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*Retraction*

# Retracted: A Novel Deep Learning Model for Analyzing Psychological Stress in College Students

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] H. Zhang, "A Novel Deep Learning Model for Analyzing Psychological Stress in College Students," *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 3244692, 11 pages, 2022.

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*Research Article*

# A Novel Deep Learning Model for Analyzing Psychological Stress in College Students

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Psychological stress refers to the load or oppression that people's thoughts, feelings, and other inner processes bear, as well as the emotional shifts brought on by the school, work, society, everyday life, interpersonal connections, and other things. It can trigger people's worry and other negative feelings, making them mentally dejected and frustrated, as well as raise people's spirits to cheer up and meet stimuli and difficulties. College students are in their 20s, and they are energetic, have extreme mood swings, and are prone to mental problems. As a distinct group in the social development trend, college students are influenced by the learning and growth environment, and their understanding of the world, values, and outlook on life is maintained at the theoretical level, lacking practical thinking and experience, making it difficult to adapt in a short period of time. Excessive psychological strain is caused by new events and new contradicting conditions, which interfere with normal living and learning. This study employs a deep learning model to test and assess the psychological stress in college students, with the goal of addressing the varied psychological stresses that college students are prone to. The deep learning model employed in this paper is based on the classic ResNet50 network model, which compresses its network structure, lowering the computational cost of ResNet50 network model training and increasing the network's efficiency. To boost processing performance and save storage and computational resources, we trained a network with few parameters, a small model, and high precision. The findings of the investigation can help college officials prevent and recognize problems in students early on. It actively builds a good home-school cooperation mechanism and enhances the students' ability to cope with and solve stress through enhancing the students' behavioral experience, so that students can form a good psychological stress coping thinking and behavior, while attaching importance to the cultivation of college students' psychological quality.



## 1. Introduction

College students today live in a time of rapid social change. They are under enormous pressure as a result of the increasingly complex competition in modern society, and their psychological problems are on the rise. College students' mental health impacts not only their school, study, and life but also their long-term development. Understanding the current situation of college students' psychological problems, exploring the causes of their psychological problems, and solving the psychological and behavioral problems frequently encountered in the process of psychological development and in daily life based on their psychological characteristics are all important. Stimulating the psychological potential of college students and optimizing their psychological quality is the key to the comprehensive implementation of quality education in colleges and universities. Mental health [1, 2] is defined as a state in which a person has a sense of internal stability and can adapt to the external environment in any form in society. When confronted with obstacles and difficulties, the psychology will not be out of balance, and it will be possible to overcome them with appropriate behaviors. The state of mental health is one of stability and adaptation. It is extremely difficult to determine whether the mind is completely healthy. There is no absolute dividing line when it comes to health. Stress is a state of tension that occurs when an individual's body and mind feel threatened. It is also known as "stress" and "tension." A person's body and mind will suffer serious harm if they are subjected to high levels of stress for an extended period.

College students' mental health issues are primarily manifested by high psychological pressure, poor psychological endurance, and poor psychological adjustment ability. The primary core issue is psychological stress. With the advancement of artificial intelligence, it is a challenge to use intelligent technology [3, 4] to collect and analyze psychological pressure data from college students to assist college and university management and carry out student management work smoothly. Reference [5] investigated the relationship between search behavior and personality traits. Reference [6] proposes an algorithm for predicting mental health problems based on network usage behavior. The role of emotional factors in doctoral students' network information retrieval is discussed in [7]. A new method for detecting depression using time-frequency analysis of network behavior was proposed in [8]. Reference [9] proposes a new method for predicting the future severity of mental illness (MIS) in Instagram users. The traditional method of assessing psychological stress relies heavily on questionnaires and manual interaction. Some methods are used to assess students' psychological stress over time by administering daily or multiple questionnaires and conducting manual interviews [10]. Wearable devices are used to assess the psychological stress of students [11]. This method typically takes a long time to collect data and is only effective for a subset of students who participated in the survey activities. Another relatively new approach is to collect and analyze students' historical data, primarily using machine learning, and then process various data to build models with appropriate features to assess students' psychological stress, such as using students' Internet access. There are uses of students' learning, sleep, consumption, mobile phones, and smartwatches and other information to assess students' psychological stress [12–16]. This model generally uses the information of existing records to predict and does not need to be reoperated every time the survey is completed, and after the model is built, it can be extended. The characteristics and appropriate model are critical and will have a significant impact on the performance of the evaluation model.

To overcome the shortcomings of traditional research methods, such as the long period and limitations, only use data that is convenient to use within the school, and this experimental study uses data of students who are completely organically recorded in the school to study the effectiveness of the psychological stress assessment of students. Based on the deep learning model [17], the various behaviors of the students are constructed, and the data features are constructed to evaluate the psychological stress of the students. This paper's main work consists primarily of the following aspects.

(1) Conduct research into the signs, causes, and effects of psychological stress in college students. Additionally, identify the primary aspects that contribute to college students' psychological stress.
(2) A deep learning model is proposed for analyzing college students' psychological stress. Given the inherent limits and high computational load of the traditional ResNet50 deep learning model, this research offers an enhanced ResNet50 model for the assessment and analysis of college students' psychological stress. The modified ResNet50 model employed in this study has the advantages of fewer training parameters, a small model size, and high precision, which can significantly increase computing performance and conserve storage and processing resources.
(3) Using the deep learning model, the findings of psychological stress among college students are studied, and a series of pertinent countermeasures are proposed in order to alleviate college students' psychological strain and assist university staff in managing students efficiently.

## 2. Knowledge about Psychological Stress of College Students

*2.1. The Primary Source of Psychological Stress for College Students.* The three main sources of psychological strain on college students can be stated as follows: one is family circumstances. Education and the family environment are important factors in a person's development and progress. Children's first teachers are their parents, and their words and actions will have a significant impact on their conduct and personality development. The majority of our country's only children have been cared for by their elders since childhood, and they lack self-care and hands-on skills, as well as a poor ability to resist pressure and a lack of education for setbacks. They are frightened and dejected when they face difficulties. Second, there is the issue of school. Schools play a vital role in the development of college students' physical and mental health because they are the primary location where they live and study. Teachers and parents place a greater emphasis on grades in middle school, ignoring students' ideological and psychological education. As a result, some college students will have poor psychological quality, be unable to adapt to their new environment once they arrive at university, and will experience a variety of psychological issues. Most colleges and universities have set up psychological counseling facilities, but they can only help with the surface issues. Counselors and professors do not truly enter the lives of their students, understand them, or pay attention to them, and their psychological issues cannot be alleviated. Personal characteristics of pupils are the third factor to consider. Many college students have weak self-control and are unable to objectively assess themselves while pursuing personal development. College students lack a thorough awareness of society and are easily influenced by negative conceptions and negative forces during the formation and development of their personalities, resulting in withdrawn and indifferent personalities.

*2.2. ResNet Deep Learning Model.* An important new feature of the ResNet model [18] is that it uncovers the issue of model "degeneration," which refers to an increase in model error rate as the network depth declines. The ResNet model was created in answer to this issue. Reducing gradient disappearance and enhancing model training accuracy are the main goals of a deep residual network's "shortcut connection," which can bypass one or more layers in order to transport findings from the previous layer directly to the next layer of the network. ResNet's residual structure uses two mapping methods: identity mapping and residual mapping, with a final output of $y = F(x) + x$ as the result. The identity map refers to itself, which is $x$, and the residual map refers to $y\text{-}x = F$, as the name suggests ($x$). There are two varieties of basic residual block design, as shown in Figures 1 and 2, respectively. As can be seen in Figure 2, this residual structure is developed as a bottleneck type for deep ResNet models with 50 or more layers. To accomplish this, a $1 \times 1$ convolution layer is placed before and after the $3 \times 3$ convolution layer in order to lower the input and output sizes.

The shortcut in Figures 1 and 2 skips one or more layers with distinct stages in order to combine with the main path, and the structure's output is

$$x_l = F_l\left(x_{l-1}, W_l\right) + x_{l-1}, \tag{1}$$

where $W_l$ stands for the $i$-th residual unit's parameter, while $x_l$ stands for the $l$-th residual unit's output. The following formula can be obtained:

$$x_{l+1} = F_{l+1}\left(x_l, W_l\right) + x_l. \tag{2}$$

Because the output of any deep residual unit can be combined with the output of any shallow residual unit to add multiple residual units, each residual unit's final stacking output is given by

$$x_L = \sum_{i=l+1}^{L} F_i\left(x_i - 1, W_i\right) + x_l. \tag{3}$$

A linear projection must be added if the input and output dimensions of each residual unit differ.

$$x_l = F_l\left(x_{l-1}, W_l\right) + W_S x_{l-1}. \tag{4}$$

The ResNet model uses $3 \times 3$ small convolution kernels, replacing one large convolution kernel with multiple small convolution kernels, like the VGGNet model. However, it deepens the model and makes model training more difficult. When the size of the output feature map is halved, the number of filters is doubled, and the feature map downsampling step is increased to 2. When the size of the input and output feature maps is the same, the number of filters remains constant.

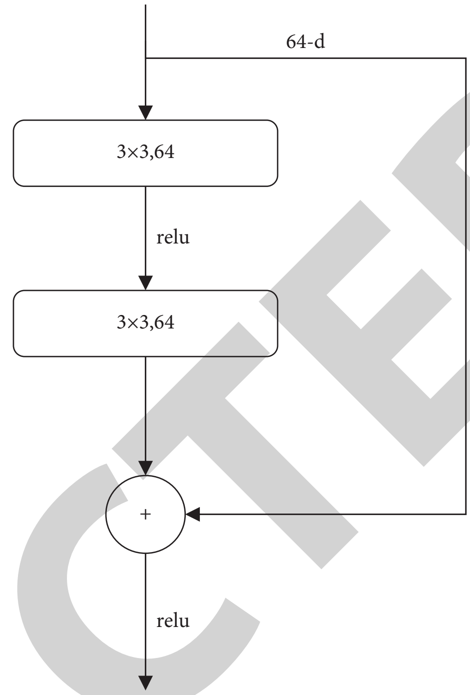


Figure 1: ResNet34 residual block structure.

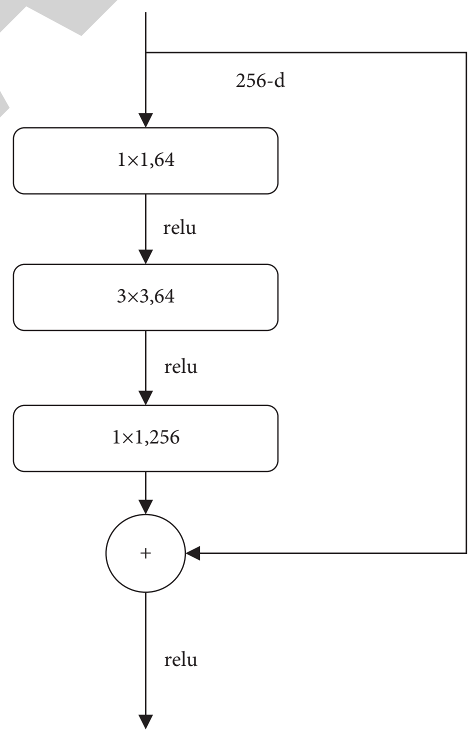


Figure 2: ResNet50 residual block structure.

## 3. Deep Learning Model-Based Psychological Stress Analysis of College Students

*3.1. Examining the Psychological Stress of College Students.* Four different data sources were used to create the datasets. The student's family level, student's bursary level, average student's canteen consumption, number of students' canteen consumption, and average student's grades are all estimated individually based on the source data. The deep learning model is utilized to analyze the psychological pressure of pupils based on the gathered characteristic data. Figure 3 depicts a psychological stress analysis framework for college students based on the deep learning model.

*3.2. Improved ResNet50 Model Structure Design.* Although ResNet's "addition" function can solve the problem of

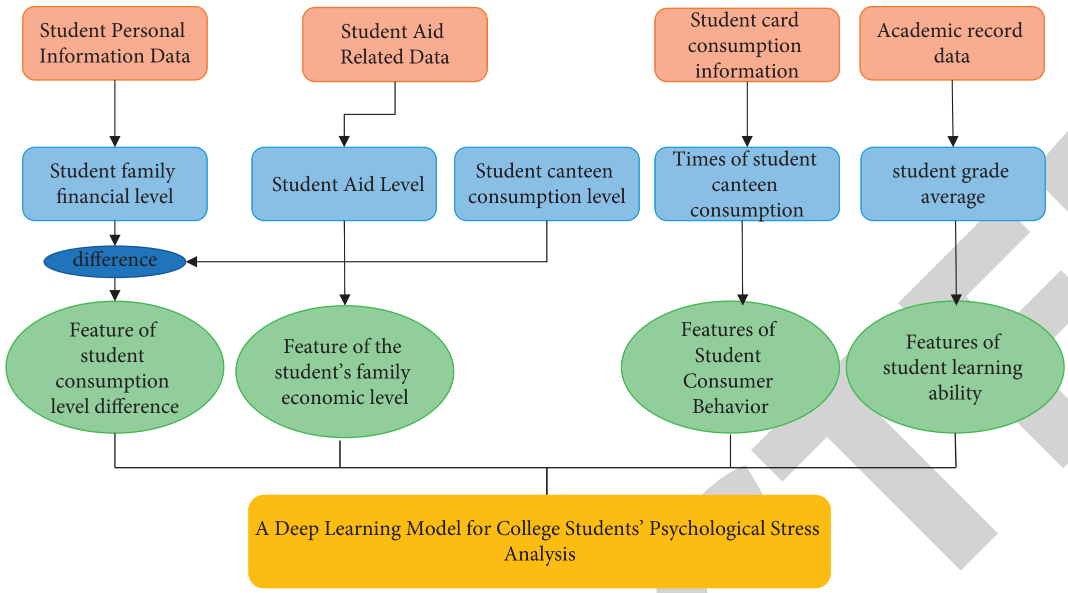


Figure 3: Analysis framework of college students' psychological stress based on deep learning model.

gradient disappearance and explosion by extending the network, it also increases the number of parameters and raises the difficulty of training. The lightweight of the network model is realized based on the idea of cost savings and taking into account the actual operability and training speed of the network model. This paper compresses the ResNet50 network structure with reference to the network structure of MobileNet [19], lowering the computational complexity of ResNet50 [20] network training and enhancing its operating efficiency. MobileNet's fundamental unit is depthwise separable convolution (DSC). Standard convolution is decomposed into depth convolution and point-by-point convolution by DSC. Among them, depth convolution convolves each input channel independently; that is, each channel has $k$ distinct convolution kernels and each channel generates $k$ new channels. If $c$ channels are input at this moment, $kc$ channels are output, with $k$ typically equal to one. The point-by-point convolution is a standard $1\times 1$ convolution that treats the depthwise convolution-generated $kc$ feature maps in their whole and executes standard convolution after combination. The network's parameter count can be significantly reduced. The calculation formulas of standard convolution and DSC are shown in equations (5)–(8).

$$\operatorname{conv}(W,y)_{(i,j)} = \sum_{k,l,c}^{K,L,C} W_{(k,l,c)}\, y_{(i+k,j+l,c)}, \tag{5}$$

$$\operatorname{pconv}(W,y)_{(i,j)} = \sum_{c}^{C} W_{(c)}\, y_{(i,j,c)}, \tag{6}$$

$$\operatorname{dconv}(W,y)_{(i,j)} = \sum_{k,l}^{K,L} W_{(k,l)}\, y_{(i+k,j+l)}, \tag{7}$$

$$\operatorname{sconv}\left(W_p,W_d,y\right)_{(i,j)} = \operatorname{pconv}_{(i,j)}\left(W_{(p)},\operatorname{dconv}_{(i,j)}\left(W_d,y\right)\right). \tag{8}$$

Assume that the convolution input feature map is $w\times h\times c_1$, the output feature map is $w\times h\times c_2$, and the convolution kernel is $n\times n$, where $w$ , $h$, and $c$ are the width, height, and number of channels of the feature map, respectively. The number of parameters and calculations required by the standard convolution and DSC methods can be calculated from this. Table 1 shows a comparison of standard convolution and DSC.

When $n>1$, $n^2c_1+c_1c_2<n^2\times c_1\times c_2$, $wh(n^2c_1+c_1c_2) < whn^2c_1c_2$. It demonstrates that DSC can significantly reduce network parameters compared with standard convolution, and DSC has a lower computational complexity than standard convolution. When $n=1$, DSC has a greater parameter quantity and a larger computation amount than normal convolution. Thus, this paper employs DSC to replace traditional convolution in the residual network, reducing the number of parameters and computations. Figure 4(a) shows the initial structure of resnet_2b in the first residual block of ResNet50.

Three conventional convolution layers are shown in Figure 4(a). The initial $1\times 1$ convolution is for dimensionality reduction, which means that the 256-dimensional channel will be reduced to 64-dimensional and then restored by a $1\times 1$ convolution at the end, achieving the goal of reducing the number of parameters. The $3\times 3$ standard convolution in the residual unit is replaced in this study, but the two $1\times 1$ standard convolutions before and after are kept. According to the literature [21], dropout should be put between the convolutional layers when employing dropout in the ResNet residual block, as opposed to the identity section of the residual block in literature [22], and hence this paper does so. To prevent overfitting, a dropout layer is introduced after the second convolutional layer. Figure 4(b) shows the revised structure, where DSConv stands for depthwise separable convolution.

The residual unit has relu and BN in addition to the convolutional layer, as seen in Figure 4. Relu is a piecewise linear function among them. If the output is less than zero, it will be set to 0; if it is more than zero, it will remain unchanged; that is,

Table 1: Comparison of standard convolution and DSC.

| | Parameter amount | Calculated amount |
|---|---|---|
| Standard convolution | $n^2 \times c_1 \times c_2$ | $whn^2c_1c_2$ |
| DSC | $n^2c_1 + c_1c_2$ | $wh(n^2c_1 + c_1c_2)$ |

$y = \max(0, x)$. The output will become scanty after relu. BN stands for batch normalization, which means that the data is normalized in batches. The variance is 1, and the mean is 0. As a result, by adding BN operations to the network, gradient backpropagation can be improved during training, preventing gradient disappearance or explosion. The BN operation's specific computation steps are as follows: assume a batch is labeled $M = \{x_1, \ldots, x_m\}$. Calculate the batch's mean and variance first. Second, normalize the batch's i-th training sample. Finally, multiply the sample quantity by offset. The BN operation's relevant calculation processes are as follows:

$$\mu_M^2 = \frac{1}{m}\sum_{i=1}^{m} x_i, \tag{9}$$

$$\sigma_M^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_M)^2, \tag{10}$$

$$\widehat{x}_i = \frac{x_i - \mu_M}{\sqrt{\sigma_M^2 + \varepsilon}}, \tag{11}$$

$$y_i = \gamma \widehat{x}_i + \beta. \tag{12}$$

Furthermore, the placements of relu and BN in the network can be combined in a variety of ways, as shown in Figure 5. To begin, the locations of relu and BN in Figure 5(a) are Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-. According to [23], the relu function was inserted in front of the convolutional layer, resulting in the BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu- (b). Reference [23] later presented the model depicted in Figure 5(c), which deleted the first relu and added BN at the end to equalize the last volume, based on Figure 5(b): BN-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv-BN-relu-Conv. The reason for lowering the relu function is that they discovered that utilizing too many relu functions does not improve the model's performance but compromises its accuracy.

By contrast, in this study, the preactivation approach is chosen, the initial relu is removed, and a BN operation structure is added at the end, resulting in the model structure shown in Figure 5(c). As a result, Figure 6 depicts the final residual unit structure in this research.

## 4. Data and Analysis from Experiments

*4.1. Experimental Data.* The research object of this paper is a total of 300 students in the 2017 grade of a university. Because the abnormal psychological pressure of college students leads to the real data of counseling or abnormal behavior is more sensitive, this research adopts the method of conducting psychological questionnaires to obtain positive and negative labels and then scored the quality of the questionnaire and finally selected 280 valid student samples as the research object. After repeated comparisons and investigations, the labels of these 280 students were highly reliable. The data used in this study mainly include the following information and records: records of students' personal information, records of students' academic performance, records of students' campus card consumption, and records of students' acquisition of financial aid in school. The detailed description of each information is shown in Tables 2–5.

According to the experimental requirements and data sources, the data source will generate four major data characteristics after processing, which will be used for the subsequent operation and processing of the model.

(1) *Characteristics of Difference in Student Consumption Level.* The characteristic obtained by the average student canteen consumption is calculated from the student's personal information and student card consumption information. The nonconformity of family economic conditions is used to study the influence of this factor on students' psychological pressure. In general, a family with good economic conditions but a small amount of student consumption or a family with poor economic conditions but a large amount of student consumption indicates that there is a problem of consumption level difference.

(2) *Economic Characteristics of Students' Families.* The data obtained from the student financial aid record data source are processed to obtain the data of each student's financial aid in school, which is used to measure whether the student's family has financial difficulties. It is generally believed that the family financial situation of students applying for financial aid is difficult, and the larger the amount of financial aid, the more serious the situation.

(3) *Student Consumption Behavior Characteristics.* The data obtained by the consumption data source of the student card is processed to extract the consumption frequency information of the students eating in the canteen. Because canteen consumption is basic life information and may occur every day, it is generally believed that students with better economic conditions may have more meals outside or in restaurants, while students with poor economic conditions may eat in the canteen more often because the canteen is cheap.

(4) *Student Learning Ability Characteristics.* After processing the data source of students' academic

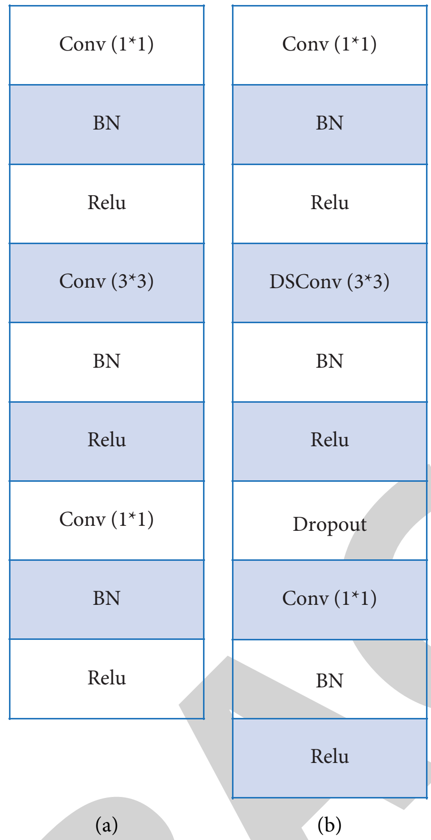


FIGURE 4: Structure comparison before and after resnet_2b improvement. (a) Before improvement. (b) After improvement.

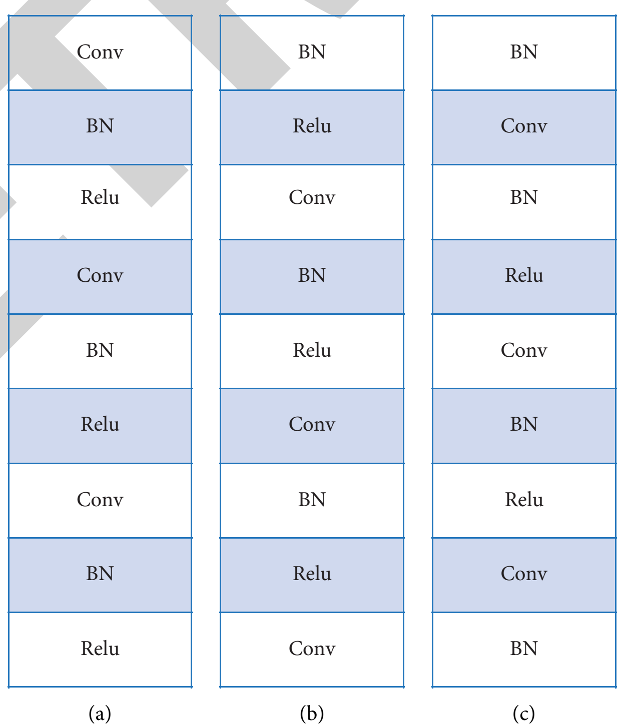


FIGURE 5: Location of BN and relu in the network. (a) Model a. (b) Model b. (c) Model c.

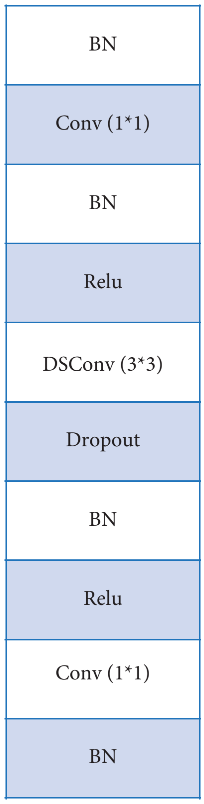


Figure 6: Improved residual unit structure.

records, the average of each student's academic performance is obtained as the student's learning characteristics. Study pressure occupies a large proportion in the influence of college students' psychological pressure, which will affect scholarships and various evaluations.

Using the fivefold cross-validation method, the data is divided into five parts, four of which are taken as the training set and one as the test set. After ten training tests, the average value is taken as the result, so that the entire data set. $T$ represents all data sets, $T_{\text{training}}$ represents the training set, $T_{\text{test}}$ represents the test set, TT represents the positive sample set, and TN represents the negative sample set. Table 6 shows the details of the dataset.

*4.2. Experimental Setup.* The parameter settings in the model training process are shown in Table 7. The evaluation indicators include accuracy ACC, G-mean, and F1-score. G-mean and F1-score can evaluate the effect of the model more reasonably. G-mean comprehensively refers to the true positive rate and true negative rate. The calculation formulas of these two parameters are based on the number of their own true positive categories. As the denominator, the calculated samples of each label calculate the correct probability separately and will not lose the evaluation effect due to unbalanced samples. F1-score is calculated from the recall rate and the precision rate, and precision rate will be affected by the imbalance of the sample to a certain extent, and the penalty for misjudging negative samples to positive samples is large. So in general, G-mean is slightly better than F1-score.

*4.3. Experimental Results and Analysis*

*4.3.1. Learning Rate Optimization Experiment.* Using the improved ResNet50 model to process the previously mentioned dataset, the experimental accuracy obtained on the training set and test set is shown in Table 8.

After graphing the data in the table, as shown in Figure 7. It can be seen that when the learning rate is 0.001, the accuracy of both the training set and the test set is the highest. Therefore, the learning rate finally selected in this paper is 0.001.

*4.3.2. Recognition Rate Experiments of Different Models.* In order to verify the effect of using the improved ResNet50 model on the psychological stress analysis of college students, the selected comparison models mainly include convolutional neural network (CNN) [24], recurrent neural network (RNN) [25], long short-term memory network (LSTM) [26], and ResNet50 [27]. The parameter settings of each model refer to the settings in the above articles. The experimental results of each model on the test set are shown in Table 9 and Figures 8–10.

From the experimental results, we can see that the classification results of each deep learning model on the data all exceed 0.8, achieving a relatively good effect.The experimental results of the ResNet50 model are better than other classic models, which is why this paper chooses ResNet50 as the basic model.The experimental results obtained by the improved ResNet50 model used in this paper are the best. The improved ResNet50 has a slight increase in the recognition rate compared with the original ResNet50. This is because in the process of improving the residual structure, the positions of the BN layer and the relu activation function are adjusted. Placing the activation function in front of the convolutional layer can make it perform better than the traditional one. In addition to selecting the preactivation method, the first relu activation function is removed, and a BN layer is added at the end; that is, the BN-Conv-BN-relu-DSConv-BN-relu-Conv-BN structure is finally presented in the previous article. At the same time, the improved model is smaller than the original ResNet50 model, and the model size is reduced by about 35%. This is precisely because we use DSC to replace the $3 \times 3$ standard convolution in the residual block and the effect of replacing the fully connected layer with the GAP layer.The parameters of the model are greatly reduced, which also saves computing costs and reduces hardware requirements for subsequent use of the model.

*4.3.3. Experiments on the Effect of Different Characteristics on Psychological Stress.* Here, we analyze the importance of each feature to the model used. In the experiment, students' family economic characteristics F1, students' consumption behavior characteristics F2, students' learning ability characteristics F3, and students' consumption level difference characteristics F4 are used. These four features have different effects on the evaluation performance of the model used. We studied which factors had a more significant impact on

Table 2: Student personal information record fields and their meanings.

| Items | Meaning |
|---|---|
| Student ID | Student ID |
| Gender | Boys or girls, to study differences in psychological stress |
| Identity number | ID card number, used for calculation of family economic conditions |
| Name | Student name |
| College | Students attending college |
| Home province | The province where the student's family resides, which is used for the calculation of family economic conditions |

Table 3: Student grade fields and their meanings.

| Items | Meaning |
|---|---|
| Student ID | Student ID |
| Course title | Course name taken |
| Credit | Course credits |
| hours | Course hours required |
| Test scores | Achieve grades, marks, or merit grades |
| Course inspection method | Percentage system, two-level system, five-level system, etc. |
| Course category | Public or professional courses, etc. |

Table 4: Campus consumption card records.

| Items | Meaning |
|---|---|
| Student ID | Student ID |
| Consumption time | Student spending time, day/month/year + time |
| Amount of consumption | Consumption amount, in "cents" |
| Consumer use | Canteen window name, hot water charges, school bus charges, etc. |

Table 5: Student financial aid data.

| Name | Meaning |
|---|---|
| Student ID | Student ID |
| Name | Student name |
| Bursary amount | Bursary amount |
| Bursary level | Different levels by amount |

students' psychological stress state. The effect of each feature on the model used is shown in Table 10.

From the experimental results, it can be seen that the feature of student consumption level difference F4 has the greatest impact on the model evaluation effect, followed by the feature of student consumption behavior F2, then the feature of student learning ability F3, and the smallest is the feature of student family economy F1.The difference between students' consumption level feature F4 reflects the difference between the students' actual consumption level and the expected consumption level. When the difference

Table 6: Fivefold cross-validation dataset composition.

| Dataset | Element |
|---|---|
| TT | $TT_1$, $TT_2$, $TT_3$, $TT_4$, and $TT_5$ |
| TN | $TN_1$, $TN_2$, $TN_3$, $TN_4$, and $TN_5$ |
| $T$ | T training; T test |
| $T_{\text{training}}$ | $TT_1$, $TT_2$, $TT_3$, $TT_4$, $TN_1$, $TN_2$, $TN_3$, and $TN_4$ |
| $T_{\text{test}}$ | $TT_5$ and $TN_5$ |

Table 7: Parameter settings.

| Parameter | Value |
|---|---|
| Epochs | 500 |
| Batch_size | 16 |
| Class_number | 3 (0 is low, 1 is medium, and 2 is very stressed) |
| Learning_rate | 0.001 |
| Decay | 0.001 |

Table 8: Learning rate experiment.

| Learning_rate | Training set | Test set |
|---|---|---|
| 0.3 | 0.6453 | 0.6026 |
| 0.2 | 0.6520 | 0.6238 |
| 0.1 | 0.6629 | 0.6383 |
| 0.05 | 0.6915 | 0.6534 |
| 0.01 | 0.7236 | 0.7005 |
| 0.005 | 0.8466 | 0.8274 |
| 0.001 | 0.8664 | 0.8372 |

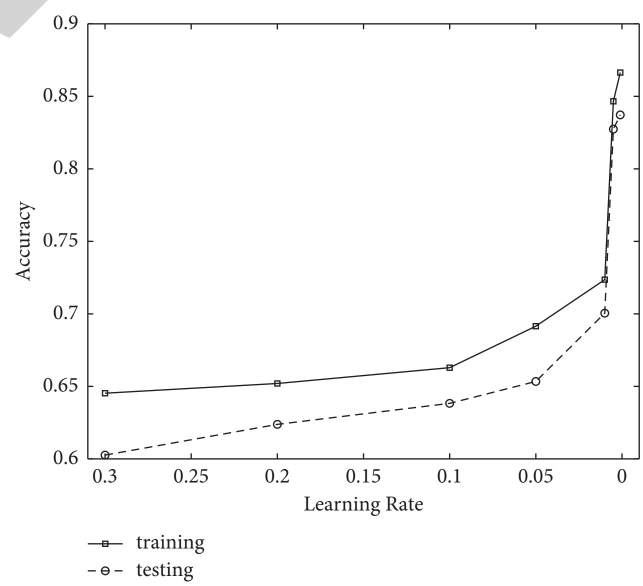


Figure 7: Learning rate experiment.

becomes larger, it means that the student's consumption level conflicts with the economic conditions. In-depth speculation is that either the consumption is reduced because of recent changes in the family, or the forced consumption is caused by the desire to be with the group for fear of being discovered by friends. Student consumption

Table 9: Experimental results of each model.

| Model | ACC | G-mean | F1-score |
| --- | --- | --- | --- |
| CNN | 0.8114 | 0.8322 | 0.5787 |
| RNN | 0.8005 | 0.8119 | 0.5982 |
| LSTM | 0.8190 | 0.8362 | 0.5775 |
| ResNet50 | 0.8214 | 0.8524 | 0.5871 |
| Proposed | 0.8372 | 0.8663 | 0.6336 |

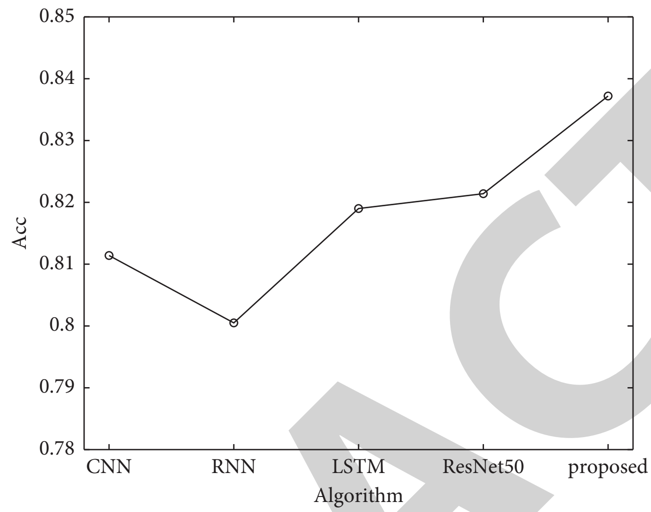


Figure 8: Acc of each model.

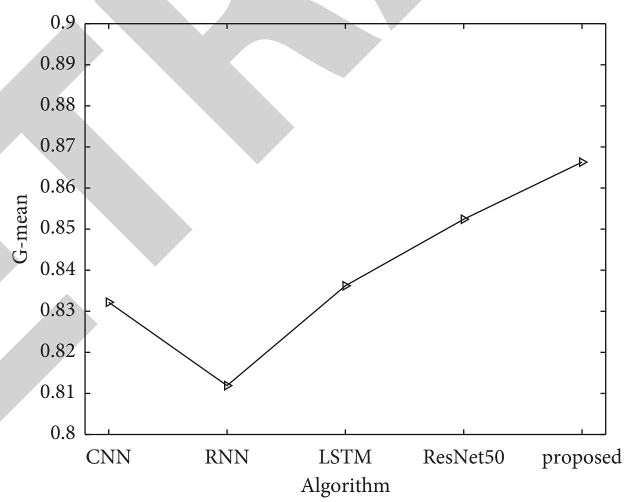


Figure 9: G-mean value of each model.

behavior characteristic F2 reflects the frequency of students' consumption in the canteen. If the frequency is increased, it may be caused by family economic factors, because the cost of dining out and takeaway will be significantly higher than the cost of the school canteen. The low influence of student learning ability feature F3 and student family economic feature F1 may be because these two features are long-term values; they reflect a normal phenomenon that has always existed among students. On the other hand, the difference between student consumption level feature F4 and student consumption behavior characteristic F2 is a short-term characteristic because it selects the consumption situation in

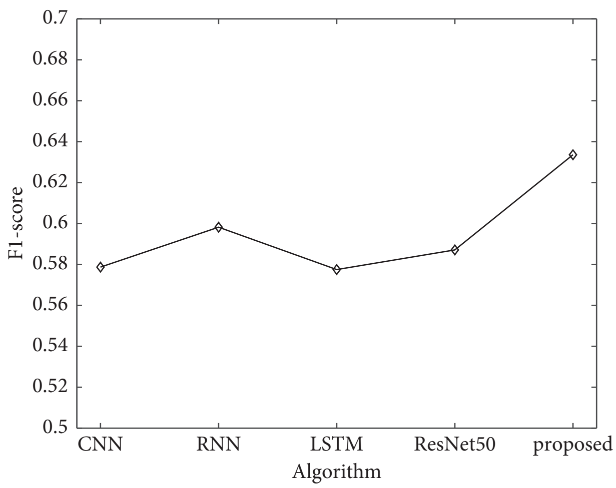


Figure 10: F1-score value of each model.

Table 10: The influence of each feature on the model used.

| Features | ACC | G-mean | F1-score |
|---|---|---|---|
| F1 | 0.7836 | 0.8080 | 0.5463 |
| F2 | 0.7120 | 0.6921 | 0.4762 |
| F3 | 0.7452 | 0.7343 | 0.5021 |
| F4 | 0.6784 | 0.5982 | 0.3438 |

the last three months. It is more affected by the recent conditions and can better reflect the recent psychological stress state of students.

## 5. Conclusion

Mental health is very important to college students. A healthy psychological state is conducive to the development of college students and is the key to adapting to the society. College students are facing a series of psychological pressures. If the psychological pressures cannot be solved well, the students will experience psychological obstacles and even suffer from mental illness. Solving the psychological problems of college students is also closely related to the schools and their parents. Only by correctly understanding and solving the psychological pressure of college students can schools guide college students to become talented more effectively. This paper uses a deep learning model to evaluate and analyze the psychological stress of college students and based on the experimental results assist college staff to pay attention to college students' psychological health education and establish a psychological crisis intervention mechanism for college students in time to help college students reduce psychological pressure. The experimental results show that the deep learning model used in this paper can achieve satisfactory analysis results, with an accuracy rate of more than 80%. In order to better study the factors that affect the psychological stress of college students, this study extracted different characteristics and conducted an experimental study. The experimental results show that the consumption level of college students will affect the implementation effect of the model, which fully shows that this feature is one of the factors that cause the greatest changes in college students' psychological pressure. However, this study still has some limitations. For example, the selection of data features has a greater impact on the model. This is also the direction that this paper will continue to study in the future.

## Data Availability

The labeled datasets used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no competing interests.

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