

DESIGN OF EARLY WARNING SYSTEM FOR MENTAL HEALTH PROBLEMS BASED ON DATA MINING AND DATABASE



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PROJETO DE SISTEMA DE ALERTA PRECOCE PARA PROBLEMAS DE SAÚDE MENTAL COM BASE NA MINERAÇÃO DE DADOS E BANCO DE DADOS

DISEÑO DE UN SISTEMA DE ALERTA TEMPRANA DE PROBLEMAS DE SALUD MENTAL BASADO EN LA MINERÍA DE DATOS Y EN LA BASE DE DATOS

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ABSTRACT

Introduction: Data mining technology is mainly employed in the era of big data to evaluate the acquired information. Subsequently, reasoning about the data inductively is fully automated to discover possible patterns. **Objective:** Recently, data mining technology in the national mental health database has deepened and can be effectively used to solve various mental health early warning problems. **Methods:** For example, it can be applied to mine psychological data and extract the most important features and information. **Results:** This paper presents the design of an early warning system for mental health problems based on data mining techniques to offer some thoughts on early warning of mental health problems, including data preparation, data mining, results in analysis, and decision tree algorithm. **Conclusion:** The experimental results indicate that the results of the early warning system in this paper can achieve an accuracy rate of more than 96% with a high accuracy rate. **Level of evidence II; Therapeutic studies - investigating treatment outcomes.**

Keywords: Data Mining; Database; Mental Health; Early Warning Systems.

RESUMO

Introdução: A tecnologia de mineração de dados é empregada principalmente na era da big data para avaliar as informações adquiridas. Posteriormente, raciocinar indutivamente sobre os dados de forma totalmente automatizada para descobrir possíveis padrões. **Objetivo:** Recentemente, a tecnologia de mineração de dados no banco de dados nacional de saúde mental tem se aprofundado e pode ser efetivamente utilizada para resolver vários problemas de alerta precoce da saúde mental. **Métodos:** Por exemplo, ela pode ser aplicada para a mineração de dados psicológicos e extrair as características e informações mais importantes. **Resultados:** Este documento apresenta o projeto de um sistema de alerta precoce para problemas de saúde mental baseado em técnicas de mineração de dados, com o objetivo de oferecer algumas reflexões sobre alerta precoce de problemas de saúde mental, incluindo preparação de dados, mineração de dados, análise de resultados e algoritmo de árvore de decisão. **Conclusão:** Os resultados experimentais indicam que os resultados do sistema de alerta precoce neste trabalho podem alcançar uma taxa de precisão de mais de 96% com uma alta taxa de precisão. **Nível de evidência II; Estudos terapêuticos - investigação dos resultados do tratamento.**

Descritores: Mineração de dados; Base de dados; Saúde mental; Sistemas de Alerta Rápido.

RESUMEN

Introducción: La tecnología de minería de datos se emplea principalmente en la era de la big data para evaluar la información adquirida. Posteriormente, razonar inductivamente sobre los datos de forma totalmente automatizada para descubrir posibles patrones. **Objetivo:** Recientemente, la tecnología de minería de datos en la base de datos nacional de salud mental se ha profundizado y puede ser utilizada eficazmente para resolver varios problemas de alerta temprana de salud mental. **Métodos:** Por ejemplo, puede aplicarse para minar datos psicológicos y extraer las características e información más importantes. **Resultados:** Este trabajo presenta el diseño de un sistema de alerta temprana de problemas de salud mental basado en técnicas de minería de datos, con el objetivo de ofrecer algunas reflexiones sobre la alerta temprana de problemas de salud mental, incluyendo la preparación de los datos, la minería de datos, el análisis de los resultados y el algoritmo de árbol de decisión. **Conclusión:** Los resultados experimentales indican que los resultados del sistema de alerta temprana de este documento pueden alcanzar un índice de precisión superior al 96% con un alto índice de precisión. **Nivel de evidencia II; Estudios terapéuticos - investigación de los resultados del tratamiento.**

Descriptorios: Minería de Datos; Base de Datos; Salud Mental; Sistemas de Alerta Temprana.



INTRODUCTION

In recent decades. Computer storage devices, as well as the speed of network transmission and data exchange, have increased significantly. The development and implementation of these technologies have accelerated the development of database technology. Especially since the 1970s, the relatively structured data tables stored in database systems have been extended to various fields of culture, politics, economics, social life, and social management.

Help psychologists make psychological judgments and prevention more scientifically and quickly, and timely conduct psychological counseling and intervention, improve work efficiency, and reduce the occurrence of psychological problems.

Lu H proposed a method to discover symbolic classification rules using neural networks. and experimental results clearly demonstrate the effectiveness of the method.¹ To test its capability of generalization and promote the wide application of IQA techniques in practical applications, Ma K built a large-scale Waterloo detection database, which currently includes 4744 original natural images and 94 880 Distortion pictures. ma K proposed three test criteria for evaluating the performance of IQA models, i.e., original/distortion image recognition test, list ranking consistency test, instead of subjective test to collect the average opinion score of each image for matching preference consistency test (P-test). This research is costly and impractical.² Harley M presented the DEmlia-Romagna Early Warning System (ER-EWS), which includes several ranges of numerical phantoms (COSMO, ROMS, SWAN, and XBeach.) He performed three different reanalysis models: a default forecast (DF) model which is built on 3-day forecasts of swells and water heights and default XBeach parameters; an offshore prediction that uses wave and water level measurements and default XBeach parameter measurements; There are algorithms and models in this method that are worth learning, but the study is more one-sided.³

The innovations of this paper are: (1) Propose the use of PEP post-pruning algorithm to pruning the decision tree; (2) Design a mental health data analysis platform based on Hadoop; (3) Propose a system database design.

METHODS

Design Method Of Mental Health Problem Warning System Based On Data Mining And Database

Process of Data Mining

1. Data preparation

Data preparation consists of two steps: identification of mining objects and data pre-processing. Data preparation is a very important and probably the longest part of the data mining process.^{4,5} The study and all the participants were reviewed and approved by Ethics Committee (NO. HJ1204178)

2. Data mining

The data pre-processed data is used as the data source for data mining, and certain mining algorithms are used for in-depth analysis, which is the process of data mining.⁶ Data mining includes several parts, such as determining the type of mining tasks, selecting mining algorithms, and comparing data.^{7,8}

3. Result analysis

Result analysis is to use corresponding analysis methods to interpret, evaluate, and evaluate the mining results based on the mining operations.⁹

Common Data Mining Techniques

1. Statistics

Statistics is a long-established discipline and it is also the most fundamental technical tool for data mining. Frequently used statistical

analysis methods include discriminant analysis, principal component analysis, element theory, and multiple regression analysis.¹⁰

2. Cluster analysis

One of the most important techniques of data mining is cluster analysis. Cluster analysis is based on the actual characteristics of each other to cluster or classify, and can find the existing rules and representative methods. In the past, the clustering method of multivariate statistical analysis has been used, but in recent years, new clustering methods such as fuzzy clustering and neural network clustering methods have emerged.¹¹

3. Decision of tree classification technology

The decision-making of tree classification technology refers to the use of tree structure to carry out classification work or collective work according to various characteristics. It is very easy to explore the internal rules of the tree structure. It is very easy to explore the inner rules of classification work or assembly work.^{12,13} This article uses decision tree data mining technology.

Decision Tree Algorithm

1. Overview

The essence of decision tree algorithms is to classify the analyzed data using a set of rules. Most decision tree algorithms are greedy algorithms that construct decision trees in a top-down divide and retain retrospective manner starting with a set of practice samples and their associated category labeling.^{14,15}

2. Information gain

Amount to information required for identifying the tuples on tuples attribute M between before and after tuples segmentation.^{16,17} has the following connection.

$$(M)_{Gain} = (L)_{Info} - (L)_{Info_M} \quad (1)$$

$$(L)_{Info} = - \sum_{i=1}^k Q_i \log_2(Q_i) \quad (2)$$

$$q_i = Q(t \in C_i | \forall t \in L) \quad (3)$$

$$(D)_{Info_N} = \sum_{j=1}^n \frac{|L_j|}{|L|} \times (L_j)_{Info} \quad (4)$$

Since the property M has a known value, the entropy value decreases. This decrease in entropy can be obtained by the following equation

$$Gain(N) = Info(D) - Info_N(D) \quad (5)$$

Classification actually extracts from the system information that will reduce the level of chaos in the system and move the system in a direction that is both more disciplined, more orderly, and less structured.^{18,19}

3. Information gain probability

There is a tendency for information benefit metrics to use the partitioning of attributes that have greater numbers of branches, using a gain rate metric that normalizes the information gain by the split information value.²⁰ The split information is defined by the following equation.

$$SplitInfo_N = - \sum_{j=1}^n \frac{|L_j|}{|L|} \times \log_2 \left(\frac{|L_j|}{|L|} \right) \quad (6)$$

The yield is defined as.

$$\text{GainRatio}(N) = \frac{\text{InfoGain}(N)}{\text{SplitInfo}(N)} \quad (7)$$

4. Gini Index

Genie exponent is a metric employed in CART operator. Purity of a partition of data or trained metric L is measured based on the Gini index.^{21,22} It is defined as the equation.

$$(L)_{Gini} = 1 - \sum_{i=1}^k Q_i^2 \quad (8)$$

$$q_i = q(t \in C_i | \forall t \in L) \quad (9)$$

Ginny exponents are obtained for each attribute as a binary division. Assume that the attribute N on L has a certain binary division by L being divided into L_1 and L_2 . this division has a Gini exponent whose definition is

$$(L)_{Gini_N} = \frac{|L_1|}{|L|} (L_1)_{Gini} + \frac{|L_2|}{|L|} (L_2)_{Gini} \quad (10)$$

The reduction of trash as a result of such division is specified as

$$\Delta Gini(M) = (L)_{Gini} - (L)_{Gini_N} \quad (11)$$

5. Tree pruning

The specific implementation of pruning is to cut off several branches based on a certain pruning algorithm, and then replace them with leaves.

$$r(t) = e(t) / n(t) \quad (12)$$

The PEP algorithm modifies it to:

$$r'(t) = [e(t) + 1/2] / n(t) \quad (13)$$

Let S be the subtree T_t of T, L(S) represents the number of T_t leaf nodes, then the classification error rate of T_t is:

$$r'(T_t) = \frac{\sum e(s) + \frac{L(S)}{2}}{\sum n(s)} \quad (14)$$

For simplicity, in quantitative analysis, the number of errors is used instead of the error rate, then:

$$e'(t) = e(t) + 1/2 \quad (15)$$

And for the subtree T_t there are:

$$e'(T_t) = \sum e(s) + \frac{L(S)}{2} \quad (16)$$

The PEP algorithm adopts a top-down approach. When the following inequality is satisfied, T_t should be pruned and replaced with the corresponding leaf node²³.

$$e'(t) \leq e'(T_t) + S_e(e'(T_t)) \quad (17)$$

Where T_t represents the subtree with node t as the root node, $S_e(e'(T_t))$ is the standard error, defined as:

$$S_e(e'(T_t)) = \sqrt{\frac{e'(T_t)[n(t) - e'(T_t)]}{n(t)}} \quad (18)$$

where $e(t)$ denotes a quantity of misclassified instances of node t while $n(t)$ stands for a quantity of training set of node t. Since each subtree is visited at most once during the pruning process of the PEP algorithm, the algorithm is faster and more effective than other algorithms. It is considered as one of the most accurate pruning algorithms.^{24,25}

The methodological part of this paper uses the above-mentioned methods for the design and research of data mining as well as database based early warning system for mental health problems.^{26,27} Its process are illustrated by Table 1.

Design experiment of mental health warning system based on data mining and database

Hadoop-based Mental Health Data Analysis Platform

1. Hadoop framework

It is an open source, distributed base framework developed by Apache. Its two core concepts are MapReduce, a distributed programming model, and HDFS, a distributed file system.²⁸ The main advantage of this framework is the high efficiency of data processing. the parallel working model in the Hadoop framework can speed up data processing and process large amounts of data in a short time.^{29,30}

2. Overview of Hadoop

The Hadoop framework consists of two main parts. A file system was able to be implemented in Hadoop in the form of a distributed HDFS, MapReduce is an equally presented distributed concurrent calculation platform realized within Hadoop.

Hbase is a distributed mental health database developed by Google on the basis of BigTable. This offers access the mental health statistics in real time. It retrieves mental health information by means of primary bonds as well as fields, making it better suited for the storage of loosely defined data.

Pig, Hadoop's scripting language, which allows querying and manipulating mental health data structures in programs.

System Database Design

This trial suggested using these steps in the design trial for a mental health early warning system using data extraction and database. An experimental procedure is presented below in Table 2.

Table 1. Technology course for approaching.

Methodology for designing an early warning system for mental health problems based on data mining and database				
The process of data mining	2.2	Common data mining techniques	2.3	Decision tree algorithm
Data preparation	1	Statistics	1	Overview
Data mining	2	Cluster analysis	2	Information gain
Result analysis	3	Tree classification technology decision	3	Gain rate
Knowledge assimilation	4	Artificial neural network algorithm	4	Gini indicator
			5	Tree pruning

Design and analysis of mental health problem early warning system based on data mining and database

Algorithm Comparison

1. The classification accuracy of the verification sample set of the class is 0.8125, that is, the students who are indeed "abnormal" have the possibility of 0.8125 to return the correct result "abnormal", as shown in Table 3 and Figure 1.

There is no over-fitting in the application of this model, that is to say, in actual problems, assuming that other symptoms are the same, they will not be classified into different classes due to subtle differences in decision tree classification.

2. Using the "tic" and "toc" functions in MATLAB can get the speed of establishing models of different algorithms and using models for classification. The specific time comparison is shown in Table 4 and Figure 2.

The modeling time based on the BP neural network algorithm model is the longest, which takes 6.9546 seconds; the modeling time based on the pattern recognition network model and the random forest is in the middle, which takes 1.7631 seconds and 1.3427 seconds respectively; the modeling time based on the CART decision tree model is the shortest. It only takes 0.5362 seconds. The classification time is between 0.02 and 0.03 seconds, with little difference.

3. The best algorithm for this study was selected based on four evaluation metrics: accuracy, precision, recall, and F-value. The specifics were plotted as graphs, which are shown in Table 5 and in Figure 3.

According to the algorithm performance evaluation as shown in Figure 3, it can be seen that a CART decision table tree is more applicable to the present study with more reliable forecast outcome. As a result, the CART decision tree algorithm will be used to establish a mental health early warning model for this study and application.

Experiment Analysis

1. The analysis nodes were employed for assessing model accuracy according to this paper's methodological part of the decision tree model. Table 6 and Figure 4 show the prediction accuracy for all samples from

Table 2. Some steps of this experiment.

Design experiment of mental health warning system based on data mining and database	3.1	Hadoop-based mental health data analysis platform	1	Hadoop framework
			2	Overview of Hadoop
			3	JSON
	3.2	System database design	1	Select database
			2	Add user record
			3	Database security design

Table 3. Classification accuracy of decision tree.

Sample category	Normal		Abnormal	
	Correct	Error	Correct	Error
Test Results	Correct	Error	Correct	Error
Accuracy	0.9754	0.0246	0.8125	0.1875

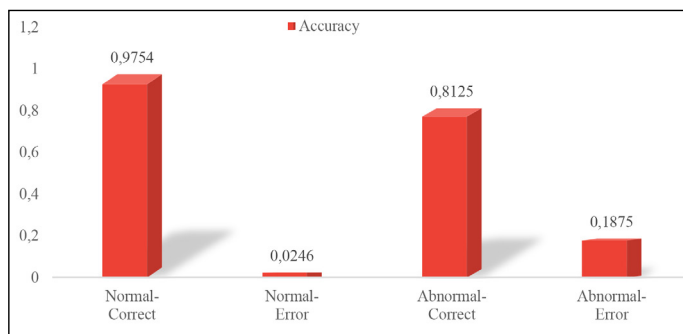


Figure 1. Classification accuracy of decision tree.

Table 4. Running time of four algorithms (s).

Algorithm	Modeling time	Classification time
CART decision tree	0.5362	0.0217
Random forest	1.3427	0.0278
BP neural network	6.9546	0.0291
Pattern recognition network	1.7631	0.0286

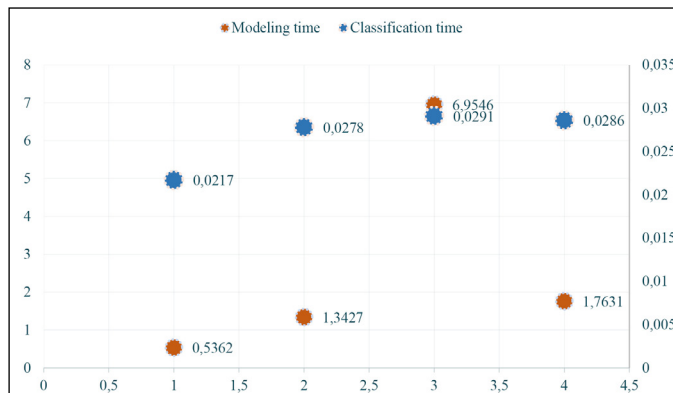


Figure 2. Four algorithm operation time (s).

Table 5. Algorithm performance evaluation.

	Accuracy	Precision rate	Recall rate	F value
ID3	89.64%	69.47%	54.12%	52.34%
C4.5	92.31%	75.18%	50.74%	57.07%
CART	97.25%	89.73%	60.26%	71.55%

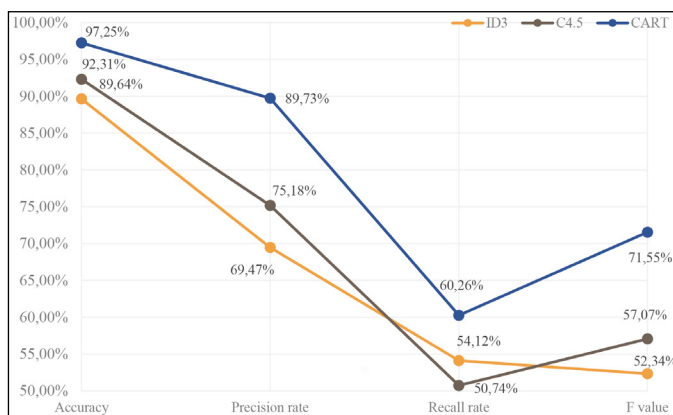


Figure 3. Evaluate the Algorithm's Capabilities.

both practice and test sets for simple Individual Horizontal models for decision making trees, Simple and complex financial decision tables for clinical simulation.

In terms of precision for assessment collection, simple early warning models were approximately the same as those for multiple warning models, suggesting that simple early warning models can be used to guide psychologists in different levels of mental health diagnosis.

2. To better test the generalization ability of the model, the stability of the model for different datasets can be better judged by considering the differences in the datasets collected from different populations. After classifying the data from different populations, they were put into the model as a test set for quantitative testing. The test results were presented at Tables 7 together with Figure 5.

According to the results of testing the data sets of four different groups of people, the overall accuracy of the model can reach more than 96%, the accuracy rate of early warning results can reach more than 90%, the recall rate can basically reach more than 58%, and the F value is Stable above 73%.

Table 6. Forecast outcomes for all four projects.

Predicted outcomes	Accuracy of the control group	Accuracy of the measurement collection	Precision accuracy for total volume of specimen
Easy individual horizontal pattern	81.47%	82.15%	77.19%
Simple clinical model	93.42%	95.63%	93.17%
Complex clinical	97.81%	97.18%	96.74%

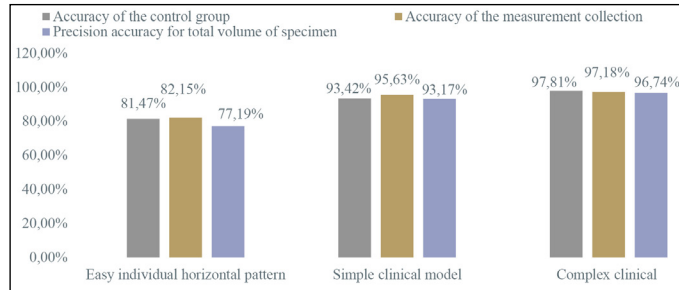


Figure 4. Results of the three ways of inquiry.

Table 7. Model test results.

	Number of samples	Accuracy	Precision rate	Recall rate	F value
Juvenile	264	96.32%	91.65%	61.23%	75.61%
Youth	382	98.25%	92.14%	58.47%	73.28%
Middle aged	347	97.17%	90.68%	60.59%	74.73%
Old age	213	96.09%	91.49%	59.94%	75.48%

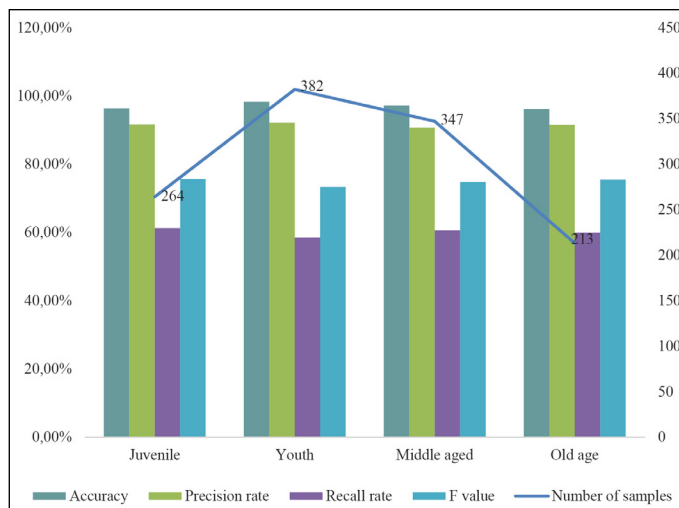


Figure 5. Model test results.

3. Training data were used to build random decision trees, validation data were used to verify the built decision trees, and finally the correctness of the decision trees for each type of data was recorded. The experimental results are presented in Tables 8 and in Figure 6.

From the experimental results, it can be seen that the classification accuracy of the stochastic decision tree algorithm is high in the cases

Table 8. Classification accuracy of multiple random decision trees.

Verification times	Low risk	Medium risk	Higher risk	High-risk	Average
1	95.25%	84.31%	73.25%	59.43%	78.06%
2	94.76%	86.34%	71.44%	60.28%	78.21%
3	96.38%	81.27%	72.52%	62.57%	78.19%
4	97.27%	85.32%	74.27%	61.89%	79.69%
5	96.13%	87.57%	75.36%	60.74%	79.95%

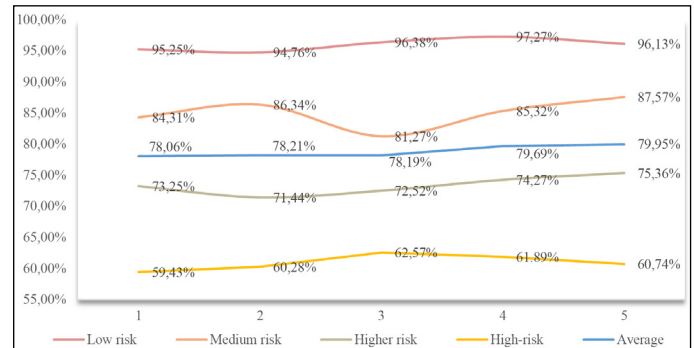


Figure 6. Classification accuracy of multiple random decision trees.

of low risk, medium risk and high risk; The calculated results show that the combined classification of classification accuracy of the decision train shows 78.82%. This analysis is mainly due to the small amount of high-risk data in the training dataset, resulting in insufficient training for this type of branches.

CONCLUSIONS

In this paper, based on the existing psychological assessment system, we use data mining related techniques to establish a psychological data mining model to mine information about people's psychological potential and present it to psychologists or related experts in a timely manner. Meanwhile, according to the different characteristics of classification algorithms in data mining, the decision tree algorithm is applied to the early warning system of mental health problems.

This paper develops an early warning system for college students' mental health problems based on data mining and database using C/S structure, which realizes the automation of people's basic information and psychological evaluation information collection, and increases the depth of psychological problem data analysis through the application of data mining technology. There are still some shortcomings and deficiencies in the mining of psychological data in this article. In the actual implementation process, we encountered some unexpected problems. Due to the limited space of this article, we did not elaborate on it. In order for this study to play a greater role in assisting decision-making in the early warning of mental health problems, a lot of work needs to be done in future research.

The author declare no potential conflict of interest related to this article

AUTHORS' CONTRIBUTIONS: Every author has made an important contribution to this manuscript. BL: writing, revision, analysis of the data, statistical analysis and revision.

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