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A Machine Learning-supported ***Analysis*** *of University Students' Mental Health*

Yin Peng*

College of Sports and Health, Linyi University, Linyi, China

pengyin829@163.com

**corresponding author*

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Abstract: Psychological stress is a psychological stress response that occurs when a person is faced with an overwhelming situation. Research has shown that the right level of stress can lead to progress and the realisation of one's potential. For students, appropriate levels of stress can enhance their learning and contribute to their growth and development. However, excessive psychological stress can be physically and psychologically distressing, and can even lead to suicidal behaviour. If students with abnormal psychological stress can be identified in time, schools can provide timely help and intervention to alleviate the psychological stress. The main objective of this paper is to develop a study on the analysis of university students' mental health based on machine learning. To investigate the difference between supervised and unsupervised learning, the LOF algorithm was also introduced for comparison. Experiments show that the G-mean value of ES-ANN improves by approximately 8 percentage points and the F1 value by approximately 4 percentage points over the best benchmark algorithm. Compared to traditional questionnaire-based methods, the daily campus data has a higher degree of authenticity and real time, which helps schools to identify students with high psychological stress in a timely manner. The research in this paper suggests that this idea is potentially feasible and deserves further validation and improvement in practice.

1. Introduction

With the increasing pressure of employment and the challenges of social life, students are under more and more pressure in their studies and lives, and are more likely to suffer adverse effects from excessive psychological stress. Traditional psychological stress surveys are difficult to implement on a large scale due to the complexity of the operation and long deadlines, while students may not

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take them seriously if they are only surveyed through a questionnaire at school, and have to wait for students to take the initiative to approach the psychology centre or counsellors in order to grasp the state of their psychological stress. In contrast, assessment by means of big data mining is a new model that is more proactive, efficient and can be implemented universally [1-2].

In a related study, Koustuv argues that there is a growing concern about the mental health of university students and that it is difficult to assess the mental health needs of this group in real time and at scale [3]. The prevalence and widespread use of social media, particularly among young people, provides opportunities for various stakeholders to proactively assess the mental health of university students and provide timely and tailored support.

Thomas' key findings from data collected from 699 students suggest that there is no significant relationship between total ICT use scores, mental health and psychological and emotional well-being [4]. The results were relatively consistent with the initial study, except in terms of social well-being. In the context of the study, it was concluded that there were no risk factors for ICT use patterns on the psychological health and well-being of distance open learning students.

Mahfuzulhoq et al. used a Google survey form to collect data. After training and testing the dataset with five algorithms, the best method for predicting depression among Bangladeshi university students was found [5]. Various prediction algorithms were compared, and an Android mental health mobile application was also designed and developed to provide psychological support to university students.

This paper proposes a method for assessing psychological stress among university students based on daily campus data. The paper first identifies data sources on university campuses that can be used for psychological assessment, including students' personal information, course grade records, campus card spending records, and bursary records. Then a computational method for extracting features from these data sources is given, and finally the features are obtained for training a machine learning model. An integrated sampling neural network (ES-ANN) model for unbalanced sample data is proposed. The training process is prone to more severe data imbalance as the proportion of students with high psychological stress is small in relation to the total number of students. To address this problem, an integrated sampling neural network (ES-ANN) model is proposed. The model consists of multiple neural network models, each using an undersampling algorithm, and then using integrated learning techniques to synthesise the classification results of each neural network.

2. Design Research

2.1. Student Psychological Stress Assessment Model

In order to obtain better experimental results in an unbalanced sample set, the ES-ANN integrated sampling neural network model was introduced, while the LOF outlier detection model was introduced for comparison in order to compare the differences between supervised and unsupervised learning in dealing with such problems [6].

Integrated Sampling Neural Network (ES-ANN) models [7-8]: after obtaining all the data features needed for model training, it is the specific data that is substituted into the model for computation, for supervised neural network models, called EnsemblesamplingANN, which can make good use of the entire data set [9-10]. d denotes all datasets, D training denotes the training set, D test denotes the test set, DT denotes the set of positive samples and DN denotes the set of negative samples as in Table 1.

Table 1. Composition of the ten-fold cross-validation dataset

Steps	Assembling	Constituent elements
1	DT	DT1,DT2,DT3,…DT10
2	DN	DN1,DN2,DN3…DN10
3	D	Training D, Test D
4	D Training	DT1,DT2…DT9,DN1,DN2…DN9
5	D Test	DT 10,DN 10

Because of the need to solve the problem of unbalanced samples, the best results are obtained by taking n=5 weak classifiers in the actual parameter search test. DT denotes the set of positive samples in the training set, DN denotes the set of negative samples in the training set, and D1~5 denotes the training set of five weak classifiers as shown in Table 2.

Table 2. Data composition of the training set of the weak classifier

Steps	Assembling	Constituent
1	DN Training	DN Training1,DN Training2,…DN Training5
2	D1	DT Training,DN Training1
3	D2	DT Training,DN Training2
4	D3	DT Training,DN Training3
5	D4	DT Training,DN Training4
6	D5	DT Training,DN Training5

These weak classifiers are all used in the neural network algorithm, and the final prediction of the integrated sampling neural network relies on the five weak classifiers to vote [11-12].

The neural network is built using the keras library with the tensorflow library as the lower layer support and three hidden layers [13-14] with 64,8,2, nodes respectively. The hidden layers use relu as the activation function and the output uses softmax for classification. The loss function uses category cross-entropy, with y and y^ as the actual output and labelled result respectively, which is calculated as follows

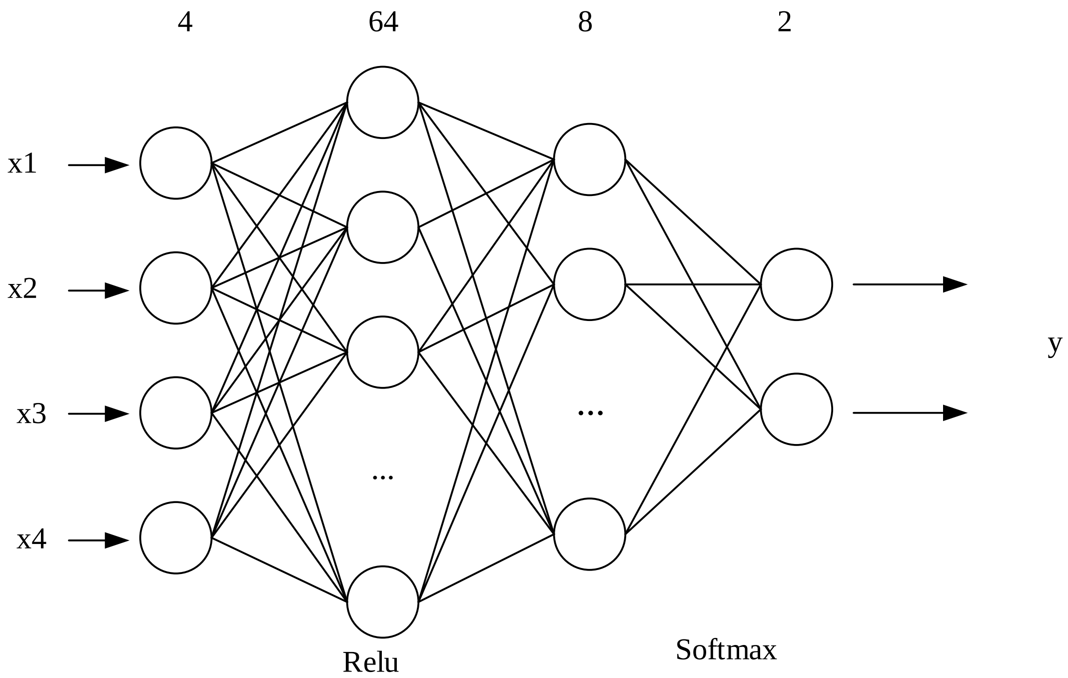

Figure 1. Neural network structure diagram

The structure of each weak classifier neural network is shown above [15-16], and the structure of the integrated sampling neural network used by the model is shown in the following figure.

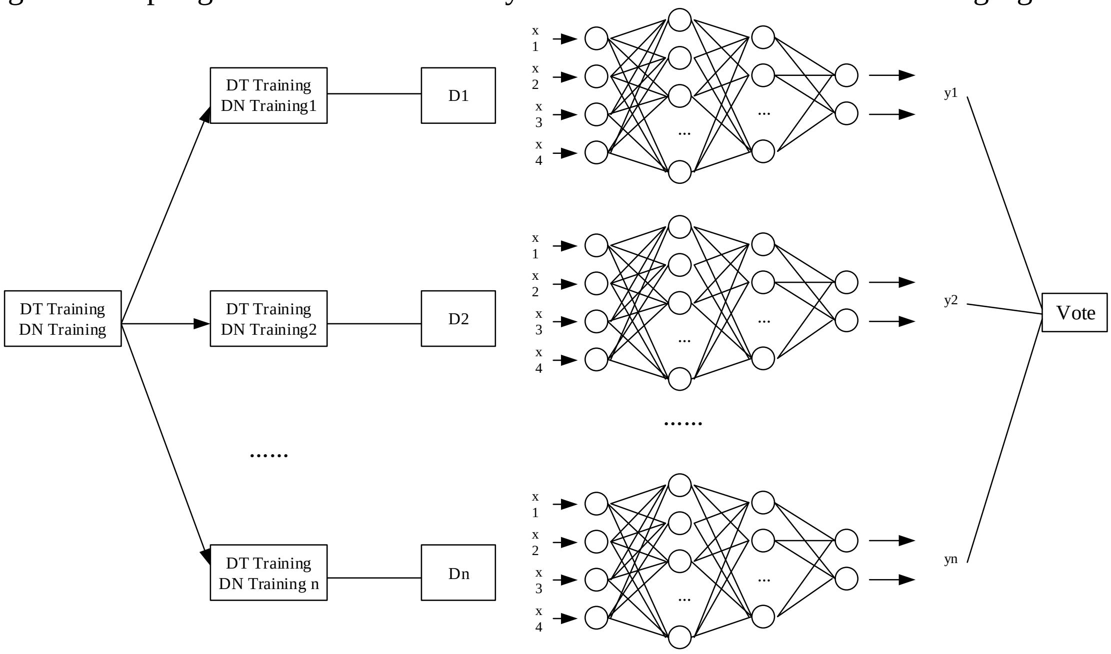

Figure 2. Structure of the integrated sampling neural network ES-ANN

The model uses the adam (Adaptive Moment Estimation) optimization algorithm, which is a method that will calculate an adaptive learning rate for each of its parameters [17-18]. The algorithmic idea is equivalent to the combination of RMSprop + Momentum algorithm [19-20].

2.2. Machine Learning Model Evaluation Methods

According to general principles, common evaluation metrics for classification algorithms include precision, accuracy, completeness and F1-score.Also, the confusion matrix of classification results, which can be used to observe the overall situation of classification results, with higher values on the main diagonal indicating better model effectiveness. The main parameters for assessing the effectiveness of the model are calculated by the formulae shown in (1), (2), (3) and (4) respectively.

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{4}$$

There are also some proposed specialised assessment criteria more suitable for unbalanced samples, true class rate (ACC+), true negative class rate (ACC-), and G-mean, calculated as shown in (5), (6) respectively.

$$ACC_{+} = \frac{TP}{TP+FN} \tag{5}$$

$$ACC\_ = \frac{TN}{TN+FP} \tag{6}$$

The confusion matrix is shown in Table 3

Table 3. Confusion matrix for classification results

The real situation	Predicted results	
	Positive Example	Counterexamples
Positive Example	TP (True Example)	FN (False counterexample)
Counter-examples	FP (False Positive Example)	TN (True Counterexample)

3. Experimental Study

3.1. Course Selection Behavioural Characteristics

Course selection behaviour features are constructed from student course selection data to correlate with student course pressures and preferences. The data structure of the student course selection data is shown in Table 4.

Table 4. Data structure for course selection data

Field name	Field type	Field length	Field meaning	Field example
Id	Int	11	Self-incrementing id	75277113
Stuempno	Varchar	255	Unique student identifier	73398528aca10ad5
Course_code	Varchar	32	Course code	B1800830
Course_name	Varchar	100	Course name	Foundations of thought and ethics i
Credit	Double	-	Course credit	1.5
Course_type	Varchar	32	Course category	A compulsory public course
Year	Varchar	9	Academic year	2018-2019
Term	Varchar	1	Semester	1

Course-related statistical features include the number of courses taken in the current semester, the total number of credits taken, as well as the number of courses by category and the number of credits. Course categories include compulsory public courses, foundation courses, compulsory professional courses and professional elective courses. In addition, the course selection data is used to construct a preference profile for students to take courses, such as whether or not to take psychology-related courses, with a value of 0 or 1 for this dimension, i.e.

$$f(x) = sigh(x) = \begin{cases} 1, x \geq 1 \\ 0, x = 0 \end{cases} \tag{7}$$

x is the number of psychologically related courses chosen by the student.

The higher the academic pressure, the higher the demands on students' stress tolerance, and the more likely it is that students will have an imbalance in their psychological state. Statistically, the total number of credits in the current semester for the depressed and non-depressed groups is 24.27 and 24.12 respectively, and the average number of courses is 9.40 and 9.33 respectively, which is not very different between the different groups. The variability in this feature dimension is not very large.

3.2. Outlier Detection (LOF) Model

To investigate the difference between the classification algorithm and the outlier detection algorithm, the four main features were also substituted into the density-based LOF model used for outlier detection, which is an unsupervised model and therefore does not require a training process. As shown in Equation (2.16), we only need to set its kth distance neighbourhood Nk(p), i.e. the number of points around each point reference, which works best when k=15.

The LOF algorithm calculates the LOF (local outlier factor) for each point as a local outlier factor, and then sorts them to take the top 10% of samples as outliers according to the set outlier probability.

Finally, the student psychological stress assessment algorithm consists of two models, ES-ANN and LOF, and the main algorithm flow is as follows.

Psychological Stress Assessment Algorithm

Input: dataset to calculate four major eigenvalues FNT. fgc fsnfd
    ES-ANN learning rate a
    Number of ES-ANN weak classifiers n
    LOF kth nearest neighbour distance
    LOF anomaly rate value 0.1
Outputs.
    Randomly initialize the es-Ann network weights, assign each weak classifier a randomly selected positive
    samples and all negative samples as the training set
Repeat
    Optimize the es-Ann algorithm category cross-entropy according to the adam algorithm
    Update
until convergence
    Calculate es-Ann test set results
    Calculate LOF outlier detection results

Figure 3. Psychological Stress Assessment Algorithm

4. Experiment Analysis

4.1. Experimental Parameter Selection

There are three main parameters that affect the results of this experiment, one is the number of weak classifiers n of the integrated sampling neural network, one is the learning rate α of the neural network training, and the last one is the kth distance domain k value of the anomaly detection algorithm LOF. To start with the supervised learning part of the integrated sampling neural network algorithm, the learning rate α for each weak classifier has to be determined before deciding on the number of weak classifiers n, and thus the effectiveness of the overall model. This is shown in Tables 5 and 6.

Figure 4 shows the results for the default selection of 5 weak classifiers, which shows that the learning rate α is clearly optimal when set to 0.001, which is also consistent with the results of the recommended parameters from online research.

Table 5. Optimization of the learning rate parameter α

Number of weak classifiers n	Learning rate α	Training set ACC	Test set ACC
5	0.5	0.66	0.61
5	0.1	0.66	0.63
5	0.05	0.71	0.68
5	0.01	0.78	0.73
5	0.001	0.88	0.80

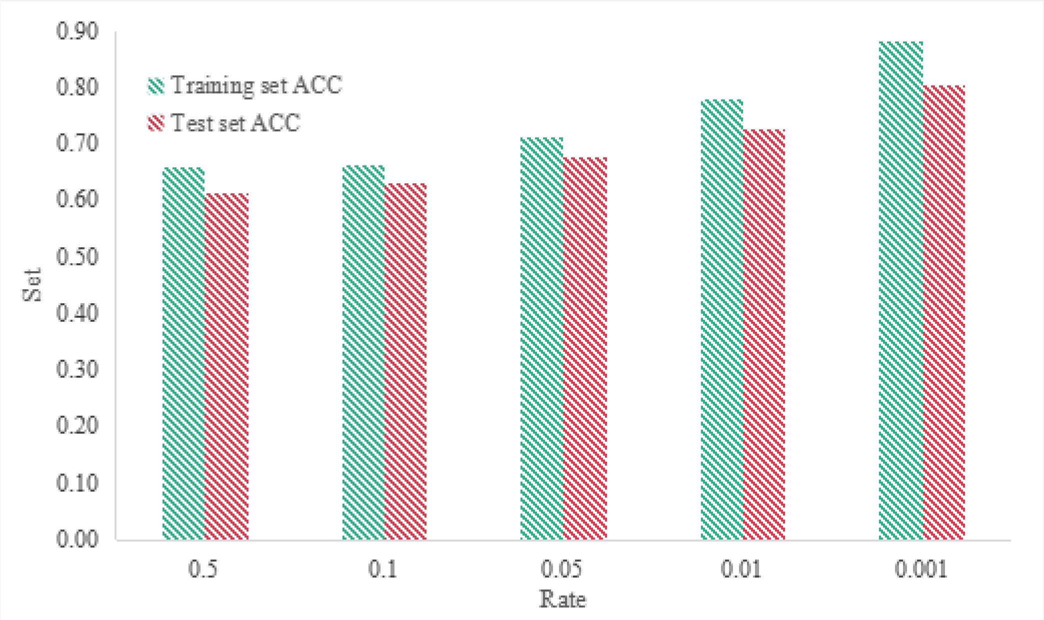

Figure 4. Learning rate α merit search effect graph

Table 6. Number of weak classifiers parameter n Optimization search

Learning rate α	Number of weak classifiers n	Training set ACC	Test set ACC
0.001	1	0.939	0.900
0.001	3	0.771	0.697
0.001	5	0.881	0.803
0.001	7	0.782	0.740

The results are shown in Figure 5 above, if the number of weak classifiers n=1, it is actually a neural network model without integrated sampling process. This is due to the non-equilibrium problem of the sample, and the accuracy at this point basically reflects the probability distribution of the sample, and in fact such a model has little practical application.

At n=3,5,7 the algorithmic model of the integrated sampling neural network is used, only because the number of weak classifiers is chosen differently, and the difference in the number of weak classifiers will lead to a change in the structure of the positive and negative sample ratios and feature learning in the training set of each weak classifier. The effect increases at the beginning and can be seen to be best at n=5, and then decreases significantly at n=7, probably because the small experimental sample set, split into 7, results in poor feature learning in each training set, and the small training data results in a decrease in weak classifier performance. It can be seen that the best results are obtained with n=5, as each weak classifier is well trained and the overall model works best.

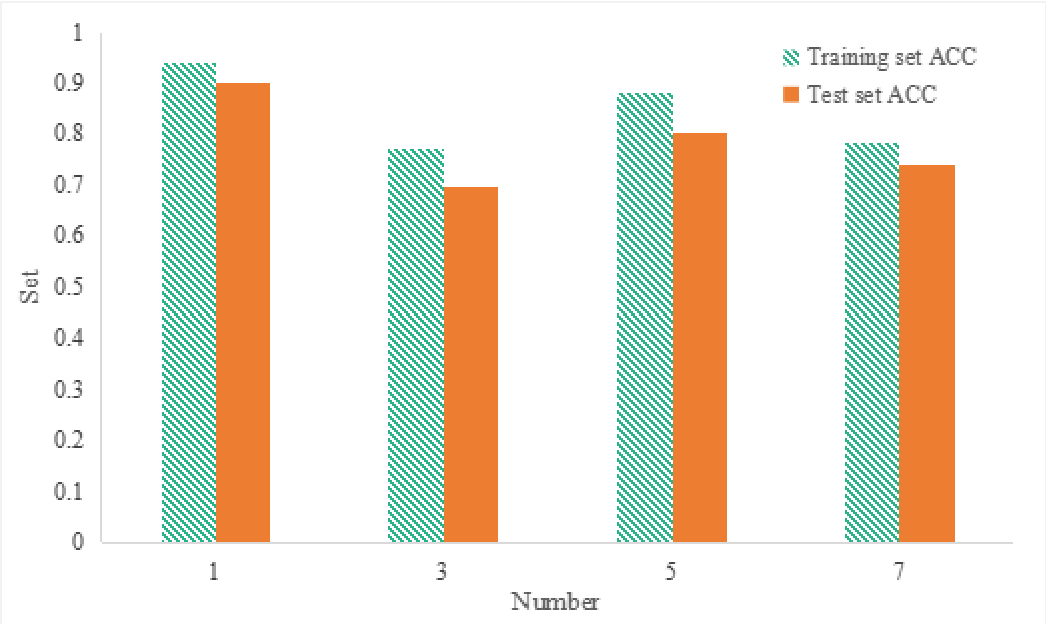

Figure 5. Number of weak classifiers parameter n Optimization search effect

Similarly, in the anomaly detection algorithm LOF, we need to investigate the effect of taking different values of k for the kth distance domain on the effectiveness of the model. The accuracy results for taking k=5,10,15,20,25,30,35 are shown in Table 7 below.

Table 7. kth distance nearest neighbor search

Kth distance nearest neighbour	Accuracy acc (anomaly rate 0.1)	Accuracy acc (anomaly rate 0.2)
5	0.84	0.78
10	0.90	0.80
15	0.93	0.83
20	0.92	0.85
25	0.92	0.85
30	0.93	0.84
35	0.93	0.84

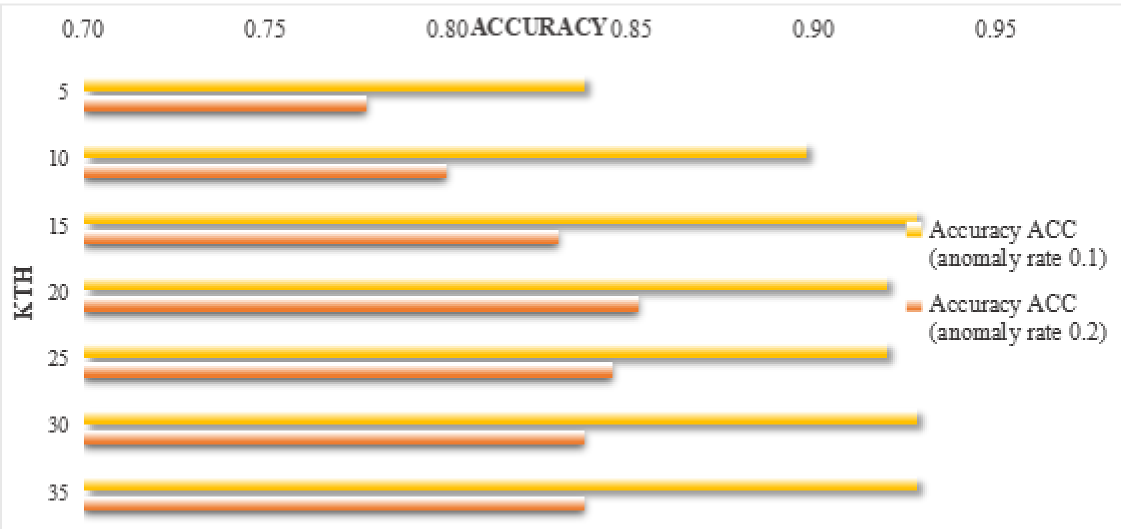

Figure 6. kth distance nearest neighbor search effect

This is because we set the anomaly rate to 0.1 according to the actual situation of the sample, which actually limits the number of false positives to negative samples and makes the LOF effect better from the ACC alone. The accuracy ACC of the LOF algorithm starts to increase with increasing k values, as the algorithm is strengthened by taking into account the density of more nearby points, peaks at around k=15, then decreases a little, peaks again at k=30, and then stabilises. However, with larger k values the running time grows because of the number of surrounding sample points that need to be computed for each sample, so k=15 is chosen as the optimal number.

4.2. Comparison of the ES-ANN and LOF Models

When the integrated sampling neural network ES-ANN and the anomaly detection LOF models are compared in terms of all evaluation metrics, the data are as follows

Table 8. Performance results of the two models

Algorithms	R	P	ACC+	ACC-	G-mean	F1-score
ES-ANN	0.88	0.43	0.88	0.77	0.82	0.58
LOF	0.71	0.55	0.71	0.95	0.82	0.62

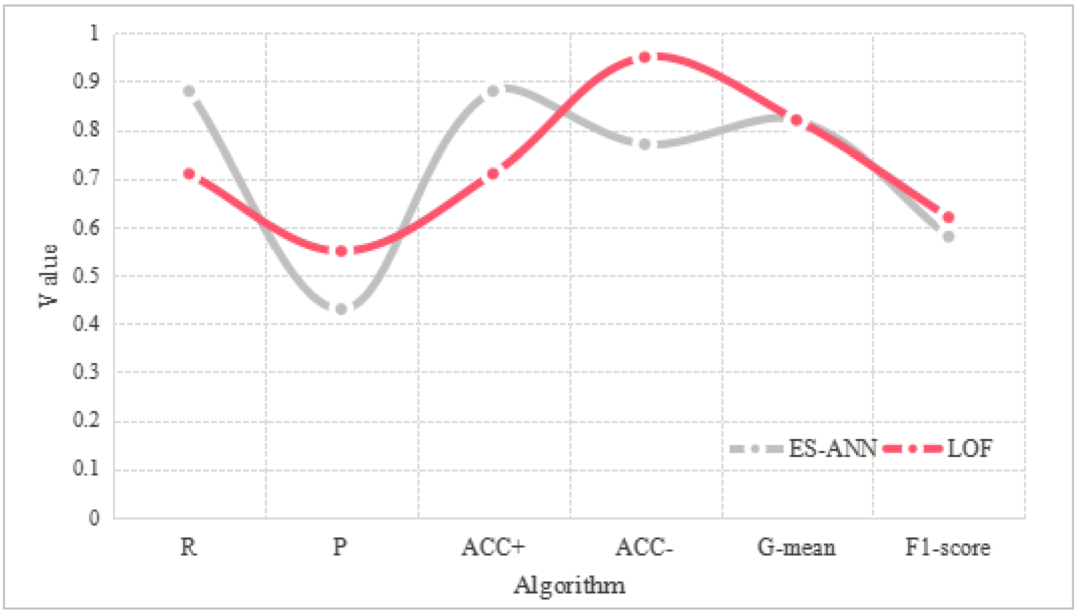

Figure 7. Analysis of the performance results of the two models

Figure 7 shows that the ES-ANN model is more effective in judging the true positive class as positive class, while the LOF model is more effective in judging the true negative class as negative class, and the G-mean values of the two models are almost equal. The good effect of the LOF is due to the fact that the F1-score of the LOF is higher due to the fact that the exception rate of 0.1 is set to limit the number of negative classes misclassified as positive classes and the fact that the test set is all samples, so that a small number of misclassifications has a small impact on the whole. Overall, the supervised ES-ANN algorithm works better and the logical interpretation is more reasonable than using the unsupervised LOF algorithm directly.

5. Conclusion

Preventing students' psychological crisis behaviour and helping them to overcome their psychological crisis is not only a very common but extremely important issue related to students' psychological health, but also a very necessary and urgent practical issue related to students' family happiness, university talent training and social harmony and stability. With the rapid development of the economy and society, the development and growth environment of students is becoming more and more complex and uncertain, and students' psychological crisis behaviour presents new characteristics and patterns, which puts forward new requirements for theories and methods of student psychological crisis intervention, and new challenges for the concepts and strategies of student mental health management.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Watt A S V D, Roos A, Bui E, et al. An Attachment Theory Approach to Reframing Romantic Relationship Breakups in University Students: A Narrative Review of Attachment, Neural Circuitry, and Posttraumatic Stress Symptoms. Journal of Couple and Relationship Therapy, 2021, 21(2):129-150. https://doi.org/10.1080/15332691.2021.1908197

[2] Nejatian M, Alami A, Tehrani H, et al. Attitude, Intent and Different Aspects of Marriage in University Students: A Path Analysis. Journal of Divorce and Remarriage, 2021, 63(3):184-199. https://doi.org/10.1080/10502556.2021.1993024

[3] Koustuv Saha, Munmun De Choudhury: Assessing the mental health of college students by leveraging social media data. XRDS 28(1): 54-58 (2021). https://doi.org/10.1145/3481834

[4] Thomas McDonald van der Merwe: ICT use patterns, mental health symptoms and the well-being of the open distance learning student: a replication study with historically advantaged students. Int. J. Learn. Technol. 15(4): 360-383 (2020). https://doi.org/10.1504/IJLT.2020.113884

[5] Abu Bakkar Siddique, Mahfuzulhoq Chowdhury: A machine learning-based approach to predict university students' depression pattern and mental healthcare assistance scheme using Android application. Int. J. Data Anal. Tech. Strateg. 14(2): 122-139 (2021).

[6] Jenkins V, Ericksen K S, Livingston V, et al. An examination of the help-seeking behaviors of HBCU students by gender, classification, referral source, and mental health concerns. Social Work in Mental Health, 2021, 20(3):334-349. https://doi.org/10.1080/15332985.2021.2011823

[7] Wu J, Mcclurg V M, Mccallum R S, et al. An Investigation of an Early College Entrance Programs Ability to Impact Intellectual and Social Development. Roeper Review, 2021, 44(2):111-122.

[8] Tewary S, Altaf R, Pandya N, et al. Assessing the efficacy of didactic modules in educating health care professionals in interprofessional geriatrics care. Educational Gerontology, 2021, 47(10):463-469. https://doi.org/10.1080/03601277.2021.1997198

[9] Tarver T A, Haupt S, Cyrus J W, et al. Designing a Workflow for Online Learning Objects Created by Health Sciences Librarians. Medical Reference Services Quarterly, 2021, 41(2):213-221.

[10] Prasath P R, Lim A L S, Steen S. A Strength-Based Support Group for International College Students: A Pilot Study. The Journal for Specialists in Group Work, 2021, 47(1):63-82. https://doi.org/10.1080/01933922.2021.2000085

[11] Ortiz Y L, Zha S, Moore P, et al. An Examination of Pre-Service Teachers' Interpersonal Dispositions in the Readiness Assurance Stage of Team-Based Learning. Action in Teacher Education, 2021, 43(1):4-19. https://doi.org/10.1080/01626620.2019.1694600

[12] Jeff Biegun, Jason D. Edgerton, Lance W. Roberts: Measuring Problem Online Video Gaming and Its Association with Problem Gambling and Suspected Motivational, Mental Health, and Behavioral Risk Factors in a Sample of University Students. Games Cult. 16(4): 434-456 (2021). https://doi.org/10.1177/1555412019897524

[13] B. L. Radhakrishnan, E. Kirubakaran, R. V. Belfin, Sudhakar Selvam, Kulandairaj Martin Sagayam, Ahmed A. Elngar: Mental health issues and sleep quality of Indian employees and higher education students during COVID-19 lockdown. Int. J. Intell. Eng. Informatics 9(2): 193-210 (2021). https://doi.org/10.1504/IJIEI.2021.10040086

[14] Fabiano Souza Pereira, Guilherme Guimarães Bevilacqua, Danilo Reis Coimbra, Alexandro Andrade: Impact of Problematic Smartphone Use on Mental Health of Adolescent Students: Association with Mood, Symptoms of Depression, and Physical Activity. Cyberpsychology Behav. Soc. Netw. 23(9): 619-626 (2020). https://doi.org/10.1089/cyber.2019.0257

[15] Nasser Ali Aljarallah, Ashit Kumar Dutta, Majed Alsanea, Abdul Rahaman Wahab Sait: Intelligent Student Mental Health Assessment Model on Learning Management System. Comput. Syst. Sci. Eng. 44(2): 1853-1868 (2021).

[16] Keith Kirkpatrick: Artificial intelligence and mental health. Commun. ACM 65(5): 32-34 (2021). https://doi.org/10.1145/3524017

[17] Eric B. Elbogen, Megan Lanier, Sarah C. Griffin, Shannon M. Blakey, Jeffrey A. Gluff, H. Ryan Wagner II, Jack Tsai: A National Study of Zoom Fatigue and Mental Health During the COVID-19 Pandemic: Implications for Future Remote Work. Cyberpsychology Behav. Soc. Netw. 25(7): 409-415 (2021). https://doi.org/10.1089/cyber.2021.0257

[18] Brenda K. Wiederhold: The Escalating Crisis in Adolescent Mental Health. Cyberpsychology Behav. Soc. Netw. 25(2): 81-82 (2021). https://doi.org/10.1089/cyber.2021.29237.editorial

[19] Maria Chiara Fastame: Are subjective cognitive complaints associated with executive functions and mental health of older adults? Cogn. Process. 23(3): 503-512 (2021).

[20] Guilherme F. Marchezini, Anísio M. Lacerda, Gisele L. Pappa, Wagner Meira Jr., Débora M. Miranda, Marco A. Romano-Silva, Danielle S. Costa, Leandro Malloy Diniz: Counterfactual inference with latent variable and its application in mental health care. Data Min. Knowl. Discov. 36(2): 811-840 (2021).https://doi.org/10.1007/s10618-021-00818-9