**Computer Fraud and Security**
**ISSN (online): 1873-7056**

# The Application of Computer Technology in College Students' Mental Health Education and Psychological State Recognition and Early Warning

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**Abstract:**
To address the challenge of traditional questionnaires failing to accurately reflect individuals' psychological states, this paper proposes the integration of computer technology into mental health education for college students to identify psychological states and issue timely warnings. The study adopts an improved pyramid optical flow algorithm combined with a micro-expression recognition algorithm based on three-dimensional convolutional neural networks (3D-CNN). This combination further enhances the technical robustness. First, preprocessing algorithms are used to crop facial images; then, the pyramid optical flow algorithm is employed to extract facial features from the images, capturing dynamic characteristics of micro-expressions. Based on these steps, 3D-CNN is used to train the feature data, achieving efficient recognition of micro-expressions. Experimental results show that the micro-expression recognition accuracy on the CASME dataset reached 89.1%, with an F1 score of 0.6742, outperforming other traditional methods. The proposed algorithm significantly reduces model training parameters and computation time while exhibiting stronger feature learning capabilities. By accurately identifying students' psychological states, it provides objective data support for mental health education in colleges and, more importantly, offers an effective solution for early warning of psychological problems.

**Keywords:** pyramid optical flow method, 3D convolutional neural network, micro expression recognition, facial recognition, psychological warning

## INTRODUCTION

In recent years, China has been gradually transitioning into an information-based society in recent years. Along with this change, the use of computers has become increasingly widespread. In conducting online teaching in higher education, full use of network technology should be made to improve the teaching quality of ideological and political theory courses in colleges and universities[1,2]. It centers on students and is supplemented by teachers. Teachers make full use of various online psychology resources to stimulate students' strong interest in acquiring mental health information, thereby enhancing the attractiveness and effectiveness of their learning experiences[3]. Additionally, by using computer multimedia and other teaching methods, students are guided to independently search for mental health knowledge on the internet and engage in challenging psychology topics with the help of social networks. It is evident that network technology plays a significant role in conducting mental health education for college students[4,5]. In recent years, with the rapid development of artificial intelligence technology, the applications of facial recognition and micro-expression recognition technologies in mental health education have received substantial attention. Facial recognition technology primarily relies on the automated detection of facial features, providing reliable data support for mental health assessments[6]. Similarly important, micro-expression recognition technology captures subtle facial expression changes to further analyze the test subject's potential emotional state, offering technical support for early warning of psychological issues. To enhance the accuracy of psychological state recognition and further improve efficiency, integrating deep learning models such as three-dimensional convolutional neural networks (3D-CNN) has proven highly effective. By combining the aforementioned technologies with psychological education, college administrators can better achieve dynamic monitoring of students' psychological states, formulate improved personalized intervention plans, and provide technical support for enhancing the intelligence level of mental health education. These applications not only address the shortcomings of traditional mental health education in terms of real-time response but also lay a solid foundation for building an intelligent, data-driven mental health management system[7]. This paper will explore the current application status and prospects of computer technology in college students' mental health education, analyze its advantages in psychological assessment, intervention, and prevention, and further elaborate on how these emerging technologies can improve the effectiveness of mental health education.

## LITERATURE REVIEW

With the rapid development of the Internet, computer technology has been deeply integrated into various fields of economic and social development, and has become an inexhaustible driving force to promote its innovative development. Effective management of data in the network through computers has become the main way and key link to improve work efficiency at present. Therefore, a deep understanding of the advantages and characteristics of computer technology in managing data is of great significance for improving the data management level of college students' mental health education network platforms. Based on deeply analyzing the status quo of university students' psychological health education, Shi, X. G. and others put forward some suggestions on how to promote the healthy development of psychological health education in colleges [8]. Yan, L. and others believe that the growing social pressures and evolving times have led to an increase in mental health challenges among college students, with psychological issues becoming more prevalent. As a result, providing mental health education in private independent colleges is essential. Such education helps students confront their personal development and current challenges with a positive mindset, which in turn, prepares them to better navigate society after graduation [9]. Zhao et al. investigated the development and implementation of a genetic algorithm-based evaluation system for assessing the quality of psychological education among college students. Given the intensifying social competition and fast-paced lifestyle, mental health problems among today’s students not only impact their personal development but also the future of society and the nation. They introduced a weighted evaluation model designed for both domestic and international psychology education programs. Universities are encouraged to leverage their resources to effectively deliver mental health education to all students, enhancing their psychological resilience and self-care awareness [10].

In response to this, the author proposes an algorithm for micro expression recognition of psychological states based on neural networks, and uses this algorithm to objectively and accurately evaluate and warn students' psychological states. Micro expressions are involuntary and rapid facial movements, typically lasting about 0.2 seconds, that can reveal the emotions an individual wants to hide. However, due to the extremely short occurrence time of microexpressions and their usually only appearing in specific facial areas, it is difficult to recognize and analyze them. The author combined improved neural network algorithms to construct an effective lightweight micro expression recognition method, which provides effective support for psychological state warning.

## METHOD

### Algorithm Framework Design

The design of the algorithm framework is aimed at efficiently extracting key information from micro expression datasets. As shown in Figure 1, we first carried out a series of detailed facial image preprocessing work to ensure the accuracy and efficiency of subsequent processing. Subsequently, the Improved Optical Flow method was employed to estimate the feature relationships between adjacent frames in the image sequence. Finally, all preprocessed feature data is input into a 3D-CNN for training. 3D-CNN can learn and simulate how the human visual system perceives complex patterns in images through deep structures [11]. It effectively extracts and fuses data features through multi-layer convolution operations and pooling techniques, thereby achieving facial expression classification tasks. After training with 3D-CNN, the algorithm can accurately recognize the emotions or feelings expressed by users based on different features of facial expressions, such as the opening and closing of eyes, the degree of opening and closing of the mouth, and the movement of facial muscles [12].

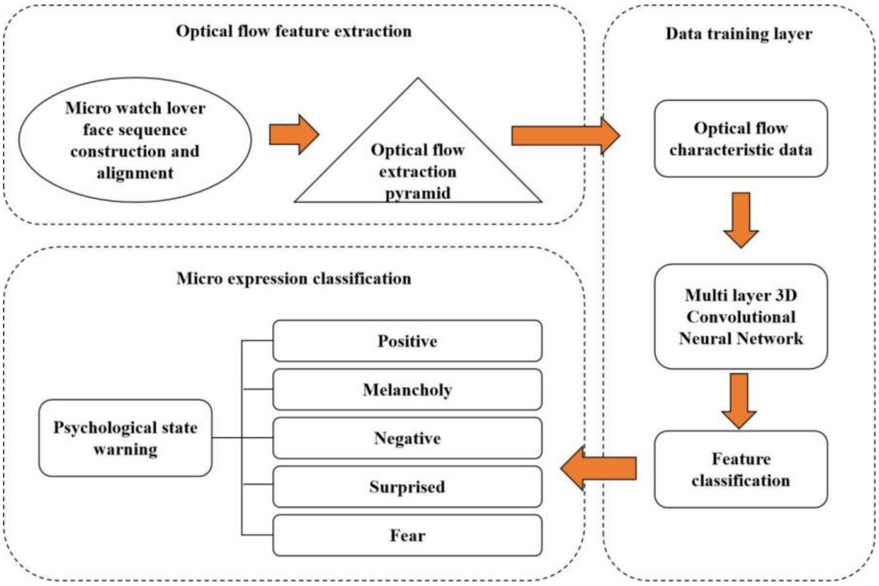


Figure 1. Algorithm framework

**Facial Image Preprocessing Algorithm**

The degree of discretization of facial data in commonly used datasets is relatively severe, and the position and size of the face are not fixed. Due to the fact that the expression recognition algorithm in the article only recognizes faces, an active alignment algorithm is used to crop and align facial data [13]. Firstly, use eye detection algorithms to mark the positions of both eyes, then recognize the main feature points, and finally extract the contour to obtain the facial image. The formula used for clipping is as follows:

$$f(x,y)=\frac{\sum_{i=1}^{N}W\left(\sqrt{(x-x_i)^2+(y-y_i)^2}/D_i\right)S_i(x,y)}{\sum_{i=1}^{N}W\left(\sqrt{(x-x_1)^2+(y-y_1)^2}/D_i\right)} \quad (1)$$

In the formula, $(x,y)$ is any coordinate within the image, W is the weight size of the image, $D_i$ is the distance from control point $(x_i,y_i)$ to the reference frame, and $S_i$ is the cropping kernel function. Equation (1) can be used to crop and align all images in the set of image sequences.

For an image sequence, the most important image frames are the start frame, end frame, and keyframe. Among them, keyframes refer to the moments when facial expression motion and deformation reach their maximum values, while the starting and ending frames are the images corresponding to the initial and final expressions of the face. The author uses optical flow method to select keyframes and extract important feature points of the image (See Figure 2) [14].

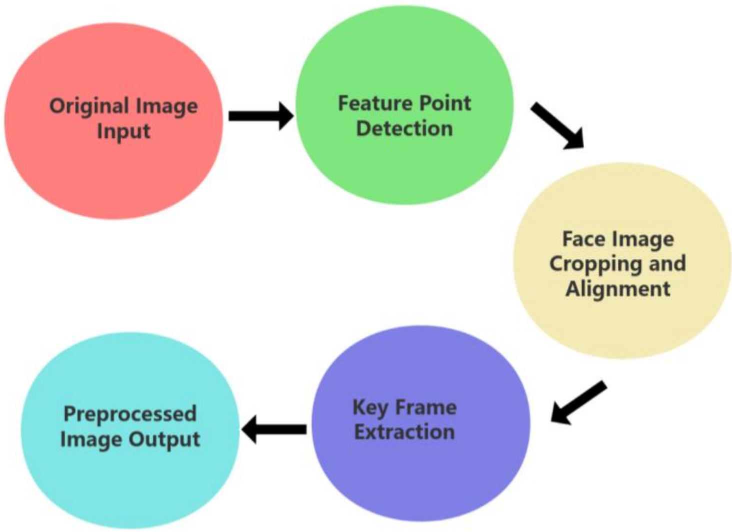


Figure 2. Data processing flowchart

**Feature Extraction Algorithm Based on Improved Optical Flow**

Optical flow method refers to a method that uses the instantaneous velocity of pixel movement in adjacent frames as a measure, compares the correspondence between pixels in adjacent frames, and calculates the motion of objects in adjacent frames. When applying optical flow method, it is necessary to ensure that the brightness between adjacent frame images is stable and unchanged, and the pixel movement between adjacent frames should also be small in order to meet the characteristics of small motion in micro expression recognition [15].

Assuming the pixel coordinates of a certain observation point in the current frame are (x, y, z), if the brightness of that pixel remains constant, the following relationship exists:

$$I(x+\mathrm{d}x, y+\mathrm{d}y, z+\mathrm{d}z) = I(x,y,z) + \frac{\partial I}{\partial t}\mathrm{d}t + \frac{\partial I}{\partial y}\mathrm{d}y + \frac{\partial I}{\partial x}\mathrm{d}x \tag{2}$$

In the formula, I represents the image frame and t is time.

Equation (2) can be derived from partial derivatives as follows:

$$\frac{\partial I}{\partial t}\frac{\mathrm{d}t}{\mathrm{d}t} + \frac{\partial I}{\partial y}\frac{\mathrm{d}y}{\mathrm{d}t} + \frac{\partial I}{\partial x}\frac{\mathrm{d}x}{\mathrm{d}t} = 0 \tag{3}$$

According to equation (3), assuming u and v are vector representations of optical flow, we have:

$$u = \frac{\mathrm{d}x}{\mathrm{d}t} \tag{4}$$

$$v = \frac{\mathrm{d}y}{\mathrm{d}t} \tag{5}$$

If all other parameters in equation (3) are known, then $(u, v)$ can be obtained as the desired value.

The author has improved the traditional optical flow method, mainly by stratifying the features of facial images and mapping and transforming them through improved algorithms, thereby improving the efficiency of the algorithm.

The running process of this algorithm is:

1) Create an image pyramid model where the base layer is the original image with dimensions x×y. The first and second layers, as well as subsequent ones, are generated through a progressive relationship. Define L as the total number of layers in the pyramid, with PL representing the image at the L-th layer. According to the empirical pyramid optical flow method, the image size of each layer will decrease by 1/4, so $P_L$ can be characterized as:

$$P_t(x,y) = \frac{1}{4}P_{L-1}(2x,2y) + \frac{1}{8}P_{t-1}(2x-1,2y) + P_{t-1}(2x+1,2y) + P_{t-1}(2x,2y+1) + \frac{1}{16}P_{L-1}(2x - 1,2y-1) + P_{L-(}(2x+1,2y-1) + P_{t-1}(2x-1,2y+1) + P_{t-1}(2x+1,2y+1) \tag{6}$$

2) Image tracking. When performing image tracking, the optical flow vectors of each pyramid layer will also be tracked. The error vector when updating the optical flow vector is as follows:

$$E_L = \sum_{x=p_x^L-w_x}^{p_x^L+w_x}\sum_{p_y^L-w_y}^{p_y^L+w_y}\left(I_L\left(p_x^L+x, p_y^L+y\right) - J_L\left(p_x^L+x+g_x^L+v_x^k, p_y^L+y+g_y^L+v_y^k\right)\right) \tag{7}$$

In the formula, $E_L$ is the optical flow vector transfer error; g is the initial value of optical flow, which can be further divided into $g_x$ and $g_y$, representing horizontal motion vector and rigid motion vector, respectively; $J_L$ is to update the image. The optical flow vector can be expressed as:

$$g_{L-1} = \left[g_x^{L-1} \quad g_y^{L-1}\right]^{\mathrm{T}} = 2(g_L + D_L) \tag{8}$$

By analyzing the optical flow vector, optical flow points, i.e. feature points, can be obtained.

**Micro Expression Recognition Based on 3D-CNN**

Traditional convolutional neural networks are a method with a deep feedforward structure that utilizes convolutional properties for computation. They are comprised of an input layer, a convolutional layer, a pooling layer, and a final output layer. This network is a two-dimensional network that can only train facial feature images on a two-dimensional plane (See Figure 3).

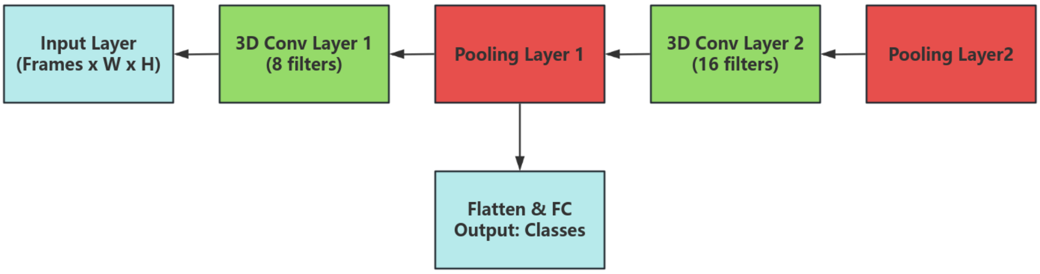


Figure 3. 3D-CNN network architecture flowchart

Due to the temporal information contained in image sequences, traditional convolutional neural networks are unable to process micro expression image sequences. Therefore, 3D convolution is used to train the image sequences. Three dimensional convolutional networks can not only extract the main features of images, but also extract the temporal features of images. Its structure is similar to that of two-dimensional convolutional neural networks, but the difference is that the basic components of three-dimensional convolution are all three-dimensional structures.

The motion information of images in 3D convolution is as follows:

$$q_{ed}^{nmj} = \tanh\left(b_{ed} + \sum_a \sum_{x=0}^{X_s-1\sum_{y=0}} \sum_{z=0} \sum_{z=1} w_{aed}^{xyz} q_{(e-1)a}^{(n+x)(m+y)(j+z)}\right) \tag{9}$$

In the formula, q represents the pixel value of a certain feature map in the convolutional layer, $X_e$, $Y_e$ and $Z_e$ are the convolution sizes in the horizontal, vertical and temporal dimensions, w represents the weight value of fully connected, and b represents the offset.

Meanwhile, the pooling layer of the 3D convolutional network prevents data fitting errors by compressing the data. The pooling layer includes maximum and average pooling structures, and the calculation methods used are the same. The final output can be unified as:

$$M = \frac{B-F+2P}{S} + 1 \tag{10}$$

In the formula, M is the final output result, B is the width of the image, F is the convolution size, P represents the compensation value, and S is the step size.

The author employs a 3D-CNN to train features derived from optical flow data and designs a 3D convolutional architecture tailored to facial data. This network comprises ten layers, including an input layer, four 3D convolutional layers, four pooling layers, an output layer, and a fully connected layer. Detailed parameters of the neural network are provided in Table 1.

Table 1. Convolutional layer information

| Convolutional layer name | Convolutional kernel size/bit | Number of convolution kernels/piece | Output/bit |
|---|---|---|---|
| Convolutional layer 1 | $4 \times 4 \times 5$ | 8 | $64 \times 64 \times 12$ |
| Pooling layer 1 | $2 \times 2 \times 2$ | 8 | $32 \times 32 \times 6$ |
| Convolutional layer 2 | $3 \times 3 \times 5$ | 16 | $32 \times 32 \times 6$ |
| Pooling layer 2 | $2 \times 2 \times 1$ | 16 | $16 \times 16 \times 3$ |
| Convolutional layer 3 | $3 \times 3 \times 4$ | 32 | $16 \times 16 \times 3$ |
| Pooling layer 3 | $2 \times 2 \times 2$ | 32 | $8 \times 8 \times 2$ |
| Convolutional layer 4 | $3 \times 3 \times 3$ | 64 | $8 \times 8 \times 2$ |
| Pooling layer 4 | $2 \times 2 \times 1$ | 64 | $4 \times 4 \times 2$ |

**Model Parameter Evaluation Indicators**

For classification algorithms, accuracy (Acc) and recall (Rec) are usually used as evaluation metrics. Accuracy measures the ratio of correctly identified samples to the overall number of samples in a dataset, whereas recall indicates the ratio of correctly predicted samples to the total number of true positive samples. The formulas for these metrics are:

$$S_{\mathrm{Acc}} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{11}$$

$$S_{\mathrm{Rec}} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{12}$$

In order to comprehensively consider accuracy and recall, F1 value is used as another performance indicator, which can be characterized as:

$$S_{\mathrm{F1}} = \frac{2 \times S_{\mathrm{Acc}} \times S_{\mathrm{Rce}}}{S_{\mathrm{Acc}} + S_{\mathrm{Rec}}} \tag{13}$$

**Experimental Dataset and Platform**

At present, the most commonly used micro-expression databases are CASME and CASME II, both of which are high-quality micro-expression image sequences. The experimental dataset contains a total of 5 types of micro-expressions, including positive (31 samples), sad (26 samples), negative (52 samples), surprise (31 samples), and fear (46 samples), with a total of 186 samples. These data samples are sourced from the CASME II dataset and were captured using high-frame-rate cameras (200 fps), with all images standardized to a resolution of 640×480. The specific information of the dataset is shown in Table 2. The average duration of the experimental samples is 0.2 seconds, covering participants of different genders and age backgrounds to ensure data diversity.

Table 2. Dataset information

| Micro-expression Category | Number of Samples | Proportion (%) | Average Duration (seconds) | Expression Amplitude Description |
|---|---|---|---|---|
| Positive | 31 | 16.67 | 0.15 | Smiling, pleasant, small amplitude |
| Sad | 26 | 13.98 | 0.25 | Drooping corners of eyes, muscle tension |
| Negative | 52 | 27.96 | 0.20 | Frowning, displeased, medium amplitude |
| Surprised | 31 | 16.67 | 0.18 | Raised eyebrows, slightly open mouth |
| Fearful | 46 | 24.73 | 0.30 | Wide-open eyes, tightly furrowed brows |
| Total | 186 | 100 | - | - |

The experimental configuration information is shown in Table 3. Meanwhile, the author uses TensorFlow as a deep learning framework and scripts written in Python as the implementation platform for the algorithm.

Table 3. Experimental configuration information

| Project | Concrete Content |
|---|---|
| CPU | i7 10700 |
| GPU | GTX 2080Ti |
| system platform | Ubuntu 18.02 |
| framework | TensorFlow |

## RESULTS AND DISCUSSION

Firstly, the original optical flow method and pyramid optical flow method are used to recognize faces, and the results of capturing facial features between the two are compared. Meanwhile, the performance evaluation of optical flow method is conducted using EPE and AE, where EPE represents the Euclidean distance error value of optical flow and AE represents the angle error value of optical flow vector. The tracking results are shown in Table 4.

Table 4. Optical flow feature extraction information

| project | Primitive optical flow method | Pyramid optical flow method |
|---|---|---|
| Number of feature extractions in the first frame/piece | 40 | 57 |
| Number of feature extractions in the second frame/item | 32 | 41 |
| EPE | 4.14 | 2.44 |
| AE（°） | 5.75 | 3.44 |

According to Table 4, using the pyramid optical flow method can capture facial movements in a more detailed manner and obtain more facial feature points. And in terms of EPE and AE error indicators, the error of this algorithm is relatively lower. This indicates that the pyramid optical flow method used by the author has better performance.

In experimental testing, the number of convolution kernels affects the accuracy and computational speed of the algorithm. Choosing fewer convolution kernels can result in longer computation time, while choosing too many can lead to a decrease in accuracy. Therefore, a total of 8, 16, 32, and 64 convolution kernels were selected and the test results were compared. The influence of the number of convolution kernels on the experimental results is shown in Table 5.

Table 5. Influence of convolutional kernel on experimental results

| Number of convolution kernels | Identification accuracy（%) | F1 value | Calculation time/s |
|---|---|---|---|
| 8 | 90.4 | 0.6782 | 151.5 |
| 16 | 90.1 | 0.6743 | 132.4 |
| 32 | 89.1 | 0.6742 | 77.4 |
| 64 | 87.1 | 0.6441 | 54.2 |

According to Table 5, when the number of convolution kernels is 32, the recognition accuracy of the CASME dataset is 89.1%, and the F1 value can reach 0.6742. Therefore, the number of convolution kernels selected for this time is 32, which can ensure both accuracy and shorter computation time for the algorithm.

Then conduct comparative algorithm testing and select different micro expression recognition algorithms to train the image sequence. The comparison algorithms are CNN, CNN+LSTM, LBP, LBP-TOP, and this algorithm.

Table 6. Test results

| algorithm | Recognition accuracy (%) | F1 value |
|---|---|---|
| CNN | 77.4 | 0.5672 |
| CNN+LSTM | 81.5 | 0.6114 |
| LBP | 83.1 | 0.6224 |
| LBP-TOP | 84.4 | 0.6312 |
| This algorithm | 88.1 | 0.6742 |

From Table 6, it can be seen that the detection accuracy of the CNN algorithm is 77.4%, which is the worst among all algorithms, and the F1 value is also the lowest. Compared with other algorithms, this algorithm combines pyramid optical flow algorithm and 3D convolutional neural algorithm, with an accuracy of 89.1% and an F1 value of 0.6742, which is the highest among the compared algorithms. This indicates that the algorithm has superior performance and can judge facial data to provide early warning of the psychological state of the detected person.

## CONCLUSION

This paper proposes the application of computer technology in college students' mental health education and psychological state recognition and early warning. Through experimental validation on the CASME II dataset, the results of the study demonstrate that the algorithm proposed in this paper exhibits excellent accuracy in micro-expression recognition tasks. The highlight lies in the fact that this algorithm, while reducing training parameters, can accurately extract temporal dimension features, which indicates its superiority in dynamic expression analysis. Although this study has achieved certain progress, there are indeed some limitations. The imperfection lies in the fact that the experimental samples in the study are based solely on the CASME II dataset, which results in a limited number of samples and an imbalance in category distribution. In future research, more data sources will be introduced to further enhance the generalization ability of the model. In terms of mental health education, further optimization of micro-expression recognition will be conducted to design personalized and intelligent psychological intervention programs.

In summary, this study provides technical support for the recognition and early warning of college students' psychological states. Based on the shortcomings identified in the research, further optimizations will be made to meet the broad application of micro-expression recognition technology in practical scenarios.

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