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Anxiety Recognition of College Students Using a Takagi-Sugeno-Kang Fuzzy System Modeling Method and Deep Features

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ABSTRACT College students are the most active, most sensitive, and most prone group with respect to various psychological problems in contemporary society. In recent years, with the intensification of social competition, including various pressures such as studies, examinations, economic loss, emotional loss, and employment, the incidence of anxiety, depression and suicide rates has increased. To effectively pay attention to the psychological development of college students and to strengthen mental health education, this research proposes a method to automatically identify the anxiety of college students using a Takagi-Sugeno-Kang (TSK) fuzzy system and deep features. First, preprocess the collected EEG of college students. Secondly, use convolutional neural network (CNN) to extract deep features from the input data. Finally, TSK fuzzy system is used to classify features to obtain the final recognition result. Through experiments on standard data sets and self-made data sets, the experimental results verify the superiority of the anxiety identification method used in this study. The experimental results further demonstrate that the depth features have richer information than traditional features. The noise immunity of TSK fuzzy system makes it show good classification performance and generalization. The recognition results can quickly locate students with anxiety disorders and narrow the scope of investigation for students with psychological problems. The automatic recognition of college students' anxiety can improve the efficiency of schools and teachers in investigating students' psychological problems. This research has very good practical application value.

INDEX TERMS College students, anxiety recognition, TSK fuzzy system, deep features.

I. INTRODUCTION

Anxiety is the main problem of college students' mental health. College students are the mainstay of the country's development, and their psychological quality is directly related to the country's future development level. Studies have shown that anxiety is an important cause of sub-par health. Over time, a sub-par health state will become more serious [1]–[3]. Long-term anxiety is also a major factor leading to many chronic diseases. In severe cases, it can lead to extreme phenomena such as self-harm and suicide. Stress, anxiety and depression directly affect the suicide rate of college students. Physical and mental illnesses caused by anxiety or stress have become major reasons why college

students take a leave of absence from school, drop out or commit suicide. Various college students have different psychological problems. It is possible to determine the core factors affecting the psychological problems of college students as soon as possible, thereby improving the overall mental health of college students. Enhancing their ability to withstand setbacks will improve their ability to adapt to society. It is of great significance to improve their personalities and enable contemporary college students to realize their fullest potential and their value in life. The effective identification of anxiety has become the basis of the early detection of groups of anxious individuals and the timely provision of mental health assistance measures.

The study of emotions through physiological signals has become increasingly mature. Various intelligent recognition algorithms are used in various fields [4]–[12], among which

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methods for emotion recognition are introduced as follows. The MIT laboratory led by Picard performed a series of emotional recognition experiments with multiple physiological parameters through signal preprocessing and pattern recognition algorithms. They extracted 40 features from the five recorded physiological signals. Through different feature selection algorithms and classifiers, the best recognition rate that was achieved was 82.5% [13]. The value of Picard's research is that he explored the feasibility of emotion recognition based on multiple physiological signals. For emotion recognition, a new research method and research idea was proposed, which had very important significance for subsequent research. Subsequently, emotion calculation was applied to the judgment of the overall state of the driver in the driving environment, and the Fisher projection matrix was combined with the linear discriminant to process the original signal [14]. Later, the MIT laboratory began to develop new tools to help autistic patients. They developed wearable devices that communicate with mobile phones wirelessly, so that people with autism could understand their status and adjust themselves in time. In one study [15], the medium that induces the subjects' emotions is music. The music used was chosen by the subjects themselves. These songs are what they think can represent the four emotions of joy, anger, sadness, and pleasure required for the experiment. This can evoke corresponding memories. They collected four signals (EMG, ECG, SC, and RSP) and classified them through a variety of algorithms. The best recognition rate was over 90%. One study [16] reported the induction of the emotions of the subjects through audio materials and video clips. They collected four kinds of physiological signals from hundreds of subjects and used the support vector machine algorithm (SVM) to classify and recognize the four emotions. They increased the number of subjects from the original one to hundreds. They found that, using the same algorithm, when the number of emotion recognition types increased, the recognition rate dropped slightly. One study [17] proposed building a multidimensional user experience interface to increase the sense of social presence on the basis of predecessors. They use movie clips to induce emotions. The emotion category was 6, and the optimal recognition rate was over 70%. One study [18] used the International Affective Picture System (IAPS) to induce corresponding emotions. After the experimental data were collected and preprocessed, the neural network classifier was used to classify 6 emotions.

At present, the recognition of anxiety disorders in emotion recognition mainly relies on the careful observation of school teachers, class members, and classmates, as well as questionnaire surveys. There are many loopholes in this approach. One is that there are few teachers and many students, and potentially neglected students with mental illness are likely to occur. The second is that the method of investigation may not be scientific and effective, as is the case for questionnaire surveys, and not necessarily all students will truthfully answer questions in a questionnaire. The third is that the investigation is not continuous work. It often occurs

once a semester and is not rigorous. In summary, this research proposes an automatic anxiety recognition method based on deep features and machine learning [19]–[27]. The main work of this paper is summarized as follows.

(1) Since the physiological indicators can most truly reflect the emotions of the subjects, EEG data is used as anxiety identification data.

(2) Traditional feature extraction methods are easy to lose data features, which affects the final recognition accuracy. So this research uses the deep learning algorithm CNN to extract the deep features of the input samples. The original sample information carried by the depth feature is richer.

(3) The TSK fuzzy system is used for the final classification. The system is simple to implement and has strong generalization. The final decision result obtained has a good recognition effect. The anxiety recognition method used in this study can effectively identify individuals who are potentially suffering from anxiety in a group of college students. This greatly reduces the workload of college students' mental health managers.

II. RELATED WORKS

A. EMOTION INTRODUCTION

Emotion, as a concrete manifestation of emotion, has different results due to internal or external stimuli related to personal happiness [28]. Emotion is multidimensional, including experience, behavior, and physiological responses [29]. Each person's reaction to a certain emotion differs to various extents [30]. People's emotional responses will not change in exactly the same manner in the context of certain emotions. For example, some people tend to lose their temper when they are anxious and keep talking. Some people keep eating and do not talk when they are anxious. Nevertheless, although the difference in external performance is large, internal physiological signals will change. Therefore, emotion recognition requires a combination of multiple methods. Similarly, different people have different tolerances and subjective understandings, and there will be differences in appropriateness or excessiveness, acceptability or intolerance, and understanding or incomprehensibility [31]. Even though emotion is an internal psychological activity, it still manifests itself through external media such as the face, limbs, and torso [32]. In daily life, most people have basic methods for judging each other's emotions, including observing facial expressions and gestures. However, these are very easily affected by the subjective consciousness of the observed person, especially when the observed person is unwilling to express their emotions, and it is not easy to accurately judge their emotions.

Because emotions are closely related to physical health and normal life, the realization of emotion recognition has increasingly aroused the interest of researchers. On the one hand, emotion recognition can be used as an auxiliary means for subjective judgment of emotions; on the other hand, it is also the basis of research of artificial intelligence

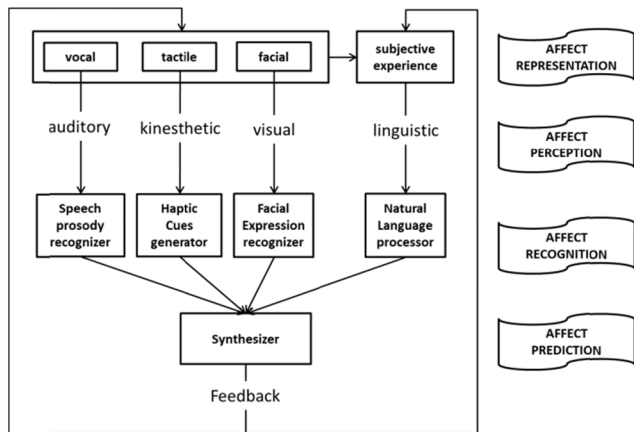


FIGURE 1. A model of users' emotions.

and human-computer interactions. Emotion recognition integrates and judges the characteristic information expressed in various ways. Common emotion recognition methods at this stage are as follows: ① Physiological signal recognition. Analyze and judge by collecting physiological signals such as respiration, heart rate, and skin electricity. ② Recognition of emotional external behavior performance. Recognize through facial expressions, intonation voice, gestures and postures when speaking. The classic model of user emotion recognition system [33] is shown in FIGURE 1.

B. ANXIETY AND ITS EFFECTS

Most people have varying degrees of anxiety in their daily lives. This state is formed during people's evolution. It is a kind of worry and guard against possible dangers. Therefore, anxiety has a positive side. If one can be aware of the threat, he or she can moderately adjust. If one can build the confidence to overcome it to gain relief, then anxiety has an obvious stimulating effect. Excessive anxiety not only lasts for a long time but also affects normal life. Severe and persistent anxiety reactions can cause low work efficiency and decreased social activities. Therefore, it is necessary to recognize the characteristics of anxiety in order to make timely and accurate judgments.

Anxiety is not only a compound emotional state, but it also has motivational meaning. It is an internal drive, and individuals with anxious mood have external behaviors and internal physical changes. These changes are caused by the hyperactivity of the autonomic nervous system. Different people have different anxiety states, different degrees, different causes of anxiety, and different external manifestations. Nevertheless, there remains consistency in the various performances. In the sympathetic nervous system, it usually manifests as a faster heartbeat, deeper breathing, and others. In terms of parasympathetic activity, there may be nausea, vomiting, or diarrhea. Anxiety can be divided into trait anxiety and state anxiety. Trait anxiety is usually relatively stable and shows different characteristics depending on the body. State anxiety is an individual's stress response to changes in

TABLE 1. Main manifestations of anxiety.

Symptom	Specific performance
Psychological symptoms	Worry, anxiety, fear, anxiety, etc.
Physical symptoms	Chest tightness, shortness of breath, shortness of breath, palpitation, dizziness, difficulty falling asleep, frequent urination, urgency, loss of appetite, skin sweating, cold hands and feet, etc.
Behavior	Stiff expression, unnatural posture, restlessness, slurred speech, difficulty concentrating, and emotional ups and downs, etc.

the surrounding environment, a reflection of a short period of an emotional state, also known as situational anxiety. Its main manifestations are shown in TABLE 1.

Contemporary college students are more or less anxious in the context of fast-paced social pressure. Anxiety is a growth process that everyone experiences. Appropriate anxiety can allow college students to stimulate their original potential. For example, anxiety in the early stage of an exam may make learning more efficient and expedite the review rhythm. However, if one is in a state of anxiety for a long time and his or her mood is not relieved, it will cause serious damage to the college student both physically and mentally. Anxiety and depression are inseparable, and often anxiety can trigger depression. Research on patients with depression also shows that many depressed patients have an anxiety state, and anxiety may occur before depression occurs. Not only do the diagnoses of anxiety and depression tend to occur at the same time, but their symptoms are highly correlated. Therefore, our prevention and intervention of anxiety will also alleviate individual depression. There are many factors that affect anxiety. In terms of physiological factors, a group of studies on twins and pedigree investigations found that there is obvious family aggregation in anxiety. Genetic factors account for 25% to 37% of the cause and play a moderate role. Social environmental factors, parental rearing styles, and the occurrence of early traumatic events all lead to the occurrence of individual psychological problems. Family structure is also a factor that causes anxiety. Single-parent families caused psychological problems due to premature family breakdown.

C. PHYSIOLOGICAL SIGNALS

When a person's emotions are in a noncalm state, various physiological signals of the person will change. Based on this principle, this study will collect human physiological signals as training data for machine learning algorithms to generate

classification models. Generally, the physiological signals used for emotion recognition include electroencephalogram (EEG), electrocardiogram (ECG), heart rate, skin electricity, skin temperature, blood volume pulsation rate, respiration rate, and others. In actual applications, these physiological signals need to be preprocessed, baseline data need to be removed, and feature extraction operations are required before they can be input into the trained recognition model.

D. RECOGNITION OF ANXIETY BASED ON PHYSIOLOGICAL SIGNALS

Physiological signals have the characteristics of objectiveness and reality in practical application scenarios, so they are widely used in emotion recognition. The flowchart of the method for identifying anxiety based on physiological signals is shown in **FIGURE 2**.

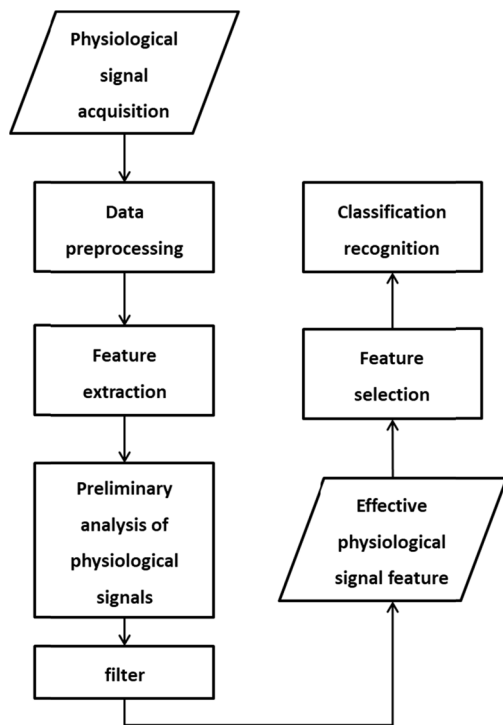


FIGURE 2. Flow chart of anxiety recognition based on physiological signals.

First, we performed preprocessing such as filtering on the collected physiological signals; we then performed feature extraction [34], [35]. The purpose of feature selection is to reduce the dimensionality of the feature space so that the feature space is composed of optimal features. Because there may be complex relationships between features, we simply sorted the features based on their separability and selected the better features. The feature combination obtained in this way is not the optimal feature set in most cases. In real life, data usually show various characteristics; however, usually only part of it is related to the target event. In this case, feature selection is very important for fast learning and improving storage quality. Relief algorithm [36] is a commonly

used feature selection algorithm. Finally, we used the classifier [37]–[40] for classification recognition.

III. ANXIETY DISORDER RECOGNITION BASED ON THE TSK FUZZY SYSTEM AND DEEP FEATURES

A. ANXIETY DISORDER RECOGNITION PROCESS BASED ON THE TSK FUZZY SYSTEM AND DEEP FEATURES

The anxiety recognition data used in this study are EEG signals. The method of feedback of the emotional state through EEG signals is authentic and effective [41]–[44]. The specific identification process is shown in **FIGURE 3**.

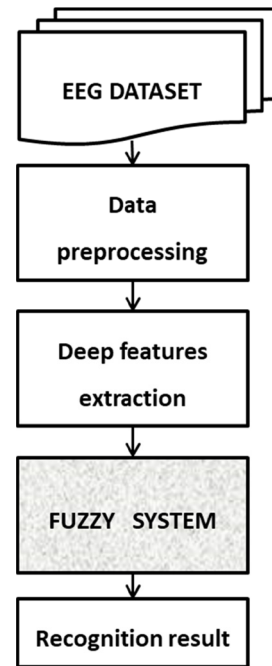


FIGURE 3. Anxiety disorder recognition flowchart based on TSK Fuzzy system and deep features.

As shown in Figure 3, we first preprocessed the collected EEG. During the acquisition process, it is inevitable that there will be some interference in the acquired signal due to factors such as the experimental environment, equipment or the human body. Common interferences include motion artifacts, irrelevant physiological signals, and internal interference of acquisition equipment. Denoising can be done by filtering. The second step is to perform feature extraction on the preprocessed data [45], [46] to reduce the feature dimension. This study uses CNN to extract the depth features of the input samples. The third step is to train the classifier. We input the feature data of the training set to the modeler. The fourth step is to obtain the final decision result. We input the characteristic data of the test set into the trained classifier to determine which of the input sample sets are anxiety patients.

B. TAKAGI–SUGENO–KANG FUZZY SYSTEM

Commonly used model systems include the Takagi-Sugeno-Kang (TSK) model [47], [48], the Mamdani-Larsen (ML) model [49], and a generalized fuzzy model (GFM) [50].

TABLE 2. Symbol introduction.

Symbol	Explanation
$\mathbf{x} = [x_1, x_2, \dots, x_N]^T$	Input vector, $x_i \in R^d$
A_i^k	The fuzzy subset corresponding to the i -th dimension input in the k -th fuzzy rule
$\tilde{\mathbf{w}}$	Consequent parameters, $\tilde{\mathbf{w}}_j$ is the consequent parameter vector of the j -th category
$\tilde{\mathbf{x}}$	Transformed input vector \mathbf{x}
\wedge	Fuzzy conjunction operation
u_{jk}	The input vector $\mathbf{x}_j = [x_{j1}, x_{j2}, \dots, x_{jd}]^T$ belongs to the degree of membership of the k -th category
h	Adjustable scale parameters
C	The number of categories
y_{ij}	The probability that the i -th sample belongs to the j -th category. Its value is 1, which means the i -th sample belongs to the j -th category, and its value is 0, which means the i -th sample does not belong to the j -th category
α	Regular parameter

Because the output of the TSK model is very simple, this study uses the TSK fuzzy system. The introduction of symbols involved in the TSK fuzzy system is shown in TABLE 2.

The fuzzy inference rules of the TSK fuzzy system are as follows:

$$\begin{aligned} &\text{IF } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \wedge \dots \wedge x_d \text{ is } A_d^k \\ &\text{THEN } y^k = f^k(x) = w_0^k, \quad k = 1, \dots, K. \end{aligned} \quad (1)$$

Each rule in Eq. (1) has its corresponding input vector $\mathbf{x} = [x_1, x_2, \dots, x_d]^T$. The fuzzy set $A^k \subset R^d$ in the input space is mapped to the fuzzy set $f^k(x) \subset R$ in the output space. After a series of operations, including multiplication, conjunction, addition, disjunction, multiplication, implication, and defuzzification of the output. The final output expression

of the TSK fuzzy system is as follows:

$$y^0 = \sum_{k=1}^K \frac{\mu^k(x)}{\sum_{k'=1}^K \mu^{k'}(x)} f^k(x) = \sum_{k=1}^K \tilde{\mu}^k(x) f^k(x) = \sum_{k=1}^K \tilde{\mu}^k(x) w_0^k \quad (2)$$

where

$$\mu^k(x) = \prod_{i=1}^d \mu_{A_i^k}(x_i) \quad (3)$$

$$\tilde{\mu}^k(x) = \frac{\mu^k(x)}{\sum_{k'=1}^K \mu^{k'}(x)} \quad (4)$$

Here, the Gaussian function is used as the membership function, and the expression of Part $\mu_{A_i^k}(x_i)$ in Eq. (3) is transformed as follows:

$$\mu_{A_i^k}(x_i) = \exp\left(\frac{-(x_i - c_i^k)^2}{2 \delta_i^k}\right) \quad (5)$$

The two parameters c_i^k and δ_i^k in Eq. (5) can be obtained using any clustering algorithm. This paper uses the classic fuzzy C mean (FCM) to get the calculation formula of the two parameters as follows:

$$c_i^k = \frac{\sum_{j=1}^N u_{jk} x_{ji}}{\sum_{j=1}^N u_{jk}} \quad (6)$$

$$\delta_i^k = \frac{h \cdot \sum_{j=1}^N u_{jk} (x_{ji} - c_i^k)^2}{\sum_{j=1}^N u_{jk}} \quad (7)$$

According to the strategy of reference [47], let

$$\tilde{\mathbf{x}} = (\tilde{\mu}^1(x), \tilde{\mu}^2(x), \dots, \tilde{\mu}^K(x))^T \quad (8)$$

$$\tilde{\mathbf{w}} = (w_0^1, w_0^2, \dots, w_0^K)^T \quad (9)$$

At this time, the expression of Eq. (2) becomes the following:

$$y^0 = \tilde{\mathbf{w}}^T \tilde{\mathbf{x}} \quad (10)$$

The least square method optimizes the parameter $\tilde{\mathbf{w}}$, and the target formula obtained is as follows:

$$\min_{\tilde{\mathbf{w}}} J(\tilde{\mathbf{w}}) = \frac{1}{2} \sum_{j=1}^C \sum_{i=1}^N \|\tilde{\mathbf{w}}_j^T \tilde{\mathbf{x}}_i - y_{ij}\|^2 + \frac{\alpha}{2} \sum_{i=1}^C \tilde{\mathbf{w}}_j^T \tilde{\mathbf{w}}_j \quad (11)$$

Use the Lagrange multiplier method to derive the parameter $\tilde{\mathbf{w}}_j$ in Eq. (11), and set its derivative to 0. The expression

for the parameter \tilde{w}_j is as follows:

$$\tilde{w}_j = \left(\alpha I_{((d+1)*K) \times ((d+1)*K)} + \sum_{i=1}^N \mathbf{x}_i \mathbf{x}_i^T \right)^{-1} \left(\sum_{i=1}^N \mathbf{x}_i y_{ij} \right) \tag{12}$$

The execution steps of the TSK fuzzy system are as follows:

- Step 1. Initialize the fuzzy rule number K and the regularization parameter α .
- Step 2. Determine antecedents of the TSK fuzzy system by Fuzzy C Means Clustering (FCM) to partition the dataset X .
- Step 3. Use Eq. (8)-(10) to construct a new data set.
- Step 4. Use Eq. (12) to get the parameters of the TSK fuzzy system.

IV. SIMULATION EXPERIMENT RESULTS AND ANALYSIS

A. EXPERIMENTAL DATA INTRODUCTION

To fairly evaluate the effectiveness of the proposed method for identifying anxiety disorders, this research used two types of data sets. One is the public data set DEAP; the other is a homemade data set. The DEAP database contains 32-lead EEG data of 32 subjects for 40 experiments, and emotion labels are given by the subjects. The introduction of the data set is shown in **TABLE 3**.

The homemade data experiment has a total of 20 subjects, all aged 20–24. Among them, 10 are men and 10 women. Participants are in good health, have no mental illness and have not taken any medicines within a week. Eight hours before the experiment, the subjects did not participate in any strenuous exercise. Before the experiment officially started, the subjects were in a calm state. During the experiment, 6 classic films were played to collect the EEG signals of the subjects while watching the films. The acquisition equipment is Ne Xus-10 MKII instrument. The architecture diagram of the homemade data acquisition experimental platform is shown in **Figure 4**. Through the emotion-induced experiment, 20 subjects obtained 200 physiological signal samples. Among them, there are 40 physiological signals in a calm state and 160 anxiety samples.

B. EXPERIMENTAL PARAMETER SETTINGS

There are many types of classifiers, and each classifier has its own advantages and disadvantages and applicable scenarios. The classifier used in this study is the TSK fuzzy system. Contrast classifiers mainly include Support Vector Machine (SVM) [37], KNN [39], RF [51], RBFNN [40]. The evaluation index of recognition effect uses precision. Precision is the most commonly used evaluation method in pattern recognition, and its value is the ratio of the number of correctly classified samples to the total number of samples.

C. STANDARD DATA EXPERIMENT

In order to evaluate the effect of different feature extraction methods and classifier focus combinations on the recognition of anxiety, the recognition accuracy and standard deviation of

TABLE 3. Introduction to DEAP data set.

Online subjective test	
Number of videos	120
Video duration	1 minute emotional highlights
Method of choosing	Create 60 via last.fm emotion tags, manually select 60
Number of ratings per video	14-16
Rating scale	Valence, arousal, dominance
Score value	1-9
Physiological experiment	
The number of participants	32
Number of videos	40
Method of choosing	The clearest subset of online annotated videos
Rating scale	Valence, arousal, dominance
Score value	Like the video Familiarity with the video Familiarity: 1-5 discrete scale Other: 1-9 continuous scale
Recorded signal	32 channels of 512 Hz EEG, peripheral physiological signals, facial video

TABLE 4. Experimental results on the DEAP dataset.

Feature extraction method / Classifier		SVM	KNN	RF	RBFNN	TSK
PCA	Precision	0.7201	0.6882	0.6921	0.7345	0.7465
	Std	0.0204	0.0115	0.0140	0.0123	0.0138
LDA	Precision	0.7189	0.6825	0.7044	0.7287	0.7373
	Std	0.0146	0.0934	0.0129	0.0102	0.0167
CNN	Precision	0.7432	0.7058	0.7162	0.7560	0.7668
	Std	0.0133	0.0087	0.0102	0.0092	0.0107

the comparison experiment on the DEAP data set are shown in **TABLE 4** and **Figure 5**. Run each comparative classification model 10 times on the DEAP data set and take the average value. The experimental results obtained are shown in **TABLE 4** and **FIGURE 5**.

In **TABLE 4**, the value of each column in row 5 is larger than that in rows 1 and 3. This shows that no matter which classifier is used, the results of deep feature extraction are always the best. Comparing the 5 values in the 5th row, the classification accuracy value obtained by the TSK model

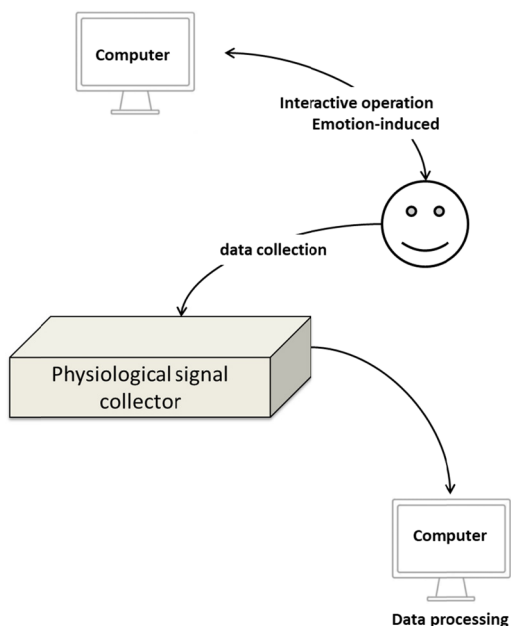


FIGURE 4. Self-made data acquisition platform architecture diagram.

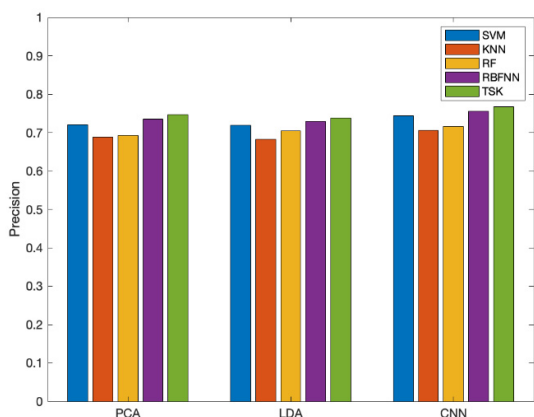


FIGURE 5. The recognition effect of each model on the DEAP data set.

system is the largest. This shows that when using depth features, among the classification results obtained by different classifiers, the TSK fuzzy classifier used in this study has the best effect. Because the TSK fuzzy system used in this paper has better noise immunity, it can reduce the influence of noise points. The TSK fuzzy system has the best recognition effect. The second is RBFNN. This fully shows that as long as the parameters of the neural network are selected appropriately, a good classification effect can be obtained. The classification effect of SVM is not very different from those of TSK and RBFNN. Compared with SVM, TSK and RBFNN, RF and KNN are much less effective. It is further explained that when different emotion recognition classifiers are chosen, the recognition accuracy varies greatly. It can be seen from the standard deviation parameter that although the TSK fuzzy system used in this article has the best recognition

accuracy, the stability of the algorithm is not as good as other comparison algorithms. In terms of stability, KNN and RBFNN are better, followed by the other three algorithms.

D. SELF-MADE DATA EXPERIMENT

We ran each model 10 times on the homemade data set and take the average value. The experimental results obtained are shown in TABLE 5 and FIGURE 6.

TABLE 5. Experimental results on the homemade data set.

Feature extraction method / Classifier	SVM	KNN	RF	RBFNN	TSK	
PCA	Precision	0.7117	0.6622	0.6789	0.7216	0.7343
	Std	0.0139	0.0110	0.0132	0.0109	0.0125
LDA	Precision	0.7019	0.6572	0.6743	0.7128	0.7230
	Std	0.0152	0.0108	0.0124	0.0123	0.0135
CNN	Precision	0.7210	0.6956	0.7177	0.7446	0.7523
	Std	0.0142	0.0091	0.0110	0.0097	0.0114

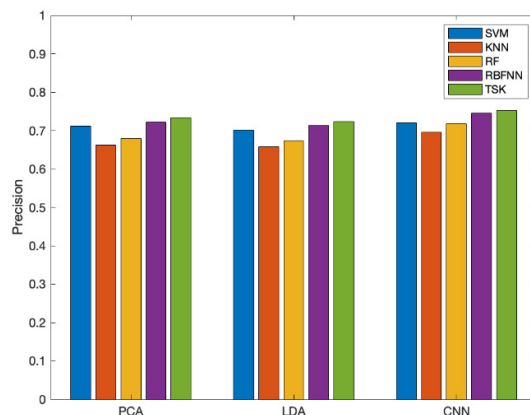


FIGURE 6. The recognition rate of each model on the homemade data set.

Since the homemade data set collection environment and process do not have public data set DEAP specifications, there will inevitably be some noise in the data collection process. Although some preprocessing will be performed on the homemade data set, it can be seen from the experimental results shown in TABLE 5 and FIGURE 6 that the recognition effect on the homemade data set was not as good as that on the public data set. However, although the overall recognition effect has declined, the classification effect of the TSK classifier is still better than other comparison algorithms. The order is RBFNN, SVM, RF, and KNN. From the std data, it can be seen that the stability of the algorithm is consistent with that of the public data set. The stability of KNN and RBFNN is good, and the stability of the TSK used is average.

V. SIMULATION EXPERIMENT RESULTS AND ANALYSIS

The mental health problems of college students caused by various social problems cannot be ignored. College students

suffer from home isolation, which affects their normal life and study. The mental health problems of college students caused by such issues cannot be ignored. College students with poor psychological qualities are prone to psychological problems such as anxiety, panic, and depression, leading to behaviors such as being tired of the world and of studying. This brings challenges to the psychological counseling of the group. To better grasp the psychological dynamics of students, it is critical to always identify the students with anxiety. This study uses TSK fuzzy system and depth features to automatically identify anxiety patients among college students. Through experiments on standard data sets and self-made data sets, the experimental results verify the superiority of the anxiety identification method used in this study. The experimental results further demonstrate that the depth features have richer information than traditional features. The noise immunity of TSK fuzzy system makes it show good classification performance and generalization. It can automatically identify individual college students suffering from anxiety, and can provide timely targeted psychological counseling, which is beneficial to the physical and mental health and coordinated development of students. This fully demonstrates the practical application value of this research.

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