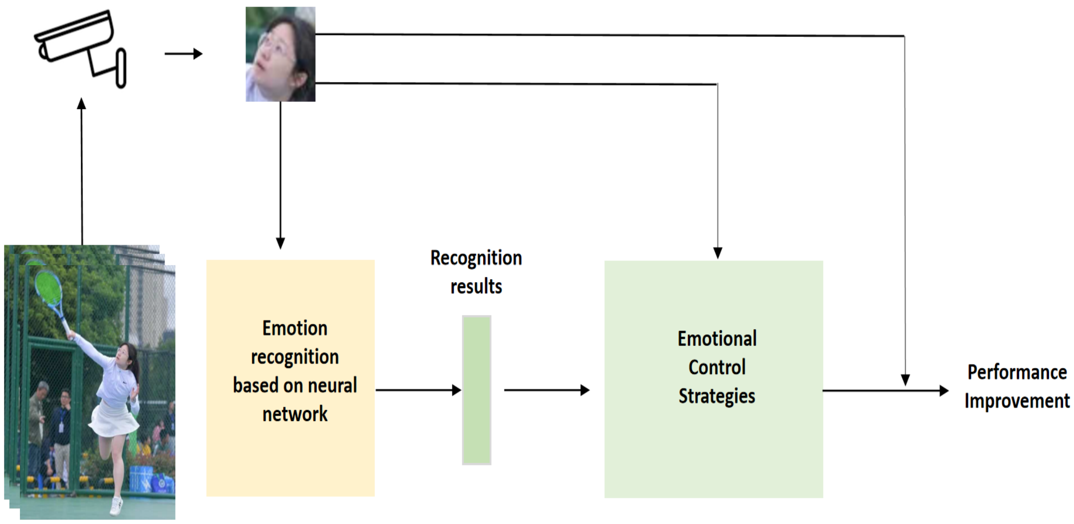


Figure 4. Schematic diagram of methods for emotional regulation and performance improvement of college athletes

4. Experiment and Results

4.1 Dataset

For the experiment, two datasets pertaining to facial expression recognition were used, both of which are publically accessible. This study utilized two datasets, namely the Extended Cohn-Kanade (CK+) and Japanese Female Facial Expressions (JAFFE), to investigate facial expressions.The CK+ dataset had a sample of 123 participants, with ages ranging from 18 to 50 years. The sample encompassed individuals from various ethnic backgrounds, including European Americans, non-Europeans, and individuals of other nationalities. The dataset has a total of seven distinct categories of emotional expressions, including happiness, sorrow, fear, wrath, disgust, surprise, and contempt. The numerical value enclosed in parentheses denotes the frequency of occurrences for a specific category of expressions. A total of 327 sequences, which were appropriately annotated, were chosen from the larger set of 593 picture sequences that constituted the CK+ dataset. In this particular chapter, a total of three frames exhibiting peak formation were chosen from the labeled sequences, resulting in the acquisition of 981 photos.The JAFFE dataset has a total of 231 facial photographs, featuring seven distinct expressions. These expressions were captured from a sample of 10 female students. The dataset includes the following six fundamental expressions: happiness, sadness, fear, anger, disgust, surprise, as well as a neutral expression. The provided figures, namely Figure 5 and Figure 6, display sample images.

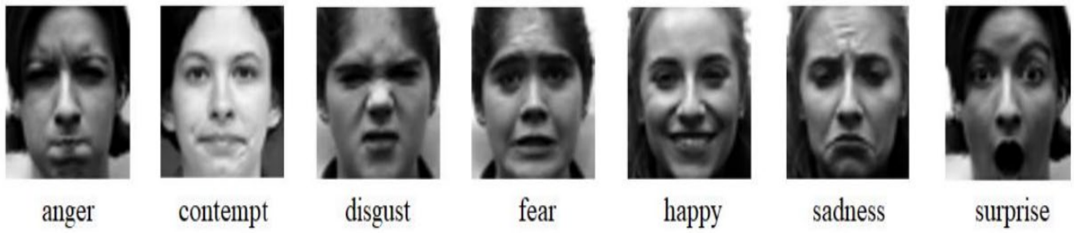


Figure 5. Examples of CK+ dataset

Figure 6. Examples of JAFFE dataset

4.2 Preprocessing

This work presents the division of the CK+ and JAFFE datasets into three distinct subsets, namely the training set, validation set, and test set. The division ratio employed for this partitioning is 6:2:2. To enhance the model's generalization capability and mitigate the issue of overfitting, the images are initially subjected to a random rotation of 15 degrees. In order to prioritize the extraction of facial features and minimize the influence of extraneous elements, it is advisable to crop the face region from the central area of the image.

This approach facilitates the analysis of expression features. The data is subjected to normalization before to training and the utilization of the Adam optimizer. The process of normalisation enhances the activation function by assigning it a more appropriate value, facilitating the effective spread of the gradient, and expediting the convergence of the model. The initial learning rate is set at 0.01, while the batch size is defined as 64. Furthermore, it should be noted that the duration of the training period for each experiment is 300 units.

4.3 Evaluation indicators

The validity of the approach was assessed using Precision, Recall, and Specificity. In this context, TP represents True Positive, TN represents True Negative, FP represents False Positive, and FN represents False Negative. Precision, also known as positive predictive value, is a quantitative metric that assesses the accuracy of identifying meaningful facial expressions within a set of categorized facial expressions.

Additionally, it can be defined as the proportion of accurate forecasts relative to the total number of predictions made.

$$Pr\,e\,cision = \frac{TP}{TP+FP} \quad (7)$$

Recall is calculated for all the facial expression images that are correctly classified among all the facial expression images in the dataset with the following formula:

$$Re\,c\,all = \frac{TP}{TP+FN} \quad (8)$$

Specificity is for real emoticons, but it represents the proportion of negative messages that an emoticon correctly predicts out of all real negative messages, with the following formula:

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

4.4 Experimental results and analysis

The confusion matrices of C-ECA-R18 and C-G-ECA-R18 on the CK+ dataset are given in Figure 7, in addition to their comparative results in Precision, Recall and Specificity in Tables 1 and 2.

Table 1. Precision with Recall and Sprecificity under C-ECA-R18.

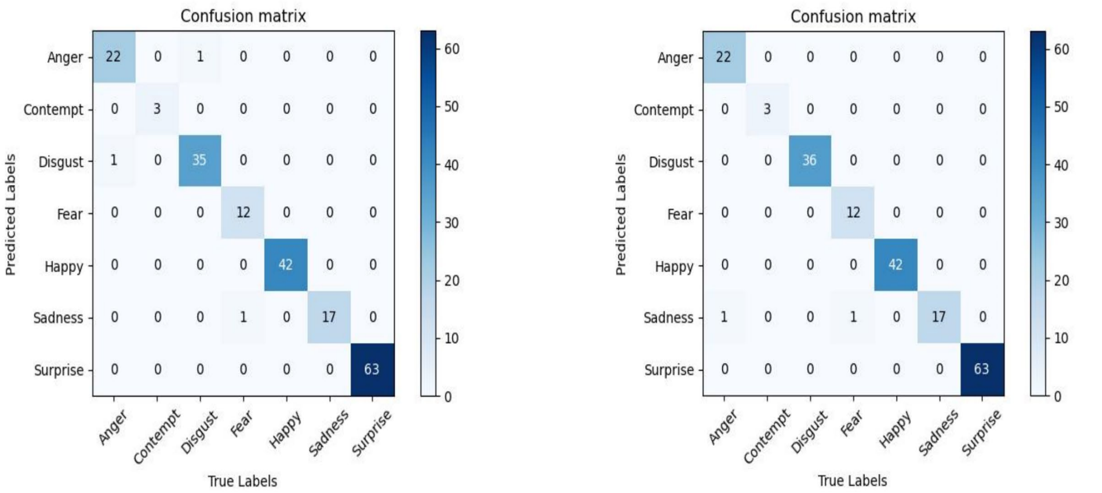
Class	Precision(%)	Recall(%)	Specificity(%)
Anger	94.13	95.36	98.64
Contempt	99.00	96.78	96.37
Disgust	97.01	97.69	95.29
Fear	96.02	96.18	94.87
Happy	99.02	98.02	99.58
Sadness	98.71	99.11	98.27
Surprise	100.00	95.71	97.55

Table2: Precision with Recall and Sprecificity under C-G-ECA-R18.

Class	Precision(%)	Recall(%)	Specificity(%)
Anger	99.00	97.76	100.00
Contempt	95.69	98.88	97.22
Disgust	98.36	96.55	96.36
Fear	97.02	100.00	97.18
Happy	95.05	99.19	100.00
Sadness	96.76	98.77	97.25
Surprise	99.00	96.88	99.21

From the Recall in Table 1 and Table 1, the Recall of C-G-ECA-R18 is

100%, which is better than the Fear of 97.2578% under C-ECA-R18. the Specificity of Anger and Happy also reaches 100%. It is obvious that C-G-ECA-R18 is superior to C-ECA-R18 in the CK+ and JAFFE dataset because it proves that the proposed method can effectively identify the emotions of college students' sports.



(a) C-ECA-R18

(a) C-G-ECA-R18

Figure 7. Comparison of repair effects of different algorithms

The "True Label" in Figure 7 represents the true expression, the "Predicted Label" represents the predicted expression, and the diagonal lines represent the correct number of different categories of expressions. Both graphs have one incorrect prediction for true anger (Anger). Looking at the Precision in Tables 1 and 2, Anger is 94.13% under C-ECA-R18 and 99% under C-G-ECA-R18.Disgust has a Precision of 97.01% under C-ECA-R18 and 98.36% under C-G-ECA-R18. In general, it can be observed that C-ECA-R18 exhibits a total of three prediction mistakes, but C-G-ECA-R18 demonstrates only two errors. It is worth mentioning that both (a) and (b) posit the notion that Fear is synonymous with Sadness, implying that differentiating between these two emotional states presents a greater challenge.

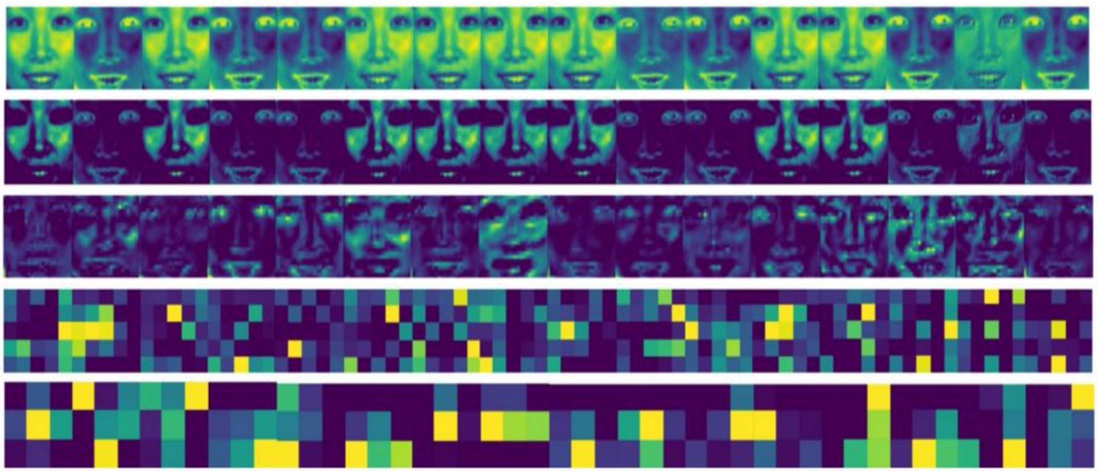


Figure 8. Visualisation of facial expression features in college athletes

The visual feature map depicted in this figure illustrates the intermediate stage of facial expression identification among college athletes using the C-G-ECA-R18 method. The regions highlighted in yellow and green denote the salient aspects of facial expressions.The C-G-ECA-R18 framework effectively emphasizes the key aspects of facial expressions, including the regions encompassing the eyes, nose, and mouth. Despite the blurring of the feature maps, it is noteworthy that the yellow and green blocks continue to prioritize the crucial areas related to facial emotions. Additionally, the model can also acquire knowledge about other edge feature ranges. Hence, this substantiates the viability of employing the suggested approach for the purpose of regulating emotions and enhancing performance among collegiate athletes.

5. Conclusion

The presence of various emotions experienced by athletes on the sports field can have an impact on their levels of attention, decision-making processes, and subsequent conduct. Investigating the regulatory impacts of various emotion control tactics on diverse emotions can facilitate athletes in promptly adapting their state on the sports field and achieving optimal performance at their appropriate competitive level. This study presents an innovative approach to enhance athletes' emotional management and performance through the utilization of emotion recognition and deep learning technology. The proposed model introduces an emotion recognition network that incorporates a robust attention mechanism and a residual network. This model has the capability to effectively capture significant characteristics of expressions over the entirety of the process, resulting in the formation of a robust attention function.

Strong attention refers to the incorporation of channel and spatial attention mechanism (CBAM) prior to the ResNet residual module in order to effectively capture significant characteristics of expressions. The Global Effective Channel Attention (G-ECA) mechanism is afterwards incorporated into the residual module in order to augment the extraction of crucial features. Ultimately, when CBAM is reintegrated into the residual module, it assumes an auxiliary extraction function, therefore mitigating the loss of valuable facial information. Additionally, the proposed model was implemented in simulations using two publicly available benchmark expression datasets, namely CK+ and JAFFE. The experimental findings provided evidence of the efficacy of the proposed approach. Ultimately, the emotion recognition findings inform the development of a standardized approach to enhance emotion control and optimize performance among collegiate athletes.

Conflicts of Interest

The authors do not have any possible conflicts of interest.

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