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Depression Classification Based on Deep Learning Sentiment Classification Model

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Abstract: *Depression is a common psychological disorder. As the pace of life in modern society accelerates, competitive pressure continues to increase, and the incidence of the disease is on the rise. With the development of brain network (Brain network is a term in medical imaging technology) technology research, many scholars have applied it in the computer-aided diagnosis of depression. At present, a large number of classification studies based on the brain network data of depression are mostly based on the brain network at a single spatial scale, and the features used are mostly clinical indicators or basic building elements of the brain network. The manifestations of depressive episodes can be divided into core symptom groups, psychological symptom groups and somatic symptom groups, but these typical symptoms do not necessarily appear in all patients. Some studies focus on comparing feature selection methods and selecting features to derive the optimal solution for assisting diagnosis of depression, significantly improving the overall performance of the system. The task of this work is to converge neural network (CNN) models and long and short-term memory (LSTM) models, where LSTM is used to simulate the environment. The environment attribute vector comes from verbatim repetition and is extracted verbatim using the CNN model. Features are automatically found in the vector sequence. The sum feature will be retrieved locally, and then the local feature will be combined with the global feature to enhance the result. Finally, it was found that the total score of social support in the depression group was (34.84±7.66) points, and the control group was (35.62±3.19) points. The experimental results show that the social support obtained by depression patients is significantly different from that of the control group, but the utilization of social support is significantly lower.*

Keywords: *Emotion Classification Model, Deep Learning, Depression Care, Mental Illness Treatment*

1. Introduction

The pace of life in modern society is accelerating, the gap between the rich and the poor, the pressure of work and society is increasing, the gap between people's expectations and the actual situation, and the influence of long-term chronic diseases and other factors have led to the increasing number of mentally ill patients. With the rapid development of the Internet and the rapid rise of various social platforms, Internet users can share their experiences, comment and display more and more emotions on social platforms. Image processing is a very important part of mechanical learning. Pictures have the ability to visually display information. Efficiently and quickly classify images posted by users on social platforms. Then dig deeper into the user's emotional inclinations. Users can better understand their mental state [1]. The research on the visual sentiment classification of users on social platforms has aroused widespread concern in academia and industry. It can be seen that the importance of images to human life is self-evident. In the process of deep learning sentiment analysis in the treatment of depression, researchers have worked hard to discover the key elements that really work in psychotherapy, and strive to improve treatment methods in this understanding, hoping to obtain more efficient treatment and curative effects [2].

The latest advances in machine learning, especially the development of deep learning, Shen D's research covers computer-aided image analysis in the field of medical imaging, which helps identify, classify, and quantify patterns in medical images. The core of these developments is the ability to use hierarchical representations of attributes learned only from data. Rather than using self-designed functions based on specific domain knowledge, this article introduces the basic knowledge of deep learning methods, and reviews their success in image registration, anatomy and cell structure detection, tissue segmentation, computer-aided disease diagnosis and prognosis [3]. Chen Y introduced the concept of deep learning to the classification of hyperspectral data for the first time. The experimental results of widely used hyperspectral data show that the classifier built in this deep learning-based framework provides competitive performance. In addition, the proposed joint spectral space deep neural network opens a new window for future research, demonstrating the great potential of methods based on deep learning in accurate hyperspectral data classification [4]. Coleman SM shows that two-thirds of older adults have two or more medical conditions that are often more important than depression in primary care. Depression management should be the best choice for patients and an integral part of nursing, rather than a secondary issue [5]. However, there are still some shortcomings in the above scholars' viewpoints. In the end, they did not systematically discuss the research problem and put forward the future direction of further improvement. Therefore, this article will conduct an in-depth discussion and further improvement of the research problem.

Different scales of the brain network make the value of its topological properties change, and the classification effect of further using topological properties as features will also be affected. In this paper, the spatial scale of the brain network is the focus of the research, and its impact on the clinical classification of depression is discussed from many aspects, aiming to break through the barriers of neuroimaging in the study of small-scale brain networks, so as to obtain better results. Taxonomic studies based on brain network data provide a new reference scheme.

2. Depression Classification Research Method Based on Deep Learning Emotion Classification Model

2.1. Deep Learning

Deep learning is a new branch of machine learning [6-7], also known as hierarchical learning algorithm. Hierarchical learning is a set of algorithms that attempt to use a combination of multi-level nonlinear transformations to create advanced data extraction models. Deep learning is the direction of machine learning algorithms based on the efficiency of learning data.

2.2. Clinical Features of Depression

The main clinical manifestations of depression patients are loss of interest and lack of pleasure; patients may feel useless, hopeless, helpless, and worthless, often with low self-evaluation and accompanied by feelings of self blame, guilt, and deep guilt; they may feel delayed or agitated mental movement, decreased ability to speak actively, and in severe cases, inability to communicate and proceed smoothly; patients with depression often experience repeated occurrences of death, suicide, or self harm [8].

2.3. Definition of Sentiment Analysis

Sentiment analysis, also called opinion mining or sentiment mining, is a branch of data mining and computational linguistics [9]. This means extracting, analyzing, editing, challenging and justifying the content of the review text. Information is subjective, and then judgments are made based on the emotional tendencies contained in this information. The content used to edit a chapter should be reflected in all articles, and the emotional tendencies behind it should be analyzed [10]. Deep learning is a concept proposed by Hinton et al. in 2006. Deep learning can automatically extract the most essential features in the data through multi-layer non-linear feature transformation to solve various classification and pattern recognition problems [11-12]. In this section, we will introduce in detail several deep learning algorithms that are widely used in the field of text sentiment classification.

2.4. Neural Network Model

A piece of text of length n in the input data is expressed as $a_{i-(n-1)},...,a_{i-2},a_{i-1}$, and the n-gram language model maximizes the following likelihood, which is formalized as:

$$P(a_i | a_{i-(n-1)},...,a_{i-2},a_{i-1}) \tag{1}$$

The current word prediction from this model is shown in the above formula. And the input part is all the word sequences in the state. The neural network language module uses three feedforward neural

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networks, of which the first layer is the input layer. The result is the corresponding result in the y layer. The typical expression is:

$$h = \tanh(c^{(1)} + Hx) \tag{2}$$

$$y = c^{(2)} + Wx + Uh \tag{3}$$

The continuous iterative model produces better results, and it can display more semantic information for contextual data [13-14]. When the linearity is inseparable, it is necessary to add a certain penalty function under the existing constraints of seeking the optimal solution [15]. A relaxation factor is used in the penalty function, which can handle the case of inseparable linearity. The following are the common kernel functions in support vector machines:

$$K(y_i, y_j) = y_i \cdot y_j \tag{4}$$

The main function of the pooling layer in the network structure is to down-sample the feature matrix c obtained after convolution operations on the input text data sentence [16] to obtain the local optimal solution in the feature, which represents the maximum of the local feature value. During the experiment, the maximum pooling method is used for sampling, so that after the pooling layer, the obtained features are formally expressed:

$$\wp = \max(d_1, d_2, ..., d_{n-h+1}) \tag{5}$$

Neurons are the basic components of neural networks [17-18]. Based on the research of brain neuroscientists, these neurons form neural circuits similar to the human brain. The formula corresponding to the model structure of the neuron is:

$$p_j(x) = f(W^T x) = f(\sum_{i-1}^{n} W_i x_i + b) \tag{6}$$

3. Experiment of Depression Classification Research Method Based on Deep Learning Emotion Classification Model

3.1. Experiment Grouping

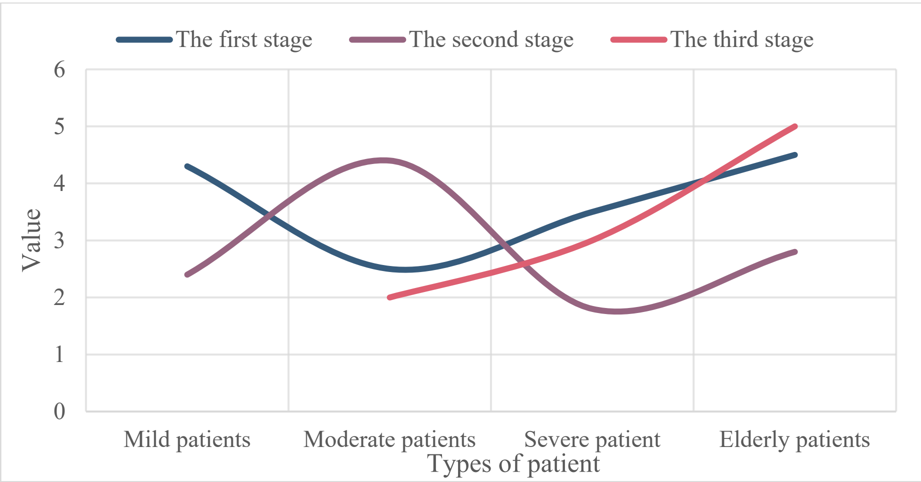

Figure 1: Different types of patients' emotions

In this paper, 80 depression patients were randomly divided into intervention group and control group. Both groups were given paroxetine after treatment [19-20].In the article, the depression degree was assessed according to SDS. The control group received medication and routine care after three months of treatment. The results show that comprehensive psychological nursing intervention can improve the treatment effect of mental disorders. Adding negative emotions improves the quality of life and helps promote the patient's speedy recovery. SDS (Self-Rating Depression Scale), is a (psychological) self-rating depression scale.The results showed that the SDS scores of the two groups of patients after admission were lower than before admission. And the observation group is lower than the control group, as shown in Figure 1.

3.2. Sample Collection

During the collection of resting-state EEG data, the subjects need to keep a quiet and relaxed state. If they are disturbed by external factors, the collected data will not accurately reflect the rhythmic activity of the brain in the resting state. Strong electromagnetic interference can affect the quality of the signal.

In order to ensure the smooth progress of the experimental research, we consulted a large number of relevant domestic and foreign literatures, referred to the nursing intervention programs adopted at home and abroad for depression, and repeatedly consulted nursing experts, psychologists, and statistics experts. The specific scheme of the experiment has been strictly designed to ensure the feasibility and scientificity of the design of the subject. The specific plan is as follows:

(1) Intervention staff: the comprehensive nursing intervention staff consists of 8 psychiatric nurses in charge, 2 psychologists and the researcher himself. All the intervention personnel participated voluntarily. Conduct intensive training before the intervention, clearly determine the purpose and significance of this research, the scope of my duties and precautions, and be proficient in the implementation rules of intervention measures.

(2) Forms of intervention: a combination of two forms: individual one-to-one individual intervention and collective group intervention [21-22]. Some common problems, such as health promotion and education, can adopt collective group intervention, and for some individual special problems, one-to-one intervention can be adopted.

(3) Time allocation: According to different comprehensive nursing intervention items, time is allocated flexibly.

(4) Effect evaluation: Two groups were evaluated using SAS and SDS scales before and after nursing intervention, and the measurement scores collected before and after the intervention were carefully organized. Statistical analysis was conducted using analysis software, and the effects of the two groups before and after the intervention were evaluated based on the analysis results. Finally, a conclusion was drawn.

3.3. Statistics

Specific steps: Researchers propose research content and objectives to eligible patients and obtain their consent, and require patients to independently complete the questionnaire (Some subjects were unable to answer the questionnaire on their own due to low education or other reasons). The researcher read the questionnaire aloud. Volunteers will choose the most appropriate option, and the mediation effect will be tested by linear regression analysis.Linear regression analysis is a method of predicting the future value of a random variable that is related to it based on the changes in one or a group of independent variables.

4. Experimental Results and Analysis

4.1. Summary of Research Results

The results of this study show that after a period of treatment, as the condition of patients with depression improves, the stigma and inadaptive strategies are reduced, and there is a significant positive correlation; adaptive strategies are increased, and are associated with stigma. The decrease in serotonin was significantly negatively correlated. Serotonin is widely present in mammalian tissues, especially in the cerebral cortex and synapses, and it is also an inhibitory neurotransmitter.In other words, as the cognitive coping style of depressed patients improves, their stigma is also reduced. This shows that stigma itself may be a kind of bad cognition of patients with depression, and stigma and cognitive coping strategies complement each other. We also found that the BDI score is proportional to the total score of stigma and various factors, that is, the more severe the depression, the stronger the stigma. This is consistent with previous research results. Through analysis of the mediating effect, we found that adaptive strategies play a mediating role between depression and stigma, that is, in addition to the predictive effect of depression on stigma, it can also be reduced by improving the patient's

ISSN 2616-5775 Vol. 7, Issue 9: 51-59, DOI: 10.25236/AJCIS.2024.070907

adaptive strategies. Stigma in patients with depression. At the same time, in the study of the relationship between dysfunctional attitudes and depressive mood and stigma, it is found that dysfunctional attitudes also play a mediating role. This may be because dysfunctional attitudes are also a kind of bad cognition, which will make depression patients Prone to stigma. Therefore, improving the patient's dysfunctional cognitive model will help reduce stigma.

4.2. Data Analysis of Research Results

In the Happy Block, the interaction between emotion type and group is significant (F(1,50)=4.45, p=0.040, ηp2=0.082).

The P1 amplitude of normal people to happy faces (4.10±0.47μV) is significantly greater than that of neutral faces (3.40±0.47μV; F(1,50)=9.14, p=0.004). On the contrary, the P1 amplitude of the happy face (4.42±0.47μV) was significantly smaller than that of the neutral face (4.89±0.47μV; F(1,50)=4.23, p=0.045).

What is interesting is that the interaction between this emotion type and the group in the sad block is completely opposite (F(1,50)=11.3, p=0.001, ηp2=0.184). The P1 amplitude (3.39±0.32μV) of normal people to sad faces is smaller than that of neutral faces (not reaching the significant level) (3.80±0.37μV; F(1,50)=3.79, p=0.057). On the contrary, the P1 amplitude (5.38±0.32μV) of the patient's sad face was significantly greater than that of the neutral face (4.79±0.37μV; F(1,50)=7.88, p=0.007). The main effect of the group was significant (F(1,50)=10.02, p=0.002, ηp2=0.169): the P1 amplitude of the patient (5.08±0.33μV) was significantly larger than that of the normal person (3.60±0.33μV).

14 Defects of emotional processing in patients with depression: based on evidence of subliminal perception and working memory. When directly comparing happiness and sadness, the interaction between emotion type and group is significant (F(1,50)=11.8, p= 0.001, ηp2=0.191).

4.3. Differences in Emotional States of Different Groups of People

Different points in the emotional space represent the description of different human emotional states, and the spatial points and emotions are linked together through mapping. This way of division makes the different dimensions in the emotional space correspond to different states of emotions. At the same time, in this way of expression, the emotional description is continuous, which is different from the discrete type mentioned above. Using the spatial mapping method, different emotional tags can find their respective positions in the dimensional model through coordinate transformation, thereby expressing the emotional state as specific spatial coordinate values, as shown in Figure 2.

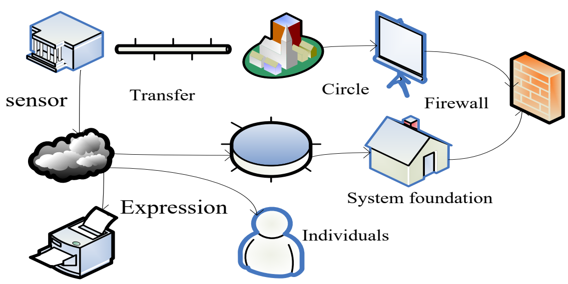

Figure 2: Two-dimensional activation degree-valence space

By comparing the description methods of two emotion models, the discrete emotion model is more concise, intuitive, and easy to understand. However, its limitation lies in its relatively limited ability to describe emotions, making it more difficult to handle the ambiguity of multiple mixed emotions. In contrast, the dimensional emotion model provides a detailed and in-depth description of emotions using coordinate data, which has strong expressive power. However, it also faces the complexity of how to map qualitative emotions to emotional spatial coordinates and the rationality of the corresponding mapping. In order to verify whether the stacked autoencoder can improve the recognition performance when increasing the number of network layers, this experiment will use the larger-dimensional

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spectrogram to expand into one-dimensional features for verification. The feature structure used in the experiment is as follows: pre-emphasis on the voice data of the CASIA data set, windowing and framing, and FFT transformation of the voice. The frame length is 512 data sampling points, and the frame shift is 256 sampling points. Energy power spectrum, 256-dimensional features of each frame are obtained. After that, PCA dimensionality reduction is performed to obtain the first 60 dimensions. According to the unified method of the size of the spectrogram in the literature, 40 frames are selected as the length of each spectrogram. Therefore, the characteristic of the obtained spectrogram expanded into one-dimensional form is 60×40=2400 dimensions. For the 2400-dimensional input vector, different stacked autoencoder network structures were constructed for experimental verification.

The first group of network structures are: [2400506], [24001200506], [2400400506], [24001200400506]. Under the same learning rate of 0.8 and momentum of 0.5, each network is trained for 50 iterations, and the recognition rate is recorded as AP, the recognition results of different network structures are shown in Table 1:

Table 1: Stacked autoencoder different network structure comparison experiment group one (unit: %)

Network structure	Recognition rate
[2400 50 6]	32.73
[2400 1200 50 6]	37.75
[2400 400 50 6]	36.73
[2400 1200 400 50 6]	41.38

The analysis of text sentiment is the ultimate goal of the system, which integrates the results of all previous training. The analysis of text emotion is to use the trained emotion model to process the text of the training set, extract the features of the text, then use these features to train the support vector machine, and finally use the trained support vector machine to predict the text to be processed. The general process is shown in Figure 3:

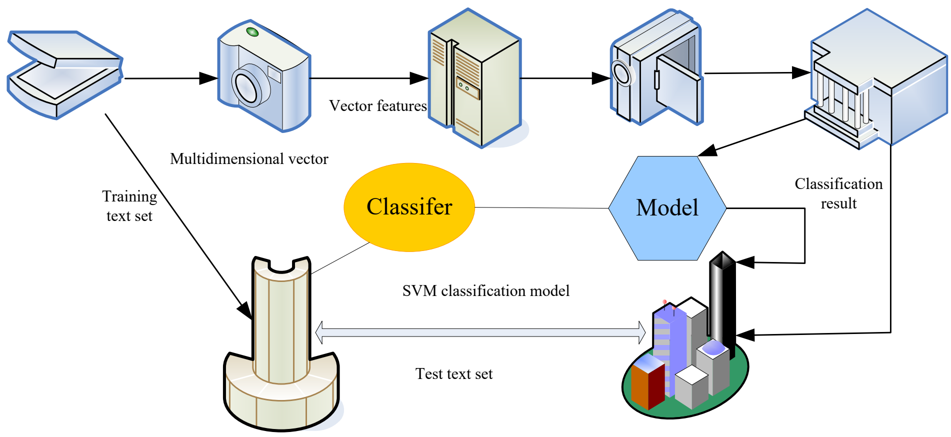

Figure 3: Analysis of text sentiment

The classification of the emotion model is actually the process of establishing the classification model of machine learning. The generated emotion model is used to extract the text features of the text to be classified, and then handed over to the support vector machine to process the classification result. The pseudo code of the emotion classification is as follows:

The labeled training sample Dtrain, the unlabeled test sample Dtest; output: the emotional category label of the test sample Dtest, are shown in Figure 4 and Table 2.

Table 2: Statistics on the prevalence of autism in the United States

Years	Birthday	Sickness per 1,000 children Number	Prevalence
2000	1992	6.7	1/150
2002	1994	6.6	1/150
2004	1996	8.0	1/125
2006	1998	9.0	1/110
2008	2000	11.3	1/88
2010	2002	14.7	1/68
2012	2004	14.6	1/68

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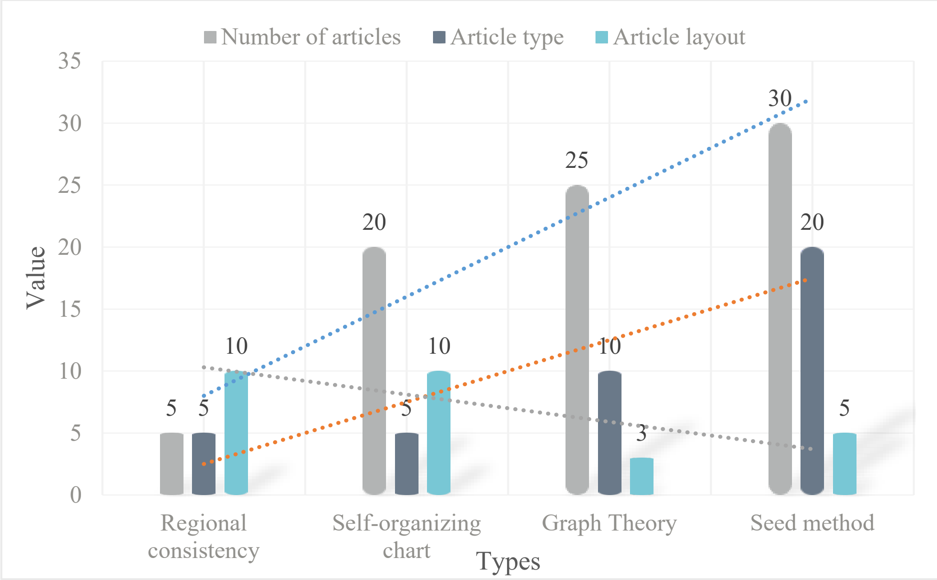

Figure 4: Statistics of autism methods and number of articles based on rs-fMRI analysis

This paper mainly studies the diagnosis of autism based on deep learning. The main experimental process is feature learning and predictive classification. The purpose of using this method is to use computer-aided diagnosis to realize the classification and prognosis of autism. The 656 samples that have been preprocessed before are divided into ASD group and TD group, and the two groups are labeled respectively (ASD group is 1 and TD group is 2). These samples are divided into training set and test set. The samples of the training set are trained layer by layer to extract features with the stack autoencoding network, and then the Softmax classifier is used for supervised learning fine-tuning, and a network model is obtained through experiments. Finally, the test set is placed on the network. Test under the model to test the accuracy of the model's classification. The framework of the ASD classification system is shown in Figure 5.

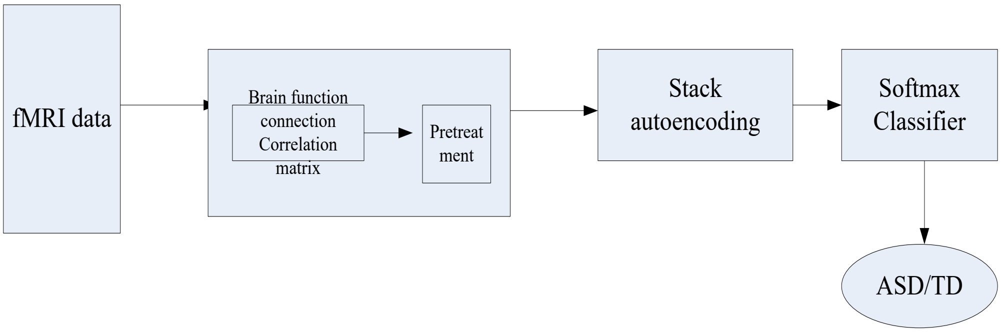

Figure 5: ASD Classification System Framework

Model training uses the leave-one-out method to train the speech emotion recognition model in a speaker-independent manner. The model uses the CTC/Attention model and performs a 15-fold cross-validation experiment in a speaker-independent manner. The cross-validation experimental results are shown in Table 3:

Table 3: Cross-validated experimental results

CV	UAR[%]	CV	UAR[%]
1	68.3	9	72.1
2	66.4	10	67.6
3	66.8	11	68.7
4	67.4	12	70.1
5	72.5	13	67.9
6	69.3	14	70.0
7	66.5	15	71.4
8	71.6	Average UAR	69.1

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Through the sample survey, the subjective emotional information data collection table is generated, as shown in Table 4 and Table 5:

Table 4: Data collection form for subjective emotion information

data set	Data set category	The amount of data	Number of categories	classification name	Data Sources
W1	Emotions set	61108	2	Subjective	Weibo
W2	Multi-category emotions set	19510	7	Happiness	Weibo
W3	Emotional polarity data set	9856	2	Positive	Product Reviews

Table 5: Division of subjective and objective sentiment data set and sentiment polarity data set

data set	Subjective and objective sentiment data set		Emotional polarity data set	
	subjective	objective	Positive	Negative
Training set	13785	28993	3432	3469
Validation set	1950	4160	475	510
Test set	3775	8445	1006	964

Different types of depression patients exhibit completely different emotional states. The following Figure 6 will make a comparison for better research and improvement of treatment methods.

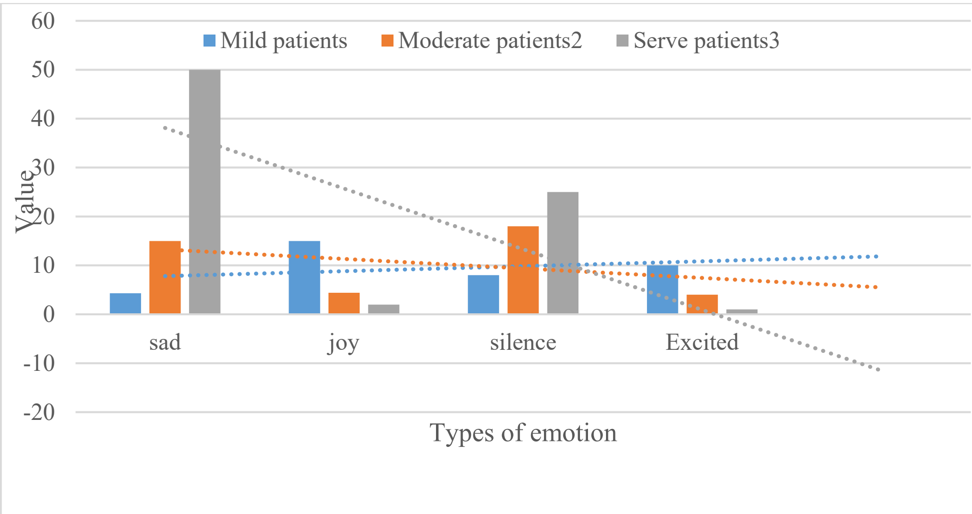

Figure 6: Emotional analysis

5. Conclusion

The executive function level of adolescents with depression has varying degrees of correlation with their depression, automatic thinking, life events, family adaptability and education level. Negative life events and negative automatic thinking can aggravate the degree of depression in patients, and then directly or indirectly affect their executive functions. This article mainly studies the crowd sentiment analysis method based on deep learning, which mainly studies the estimation method of crowd happiness, and conducts experimental verification of various methods, and proposes an optimal deep learning-based solution method. With the development of society, depression has become more and more common, and there are more and more causes of illness, such as postpartum, late pregnancy, post-traumatic, etc. This study shows that through psychological nursing treatment, significant results have been achieved. Therefore, good treatment will help patients recover as soon as possible, prevent recurrence, increase their psychological quality, and arouse their confidence and courage.

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