

## Retraction

# Retracted: A Recognition Method of Athletes' Mental State in Sports Training Based on Support Vector Machine Model

### Journal of Electrical and Computer Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] Y. Li, "A Recognition Method of Athletes' Mental State in Sports Training Based on Support Vector Machine Model," *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 1566664, 9 pages, 2022.

## Research Article

# A Recognition Method of Athletes' Mental State in Sports Training Based on Support Vector Machine Model

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Athletes participate in competitive competitions, and the ultimate goal is to better display their personal competitive level in the competition so as to achieve the goal of defeating their opponents and winning the competition. In all types of competitions, most matches are instantaneous, and opportunities are fleeting. The instantaneous nature and fierce competition of sports competitions require athletes who participate in sports competitions to have a high psychological quality. It can be seen that the quality of the mental state directly determines the performance of the athletes in usual training and competition. In the process of sports, if athletes can obtain real-time changes in their mental states when they encounter various situations, they can formulate more targeted and effective training or competition strategies according to the athletes' states. For the opponent, by analyzing the opponent's psychological state during exercise, the game strategy can be adjusted in real time in a targeted manner, and the probability of winning the game can be provided. Based on this background, this paper proposes to use support vector machine (SVM) to identify the mental state of athletes during exercise. This paper first collects the data of body movements and facial expressions of athletes during training or competition. Use multimodal data to train an SVM model. Output the emotional state of athletes at different stages based on test data. In order to verify the applicability of the method in this paper to the athlete subjects, several comparative models were used in the experiment to verify the performance of the used models. The experimental results show that the accuracy rate of emotion recognition obtained by this method is more than 80%. This shows that the research in this paper has certain application value.

## 1. Introduction

The mental state of an athlete is very important for training or competition. Mental states can be refined into different emotions. Every athlete will have emotions in the process of exercising, and emotions are actually a kind of psychological activity [1, 2]. The human cerebral cortex and the subcortical nerve center work together to generate emotion. In sports competition, the emotional state of athletes has a very important relationship with the results of the game. How to perceive and regulate the emotional state of athletes is an important issue that coaches focus on [3]. Usually, when athletes participate in sports competitions, their emotions are very obvious. Athletes' emotional arousal varies with the level of the sport they compete in. The higher the level of the competition, the stronger the emotion of the athlete. Strong

emotions may also cause insomnia, anorexia, and so on. The main reasons why athletes have such strong and vivid emotions when participating in sports are as follows: First, during strenuous exercise, the power of your own respiratory system and cardiovascular system is faster and stronger than usual. This will make the nervous system more excited, which will make the athlete's mood high. Second, sports competition itself will prompt athletes to have some strong emotions. In the process of participating in sports competitions, athletes may win the competition or lose the competition. This is prone to some complex emotions. In addition, the evaluation given by the audience will also arouse the emotions of the athletes. The factors that affect the emotional changes of athletes mainly include the following: (1) The significance and scale of holding sports competitions, (2) the tasks that athletes need to complete in the sports

competition, (3) strength comparison of athletes participating in sports competitions, (4) the surrounding environment of the sports competition venue, the audience's mood, and the number of spectators, (5) the mental preparation of the athletes before the official start of the sports competition and their expectations for the competition, (6) the athlete's own character characteristics, and (7) the training situation of the athletes themselves.

Athletes have strong emotions in the process of participating in sports, which are crucial to winning the competition. This is because the athlete can stimulate a lot of strength from it so that the athlete is not easy to feel tired. At this time, the intensity of the athlete's neural activity is also greater than usual, and they can show rapid reaction ability during the competition. For example, when a high jumper is in a formal competition, the athlete will be excited. This kind of emotion has a great impetus for his jumping, which can make him perform exceptionally well. This emotion can also be referred to as an empowering emotion. If the athletes do not have these power-giving emotions during the competition, it is difficult to obtain good results in the competition. However, athlete's strong emotions sometimes also have some negative effects, such as athlete's high tension, feeling negative about competition, lack of confidence, and so on. Combining actual cases, it can be seen that some athletes are overly emotional and may experience trembling when speaking, rapid heartbeat, and facial congestion. If the emotion regulation cannot be carried out in time and correctly, it will lead to mistakes in the game. This emotion is also known as a debilitating emotion. In view of this, coaches should understand emotion-related knowledge and take effective measures to guide athletes so that athletes can generate enhanced emotions in the process of participating in sports competitions, give full play to their own strength, and obtain excellent results.

Therefore, the accurate identification of the mental state of athletes is the key to whether the follow-up guidance measures are effective. Emotion recognition has been widely studied and applied in various fields. For example, emotion recognition is used in medical care [4–6], education [7–9], service industry [10–12], and other fields. For emotion recognition methods, there are mainly scale methods [13, 14], machine learning [15–17], and deep learning algorithms [18–20]. The used recognition data are electroencephalogram (EEG) [21], electrocardiogram (ECG) [22], voice [23], video [24], expression [25], action [26], and so on. For the application field of this paper, athletes can collect audio, video, EEG, ECG, and other data when exercising. Considering that the movement of athletes cannot be affected when collecting data, and the accuracy of emotion recognition should be improved as much as possible, this paper plans to use data from two modalities of body movements and expressions. Although audio data is relatively easy to obtain, the noise is relatively large, which will reduce the accuracy of the recognition results. The contributions of this paper are as follows:

- (1) In the field of sports training, a method for identifying the mental state of athletes that does not affect the movement of athletes and is noninvasive to

athletes is proposed. And this task is converted to emotion recognition during athlete's movement.

- (2) In order to facilitate data collection without affecting the movement of athletes, this paper mainly uses multimodal data based on body movements and expressions to identify mental states. The use of multimodal data can effectively improve the accuracy of recognition.
- (3) This paper uses a variety of classifiers to classify the collected data in order to quickly identify the mental state of athletes throughout the entire exercise process. The experimental results show that SVM can achieve a recognition accuracy of more than 85%, which is important for the application of mental state assessment in sports training.

## 2. Knowledge about Sports Psychology

### 2.1. Emotional Characteristics in Sports

*2.1.1. Multiple Emotions of Athletes.* Athletes experience different emotions at different stages of exercise. There will be joy when the game is won, and sadness when the game is lost. There are other kinds of emotions. For example, long-distance runners experience a variety of emotions during a race. Excitement is experienced at the beginning of the race. This kind of emotion can ensure that athletes can give full play to their own strength to exercise. In the middle of the schedule, when the athletes start to get tired, the athletes are prone to negative emotions. Finally, in the late stage of the race, with the cheering and cheering of the audience, the athletes will overcome the previous fatigue, generate a strong excitement, and speed up the running speed until the finish line. Besides, during the competition, athletes also have various emotions due to conflicts with other opponents. For example, when football players and basketball players are playing, there will inevitably be physical collisions between players. Particularly when encountering a relatively strong collision, it is easy to cause the athlete's mood to change. At this time, it is easy for athletes to play the "emotional ball" phenomenon. This phenomenon is not conducive to the athlete's real strength, and the athlete's attention cannot be highly concentrated, which leads to the failure of the game.

In summary, it can be seen that athletes experience a variety of emotions in the process of sports. The main reason is that people's emotions are inherently diverse, and each athlete is an independent individual with different characteristics. In addition, sports competitions and sports environments have the characteristics of diversity. The coaches give good guidance to the athletes so that the athletes will not be too proud because of the victory of the game nor too discouraged because of the failure of the game and can continue to maintain a state of excitement. As the general guide and the closest person of the remote mobilization, the coach has a profound impact on the mental quality and skills of the athlete. The coaches should be sincere to the athletes before the game and summarize after the game to ensure the harmony of the entire team. If the coaches have a bad

TABLE 1: Introduction to emotion models.

Category	Details
Discrete emotion model	(1) 6 basic emotions proposed by Ekman and Friesen [27]: Anger, disgust, fear, happiness, sadness, and surprise (2) 10 basic emotions proposed by Izard [28]: Interest, happiness, surprise, sadness, anger, disgust, contempt, fear, shame, and guilt (3) 20 emotions proposed by the PANAS scale [29]: 10 positive emotions and 10 negative emotions
Dimensional emotional model	(1) The affective dimension proposed by Russell [30]: Described by two dimensions, namely, the value dimension (pleasure-nonpleasure) and the arousal dimension (activation-inactivation) (2) Four-quadrant emotional model proposed by Whissell [31]: These two dimensions are divided into four quadrants on the basis of Russell. Quadrant I represents a positive and active emotional state. Quadrant II represents negative states in the active dimension. Quadrant III represents passive negative states in the negative dimension. Quadrant IV represents the active state in the passive dimension. (3) Proposed by Mehrabian and Russell's [32] pleasure arousal dominance model: This model can distinguish between anger (positive dominance, high dominance) and fear (negative dominance, low dominance).
Component emotion model	Basic and complex emotions proposed by Plutchik [33]: The 8 basic emotions include happiness, trust, fear, surprise, sadness, anticipation, anger, and disgust. Complex emotions are combinations or mixtures of basic emotions.

attitude, blaming or abusing the players, it is easy to cause disharmony between the players and the entire team. Athletes often affect their emotions because of a word, a look, or an expression from a coach. In view of this, coaches should pay attention to the perception and guidance of athletes' mental state.

*2.1.2. The Mood Changes Rapidly.* When athletes participate in sports, their emotions change very quickly. For example, in the process of football players participating in the game, the competition environment is very complex and changeable, and the athletes will have various emotions. They need to control their emotions and play the game with strength under such a background. There are many factors that affect the rapid changes of athletes' emotions during exercise, mainly including the following aspects. First, the conditions of sports competition: under normal circumstances, the competitions with the characteristics of collective confrontation are more likely to cause the athletes' emotions to change rapidly. Second, the results of sports can easily lead to changes in the emotions of sports. Third, the subject's personality and attitude: each athlete has different personalities and different emotional tendencies on the spot, so they have different degrees of emotional changes. Combined with relevant data, it can be seen that the emotional experience of athletes is an important factor affecting the performance of sports competitions. In order to promote athletes to obtain excellent results, coaches should take effective measures to guide them. In this way, the various emotions generated by the athletes can be adjusted to ensure that the athletes can continue to maintain a strong will.

*2.2. Emotional Categories.* Emotional classification of human movement requires computers to have a certain understanding and quantification of human emotions. The basis and refinement of emotion classification are supported by psychological theories. Emotion classification work requires the application of some emotion expression model in

order to classify human emotions. In fact, there are already a variety of emotion models available in psychology. Currently, the more mature emotion classification models can be divided into discrete models, dimensional models, and component models. Discrete models preagreed a set of basic emotion labels and represented each emotional state as a combination of basic emotions. A dimensional model represents an emotional state as a point in a two- or three-dimensional space. Component models use multiple factors that make up or influence emotional states. Several different types of emotional models are described in Table 1.

### 3. Mental State Recognition Model Based on Multimodal Data

*3.1. Mental State Recognition Framework.* This paper proposes an emotion recognition algorithm to extract spatiotemporal features of video data. First, the spatiotemporal interest points of the video data are extracted. Then, the cuboids containing the interest points are found, and the intensity gradients of the cuboids are used to characterize the emotional features. In this paper, the facial expression features and the emotional features of body movements are extracted from the FABO database data, and a fusion algorithm based on canonical correlation analysis (CCA) is used to fuse the two features, and a variety of classic classifiers for emotion recognition are used. The principle of the mental state identification method for athletes proposed in this paper is shown in Figure 1.

#### 3.2. Emotion Feature Extraction Method

*3.2.1. Canonical Correlation Analysis.* The purpose of canonical correlation analysis is to identify and quantify the relationship between two sets of feature variables, that is, to find the linear combination of two sets of feature variables and use it to represent the original variable, and use the correlation between them to reflect the correlation of the original variable.

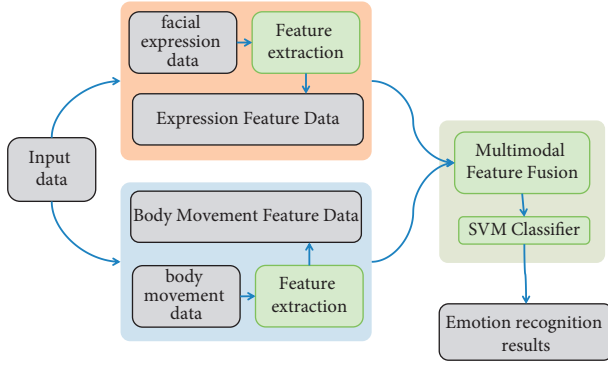


FIGURE 1: The principle diagram of mental state recognition.

For the same emotion, the spatial-temporal feature matrix of facial expressions is  $U$ , and the spatial-temporal feature matrix of body movements is  $V$ ,  $U$  and  $V$  are  $m$ - and  $n$ -dimensional matrices, respectively, as in

$$U = \begin{pmatrix} \varphi_{11} & \cdots & \varphi_{1m} \\ \vdots & \ddots & \vdots \\ \varphi_{h1} & \cdots & \varphi_{hm} \end{pmatrix}, \quad (1)$$

$$V = \begin{pmatrix} \mu_{11} & \cdots & \mu_{1n} \\ \vdots & \ddots & \vdots \\ \mu_{h1} & \cdots & \mu_{hn} \end{pmatrix}.$$

In order to obtain a certain linear combination that maximizes the degree of correlation between  $U$  and  $V$ , let  $C_u$  represent the linear combination coefficient of  $U$  and  $C_v$  represent the linear combination coefficient of  $V$  so as to maximize the correlation function of equation (2) as much as possible.

$$\theta(C_u, C_v) = \frac{C_u^T X_{UV} C_v}{\sqrt{C_u^T X_{UV} C_u} \sqrt{C_v^T X_{UV} C_v}}. \quad (2)$$

In equation (2),  $X_{UU}$  represents the variance matrix of  $U$ ,  $X_{VV}$  represents the variance matrix of  $V$ , and  $X_{UV}$  represents the covariance matrix of  $U$  and  $V$ . Using the Lagrange multiplier method, equation (2) can be transformed into the following equation:

$$\begin{cases} X_{UV} X_{VV}^{-1} X_{UV}^T C_u = \lambda^2 X_{UU} C_u, \\ X_{UV}^T X_{UU}^{-1} X_{UV} C_v = \lambda^2 X_{VV} C_v. \end{cases} \quad (3)$$

By using the singular value decomposition method for the matrix to solve equation (3),  $R$  is defined as follows:

$$R = X_{UV}^{-0.5} X_{UV} X_{VV}^{-0.5},$$

$$= (x_1, \dots, x_r) D (y_1, \dots, y_r)^T = \sum_{i=1}^r \lambda_i x_i y_i^T, \quad (4)$$

where  $r$  is the rank of the matrix  $R$ ,  $\lambda_i (i=1, \dots, r)$  is the eigenvalue of the matrix  $RTR$  or  $RR^T$ , and  $D$  is the diagonal matrix of  $\lambda_i$ ; its solution is to find  $n * m$ . The approximate solution of rank 1 obtained by the dimensional correlation

matrix uses its first  $d$  singular values to approximate  $R$ . That is,  $\sum_{i=1}^d \lambda_i x_i y_i^T$ , ( $d \leq r$ ), so equation (3) can be transformed into the following equation:

$$\begin{cases} (X_{UU}^{-0.5} X_{UV} X_{VV}^{-0.5}) (X_{VV}^{-0.5} X_{UV} X_{UU}^{-0.5}) (X_{UU}^{-0.5} x) = \lambda^2 (X_{UU}^{-0.5} x), \\ (X_{VV}^{-0.5} X_{UV} X_{UU}^{-0.5}) (X_{UU}^{-0.5} X_{UV} X_{VV}^{-0.5}) (X_{VV}^{-0.5} y) = \lambda^2 (X_{VV}^{-0.5} y). \end{cases} \quad (5)$$

Therefore, the final projection vector of CCA can be obtained by the following formula:

$$\begin{cases} C_U = X_{UU}^{-0.5} x_i, \\ C_V = X_{VV}^{-0.5} y_i, \end{cases} \quad i = 1, \dots, d. \quad (6)$$

### 3.2.2. Sparse Preserving Canonical Correlation Analysis.

The principle of sparse preservation canonical correlation analysis is to obtain the global sparse reconstruction weight between samples through the sparse representation algorithm and use this to identify the sample data, and then use the optimization strategy to integrate it into the CCA algorithm, and finally realize the feature identification fusion.

For the same emotion, the spatiotemporal feature matrix of facial expressions is  $U$ , and the spatiotemporal feature matrix of body movements is  $V$ , where  $U, V$  are  $U = [u_1, u_2, \dots, u_N] \in \mathbb{R}^{m \times H}$ ,  $V = [v_1, v_2, \dots, v_N] \in \mathbb{R}^{n \times H}$ , where  $m$  represents the feature dimension of  $U$  and  $n$  represents the feature dimension of  $V$ . The sparse reconstruction weight matrix of  $U, V$  is constructed by the minimization problem as follows:  $K = [k_1, k_2, \dots, k_H] \in \mathbb{R}^{H \times H}$ ,  $L = [l_1, l_2, \dots, l_H] \in \mathbb{R}^{H \times H}$ . The purpose of sparse preservation canonical correlation analysis is to find two sets of feature projection vectors  $C_u$  and  $C_v$  and to reduce the sparse reconstruction error of the two sets of features after projection as much as possible, while satisfying the maximum correlation between the two sets of features after projection. The objective function of equation (7) can be defined to obtain the projections  $C_u$  and  $C_v$  that can keep the optimal sparse weight vectors  $\tilde{k}$  and  $\tilde{l}$ ; namely,

$$\min_{C_x} \sum_{i=1}^H \|C_u^T u_i - C_u^T U \tilde{k}_i\|^2,$$

$$\min_{C_y} \sum_{i=1}^H \|C_v^T v_i - C_v^T V \tilde{l}_i\|^2. \quad (7)$$

Through simple algebraic operations, the following equation can be obtained; namely,

$$\sum_{i=1}^H \|C_u^T u_i - C_u^T U \tilde{k}_i\|^2 = C_u^T U (I - K - K^T + K^T K) U^T C_u,$$

$$\sum_{i=1}^H \|C_v^T v_i - C_v^T V \tilde{l}_i\|^2 = C_v^T V (I - L - L^T + L^T L) V^T C_v, \quad (8)$$

where  $\tilde{k}_i$  represents the optimal solution of the minimization problem on  $U$  and  $\tilde{l}_i$  represents the optimal solution of the minimization problem on  $V$ . At the same time, combined with the criterion of CCA, the mutual covariance of  $U$  and  $V$

is maximized. Then, the objective function of the following equation is obtained; namely,

$$\max_{C_u, C_v \neq 0} \frac{C_u^T X_{uv} w_v}{\sqrt{C_u^T \tilde{L}_{uu} C_u} \sqrt{C_v^T \tilde{L}_{vv} C_v}} \quad (9)$$

where  $\tilde{L}_{uu} = U(I - K)(I - K)^T U^T$  represents the sparse-preserving divergence matrix of  $U$  and  $\tilde{L}_{vv} = V(I - L)(I - L)^T V^T$  represents the sparse-preserving divergence matrix of  $V$ . Finally, the problem is transformed into the solution of the following equation by the Lagrange multiplier method. The two generalized eigen equations are as follows:

$$\begin{aligned} L_{uv} \tilde{L}_{vv}^{-1} L_{uv}^T C_u &= \lambda^2 \tilde{L}_{uu} C_u, \\ L_{uv}^T \tilde{L}_{vv}^{-1} L_{uv} C_v &= \lambda^2 \tilde{L}_{vv} C_v. \end{aligned} \quad (10)$$

Therefore, the two sets of projections  $C_u$  and  $C_v$  can be obtained by the generalized characteristic equation (10), and the obtained  $d$  projection vectors are the eigenvectors corresponding to the  $d$  largest eigenvalues.

**3.2.3. Multimodal Feature Fusion.** Through the above derivation of the above two algorithms, the  $d$  pairs of feature projections are, respectively, recorded as  $C_u = (\varphi_1, \dots, \varphi_d)$  and  $C_v = (\mu_1, \dots, \mu_d)$ . The eigenvectors after projection for  $U$  and  $V$  are

$$\begin{aligned} U' &= (\alpha_1^T, \dots, \alpha_d^T) \varphi = C_U^T \varphi, \\ V' &= (\beta_1^T, \dots, \beta_d^T) \mu = C_V^T \mu. \end{aligned} \quad (11)$$

Serially fuse  $U'$  and  $V'$  to get a new feature vector fusion:

$$\text{Fusion} = \begin{pmatrix} U' \\ V' \end{pmatrix} = \begin{pmatrix} C_U^T \varphi \\ C_V^T \mu \end{pmatrix} = \begin{pmatrix} C_U & 0 \\ 0 & C_V \end{pmatrix}^T \begin{pmatrix} \varphi \\ \mu \end{pmatrix}. \quad (12)$$

**3.3. SVM.** SVM is a hyperplane that can distinguish between samples of different classes in the sample space. In other words, given a set of labeled training samples, the SVM algorithm can generate an optimal separating hyperplane. The SVM algorithm's main goal is to find a hyperplane that maximizes a specific value, which is the shortest distance between the hyperplane and all training samples. The margin is the shortest distance between two points. The hyperplane is defined by the following expression:

$$f(x) = \omega_0 + \omega^T x. \quad (13)$$

In the above equation,  $\omega$  denotes the weight vector and  $\omega_0$  denotes the bias. The optimal hyperplane can be expressed in an infinite number of ways, the most common of which is by arbitrarily scaling  $\omega$  and  $\omega_0$ . The optimal hyperplane is traditionally expressed as follows:

$$|\omega_0 + \omega^T x| = 1. \quad (14)$$

In the above equation,  $x$  denotes the points that are closest to the hyperplane. These are known as support vectors. The canonical hyperplane is another name for this hyperplane.

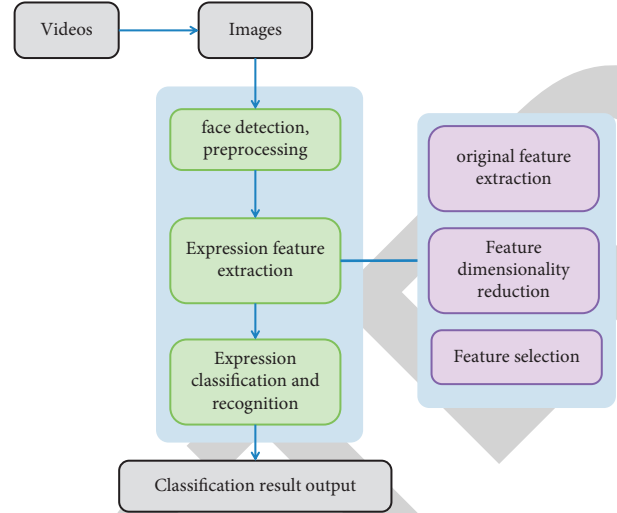


FIGURE 2: Emotion recognition process based on expression.

The distance from point  $x$  to hyperplane  $(\omega, \omega_0)$  can be calculated using geometry knowledge as follows:

$$\text{distance} = \frac{|\omega_0 + \omega^T x|}{\|\omega\|}. \quad (15)$$

Because the numerator in the expression for the canonical hyperplane is 1, the distance from the support vector to the canonical hyperplane is as follows:

$$\text{distance}_{\text{supportvectors}} = \frac{|\omega_0 + \omega^T x|}{\|\omega\|} = \frac{1}{\|\omega\|}. \quad (16)$$

Denote margin as  $M$ , which is twice the closest distance:

$$M = \frac{2}{\|\omega\|}. \quad (17)$$

Finally, maximizing  $M$  equates to minimizing the function  $L(\omega)$  while subject to additional constraints. Constraints The following are the implicit hyperplanes under which all training samples  $x_i$  are correctly classified:

$$\min_{\omega, \omega_0} L(\omega) = \frac{1}{2} \|\omega\| \text{ subject to } y_i (\omega^T x_i + \omega_0) \geq 1, \quad (18)$$

where  $y_i$  denotes the sample's class label. The weight vector  $\omega$  and bias  $\omega_0$  of the optimal hyperplane can be obtained using the Lagrangian multiplier method because this is a Lagrangian optimization problem.

## 4. Mental State Recognition Experiment

**4.1. Experimental Setup.** The FABO video database was used as the emotion database in this paper. The video is recorded synchronously by two cameras in the FABO database. The FABO database contained 23 subjects, 12 of whom were women and 11 of whom were men. All of the participants were between the ages of 20 and 50. The FABO database is

TABLE 2: Expression-based emotion recognition results.

Emotions/classifiers	BPNN	RBFNN	RF	KNN	TSK	SVM
Anger	0.589	0.767	0.673	0.778	0.583	0.878
Disgust	0.536	0.706	0.570	0.684	0.708	0.841
Fear	0.643	0.475	0.658	0.494	0.540	0.762
Happiness	0.477	0.515	0.659	0.448	0.665	0.753
Sadness	0.695	0.436	0.672	0.643	0.566	0.803
Surprise	0.497	0.630	0.654	0.580	0.737	0.820

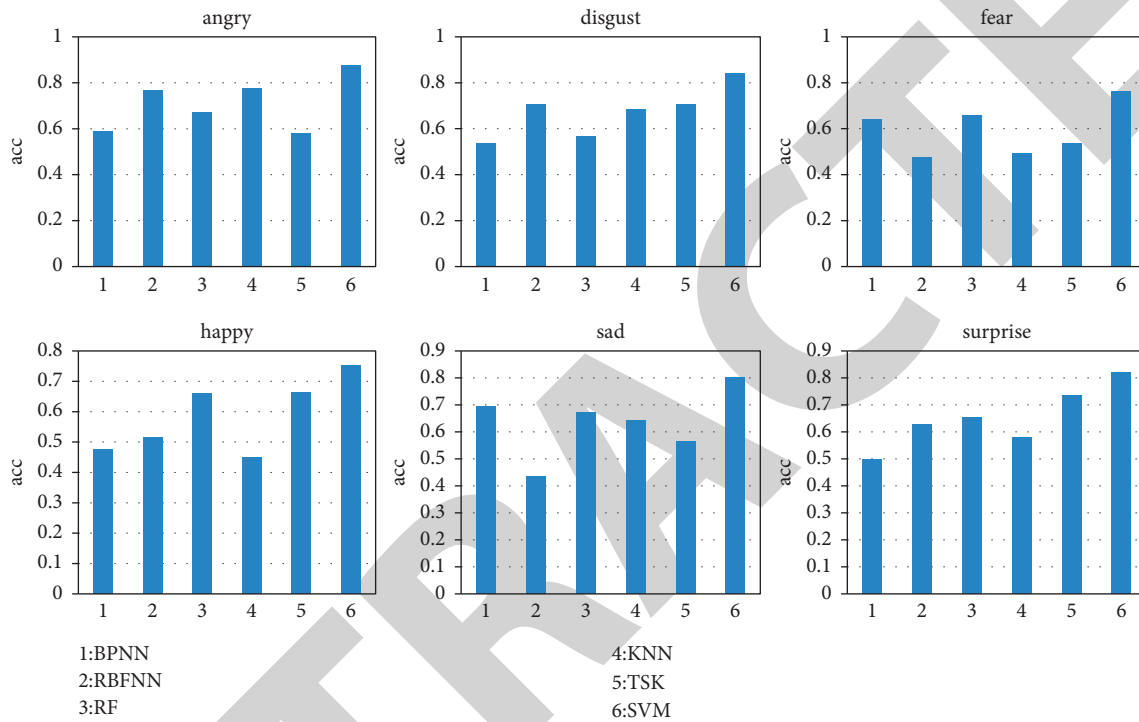


FIGURE 3: Comparison of emotion recognition results based on expressions.

primarily composed of six emotions: rage, fear, happiness, perplexity, sadness, and surprise.

In the experiment, data of 13 people expressing 6 emotions were selected, a total of 78 videos. Since the amount of data is not very large, this paper adopts the 10-fold cross-validation method to divide the videos into 13 groups with 6 data in each group. Each time, 9 groups are taken as the training set, and the remaining 4 groups are used as the test set. Each experiment was repeated 10 times, and the average value was taken. The features used in the experiment are the spatiotemporal features of facial expression videos, the spatiotemporal features of body motion videos, and fusion features. Comparative classification algorithms include BP Neural Network (BPNN), Radial Basis Neural Network (RBFNN), Random Forest (RF), K-Nearest Neighbor (KNN), and Fuzzy System (TSK). The evaluation index adopts the classification accuracy. In order to analyze the best classification effect obtained by the selection of various classifiers and feature data, the experimental part uses multiple classifiers to classify and identify individual facial expression features, individual body motion features, and the features of the fusion of the two data.

*4.2. Emotion Recognition Based on Facial Expressions.* The process of emotion recognition based on facial expressions is shown in Figure 2.

The first thing to be done is the preprocessing of the input static image or video sequence, including face detection, eye positioning, image registration, pose adjustment, cropping normalized faces, and histogram equalization, which are used to eliminate the effect of uneven lighting. The most critical step is the expression feature extraction in the second step. Usually, the dimension of the original expression features is relatively high and contains redundant information. It is necessary to choose an efficient feature dimensionality reduction and feature selection method. Through effective feature selection and feature dimensionality reduction, the dimension of features is greatly reduced, and redundant information is eliminated as much as possible, and then an appropriate classifier is selected to classify and recognize expressions and finally output the classification results. The experimental results based on facial expressions are shown in Table 2. For a more vivid comparison, the data shown in Table 2 are graphically shown in Figure 3.

TABLE 3: Experimental results of emotion recognition based on body movements.

Emotions/classifiers	BPNN	RBFNN	RF	KNN	TSK	SVM
Anger	0.733	0.527	0.659	0.444	0.709	0.764
Disgust	0.645	0.776	0.688	0.562	0.789	0.842
Fear	0.633	0.658	0.609	0.579	0.477	0.741
Happiness	0.616	0.592	0.797	0.546	0.456	0.751
Sadness	0.748	0.656	0.487	0.705	0.679	0.805
Surprise	0.506	0.618	0.442	0.651	0.438	0.681

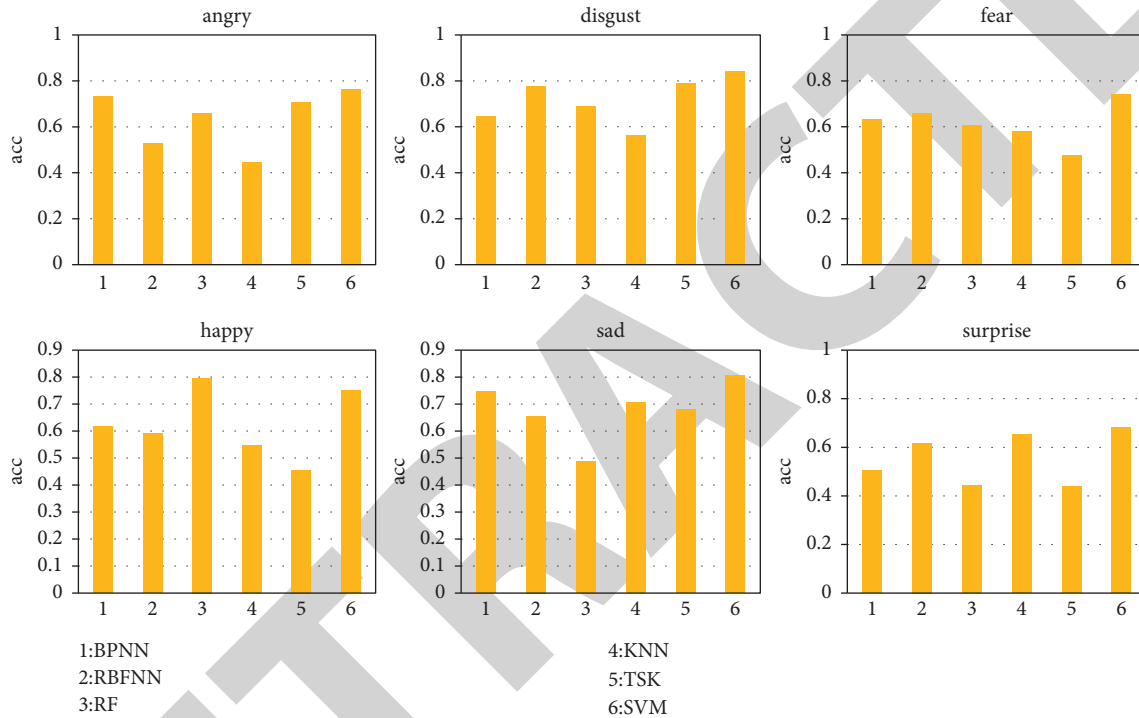


FIGURE 4: Comparison of emotion recognition results based on body movements.

The six kinds of emotion recognition results shown in the experimental results show that each classifier has completely different classification results on different emotions. On the whole, the SVM classifier has the highest recognition accuracy, and its recognition effect on anger, disgust, sad, and surprise is the best, all exceeding 0.8. The recognition rate of the remaining 2 emotions is 0.7 to 0.8 between. This shows that the classifier has a better effect on emotion classification with large expression changes and has a general effect on emotion classification with little expression change.

**4.3. Emotion Recognition Based on Body Movements.** The experimental results of emotion recognition based on body movements are shown in Table 3. For a more vivid comparison, the data shown in Table 3 are graphically shown in Figure 4.

The experimental results show that in the 6 emotions, except happy, the other 5 emotions have the best recognition effect of SVM. For happy emotions, the best recognition

effect is RF. For SVM, the recognition accuracy of disgust and sad exceeds 0.8, and the recognition of anger, fear, and happiness is between 0.7 and 0.8. The worst effect is surprise, which is less than 0.7. The effect based on SVM is still the best among several classifiers, but numerically, the recognition results based on body movements are worse than those based on facial expressions.

**4.4. Emotion Recognition Based on Fusion Features.** From the experimental results in the above two sections, it can be seen that the accuracy rate based on SVM is the highest. Therefore, SVM is selected as the classifier when performing classification experiments based on fusion feature. The experimental results are shown in Table 4. For a more vivid comparison, the data shown in Table 4 are graphically shown in Figure 5.

The experimental results show that, in addition to fear, in the classification results of the other five emotions, the classification accuracy based on the fusion feature is higher than the recognition rate of the other two separate features.



TABLE 4: Experimental results of emotion recognition based on body movements.

Emotions/features	Facial expression features	Body movement features	Fusion features
Anger	0.878	0.764	0.901
Disgust	0.841	0.842	0.895
Fear	0.762	0.741	0.760
Happiness	0.753	0.751	0.823
Sadness	0.803	0.805	0.828
Surprise	0.820	0.681	0.818

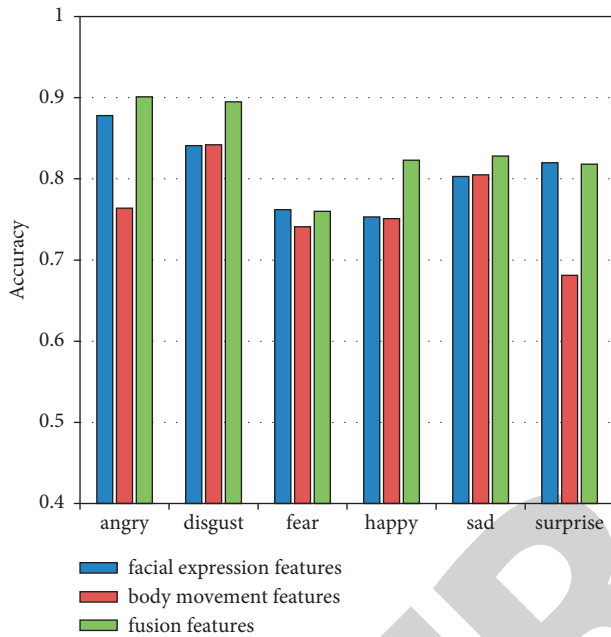


FIGURE 5: Comparison of emotion recognition results based on fusion features.

That is, the recognition effect based on fusion features is better than that based on facial expression features, and the recognition effect based on facial expression features is better than that based on body movements. And in the recognition results based on fusion features, anger can achieve a recognition rate of more than 0.9. This fully demonstrates the superiority of fusion features.

## 5. Conclusion

The mental state of athletes is an important factor affecting the performance of sports competitions. In order to promote the athletes to obtain excellent results, effective measures should be taken to guide them during normal training and actual competition. The various emotions that athletes generate should be regulated to ensure that the athlete can continue to maintain a strong will. Since athlete's emotions will continue to change with the emergence of various conditions, how to accurately perceive the athlete's mental state is the basis for subsequent guidance. In order to verify whether the method used in this paper is suitable for the analysis of the mental state of athletes, the experimental part uses separate features based on facial expressions, based on body motion features, and the fusion of the two features. In

the aspect of classifier selection, the performance of the six classifiers was compared, and the SVM was determined as the optimal classifier. The data used in the mental state analysis method used in this paper is easy to collect, and the classifier is widely used, so the performance is stable, and the feasibility is strong. The research in this paper can be further optimized, such as introducing other features for sentiment analysis to improve the classification accuracy. Other emotion evaluation models can also be used to make the analysis results of emotion more detailed.

## Data Availability

The labeled data set used to support the findings of this study is available from the corresponding author upon request.

## Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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