Data Security Mining Method for Social Media Users' Mental Health Status Test Based on Machine Learning Algorithm

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Abstract. Users who frequently use social media can easily lead to changes in their mental health status. In order to accurately predict users' mental health status, a data mining method for testing social media users' mental health status is designed based on machine learning algorithms. Perform clustering processing on the test data, calculate the centroid of each cluster and the sum of squared errors of the data set, and obtain the clustering result of the test data; extract the characteristics of social media users' mental health status, and calculate the abnormal score of the object's mental health status, Use this to distinguish the user's psychological state; build a data mining model based on machine learning algorithms, build a one-dimensional convolutional neural network framework, record the activation functions of the convolutional layer and the pooling layer, and obtain the output value of the fully connected layer; design social media user psychology Health state test data analysis algorithm to obtain a safe mining method for social media users' mental health state test data. Obtain the best period of social media users' mental health status observation through experiments. It can be seen from the experimental data that the correlation of the mental health state mining results obtained by this method is higher than 0.91, and the prediction accuracy is higher than 92%, which improves the effectiveness of mental health state prediction. The best observation period is one month to two months before the expected time.

Keywords: Machine Learning Algorithm · Social Media Users · Mental Health Status Test · Data Security Mining Method

1 Introduction

At present, with the massive Internet big data information, our society has developed into an information society, and it has gradually developed into a trend in the whole world. In the current information society, the generation, dissemination, processing and use of

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information are inseparable from the effective construction of the whole society. At the same time, the progress of information technology further provides a strong guarantee for the normal operation of the whole society. The overall level of informatization in Chinese society has basically reached the level of moderately developed countries, and China is entering a period of accelerated transformation of the information society [1]. At present, China has entered the era of big data, and this rapid development is due to the lightning-fast progress of the Internet. Countless individuals or groups have studied the massive Internet data and information, and regard it as a huge treasure, hoping to dig out their own wealth. And social media is one of the most worthy of study among these sectors. Social media represents a class of websites and technologies on which users can write, comment on, share, and communicate with each other on the Internet. At the same time, Social Media is also a type of tool and platform, where users can share insights, opinions, experiences or suggestions with each other. At present, social media covers a wide range, including Weibo (Sina Weibo, Tencent Weibo), social networking sites (Facebook)., Twitter, Renren, Friends), blogs (Sina Blog), forums (Shui Mu Nianhua), WeChat, etc.

The rapid development of social networks has dramatically changed the way people communicate. With the rapid development of society, huge work and life pressures are coming, which not only brings a heavy burden to our body, but also a variety of psychological problems are gradually increasing [2]. Especially in the university campus, events such as jumping off the building, suicide, running away, depression, etc. often occur, and some vicious injuries occur from time to time. The mental health of large objects has become one of the focuses of social concern, and has received extensive attention from all walks of life. Mental health problems are showing a growing trend around the world. Therefore, it is particularly important to use Internet big data to discover people's mental health problems in time. To this end, this paper studies data security mining methods for testing the mental health status of social media users based on machine learning algorithms. The module designed for the study method is shown in Fig. 1:

As shown in Fig. 1, the research process designed in this paper is as follows: cluster the test data and calculate the clustering results of the test data; Extract the characteristics of users' mental health, and mine abnormal scores of mental health; The data mining model based on machine learning algorithm is Innovatively constructed, the optimal classification value is calculated, and the optimal classifier is used to realize the safe mining of users' mental health test data. The test results show that the contribution of this method lies in improving the accuracy of the mental health state prediction of social media users, which can better reduce people's psychological stress and reduce the incidence of psychological problems such as depression.

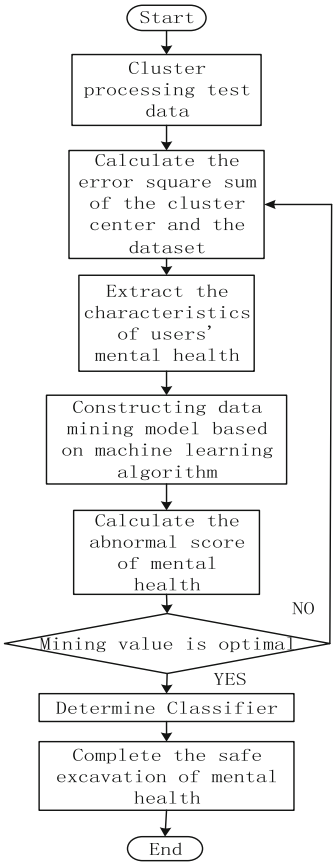


Fig. 1. Study module flow

2 Test Data Clustering

After years of development, data mining technology has achieved good results in the wide application of various fields, which is unmatched by other technical methods. Data mining technology is to dig out the hidden rules and value content in data to solve specific problems. People can also use computer applications to complete the same functions when they do not master the technology. Therefore, this paper proposes to introduce data mining technology into mental health data to mine and analyze the causes of the object's mental health problems, which provides a scientific basis for early prevention and early intervention to control the emergence of campus psychological crises.

The purpose of clustering is to group objects with similar properties together. In most cases, the data that people collect is unlabeled, and clustering can divide the data into multiple distinct groups. The data in each group has greater similarity, and the data between groups has greater exclusivity, that is, "similarity within a group and exclusivity between groups" [3, 4]. Clustering algorithms are mainly divided into partition-based

clustering, hierarchical-based clustering, grid-based clustering, density-based clustering, and model-based clustering. As one of the commonly used methods in traditional machine learning algorithms, cluster analysis is widely favored due to its practicality, simplicity and efficiency. It has been successfully applied in many fields, such as: document clustering, market analysis, image segmentation, feature learning Wait. In this study, we choose the KMeans clustering algorithm, which is a partition-based clustering algorithm, to divide the meal times and entropy of the objects. First, randomly select k sample points from the sample set and use them as the center of the cluster. Then, according to the distance of each sample to the k centroids, it is divided into the nearest clusters, and the centroid of each cluster is recalculated. This article uses the Euclidean distance, and the calculation formula is:

$$D(s_t, M_g) = \sqrt{\frac{\sum_{i=1}^{n} X_{ij}^2}{M_g}} \tag{1}$$

In formula, $D(s_t, M_g)$ represents the Euclidean distance of each sample from the initial point to the cluster; s_t is the number of sample points; M_g is the centroid position; and X_{ij} represents the cluster entropy of the data.

In the sum of error squares for all datasets, the formula is:

$$G_{SSE} = \frac{\sum_{i=1}^{k} \left| D(s_t, M_g) \right|^2}{\sum_{i=1}^{k} M_g^2} \tag{2}$$

In formula (2), G_{SSE} represents the sum of squared of the dataset.

By initialization, you can randomly select k sample points from the original N samples and treat them as the hearts of the cluster. The eucoid distance of the remaining sample to the cluster center was calculated according to formula. Based on the results of the sum of squares calculation, each sample was divided into the nearest cluster cluster cluster to obtain the clustering results of the test data.

3 Feature Extraction of Mental Health Status of Social Media Users

Some studies have found that people with mental health problems develop eating disorders, especially those with depression. Based on this fact, the consumption records of the subjects in the canteen can be extracted by the store name to analyze their eating patterns. Pay particular attention to the subject's breakfast, lunch/dinner routine. In this study, the breakfast time period is set from 6:00 to 9:00, the lunch time period is set from 11:00 to 13:00, and the dinner time period is set from 17:00 to 19:30 [5, 6]. Since there are often multiple records for each meal, the first card swiping time in a meal is taken as the meal time of the meal. For example, there are 3 records in a breakfast, and their occurrence times are 7:20, 7:21 and 7:22, then use 7:20 as the breakfast time. The regularity of a behavior can be thought of as repeatable and will be measured by the entropy of the probability of the behavior occurring within a specific time interval.

Assuming n time interval $T_n = \{t_1, t_2, \cdots, t_n\}$, for any given object, the probability of behavior $F_m = \{f_{bre}, f_{lun}, f_{din}\}$ occurring within the time interval t_i is:

$$P_d(T_n = t_i) = \frac{D_f(t_i)}{\sum_{i=1}^{n} D_f(t_i)} \tag{3}$$

In the formula, $P_d(T_n = t_i)$ indicates the probability of breakfast, lunch and dinner at any time interval; $D_f(t_i)$ indicates the frequency of any meal of the three meals in the time interval t_i [7]. According to the calculation of consumption characteristics of $P_d(T_n = t_i)$, the calculation formula is:

$$E_s = -\frac{\sum_{i=1}^{n} P_d(T_n = t_i)}{\lg P_d(T_n = t_i)} \tag{4}$$

In formula, E_s indicates the entropy of meal consumption. The smaller E_s, the more concentrated the time interval of the probability distribution.Therefore, in the clustering process of entropy value and number, the clustering results of the measured meals can be obtained.

The goal of the above methods is to discover subjects with an abnormal diet. Suppose that the smaller an object is in the cluster, and the farther away it is from the center of the cluster, the higher the anomaly score is. Calculate the exception score of the object according to the formula:

$$Y_c = dis\,(h_k, p_c) \times \left(1 - \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} f_i}\right) \tag{5}$$

In formula, Y_c represents the score of the object diet abnormality; $dis(h_k, p_c)$ represents the Euclidean distance between the object and the centroid, where h_k represents the number of objects, p_c represents the centroid point of the cluster; d_i represents the consumption entropy of the i object and the diet, and f_i indicates the regularity coefficient of the object eating.

The abnormal score is mainly aimed at the difference of dining behavior between the object, as well as the dining difference of the object in different time periods, and finally the overall diet data of the object is obtained.

4 Building a Data Mining Model Based on Machine Learning Algorithms

According to the browsing history of the object, the characteristics of the Internet are mined. According to the order of access time, a time series of Internet access is established for each object. It is hoped to dig out the online pattern of the object from the online time series. In this study, the overall framework of the designed one-dimensional convolutional neural network is shown in Fig. 2.

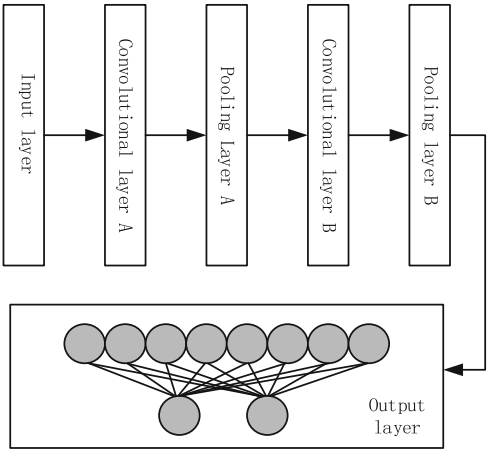


Fig. 2. One-dimensional Convolutional Neural Network framework

As shown in Fig. 1, there are five neural network layers except for the input layer. The first and third neural network layers use the convolutional layer, the second and fourth layers use the pooling layer, and the last output layer is the fully connected layer. Record the activation functions of the convolution and pooling layers separately, as shown in formula (6):

$$\begin{cases} Y_k^p = \dfrac{\sum\limits_{i=1}^{n} y_i^{p-1} * h_i^p}{\sum\limits_{i=1}^{n} b_p^i} \\ \hat{Y}_k^p = \dfrac{\sum\limits_{i=1}^{n} y_i^{p-1} \times down\left(f_k^p + k_i\right)}{\sum\limits_{i=1}^{n} b_p^i} \end{cases} \tag{6}$$

In the formula, Y_k^p and $\hat{Y}_k^p$ represent the activation functions of the convolutional layer and the pooling layer respectively, which are also the results obtained by training each tested data in different stages of the model; y_i^{p-1} represents the feature parameter corresponding to the convolution kernel; $*$ represents the multiplication operation; h_i^p represents the bias position of the convolution kernel; b_p^i represents the vector dimension of the convolution kernel in the online sequence; $down\left(f_k^p\right)$ represents the bias matrix downsampling function in the pooling layer; k_i represents the input value.

Within the full connection layer, you can get the activation function:

$$f(m) = \frac{f\left(Y_{(4)} * Y_{(3)}^2 + Y_{(1)}\right)}{f\left(Y_{(2)}^2\right)} \tag{7}$$

In formula, $f(m)$ represents the output value of the fully connected layer in a 1 D convolutional neural network; $Y_{(1)}$, $Y_{(2)}$, $Y_{(3)}$, $Y_{(4)}$ represent the output values of the first, second, third, and fourth layer, respectively.Through the above functions, a standard model of the mental health status test data of social media users can be established.

5 Design the Data Analysis Algorithm for Social Media Users' Mental Health State Test

Due to the implicit characteristics of mental health, it is impossible to directly observe the mental health status of individuals, so we can only use some explicit "behavioral samples" to measure indirectly. At present, traditional psychological testing of mental health or clinical application of patients prefers indirect methods using these phenotypes. Each assessment method consists of thousands of items, each of which can be regarded as an abstract description of a series of individual behavioral characteristics. Correspondingly, these behavioral characteristics have a certain relationship with psychological characteristics. When using these methods to assess the mental health status, firstly, the individual needs to select the corresponding options according to the fit degree of his specific situation and the content of the options; secondly, the assessor calculates the score according to the individual scoring method provided by the specific basis; finally, the evaluators put forward conclusions based on the overall evaluation results, and explain the meaning in detail, and then notify the relevant personnel in the form of text or reports.

Which of so many Internet behaviors could reflect significant effects on mental health issues is clearly critical to our research. Even different mental health issues target different internet behaviors. However, on the other hand, this particularity of cyberspace has led to a complicated trend in the relationship between Internet behavior and users' psychological characteristics. We cannot simply apply the traditional psychology research conclusions on a certain dimension of mental health to correspond to the characteristics of Internet behavior, but should first establish the most complete network user behavior type guidelines, and gradually screen and reconfirm effective Internet users on the basis of these guidelines. Correspondence patterns of the relationship between behavior and psychological traits.

In data mining technology, the algorithms used mainly include decision tree algorithm, association rule algorithm, neural network algorithm, genetic algorithm, Bayesian network algorithm and statistical analysis method. In the data analysis research of social media users' mental health, this paper chooses to use decision tree algorithm and association rule Apriori algorithm. Decision tree algorithm is a relatively classic classification data mining algorithm. It generally uses a top-down recursive form to build generative decision trees from a large number of cases. The classification model of the decision tree algorithm is a directed acyclic tree consisting of a root node, parent nodes, child nodes and leaf nodes. Typical decision tree algorithms include ID3 algorithm C4.5 algorithm and CART algorithm. Using the ID3 algorithm and the C4.5 algorithm to generate decision trees for studying mental health problems is a common method. The decision tree algorithm is used to predict and analyze the mental health data of social media users. The general idea is to first analyze and calculate which attribute has the greatest correlation with the psychological problem, as the root node of the decision tree, and then use the iterative recursive method to analyze the rest in the same way. Attributes are classified, a decision tree is formed and a classification tree model for predictive analysis is constructed, as shown in Fig. 3.

As shown in Fig. 3, the overall identification algorithm of social media users' mental health problems based on mining algorithm is mainly divided into three parts, including

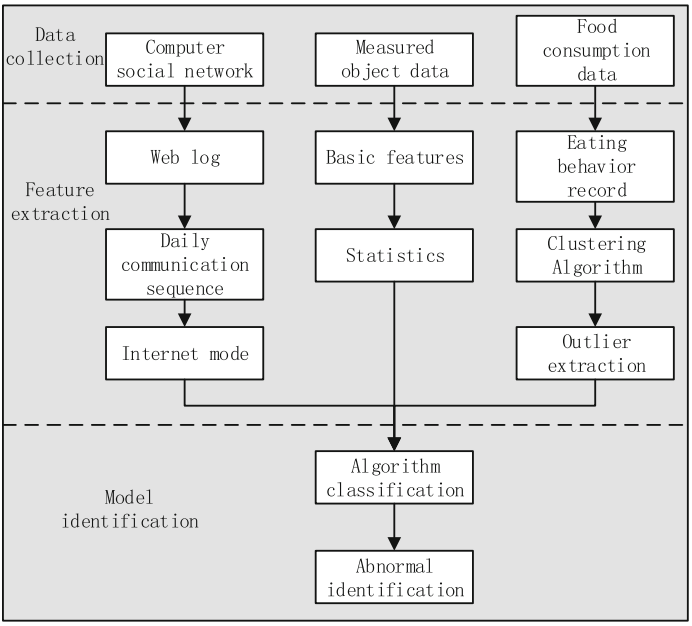


Fig. 3. Mental health state identification algorithm of social media users

data acquisition, feature extraction and model identification. In the data acquisition and preprocessing stage, we obtained three data sources, namely computer social network, basic information of the tested object, and dietary consumption data. In the feature extraction stage, relevant features such as students' online patterns and abnormal consumption scores are extracted from the above three data sources. In the model identification stage, the optimal classifier is screened out, and the abnormal points of social media users' mental health status are obtained. At this time, through the above method, a safe mining method for the test data of social media users' mental health state based on the machine learning algorithm can be obtained.

6 Experimental Test

In order to combine the social media behavior of Internet users with mental health assessment, and to integrate machine learning methods into the field of mental health assessment, this paper designs and studies a depression prediction model based on social media behavior of Internet users. This method better explores the effective way to combine the two modes. The core idea of the whole process is based on the most extensive psychological assessment methods at present, trying to replace the traditional method by using the user behavior of Internet users on social media to achieve basically the same purpose.

6.1 Acquisition and Preprocessing of Raw Data

In the acquisition and preprocessing part of raw data, on the one hand, the user's mental health assessment results are obtained through traditional scales, and on the other hand, the user's raw data on social media is obtained through Internet means, and then through step-by-step processing, the final result is formed. User network behavior characteristics are stored in the database. In the part of network behavior characteristics, it can be divided into three parts according to its process: social media API port call, data preprocessing, feature extraction and selection. In the acquisition of mental health status data, it is mainly divided into two parts: scale evaluation and data processing.

Application programming interfaces, or APIs for short, are functions that are predefined and encapsulated by website developers. Third-party personnel can directly call these functions without accessing the source code or understanding the details of the internal working mechanism of the website. At present, many social networking sites provide API interfaces. On the one hand, it is convenient for third-party personnel to develop more meaningful applications to enrich the website itself. On the other hand, it also provides a good opportunity for researchers to make it more convenient. to get the desired data.

Since the API ports provided by each website are different, the data formats of the obtained Internet users' network behavior are also different, so the data needs to be preprocessed before the next step to form the format required in the machine learning process. In the traditional machine learning process, data preprocessing is generally divided into three parts: data fusion, data cleaning and data transformation. Data fusion is to combine data from multiple data sources and store them uniformly, in other words, to realize the initialization of the data warehouse itself. The purpose of data cleaning is to remove errors or abnormal data in user data, remove redundant data, and standardize data formats. Data conversion is to convert user data into a custom normalized format, so as to facilitate the re-expansion and continuous transmission of user data.

According to the network behavior index system and the definition of specific psychological problems (such as depression, anxiety, etc.) in traditional mental health, the Internet behavior characteristics of individuals are extracted from the Internet behavior data of users. These Internet behavior characteristics can represent the overall behavior of individual users in the process of Internet communication, and are universal and specific. Then, according to the user's mental health status evaluation results, the characteristics that can represent the user's network behavior are selected.

The basic support for the establishment of the mental health model based on the social media behavior system of Internet users is the scale evaluation method in traditional psychology. Summarize. Therefore, as the establishment and evaluation standard of the model, the mental health status of some users must be obtained through the scale. There are many scales for comprehensive assessment of mental health commonly used in psychology at present, and different types of mental health have their own one or more assessment scales.

The data processing of the mental health measurement link is the same as the data preprocessing function of the network behavior part. After obtaining the mental health assessment scales of some users, the obtained scale scores need to be counted, summed and screened. Invalid or redundant assessment results will be removed.

A group of target users who are very active on social media and study in the same school are selected as the main subjects of this experiment, and the experiment time is from May 1, 2015 to May 15, 2015. Set the time period to 0.5 H_m, 1 H_m, 2 H_m, 3 H_m when the time point of May 1, 2015 is P_1, the time of 0.5 is from April 15, 2015 to May 1, 2015, and the time point of 1 is April 1, 2015 May 1, 2015; that is, the time period is the forward half month, one month, two months, and three months. Time point P_2 is half a month before P_1, that is, April 15, 2015, and the same time period is set under time point P_2. Time points P_3, P_4, and P_5 are April 1, 2015, March 15, 2015, and March 1, 2015, respectively. According to the above time points, the collected data and data can be divided into 20 data sets, as shown in Table 1.

Table 1. Time points and time periods

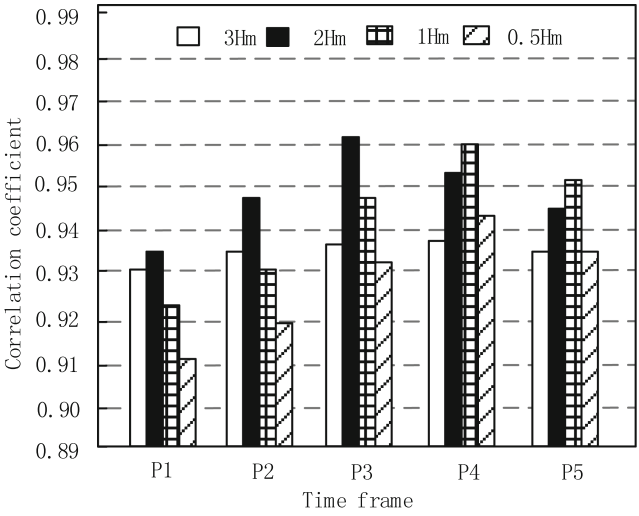
	0 Hm	0.5 Hm	1 Hm	2 Hm	3 Hm
P1	2015.05.01	2015.04.15	2015.04.01	2015.03.01	2015.02.01
P2	2015.04.15	2015.04.01	2015.03.01	2015.01.01	2014.11.01
P3	2015.04.01	2015.03.15	2015.02.01	2014.11.01	2014.08.01
P4	2015.03.15	2015.03.01	2015.01.01	2014.09.01	2014.05.01
P5	2015.03.01	2015.02.15	2014.12.01	2014.07.01	2014.02.01

These data are initially stored in text format and then transferred to the database. In the experiment, these time points are respectively used as test points for the user's mental health status.

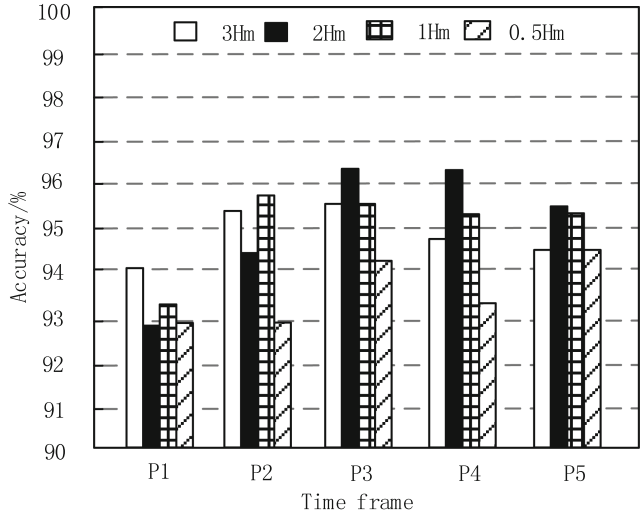
6.2 Model Accuracy Test

Set the number of convolution kernels of the two convolutional layers to 16 and 32 respectively, use reLU as the activation function, and use adam as the optimization algorithm. Furthermore, to prevent overfitting, we use three dropout layers with parameters of 0.15, 0.15, and 0.5. In the model training phase, we selected 70 positive samples and 70 negative samples to train the model. In the feature extraction stage, all experimental samples are input into the trained model, and finally the result of the fully connected layer is used as the output value. According to the trend of model accuracy level, we can analyze from both vertical and horizontal aspects. First, at the longitudinal level, we observe different time periods at the same time node (P1, P2, P3, P4, P5), as shown in Fig. 4.

The performance test results of the time node model at the longitudinal level are shown in Fig. 4. We can see that with the increase of the observation period, the correlation coefficient script presents an "inverted U"-shaped change trend. This means that in a period of time, as the observation period becomes longer, each node of the model will continuously accumulate behavior data of the user network. Compared with a smaller amount of information, these accumulated data can better describe the The behavioral habits of bloggers and the psychological factors hidden behind them. Therefore, the



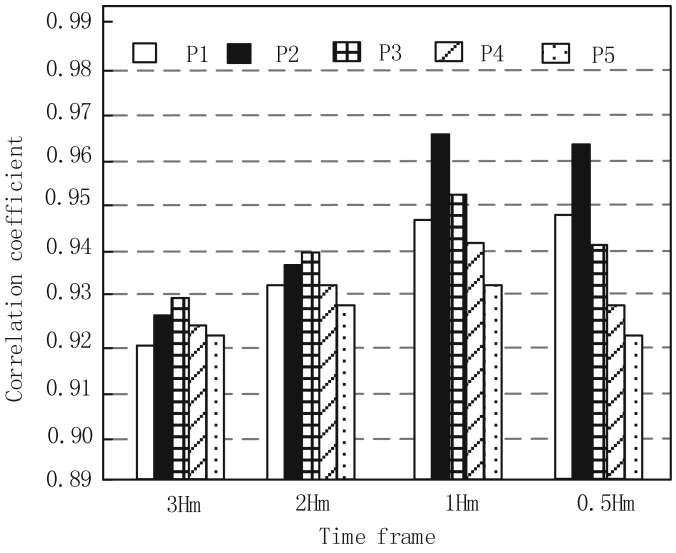
(a) Correlation test



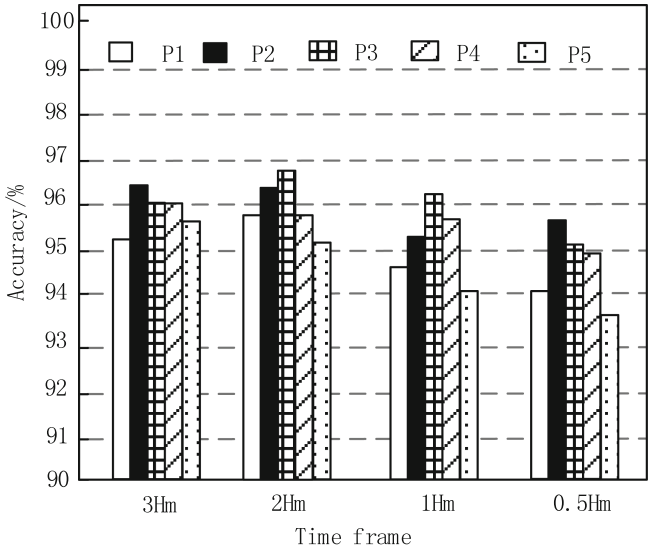
(b) Accuracy test

Fig. 4. Model performance at different time nodes

correlation between the data of social media users' mental health status test and the three-meal data gradually increased. It can be seen from Fig. 4(a) that the optimal time period is usually between one month and two months, and the most relevant data in this image is 2 Hm at time node P34. However, since depression in mental health is an unstable psychological variable that changes with time, with the further growth of original data, the correlation between online user data and mental health status gradually weakens. Predictive power is gradually diminishing. Therefore, too long observation



(a) Correlation test



(b) Accuracy test

Fig. 5. Model performance for different time periods

period is not conducive to the prediction of depression state of Weibo users. In Fig. 4(b), the prediction results under all time periods are also in the "inverted U" shape, and the accuracy rate of P3 in the 2 Hm period is also the highest overall. Therefore, the accuracy trend of the classification model can be seen in this experimental test. However, under

this trend, the mining results of the present method can still maintain over 0.91 correlation and over 92% accuracy, indicating that the mining level of the present method is relatively high.

At the lateral level, for the continuous value prediction of depression, we observed the performance at different time nodes in the same time period (0.5 m, 1 m, 2 m and 3 m), as shown in Fig. 5.

Through the model performance test results under different time periods shown in Fig. 5, it can be seen that for the same time period, the correlation of the model is not the higher the closer it is to the P1 time node, from 0.5 Hm to 3 Hm also shows a kind of Inverted U trend. In other words, for the same observation period, since the user data was obtained at the P1 time point, the P2 node in the correlation test of the model is the highest point under the same time period, that is to say, using the user's network behavior to predict the depression state has hysteresis characteristics. Under the same period of time, as the time node goes from P1 to P2, P3, and then to P4 and P5, the prediction accuracy of the model also has a clear trend of high in the middle and low on both sides. The drop from P2, P3 to P4, P5 may be caused by the data getting farther and farther away from the P1 time point. From the lateral level overall data, the mining correlation of this method is higher than 0.92, and the prediction accuracy is higher than 93%, with a good mining and prediction level.

It can be seen from the above two sets of experiments, although the best observation period is fixed, the mining and prediction results of the present method both achieve good levels. If you want to better predict the mental health status of social media users, it is best to use the data of the previous month or two to make the prediction results more accurate.

7 Conclusion

Data mining technology has been successfully applied in many fields and achieved certain results in various fields. In this paper, data mining technology is applied to the mental health data of social media users, and a data mining method for social media users' mental health testing based on machine learning algorithm is proposed. Calculate the clustering results of each data set; Innovatively extract the characteristics of social media users' mental health status, and distinguish users' mental status; Build a data mining model based on machine learning algorithm, design a data analysis algorithm, and obtain the mining results of social media users' mental health. The test results show that the mining results of social media users' mental health status obtained by this method are highly correlated, with high prediction accuracy, and improve the effectiveness of mental health mining. It is expected that the best prediction results will be obtained one to two months before the time, so as to better serve the purpose of mental health. However, due to the limitation of time and its own level, there are still some shortcomings and deficiencies in the research on the mental health data mining of social media users in this paper, and many previous assumptions have not been completed in the research. It is hoped that these remaining issues can be further studied under conditions in the future.

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