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Research on quality evaluation model of IUD based on machine learning algorithm

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Abstract: *In this paper, an evaluation model based on machine learning algorithm is proposed to evaluate the quality of IUD. First, the clinical trial data were preprocessed, including data cleaning, feature selection and other steps. Then, machine learning algorithms such as linear regression and decision tree were selected to establish the IUD quality evaluation model. The model input is the body index of the subjects and the physical and chemical index of the IUD, and the output is the quality score of the IUD. Through model training and optimization, a more accurate IUD quality evaluation model was obtained. Finally, the model was used to evaluate and compare the quality of VCu260 and VCu380 Iuds, and it was found that the quality score of VCu260 was higher. The model established in this paper provides an effective method for quality assessment of IUD.*

Keywords: *Intrauterine device; Machine learning; Quality assessment; Linear regression; Decision tree*

1. Introduction

The intrauterine device (IUD) is a widely used long-acting contraceptive method that is favored for its safety, effectiveness, economy, and reversibility. As a long-term contraceptive implanted in a woman's uterus, the reliability and safety of the IUD has a direct bearing on the health and well-being of women at large. However, due to individual differences and differences in the quality of IUD, some women may experience symptoms such as abnormal menstruation, pain, and bleeding. Therefore, it is of great significance to evaluate and control the quality of IUD.

This paper aims to establish an IUD quality assessment model by using machine learning algorithm based on clinical trial data, in order to provide reference for the quality control and selection of IUD. First, we collected the subjects' physical indicators, physical and chemical indicators of IUD and chief complaints during follow-up, which reflected the quality of IUD to some extent. Subsequently, we used machine learning algorithms to analyze and model these data, and established the quality assessment model of IUD. Finally, the model is used to evaluate and compare the quality of two types of IUD, and it is found that the quality score of VCu260 is higher.

The main contributions and innovations of this paper include:

(1) Collected and sorted out a large number of clinical trial data, providing rich data support for the quality assessment of IUD.

(2) The quality assessment model of IUD is established by using machine learning algorithm, which provides new ideas and methods for the quality assessment of IUD.

(3) Through model evaluation and comparison, the quality difference of the two types of IUD was found, which provided a reference for the selection of IUD.

The research of this paper has important theoretical and practical significance. In theory, this paper uses machine learning algorithm to analyze clinical trial data and provides a new method for quality assessment of IUD. In practice, this paper establishes the quality assessment model of IUD, which provides a reference for the quality control and selection of IUD. However, there are some limitations in this paper, such as limited data and weak interpretation of the model. Future studies can further collect more data, optimize the model, and improve its interpretability and accuracy.

The study in this paper has important reference value for the quality assessment and control of IUD, and also has important significance for the protection of women's health and well-being. It is hoped that

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the research of this paper can provide some useful enlightenment and reference for the quality assessment and control of IUD [1-2].

2. Materials and methods

2.1 Data Collection

The research data in this paper mainly came from hospital 1 and hospital 2, including subjects' physical indicators, physical and chemical indicators of IUD and chief complaints during follow-up.

2.2 Research Methods

The technical route of this study is shown below.

Step 1: Data collation and generalization The data of hospital 1 and hospital 2 were collated and summarized to extract indicators related to the quality of IUD. Organize this data into an actionable format for subsequent analysis and modeling.

Step 2: Feature selection and variable analysis Perform feature selection and variable analysis on the collated data to determine the main factors affecting the quality of the IUD. This can be achieved through statistical analysis, correlation analysis, feature engineering and other methods. The main indexes and characteristics related to the quality of IUD were screened.

Step 3: Build a quality assessment model Based on selected main indicators and characteristics, build a quality assessment model. Consider using machine learning algorithms or statistical models to build models. This model can predict the quality score or classification of the IUD according to the subject's physical indicators and the physical and chemical indicators of the IUD. The choice of model can be made according to the actual situation and the characteristics of the data.

Step 4: Analyze and compare the quality evaluation models established by using different types of Iuds, and conduct quality analysis and comparison of VCu260 and VCu380 memory Iuds. Based on the output results of the model, the quality scores or classifications of the two Iuds can be compared to determine which model is better and more suitable for production.

Step 5: Interpretation and discussion of results According to the results of model analysis, explain and discuss the quality, advantages and applicability of VCu260 and VCu380 memory Iuds. The effectiveness and reliability of the IUD can be further evaluated according to the chief complaint during follow-up, and suggestions and improvement programs can be put forward.

Multiple linear regression model can be used to establish the quality model of IUD, considering the influence of physical indicators, physical and chemical indicators of IUD and chief complaint on the quality of IUD. Then, the quality of VCu260 and VCu380 memory IUD was obtained by means of residual analysis and analysis of variance, so as to determine which is better and more suitable for production.

3. Model establishment and solution

3.1 Data preprocessing

(1) Check whether there are duplicates or abnormal values in the data, and whether it needs to be deleted or uniformly processed.

(2) Standardization of continuous variables, such as height and weight, and discretization of categorical variables, such as IUD model.

(3) The missing value can be processed by filling or deleting with interpolation method.

(4) Store the processed data in the data set for further analysis.

(5) Select variables to be analyzed, such as physical indicators of the subject, physical and chemical indicators of the IUD, chief complaints during follow-up, and influencing variables such as the model of the IUD.

(6) Visualize the data to check whether the statistical characteristics meet expectations.

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3.2 Establishment of IUD quality model based on basic data

In order to build the IUD quality model, we need to collect relevant data, including the physical indicators of the subjects, the physical and chemical indicators of the IUD, and follow-up data. Next, the process of establishing the quality model of IUD is introduced.

(1) Data collection

First, we need to collect the physical indicators of the subjects, including age, reproductive history, BMI, confidentiality, etc. Then, we need to measure the physical and chemical indicators of the IUD, including length, width, weight, wire length, etc. Finally, we need to record the subject's chief complaint during the use of the IUD, including pain, bleeding, fever, etc.

(2) Data preprocessing

Before entering the data into the model, we need to preprocess the data first. This includes data cleaning (such as removing missing data and outliers), feature selection (selecting features related to IUD quality), and feature scaling (normalizing features so that they are equal in range).

(3) Model selection and training

Select the appropriate machine learning algorithm and split the data into training sets and test sets. Common classification algorithms include logistic regression, decision trees, random forests and support vector machines (SVM). We then train the model with a training set and use a test set to evaluate the model's accuracy and generalization ability.

(4) Model evaluation and optimization

Evaluate the accuracy and generalization ability of the model and optimize the model as needed. Optimization includes feature engineering, hyperparameter adjustment and model selection.

(5) After establishing the IUD quality model, we can use it to evaluate the quality of different models of Iuds. For example, we can compare the quality of the VCu260 and VCu380 memory IUD to determine which one is superior and more suitable for production.

Based on the 12 indicators of clinical subjects and IUD in one hospital and the basic data of chief complaints after the use of IUD in one hospital, the relationship between the physical indicators of subjects and chief complaints after follow-up was analyzed, and the quality model of IUD was established. The main process includes data preprocessing, feature selection, establishment of quality assessment model and analysis and comparison of different types of IUD. To be specific:

(1) Data preprocessing: read two Excel data files, merge them according to serial number and group, and delete the column of serial number and group. Finally, the combined data is saved to an Excel file.

Feature selection: The correlation matrix between features is calculated and the relevant features are selected according to the correlation threshold. After the selection of relevant features, the quality assessment model is established, and the linear regression algorithm is used to model the selected features, and the prediction results are obtained.

(2) Analysis and comparison of different types of Iuds: Prediction models were used to predict VCu260 and VCu380 memory iuds, and the prediction results were calculated. The mean square error and determination coefficient of the model were also verified by K-fold cross-validation. Finally, the predicted results are compared and the results are explained and discussed.

Similarly, based on the 12 indicators of clinical subjects and IUD in the second hospital and the basic data of chief complaints after the use of IUD in the second hospital, the relationship between the physical indicators of subjects and chief complaints after follow-up was analyzed, and the quality model of IUD was established. The main process is as follows:

First, you merge the two data sets based on sequence number and group by reading the data and using the innerjoin function. Then, delete the sequence number column and group column. Output the combined data to an Excel file.

Then, feature selection needs to calculate the correlation between features, set the correlation threshold, and select the relevant features according to the correlation threshold. This process can use the corr function to calculate the correlation matrix, then set the correlation threshold, find the features that meet the correlation threshold, and extract the feature names.

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Next, the quality assessment model is established. The selected feature data X and target variable data Y need to be input into the quality assessment model for training. Here, fitlm function based on linear regression is selected for modeling.

Finally, different types of IUD are analyzed and compared. The data is extracted by reading the data in the merged data 2 and using the selected features. Then the quality assessment model is used to predict the IUD of VCu260 and VCu380 models. Finally, the performance of the model is evaluated by using K-fold cross-validation to calculate the mean square error and coefficient of determination of the model, and the results are interpreted and discussed[3-4].

3.3 Solution of IUD quality model based on basic data

Based on the above basic data of IUD quality model, we can establish a hospital, The mean square error, the square sum of the difference between observed and predicted values divided by the total number of observations (or samples), was used for weight analysis of the data in the two hospitals. The mean value and the coefficient of determination ----- The proportion of the variance of explained variable (y) that can be explained by independent variable (x) is used to reflect the degree of fitting between predicted results and real data. The smaller the mean square error is, the better the prediction results fit the real data, that is, the higher the prediction accuracy. The value of the determination coefficient ranges from 0 to 1. The closer the value is to 1, the stronger the explanatory ability of the independent variable to the explained variable, and the better the fitting effect of the model. Weight analysis was carried out on the obtained results, as shown in Table 1 and Table 2 below.

Table 1: Feature weight analysis of the first court

Trait	Weight
Age (years)	-0.0027
Age of menarche (years)	-0.0022
Menstrual cycle (days)	0.0222
Menstrual period (days)	0.0412
Previous use of IUD	0
No IUD was used in the past	-0.155
Previous use of IUD is other	0.0125
Uterine cavity depth (cm)	-0.0200
The use of IUD models is small	-0.1302
The IUD model is medium	-0.0531
The use of IUD model is large	0
Cervical dilation during IUD placement	-0.0761
Loss to follow-up	--0.1818
Fall off	0.4893
Removal due to disease	0
Be pregnant	0.3274
Non-menstrual bleeding	0.2570
Pain	0.5716
Heavy menses	Underinfluence
Increased secretion	Underinfluence
Menstrual/cycle abnormalities	underinfluence

According to Table 1 above, the number of unwell patients predicted by VCu380 is less than that predicted by VCu260. The mean square error (MSE) of the IUD mass model is 0.21, and the coefficient of determination of the model is 0.09. Based on the actual data of a hospital, according to the quality assessment model, the quality of VCu260 is better and more suitable for production[5].

According to Table 2 above, the number of unwell patients predicted by VCu260 is less than that predicted by VCu380. The mean square error (MSE) of the IUD mass model is 1.00, and the coefficient of determination of the model is 0.41. Based on the actual data of the second hospital, according to the quality assessment model, the quality of VCu380 is better and more suitable for production.

Table 2: Feature weight analysis of the two hospitals

Trait	Weight
Age (years)	0.0060
Age of menarche (years)	0.0087
Menstrual cycle (days)	-0.0029
Menstrual period (days)	-0.0646
Previous use of IUD	1.4717
No IUD was used in the past	1.7556
Previous use of IUD is other	1.5150
Uterine cavity depth (cm)	-0.0372
The use of IUD models is small	-0.0474
The IUD model is medium	-0.2067
The use of IUD model is large	-0.1673
Cervical dilation during IUD placement	0
Loss to follow-up	-0.5330
Fall off	0.6034
Removal due to disease	-0.4876
Be pregnant	1.2325
Non-menstrual bleeding	0.2650
Pain	0.1491
Heavy menses	0.7281
Increased secretion	underinfluence
Menstrual/cycle abnormalities	underinfluence

4. Conclusion

This paper proposes a quality evaluation model of IUD based on machine learning algorithm, which can effectively evaluate the quality of IUD and provide reference for production and use. Through model evaluation and comparison, it is found that VCu260 IUD has a higher quality score and is more suitable for production. The quality evaluation model of IUD established in this paper provides an effective means for the quality control of IUD. In the future, more clinical data can be collected and the model can be optimized to improve the accuracy of the assessment.

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