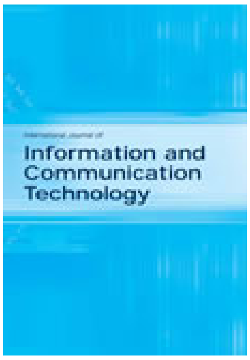


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Machine learning model-based monitoring of mental health status of college students

Baoqin Gong, Ninghua Huang

Article History:

Received:	08 December 2024
Last revised:	16 December 2024
Accepted:	16 December 2024
Published online:	22 January 2025

Machine learning model-based monitoring of mental health status of college students

Baoqin Gong

School of Marxism,
Xi'an Siyuan University,
Xi'an 710038, China
Email: gongbaoqin2022@163.com

Ninghua Huang*

School of Marxism,
Changsha University of Science and Technology,
Changsha 410011, China
Email: 20301303002@mail.hnust.edu.cn
*Corresponding author

Abstract: This article proposes a method for monitoring the mental health status of college students based on machine learning models. By integrating multidimensional data such as psychological assessment questionnaires and daily behaviour data, and using machine learning techniques such as support vector machine, random forests, and deep learning algorithms, a prediction model that can efficiently identify the mental health status of college students is constructed. This model improves the quality of data and the accuracy of model predictions through steps such as feature engineering and data preprocessing. This article used real datasets from multiple universities for experimental testing, and the results showed that the method performed well in multiple evaluation indicators such as accuracy, recall, and F1 score, demonstrating strong practicality and promotional value.

Keywords: deep learning; machine learning; mental health; college student psychology.

Reference to this paper should be made as follows: Gong, B. and Huang, N. (2025) 'Machine learning model-based monitoring of mental health status of college students', *Int. J. Information and Communication Technology*, Vol. 26, No. 2, pp.36–50.

Biographical notes: Baoqin Gong received her Master's degree from Hunan University of Science and Technology in 2019. She is currently a lecturer at the School of Marxism of Xi'an Siyuan University. Her research interests include ideological and political education, curriculum ideology and politics, and personnel training.

Ninghua Huang received her PhD from Hunan University of Science and Technology in 2024. She is currently a Lecturer at the School of Marxism, Changsha University of Science and Technology. Her research interests include cultural self-confidence, ideological and political education, and curriculum ideology and politics.

1 Introduction

In recent years, the mental health issues of college students have gradually become a focus of attention in various sectors of society. With the popularisation of higher education, the size of the college student population continues to expand, but the accompanying mental health problems have become increasingly severe. College students are at a critical stage of development in their lives, not only facing academic pressure, but also adapting to multiple challenges in interpersonal relationships, family expectations, and future career development, which greatly tests their psychological resilience. Survey data shows that the incidence of psychological problems such as anxiety, depression, and suicidal tendencies among college students worldwide is constantly increasing. This not only affects their academic performance, but also has profound impacts on their personal quality of life, social functioning, and future development. Therefore, how to effectively monitor and improve the mental health status of college students has become one of the important issues that universities and society urgently need to address (Pedrelli et al., 2015).

Traditional mental health monitoring methods often rely on psychological assessment questionnaires and subjective judgments of psychological counsellors. Although this approach can help identify students with psychological problems to some extent, it also has many limitations. Firstly, psychological assessment has a lag and passivity, usually students only actively seek help after obvious problems arise, resulting in some potential psychological problems not being detected in a timely manner (Oswalt et al., 2020). Secondly, the number of psychological counsellors is limited, making it difficult to provide sufficient psychological support to a large group of college students. In addition, psychological problems are secretive and complex, and students are often unwilling to actively expose their emotions and psychological states, making early intervention for psychological problems more difficult. Therefore, there is an urgent need for a tool that can actively, continuously, and accurately monitor the mental health status of college students, in order to help university mental health service departments better identify and respond to students' psychological problems.

In recent years, data-driven methods for monitoring mental health have gradually gained attention. Machine learning, as one of the core technologies of artificial intelligence, has been widely applied in multiple fields due to its powerful data processing and prediction capabilities. In the field of mental health, machine learning models can automatically identify possible abnormal psychological states by analysing large amounts of multidimensional data, providing a more objective, real-time, and accurate method for mental health assessment (Lattie et al., 2019). Compared with traditional methods, machine learning based mental health monitoring has several significant advantages. Firstly, it can process massive amounts of data and combine multiple dimensions of data sources, including psychological assessment data, daily behaviour data (such as social media use, exercise and sleep patterns), physiological data, etc., to achieve a more comprehensive assessment of health status. Secondly, machine learning models have self-learning capabilities and can improve the accuracy and robustness of predictions through continuous algorithm optimisation. Finally, machine learning technology can achieve automated processing, reduce human intervention, and significantly improve monitoring efficiency and response speed.

The mental health issues of college students have become an important global issue. With the development of technology, researchers have begun to explore data-driven methods to monitor and improve mental health status. This section will review the relevant work in the field of mental health monitoring in recent years, with a focus on discussing machine learning based methods, data sources, and application effects.

Machine learning, as a data-driven analysis and prediction technique, has been widely applied in mental health research. Multiple machines learning algorithms, including decision trees (Song and Ying, 2015), random forests (RF) (Breiman, 2001), and deep learning (DL) (LeCun et al., 2015), have been used for tasks such as emotion recognition, depression screening, and anxiety prediction. Decision trees perform well in processing small-scale datasets with good classification ability, while RF has received widespread attention for its robustness in dealing with high-dimensional data and complex features (Linardatos et al., 2020).

Recent studies have shown that deep learning has enormous potential in the field of mental health. Shatte et al. (2019) used convolutional neural networks (CNN) to analyse social media data and predict users' mental health status, achieving good results. In addition, Wang et al. (2022) integrated articles on deep learning in emotional computing, including models based on recurrent neural networks (RNNs) that automatically detect emotional states by analysing individual voice data, demonstrating the strong ability of deep learning in mental health monitoring.

Mental health monitoring relies on the integration of multidimensional data. Common sources of data include psychological assessment questionnaires, behavioural data, and physiological data. Psychological assessment questionnaire data typically comes from standardised scales such as the Beck depression inventory (BDI) (Jackson-Koku, 2016) and the generalised anxiety scale (GAD-7) (Spitzer et al., 2006), which are widely used to screen for mental health issues. However, relying solely on questionnaire data may miss important behavioural characteristics and dynamic changes, so more and more studies are beginning to integrate behavioural data, such as social media usage patterns (Islam et al., 2020), mobile device sensor data (Saeb et al., 2015), and exercise and sleep data (Luxton et al., 2012).

However, the use of social media data also faces privacy and ethical challenges. Researchers must ensure the anonymity of data and protect user privacy. In addition, social media data may have biases as not all users publicly share their true feelings and status on these platforms (Guntuku et al., 2017).

In addition to monitoring mental health status, many studies also focus on how to achieve automated interventions and warnings through technology. Prieto et al. (2014) developed an automated system based on text analysis, which can automatically generate suggestions and coping strategies when detecting users' low mood or increased stress. Nemesure et al. (2021) used machine learning models to predict anxiety attacks and automatically sent psychological adjustment suggestions to users when high-risk was detected, significantly reducing the recurrence rate of anxiety disorders.

Firstly, mental health issues have a high degree of individual variability, and how to construct personalised predictive models is an important research direction for the future. Secondly, data diversity and quality control are also key issues, and in the future, more high-quality datasets will be needed to train models. In addition, how to balance privacy protection and data sharing, as well as how to develop reasonable ethical norms to ensure the legality and compliance of technology applications, are also urgent issues that need to be addressed.

Based on the above background, this study proposes an innovative method of using machine learning models to monitor the mental health status of college students, aiming to provide intelligent support for mental health management in universities and help mental health service departments timely detect and intervene in potential mental health problems. Specifically, this study integrates multidimensional data, including psychological assessment questionnaire data, daily behaviour data, academic performance data, etc. In the study, we focused on analysing the performance of different algorithms in processing multidimensional data and identifying mental health issues, and verified the accuracy and stability of the model through experiments.

The innovation of this study lies in not only using multiple advanced machine learning algorithms, but also combining the complexity of mental health issues with multidimensional data to construct a more comprehensive mental health monitoring framework. Unlike previous studies, we no longer rely solely on a single psychological assessment data, but rather integrate students' behavioural data (such as social network activity, physical activity, sleep quality, etc.) to more comprehensively reflect their mental health status. For example, long-term sleep deprivation and social isolation may be early signs of depression, and these behavioural characteristics are often traceable in students' daily activities. Therefore, by inputting this data into machine learning models, the system can analyse students' behaviour patterns in real time and automatically identify potential mental health risks.

In addition, another important contribution of this study is that we have designed an efficient warning mechanism that can automatically identify abnormal psychological states. This system can monitor the psychological state of college students on a regular basis. For students with abnormal psychological states, they can be reported to the school in real time. The school can take corresponding measures to provide psychological counselling to students and reduce their mental health problems.

We believe that through this system, early identification, warning, and intervention of the mental health of college students can be achieved, thereby contributing to improving their mental health status and enhancing their academic and quality of life.

The following chapters will provide a detailed introduction to the technical scheme and experimental results of this study, including data collection and preprocessing, selection and optimisation of machine learning models, and implementation of model performance evaluation.

2 Relevant technologies

2.1 Definition and assessment of mental health

As a core concept in psychology and medicine, mental health refers to an individual's cognitive, emotional, and behavioural health status, as well as their ability to effectively cope with life stress, establish and maintain positive interpersonal relationships, and realise self-worth. According to the definition of the World Health Organization (WHO), mental health not only refers to the absence of mental illness, but also includes positive psychological functioning and emotional adaptability. Therefore, mental health problems typically manifest in various symptoms such as psychological stress, anxiety, depression, and suicidal tendencies (Kessler et al., 2005).

As a special social group, college students are in the transitional stage from adolescence to adulthood, facing various challenges such as academic pressure, career planning, interpersonal relationships, and self-identity. These pressures can easily lead to emotional fluctuations, which in turn can affect mental health status. Therefore, many university mental health service departments use standardised psychological scales such as the BDI and GAD-7.

The scores provided by these scales are a quantitative assessment of an individual's mental health status. In mathematical modelling, when evaluating mental health status, these measurements can be viewed as a time series problem, where an individual's psychological state changes over time. If $S(t)$ represents the individual's mental health status (such as depression or anxiety level) at time t, then the state change can be expressed by the following formula:

$$S(t) = S_0 + \int_0^t \Delta S(\tau) d\tau \tag{1}$$

Among them, S_0 is the initial state, and $\Delta S(\tau)$ represents the rate of change of psychological state at time τ. By analysing the time series of emotional fluctuations, researchers can determine the dynamic changes in an individual's mental health status.

Although these scales play an important role in assessing mental health, their limitations cannot be ignored. Scales typically rely on students' self-report, are susceptible to subjective biases and emotional fluctuations, and lack real-time monitoring capabilities. Therefore, by combining multidimensional data and introducing machine learning techniques, building a more dynamic and personalised mental health monitoring system has become a current research hotspot.

2.2 Emotion computing and emotion recognition

Emotional computing refers to the research field that utilises computing technology to analyse, identify, and simulate human emotions. The theoretical basis of affective computing comes from the interdisciplinary field of psychology and computer science, aiming to understand and process emotional states through technological means. Emotion is not only an important component of human psychological activity, but also a key driving factor in human behaviour and decision-making processes. Accurate identification of emotional states can provide strong support for mental health monitoring systems.

Emotion recognition is a computer technology that analyses text to determine what emotions it expresses. Emotions can be expressed through facial expressions, speech, language, and behaviour. In our study, we mainly focused on language to judge emotions because research has shown that language is one of the main carriers of expressing emotions. By analysing semantic features in text, we can effectively identify an individual's emotional state (Poria et al., 2017). The basic formula for text emotion recognition can be expressed as:

$$y = \arg\max_{c \in C} P(c \mid T) \tag{2}$$

where $P(c \mid T)$ represents the probability of emotion category c given text T, and c is the set of all possible emotion categories. By using Bayes' theorem, probability can be further expressed as:

$$P(c \mid T) = \frac{P(T \mid c) P(c)}{P(T)} \tag{3}$$

where $P(T \mid c)$ represents the likelihood of text T under a given emotional category c, $P(c)$ is the prior probability, and $P(T)$ is the marginal probability of the text. To simplify the problem, it is usually assumed that $P(T)$ is a constant and only $P(T \mid c)P(c)$ needs to be maximised.

In mental health monitoring, the goal of emotion recognition is not limited to identifying the types of emotions (such as happiness, anger, sadness, etc.), but also includes predicting the severity of mental health problems. For example, by analysing students' vocabulary patterns in social media and daily communication, it is possible to predict their emotional changes and mental health risks. Therefore, emotion recognition technology provides an important technological foundation for automated mental health monitoring.

2.3 The application of machine learning in mental health monitoring

2.3.1 Decision tree

The decision tree algorithm includes ID3, C4.5, and CART algorithms, and the most commonly used CART algorithm is gradually optimised from the first two algorithms.

Entropy is a measure of uncertainty in things, and events with higher entropy have higher uncertainty. The formula for calculating the entropy $H(X)$ is as follows:

$$H(X) = -\sum_{i=1}^{n} p_i \log p_i \tag{4}$$

where n represents that the random variable X has n different discrete values. p_i represents the probability that the value of the random variable X is i.

The conditional entropy of the random variable X is:

$$H(X \mid Y) = -\sum_{x_i \in X} \sum_{y_i \in Y} p(x_i, y_i) \log(x_i \mid y_i) \tag{5}$$

$$I(X, Y) = H(X) - H(X \mid Y) \tag{6}$$

The ID3 algorithm has the following shortcomings: firstly, it cannot handle continuous features; Secondly, using information gain as a feature selection criterion can easily lead to biased results towards features with more values. For the second question, C4.5 proposes using information gain as the criterion for splitting features, as follows:

$$O_R(F, S) = \frac{O(F, S)}{J_S(F)} \tag{7}$$

where $J_S(F)$ is as follows:

$$J_S(F) = -\sum_{o=1}^{n} \frac{|F_o|}{|F|} \log_2 \frac{|F_o|}{|F|} \tag{8}$$

where n is the total number of features required in the model, F_o is the number of samples of the target object in the model, and $|F|$ is the total number of samples.

The CART algorithm uses Gini coefficient to simplify calculations and avoid consuming a large amount of computing resources and time.

$$Ginicft(q) = \sum_{l=1}^{L} q_l(1-q_l) = 1 - \sum_{l=1}^{L} q_l^2 \tag{9}$$

where L is the total number of categories, and q_l represents the probability of the l-th category.

2.3.2 Random forest

Random forest constructs multiple decision trees, each of which learns and predicts independently, and then integrates the prediction results of the decision trees through voting to obtain the final prediction result.

1 Input the original dataset $D = \{(x_1, y_1), (x_2, y_2,), \ldots, (x_n, y_n)\}$, where x_n represents the feature vector and y_n represents the class of the sample.

2 Randomly extract from the original dataset D to obtain the sub dataset D_S.

3 Randomly select a subset of feature set F from all features.

4 Construct a decision tree using the sub dataset and the selected feature set F until one of the following conditions is met: the depth of the tree reaches the preset maximum depth, the samples in the nodes of the tree belong to the same category, or the number of samples in the nodes of the tree is less than the preset minimum number of samples. Repeat the above steps to build T decision trees.

5 The prediction result of each decision tree is $C(x)$, and the final prediction result is obtained through voting or averaging. Therefore, the prediction result of the random forest is:

$$RF(x) = \frac{1}{T}\sum\nolimits_{n=1}^{T} C_n(x) \tag{10}$$

2.3.3 Deep learning

Deep learning uses neural networks to iteratively train and form models for emotion prediction based on training data. RNN is a type of deep learning network that differs from other networks in that it introduces recurrent networks, thus possessing memory. In RNN, each time step contains information from the previous step, and through backpropagation algorithm, RNN can learn feature representations and patterns applicable to sequence data. The most commonly used variants of RNN are long short term memory networks (LSTM) and gated recurrent units (GRU), which improve the modelling ability of RNN for long-term dependencies by introducing gating mechanisms.

For time t, the specific calculation formulas for hidden layer state h_t and output state o_t are shown in equations (10) and (11):

$$h_t = f_1\left(U_{x_t} + Wh_{t-1} + b\right) \tag{11}$$

$$o_t = f_2\left(Vh_t + c\right) \tag{12}$$

where U, W, and V are the weight matrices of the input vector, b and c are the biases of the hidden layer and output layer, x_t is the input vector, and f_1 and f_2 are the activation functions of the hidden layer and output layer, respectively.

RNN can process temporal information in sequence data and model feature vector sequences with varying sequence lengths. To address this issue, some improved RNN structures have emerged, such as LSTM and GRU, which control the flow of information through gating mechanisms, preserve important information, and effectively alleviate the problems of gradient vanishing and exploding.

3 A machine learning based model for monitoring the mental state of college students

3.1 Data acquisition

Firstly, we collected psychological assessment questionnaire data and daily behaviour data, covering students' social media use, exercise intensity, and sleep patterns. These data provide comprehensive input information for the model. Daily behaviour data is collected through smartphones and wearable devices, ensuring diversity and comprehensiveness of the data. Let the collected data be $D = \{D_1, D_2, \ldots, D_n\}$, where D_I represents the dataset of the i-th individual. Each dataset consists of psychological assessment scores and behavioural data:

$$D_i = \left\{S_i, B_i\right\} \tag{13}$$

$$B_i = \left\{B_{i1}, B_{i2}, \ldots, B_{im}\right\} \tag{14}$$

where S_t represents the psychological assessment score, B_i represents behavioural data, including the behavioural characteristics of individual i.

3.2 Data processing

Due to the different sources of multidimensional data, it is necessary to preprocess the raw data in order to apply it to machine learning models. During the data collection process, there may be missing values. We have filled in the missing values to ensure the integrity of the data. Assuming there are missing values in the behavioural data, the filling method can be expressed as:

$$B_{ij}^{filled} = \frac{1}{|D|}\sum_{k=1}^{|D|} B_{kj},\ B_{ij} = NaN \tag{15}$$

where B_{ij}^{filled} is the filled value, and $|D|$ represents the number of samples.

Then, we standardise the behavioural data and psychological state data to process them at the same scale. This step aims to avoid the negative impact of differences in feature scales on model training. To eliminate dimensional differences between different data dimensions, Z-score normalisation is used to normalise the data to the same dimension:

$$B_{ij}^{norm} = \frac{B_{ij} - \mu_j}{\sigma_j} \tag{16}$$

where μ_j and σ_j are the mean and standard deviation of the j-th feature respectively.

In the process of feature extraction, we merge mental health scores and behavioural pattern data into a unified feature vector. This process not only improves the availability of data, but also enhances the accuracy and robustness of the model when dealing with complex data. The final generated feature vectors are used for subsequent machine learning model training. Based on psychological assessments and behavioural data, we constructed psychological state characteristics and behavioural pattern characteristics. Among them, using psychological assessment score S_i as the psychological state feature, key indicators such as exercise intensity, sleep duration, social media usage frequency, etc. from daily behaviour data are extracted as behaviour pattern features. If the behaviour feature vector is B_i, the final feature vector x_i can be expressed as:

$$x_i = [S_i, B_i] = [S_i, B_{i1}, B_{i2}, ..., B_{im}] \tag{17}$$

The final feature vector x_i contains all the psychological and behavioural characteristics of the individual.

3.3 Model building

3.3.1 Decision tree

Decision tree is a widely used non parametric supervised learning algorithm for classification tasks, which divides the dataset into different subsets until the samples in each subset belong to the same class or reach a predetermined stopping condition. The construction process of a decision tree includes the following steps:

1. Initial feature selection, where the decision tree selects the optimal feature at each node to partition the data. Common feature selection criteria include information gain and Gini coefficient. The information gain measures the discriminative ability of a feature based on the reduction of entropy, as shown in equations (4) and (8).
2. Construct a decision tree structure by recursively selecting the optimal features. Stop recursion when the dataset cannot be further divided or reaches the depth limit of the tree.
3. To avoid overfitting, pruning is usually performed after generating the complete tree. Pruning can be achieved by removing nodes with low information gain or limiting the maximum depth of the tree.

Decision trees can efficiently process small-scale datasets and provide clear classification paths, making them suitable for simple classification tasks related to students' mental health status. However, individual decision trees may perform poorly when there is a large amount of data or noise, so we further adopted the random forest algorithm to improve the robustness of the model.

3.3.2 Random forest

The core idea is to use the ensemble of multiple weak classifiers (i.e. a single decision tree) to reduce the risk of overfitting.

Random forest generates multiple subsets by randomly sampling from the training dataset using a self-service method. Build a decision tree on each training subset. At each node of the tree, randomly select a subset of features for splitting, rather than selecting the optimal feature from all features. In this way, random forests introduce additional randomness and reduce the variance of the model. The specific steps and formulas can be found in Section 2 of this article.

The advantage of random forest is that it can handle high-dimensional datasets and has good noise resistance. Due to its integration of results based on multiple decision trees, random forests perform well in handling complex and heterogeneous data. In this study, the random forest demonstrated strong classification ability by combining multidimensional behavioural data and psychological assessment data, especially in the case of a large sample size, which can significantly improve the model's generalisation ability.

3.3.3 Deep learning

Deep learning models perform well in processing time series data and high-dimensional data. In order to capture potential temporal dependencies in college student behaviour data, this study employed Long Short Term Memory (LSTM) networks. LSTM is able to capture long-term dependencies through memory units and performs outstandingly in predicting mental health in time series.

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{18}$$

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{19}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{20}$$

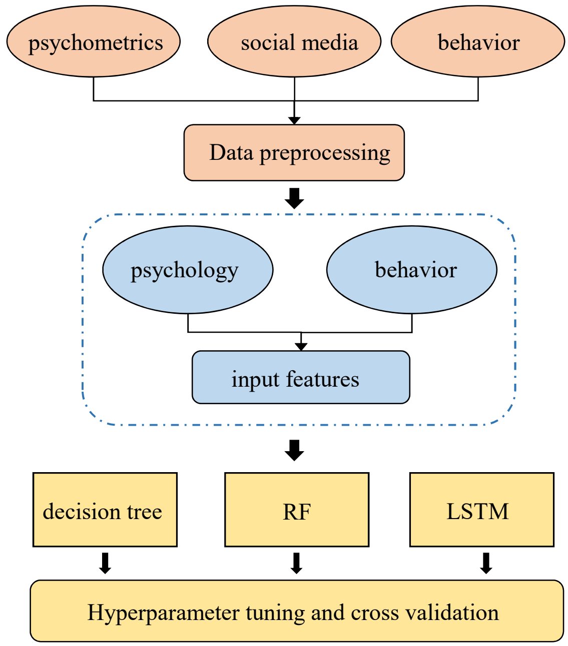
$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{21}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{22}$$

where σ is the sigmoid activation function, tanh is the hyperbolic tangent function, W and b are the weight matrix and bias vector, respectively.

The advantage of LSTM lies in its ability to capture both long-term and short-term dynamic changes when processing time series data. In this study, LSTM was used to process students' behavioural data, such as social media usage habits, exercise and sleep patterns, etc. Through temporal analysis of these data, LSTM can better capture the changing trends of students' mental health status and make accurate predictions.

Figure 1 Framework diagram of mental health monitoring model for college students (see online version for colours)



4 Experiment

4.1 Data set

To verify the effectiveness of the college student mental health status prediction system based on multidimensional data and machine learning models, we used real datasets from multiple universities, with a total of 2000 student samples and 20000 data records. Each sample contains behavioural characteristics and mental health scores, and the dataset is deduplicated, cleaned, missing values processed, and standardised. The key components of the dataset include psychological assessment questionnaires and daily behaviour data. The psychological assessment questionnaire mainly covers evaluation data of common psychological problems such as mental stress, anxiety, and depression, using standardised mental health assessment tools such as GAD-7 and BDI. Daily behaviour data includes social media usage, exercise data, and sleep patterns.

4.2 Evaluation

This article evaluates the performance of the model using metrics such as accuracy, precision, recall, and F1 score. We calculated the performance metrics of different algorithms on the test set and compared their performance in handling mental health status recognition tasks. The definitions of these indicators are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{23}$$

$$Precision = \frac{TP}{TP + FP} \tag{24}$$

$$Recall = \frac{TP}{TP + FN} \tag{25}$$

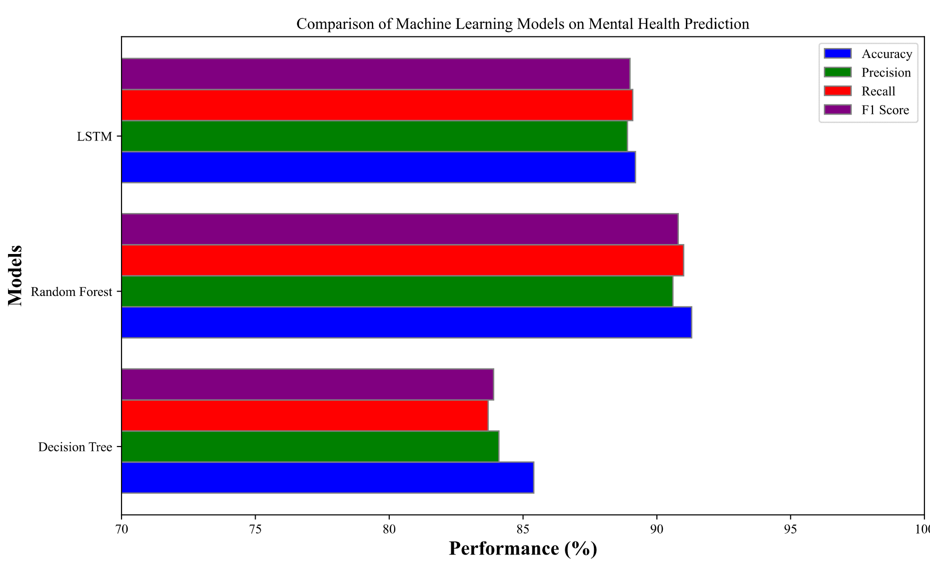
$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{26}$$

where *TP* is the true case, *TN* is the true negative case, *FP* is the false positive case, and *FN* is the false negative case.

4.3 Experimental results and analysis

From the experimental results, the random forest model performs the best in handling complex multidimensional data, with the highest accuracy (91.3%) and F1 score (90.8%). This indicates that random forest can improve the robustness of the model and reduce overfitting by integrating multiple trees when processing various behavioural characteristics and psychological assessment data.

Figure 2 Various indicators of different models (see online version for colours)

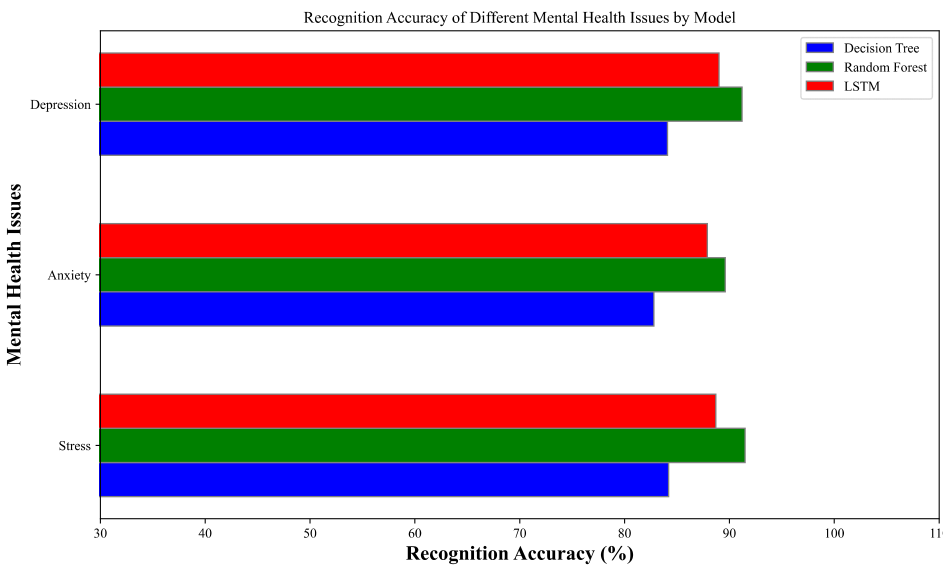


The performance of LSTM model is also outstanding, especially when processing time series behaviour data, it can better capture the dynamic changes of student behaviour. Its F1 score reaches 89.0%, although slightly lower than random forests, it performs better than decision trees on large datasets.

The performance of decision trees is relatively weak, especially when dealing with multidimensional behavioural data, as they fail to fully capture the complex relationships between different features. However, its simplicity and fast training speed make it still a valuable benchmark model.

From the perspective of identifying psychological problems, the accuracy of random forest in identifying mental stress, anxiety, and depression is higher than other models, indicating that it has better generalisation ability in dealing with multidimensional and complex psychological data.

Figure 3 The recognition rate of different models for different emotions (see online version for colours)



5 Conclusions

This article proposes a machine learning based monitoring model to address the problem of difficulty in perceiving and solving the mental health of college students. This model is built using decision trees, random forests, and LSTM algorithms, and the data is collected from various behavioural data of college students. The experimental results show that the random forest model is relatively stable, and the LSTM model has stronger generalisation ability and can achieve better performance.

Future work can be carried out from the following aspects:

1 enhance the real-time performance of the model, which can track the user's psychological state in real time and make better judgments and decisions

2 to enhance the privacy protection of the model, federated learning methods can be used to strengthen the protection of users' psychologically sensitive information.

Acknowledgements

This work is supported by The Education Department of Shaanxi Province Scientific Research Plan Project in 2022 named A Study on the Timeliness of Discourse on Ideological and Political Education in Private Colleges and Universities of New Media (No. 2022JK0150).

References

Breiman, L. (2001) 'Random forests', *Machine Learning*, Vol. 45 No. 12, pp.5–32.

Guntuku, S.C., Yaden, D.B., Kern, M.L. et al. (2017) 'Detecting depression and mental illness on social media: an integrative review', *Current Opinion in Behavioral Sciences*, Vol. 18, No. 2, pp.43–49.

Islam, M.R., Liu, S., Wang, X. et al. (2020) 'Deep learning for misinformation detection on online social networks: a survey and new perspectives', *Social Network Analysis and Mining*, Vol. 10, No. 1, p.82.

Jackson-Koku, G. (2016) 'Beck depression inventory', *Occupational Medicine*, Vol. 66 No. 2, pp.174–175.

Kessler, R.C., Berglund, P., Demler, O. et al. (2005) 'Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication', *Archives of General Psychiatry*, Vol. 62, No. 6, pp.593–602.

Lattie, E.G., Lipson, S.K. and Eisenberg, D. (2019) 'Technology and college student mental health: challenges and opportunities', *Frontiers in Psychiatry*, Vol. 10, No. 2, p.246.

LeCun, Y., Bengio, Y. and Hinton, G. (2015) 'Deep learning', *Nature*, Vol. 521, No. 7553, pp.436–444.

Linardatos, P., Papastefanopoulos, V. and Kotsiantis, S. (2020) 'Explainable AI: a review of machine learning interpretability methods', *Entropy*, Vol. 23, No. 1, p.18.

Luxton, D.D., June, J.D. and Fairall, J.M. (2012) 'Social media and suicide: a public health perspective', *American Journal of Public Health*, Vol. 102, No. S2, pp.S195–S200.

Nemesure, M.D., Heinz, M.V., Huang, R. et al. (2021) 'Predictive modeling of depression and anxiety using electronic health records and a novel machine learning approach with artificial intelligence', *Scientific Reports*, Vol. 11, No. 1, p.1980.

Oswalt, S.B., Lederer, A.M., Chestnut-Steich, K. et al. (2020) 'Trends in college students' mental health diagnoses and utilization of services, 2009–2015', *Journal of American College Health*, Vol. 68, No. 1, pp.41–51.

Pedrelli, P., Nyer, M., Yeung, A. et al. (2015) 'College students: mental health problems and treatment considerations', *Academic Psychiatry*, Vol. 39, No. 1, pp.503–511.

Poria, S., Cambria, E., Bajpai, R. et al. (2017) 'A review of affective computing: from unimodal analysis to multimodal fusion', *Information Fusion*, Vol. 37, No. 1, pp.98–125.

Prieto, V.M., Matos, S., Alvarez, M. et al. (2014) 'Twitter: a good place to detect health conditions', *PloS One*, Vol. 9 No. 1, p.e86191.

Saeb, S., Zhang, M., Karr, C.J. et al. (2015) 'Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study', *Journal of Medical Internet Research*, Vol. 17, No. 7, p.e4273.

Shatte, A.B., Hutchinson, D.M. and Teague, S.J. (2019) 'Machine learning in mental health: a scoping review of methods and applications', *Psychological Medicine*, Vol. 49, No. 9, pp.1426–1448.

Song, Y-Y. and Ying, L. (2015) 'Decision tree methods: applications for classification and prediction', *Shanghai Archives of Psychiatry*, Vol. 27, No. 2, p.130.

Spitzer, R.L., Kroenke, K., Williams, J.B. et al. (2006) 'A brief measure for assessing generalized anxiety disorder: the GAD-7', *Archives of Internal Medicine*, Vol. 166, No. 10, pp.1092–1097.

Wang, Y., Song, W., Tao, W. et al. (2022) 'A systematic review on affective computing: Emotion models, databases, and recent advances', *Information Fusion*, Vol. 83, No. 33, pp.19–52.