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Management Model of College Students and the Influence of Mental Health Education under the Background of Big Data

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Abstract: With the development of science and technology, the level of informatization construction in the education industry has been continuously improved, and a campus big data environment has gradually been formed. This article used three common classification algorithms for evaluation, using a test set to screen students with mental health problems for better education. According to the test results, the algorithm achieved a precision rate of 0.70, a recall rate of 0.59, and an F1 value of 0.68. A recognition method based on the DeepPsy network model was proposed, which used a two-dimensional convolutional neural network (2D-CNN) and a long short-term memory network (LSTM) to capture dependencies to further enhance the recognition effect. Additionally, by merging basic features and trajectory patterns, a deep learning network was created. According to the experiment, the precision rate was 0.73, and the recall rate was 0.76, with the F1 value of 0.72., making it possible to recognize 76% of students who had mental health issues.

1. Introduction

The cultivation of high-quality talents in the 21st century depends to a large extent on the development of global university education, which is characterized by fierce competition. As a crucial position for cultivating outstanding talents, the school vigorously advocates high-quality teaching as one of its main goals. Improving the maturity of college students and the availability of mental health services is an important part and prerequisite for improving the overall level of colleges and universities, and the potential, personality and adaptability of college students are enhanced through mental health education. Therefore, improving the mental health level of college students is a key step to ensure the modernization of college students. In other words, the improvement of the comprehensive quality of college students in the new period largely depends on the improvement of college students' management methods and the strength of college students' mental health education. However, the administration of college students is chaotic, and the development of university mental health education still exhibits imbalance. Therefore, innovation in college student management and mental health education research is just around the corner.

This paper's originality is the ability to uncover the innate traits and anticipated traits of college students through the study of big data, which is crucial for raising the level of college and university management. The big data is thoroughly studied. By collecting and consulting a large number of related literatures on the stage analysis of management mode and education, the coupling relationship between big data and college students' management and education, the basic principles and algorithms of data mining technology, this study also examines the impact of information technology on college students' management style and mental health education, and tries to apply data mining technology.

2. Related Work

College students' mental health has recently come to the attention of parents and educators. Researchers have made an effort to improve mental health education by using data from college students. According to Dong H's research, it is very necessary to carry out cross-sectoral liaison at the national, regional and local levels to integrate mental health into the health management system of public education [1]. Kiima D pointed out that the importance of mental health education for both human health and social education needed to be emphasized [2]. Askari M emphasized the benefit of conflict resolution and communication training for mental health [3]. Armbruster L showed that real data on the treatment of patients with mental health problems is a crucial source for benchmarking, service evaluation, and mental health education [4]. Although the current international education field attaches great importance to the mental health education of college students, and guides psychological counselors to provide psychological counseling to students, there are still many college students with mental illnesses, and the total number is countless. Moreover, a larger part of college students indicate that they have experienced abnormal mood swings or have a tendency to depression. Such mental distress inevitably has a bad impact on their physical and mental health and learning[5].

With the rapid development of contemporary social informatization construction, the education management of college students should also be advanced according to the times. With its unique and precise advantages, big data helps colleges and universities manage and educate college students, and serves individual college students, colleges and the society. Aikat J showed that the scientific method is being supplemented rapidly, and the era of big data has fundamentally changed the way of scientific research and the discovery of new knowledge [6]. Diebolt C's research found that the database of big data is huge, which is of critical importance to researchers in the field of education [7]. Zhao Y's research led to the suggestion of a deep computational model to examine the variables influencing social and mental health. The model obtained the degree of correlation between psychosocial health and these factors by comparing retrospective data on different influencing factors [8]. Williams MO pointed out that causal models can be used to explain data and test directions that are closely related to mental health [9]. Despite the fact that there have been numerous studies on big data technologies in the area of mental health, most of them have concentrated on the identification and diagnosis of mental health issues, with a lot of potential for application in the area of mental health education[10].

3. Application of Data Mining Technology Based on Big Data

3.1 Integration of Big Data and Management and Education of Colleges and Universities

(1) Stage analysis of college students' management mode and education

At present, big data has become the development direction of informatization construction in various universities, which is mainly reflected in the integration and processing of data and the mining and acquisition of valuable information [11]. Before the incorporation of electronic information technology and Internet technologies in the electronic stage and digital stage for educational management, the application of big data in the management and education of colleges and universities relied on the manual sorting of paper files [12-13]. Big data is actually a manifestation of digital management and education upgrading to a certain stage. From traditional management and education to big data management and education, it needs to go through several stages, Specifically, it is the traditional stage stage, the electronic stage stage, the digital stage stage, the current stage stage, and the big data era stage.

In the life cycle of college student management, the data of students in school mainly includes static document data, academic data, behavior data, various census data and supplementary information of students. In the subsequent data mining process, in order to protect the private information of students, the integrated campus data should be desensitized first. Secondly, according to different research goals, the desensitized data is cleaned, formatted, filled with missing values and other preprocessing work, including comprehensive and detailed feature engineering steps. Then different models are built for analysis and mining, finally combining visualization methods to display the analysis results intuitively, which is convenient to help managers in their daily work.

(2) Coupling relationship between big data and college students’ management mode and mental health education

Colleges and universities are currently primarily developing their big data platforms, big data analytic capabilities, and big data service models. College students' management and instruction can both benefit from the integration of big data. There is a theoretical correlation between the two, and its existence has laid the foundation for the precise management and mental health education of college students in the era of big data. Figure 1 depicts the association between big data, college students' management style, and mental health education.

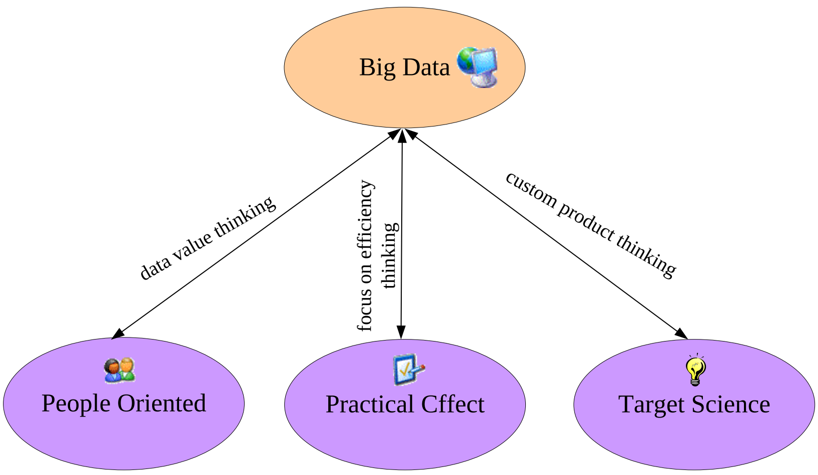


Figure 1. Coupling relationship between big data and college students' management model and mental health education

As shown in Figure 1, the management model and the mental health education of college students carry out the coupling of data value thinking and people-oriented for the college students, so as to realize the comprehensive and unlimited development of college students. Through the application of data value thinking, it is possible to unlock the potential of individuals and observe how they are able to benefit others by using science and technology, which creates a positive feedback loop for growth. The integration of data value thinking and people-oriented nature is then put into practice.

3.2 Algorithms Related to Management Mode Based on Data Mining Technology

With the rapid development of network technology, increasingly mature big data technology and pervasive data applications, human data has grown exponentially. People began to dedicate themselves to mining some potential information from these massive data, resulting in various data mining techniques.

(1) Decision tree (DT) algorithm

In the process of decision tree representation, the information gain is calculated to determine the best attribute to split. The ideal attribute is the one with the most information gain following division, and information gain is determined using information entropy. The formula for calculating the size of the measurement information is shown in Formula 1:

$$L(x_l) = \log_2 \frac{1}{q(x_l)} \tag{1}$$

According to Formula 1, $q(x_l)$ represents the probability of event x_l occurring. $L(x_l)$ is the amount of information for event x_l.

Assuming that there are n mutually incompatible events $x_1, x_2, \cdots, x_n$, and only one of them occurs, its entropy can be measured as Formula 2:

$$L(x_1, x_2, \cdots, x_n) = \sum_{l=1}^{n} L(x_l) = \sum_{l=1}^{n} Q(x_l) \log_2 \frac{1}{q(x_l)} \tag{2}$$

Assuming that X is a variable with a finite number of different values $x_1, x_2, \cdots, x_n$, its information content can be measured by its information entropy. The information entropy of X is defined as Formula 3:

$$F(X) = \sum_{l=1}^{n} Q(x_l) \log_y \frac{1}{q(x_l)} \tag{3}$$

In Formula 3, usually $y = 2$ is taken and $q(x_l) = 0$ is specified.

$$q(x_l) \log_y \frac{1}{q(x_l)} = 0 \tag{4}$$

Assuming that W is the sample set and $|W|$ is the number of samples, the samples are divided into different classes $D_1, D_2, \cdots, D_n$, and their sizes are recorded as $|D_1|, |D_2|, \cdots, |D_n|$. Then the probability of sample W is as Formula 5:

$$Q(W_l) = \frac{|D_l|}{|W|} \tag{5}$$

According to Formula 5, the average information entropy is as Formula 6:

$$F(W|D_1, D_2, \cdots, D_n) = \sum_{l=1}^{n} \left(\frac{|D_l|}{|W|} \log_2 \frac{|W|}{|D_l|} \right) \tag{6}$$

Formula 5 is the definition of information entropy for random variable X taking a finite number of values. Assuming that there are two non-independent random variables A and B, which both take finite values. Then when $B = b_i$ is known, the conditional entropy of A can be defined as Formula 7:

$$F(A|B = b_i) = \sum_i Q(a_l|b_i) \log_2 \frac{1}{Q(a_l|b_i)} \tag{7}$$

Among them, the sum is over all values of A. Given B, the average conditional entropy of A is defined as Formula 8:

$$F(A|B) = \sum_i Q(b_i) \sum_i Q(a_l|b_i) \log_2 \frac{1}{Q(a_l|b_i)} = \sum_l \sum_i Q(a_l, b_i) \log_2 \frac{1}{Q(a_l|b_i)} \tag{8}$$

In decision tree classification, assuming that X is an attribute that takes a finite number of different values $x_1, x_2, \cdots, x_n$, which can divide training sample set W into n subsets $\{W_1, W_2, \cdots, W_n\}$, then applying Formula 8, the conditional entropy of the decision tree classification divided by attribute X can be obtained as Formula 9:

$$F(W|X) = \sum_{i=1}^{n} Q(W_i) \sum_{l=1}^{n} Q(D_l|W_i) \log_2 \frac{1}{Q(D_l|W_i)} \tag{9}$$

Among them, $Q(W_i) = \frac{|D_i|}{|W|}$, and $Q(D_l|W_i)$ is the probability that subset W_i belongs to class D_l. Assuming $|W_{li}|$ represents the number of samples of class D_l in subset W_i, then Formula 10 can be obtained:

$$Q(D_l|W_i) = \frac{|W_{li}|}{|W|} \tag{10}$$

Since $F(W|X)$ is not equal to $F(W)$, the sample classification has changed.

(2) Gradient boosting decision tree (GBDT) and neural network (NN)

The implementation principle of GBDT algorithm is as follows: The input is dataset $P = \{(a_1, b_1), (a_2, b_2), \ldots, (a_n, b_n)\}$, loss function F; the output is additive model $k(a) = k_N(a)$.

The base classifier is initialized as Formula 12:

$$k_0(a) = \arg\min_\gamma \sum_{i=1}^{M} F(b_i, \gamma) \tag{11}$$

Each base classifier needs to do the followings:

$$h_{in} = -\left[\frac{\partial F(b_i, k(a_i)}{\partial, k(a_i)} \right] \tag{12}$$

For a given h_{in}, a regression tree is fit to get the leaf node H_{ng} of the tree, and $g = 1,2,\ldots,G$ is the number of leaf nodes.

The GBDT is established based on the results of the previous tree. The latter can ensure the continuity of features, and there are many nonlinear transformations, which are helpful for the transformation of features and the generation of high-dimensional features.

3.3 Mental Health Education Recognition Algorithm Based on DeepPsy

A two-dimensional convolutional neural network (2D-CNN) is used to build an eight-layer neural network layer. The first and fourth layers of the neural network layer are convolutional layers, and the same convolution is used at the same time. That is, the edges of the matrix are filled with 0. In this way, the dimension of the matrix is not change after the convolution operation. In the training of the model, the input of each student is M matrices, and the size of each matrix is $B * G$. Among them, M is the total number of days, and B is the number of page types. G is the number of time periods. The operation of the convolutional layer is shown in Formula 17:

$$a_q^i = f\left(\sum\nolimits_{p \in W_q} a_p^{i-1} * z_{pq}^i + y_q^i\right) \tag{13}$$

In Formula 17, a_q^i is the feature map corresponding to the q-th convolution kernel of the i-th layer, and a_p^{i-1} represents the input. z_{pq}^i represents the q-th convolution kernel of the i-th layer. y_q^i is the offset corresponding to the q-th kernel. $f(\cdot)$ is the activation function and $*$ is the multiplication operation.

The operation of the pooling layer is shown in Formula 18:

$$\hat{a}_q^i = f(V_q^i) down(a_q^i) + y_q^i \tag{14}$$

In Formula 18, a_q^i represents the input. V_q^i represents the weight matrix. y_q^i represents the bias and $down(a_q^i)$ represents the downsampling functions.

After going through the 2D-CNN part, the feature data is extracted. In the ninth hidden layer, the LSTM is used to capture the time dependence between day.

4. Experimental Results of the Impact of Big Data on the Management Model and Mental Health Education of College Students

4.1 Experimental Results Based on Classification Algorithms

Based on the research goal of a binary classification problem, a classification algorithm was selected as a candidate algorithm, including decision trees, gradient boosting decision trees, and neural networks, and a classifier was selected from them. The dataset was divided into training set, validation set, and test set, and the training set was used to train each classification algorithm separately. The ideal parameter combination for each potential classification algorithm was chosen after experimenting with several parameter combinations, as shown in Table 1.

As shown in Table 1, for model training and prediction, the retrieved features were fed into the classification algorithm. The accuracy rate was higher than the recall rate in all models, which is the first thing that stands out and suggests that there were fewer samples that could be accurately identified. Second, the decision tree had the best overall performance, with the recall rate seeing the most improvement. The experimental findings for comparing three popular classification methods, DT, GBDT, and NN are displayed in Table 2.

Table 1. Candidate classification algorithm parameter settings

Classification Algorithm	Parameter	Parameter Value
DT	criterion	gini
	max_depth	13
	min_samples_split	8
	min_samples_leaf	3
GBDT	learning_rate	0.02
	max_depth	11
	n_estimators	62
NN	solver	lbfgs
	alpha	le-3
	hidden_layer_sizes	（40,40）

Table 2. Results of three classification algorithms to identify students with mental health problems

Classification Algorithm	Precision	Recall	F1-Measure
DT	0.70	0.59	0.68
GBDT	0.65	0.54	0.63
NN	0.62	0.51	0.65

As shown in Table 2, The test data set was fed into the algorithm to assess its generalization capabilities, and the following experimental findings were made: The algorithm had an F1 value of 0.68, a precision of 0.70, and a recall of 0.59. The algorithm was able to recognize 59% of pupils with mental health issues, according to the test set's experimental results.

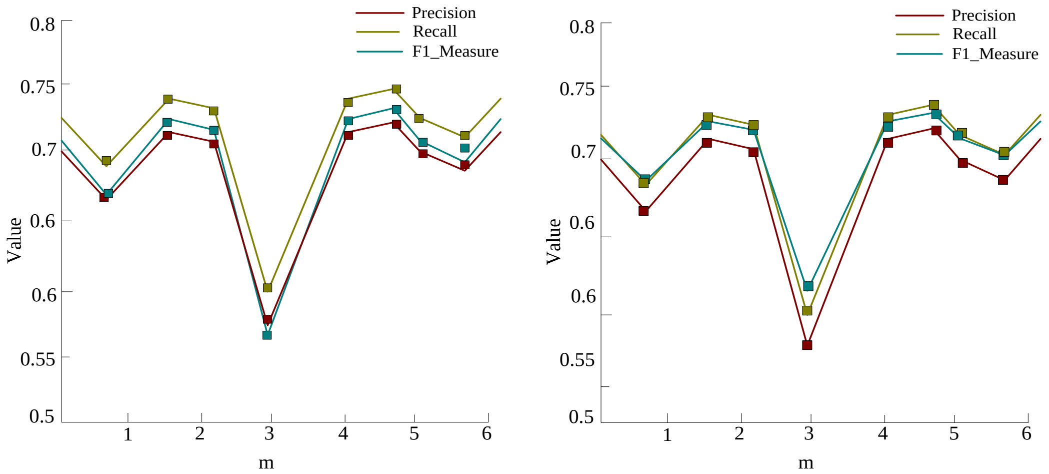
4.2 Identification Results Based on DeepPsy

(1) Parameter analysis

The DeepPsy model is mainly divided into two modules. The first module designs a joint model of 2D-CNN and LSTM, which is responsible for extracting the hidden patterns of students' online behavior trajectories. The second module uses the basic features (including abnormal scores) extracted from the four data sources as input to establish a fully connected neural network, which is responsible for building the impact of students' basic features on the identification of mental health problems, and making output connections.

When other parameters remain unchanged, the number of convolution kernels was generally set to 2^m. In the parameter adjustment process of this experiment, m was set to 1, 2, 3, 4, 5, and 6 in turn. For the parameter batch_size, if other parameters remained unchanged, m=1, 2, 3, 4, 5, 6 were also taken. The experimental results of the first convolutional neural network layer using different number of convolution kernels and the experimental results obtained using different batch_siz are shown in Figure 2.

As shown in Figure 2(a), comparing the six sets of experimental results, the fluctuation amplitudes of Precision, Recall, and F1-Measure were 3%, 6%, and 4%, respectively, indicating that the outcomes of the experiment were largely unaffected by the number of convolution kernels in the first convolutional layer. Comparing the six sets of experimental data, Figure 2(b) demonstrates that the Precision, Recall, and F1-Measure fluctuation ranges were 5%, 8%, and 6%, respectively. Batch size had a marginally bigger influence on the experimental outcomes than the quantity of convolution kernels in the first convolutional layer.



(a). Experimental results with different number of convolution kernels

(b). Experimental results with different batch_size

Figure 2. Experimental results obtained with different number of convolution kernels and different batch_size

(2) Experimental results

This paper trained the model with the following feature sets: feature set I, feature set II, feature set III, and feature set IV in order to better examine the impact of features on the experimental outcomes. Table 3 displays the experimental results of various feature combinations on the DeepsPsy model.

Table 3. Experimental results of four different feature combinations on the DeepPsy model

Data Set	Precision	Recall	F1-Measure
I	0.73	0.77	0.74
II	0.71	0.75	0.72
III	0.68	0.70	0.69
IV	0.62	0.59	0.57

As shown in Table 3, the experimental result of feature set I was the best. Secondly, with the reduction of feature types, the experimental effect gradually deteriorated, and especially the decline of feature set IV was larger, because the experiment's findings were more significantly impacted by the vast number of consumption factors. The outcomes of the trial demonstrated that a range of behavioral data can enhance the detection of mental health issues in pupils.

It was hoped to test as many of these college students as possible and pay greater attention to them in order to better educate pupils with mental health difficulties. The recall rate value of the model needed to be given additional consideration, because according to its description, it indicated the percentage of college students who were anticipated to be positive samples among those who really were. The experimental results of the DeepPsy model were also compared. For the convenience of visual comparison, the two sets of results are presented visually, as shown in Figure 3.

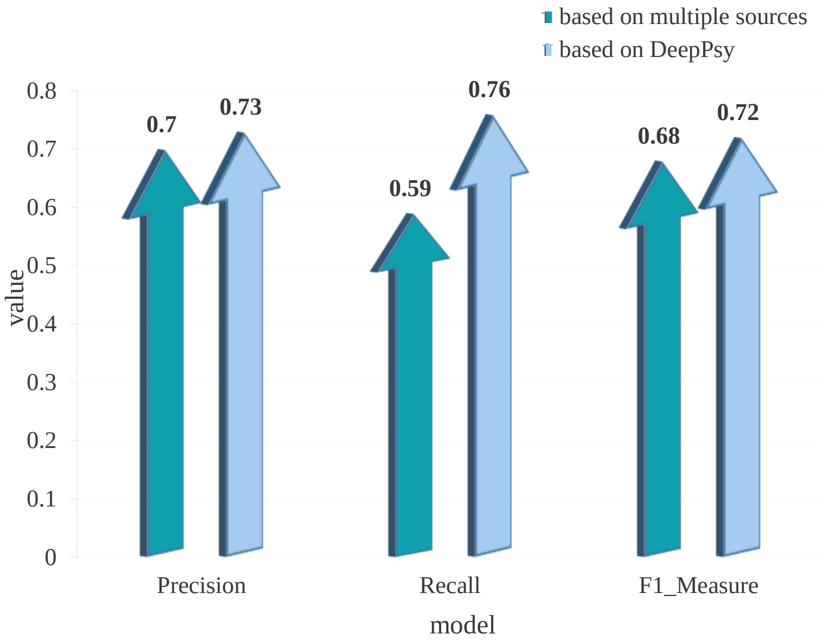


Figure 3. Comparison of DeepPsy model and multi-source data model

Figure 3 shows that the DeepPsy model had the greatest improvement, with the recall rate index rising to 0.76, 17% higher than it was before the upgrade, indicating that the model can recognize 76% of children with mental health issues. The aforementioned tests demonstrated that the validation set was used to evaluate the best algorithm classifier, and the test set was utilized to identify children with mental health issues in order to provide them with a better education. The algorithm had an F1 value of 0.68, an accuracy rate of 0.70, and a recall rate of 0.59. The online trajectory matrix was created based on the DeepPsy model's mental health problem recognition algorithm in order to better optimize the model's recognition performance. The surfing pattern of one day was extracted using a 2D-CNN, and the temporal dependence between each day was captured using an LSTM. By merging the fundamental characteristics and surfing trajectory patterns, a deep learning network was also created. According to the experimental findings, the DeepPsy model-based identification algorithm had an accuracy rate of 0.73, a recall rate of 0.76, and an F1 value of 0.72, and it could recognize 76% of students who had mental health issues. The two algorithms' experimental results were examined, and the following findings were made: College students' behavior data can be examined, and by using a range of behavior data, management innovations can be developed in accordance with the data content.

5. Conclusions

Big data research has made a significant impact on modern science and technology and has been successfully applied to a wide range of fields. This essay examined how college students are currently managed, the current state of mental health education, and the significance of psychological counseling in colleges and universities. It also made the case for the importance of using data mining technology in management research and mental health education at colleges and universities. The fundamental structure and functional modules of the data mining system for college students' management mode and mental health education were proposed after a thorough study of the data mining technology. The recognition algorithm of the DeepPsy model was applied to the already-existing college students' psychological problem database and college students' mental health assessment system to statistically predict the outcomes. Therefore, this research has good application value. Students who are at risk of mental health problems can be identified through the prediction results, so that college administrators can better understand the psychological situation of students, and give students psychological help and targeted education as soon as possible, thereby avoiding further deterioration of students' psychological condition. However, due to the large dimension of management data, with the increase of dimensions, traditional classification algorithms can no longer measure the similarity of objects well. Therefore, the next research focus is to further optimize the clustering algorithm from the perspective of dimensionality reduction.

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