

Retraction

Retracted: Application of Fuzzy Decision Tree Algorithm Based on Mobile Computing in Sports Fitness Member Management

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

1. Discrepancies in scope
2. Discrepancies in the description of the research reported
3. Discrepancies between the availability of data and the research described
4. Inappropriate citations
5. Incoherent, meaningless and/or irrelevant content included in the article
6. Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] Z. Gu and C. He, "Application of Fuzzy Decision Tree Algorithm Based on Mobile Computing in Sports Fitness Member Management," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 4632722, 10 pages, 2021.

Research Article

Application of Fuzzy Decision Tree Algorithm Based on Mobile Computing in Sports Fitness Member Management

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After the reform and the opening, the economy of our country has developed rapidly, and the living conditions of the people have become better and better. As a result, they have a lot of time to pay attention to their health, which has promoted the rapid development of the sports and fitness industry in my country. In response to the increasing development of the sports and fitness sector of my country, the current state of the administration of members of the sports fitness industry does not keep pace with the development of the sports and fitness industry of my country. Based on this, this article uses a fuzzy decision tree algorithm to establish a decision tree based on the characteristics of customer data and loses existing customers. Analyzing the situation is of strategic significance for improving the competitiveness of the club. This article selects the 7 most commonly used data sets from the UCI data set as the initial experimental data for model training in three different formats and then uses the data of a specific club member to conduct experiments, using these data files as training samples to construct a vague analysis of the decision tree to overturn the customer to analyze the main factors of customer change. Experiments show that the fuzzy decision tree ID3 algorithm based on mobile computing has the highest accuracy in the Iris data set, reaching 97.8%, and the accuracy rate in the Wine data set is the smallest, only 65.2%. The mobile computing-based fuzzy decision tree ID3 algorithm proposed in this paper obtained the highest correct rate (86.32%). This shows that, compared to traditional analysis methods, the blurred decision tree obtained for churn client analysis has the advantages of high classification accuracy and is understandable so that ideal classification accuracy can be achieved when the tree is small.

1. Introduction

With the rapid development of information, more and more data information will inevitably be created. This data not only has a particularly large amount of data but also contains a large amount of potentially valuable information. Gym clubs are increasingly facing the question of how to effectively manage and how to effectively use the useful data you need from these large amounts of data. Use the right methods to gather relevant data and information, be able to identify customer characteristics in the database in a timely manner, analyze key drivers of customer change to reduce customer turnover, and provide helpful information to managers in decision support.

The decision tree induction learning algorithm represented by the ID3 algorithm is feasible when solving classification problems, but this algorithm does not take into account the ambiguity of customer data, so there are some limitations in expressing and understanding customer characteristics. The fuzzy decision algorithm ID3 based on the theory of fuzzy mathematics is a fuzzy extension of the classical ID3 algorithm. Because it can deal with the uncertainty associated with human thought and emotion, it extends the scope of the ID3 algorithm, creating decision trees is more logical, and sorting speed Faster, can provide decision support for various areas. Then, how to effectively use business intelligence technology to make strategic decisions requires companies to analyze these customer data. Traditional

analysis methods have great limitations in solving enterprise customer relationship management, which makes the results of analysis and prediction unsatisfactory.

In the past ten years, scholars at home and abroad have conducted a large number of pioneering and fruitful researches on the application of fuzzy decision tree algorithm in management and have accumulated rich research results and research experience. Chiu et al. tried to apply the fuzzy decision tree that combines the advantages of fuzzy theory and fuzzy tree into this field by analyzing the problems in the management of high school teachers. It briefly introduces the construction principle of fuzzy decision and the algorithm of fuzzy ID3 decision tree and applies it to the management of teachers in colleges and universities. Therefore, a preliminary analysis of the reasons for the loss of high school teachers is carried out. The research of several high schools shows that the results obtained by this method are in line with the facts and therefore provide a theoretical basis for high schools to solve the problem of faculty management. However, his research did not clearly put forward the relevant data on the loss of high school teachers [1]. In Yumi's business management, it is very important to analyze the crisis of customer confiscation to improve competitiveness, which is an important branch of business intelligence. Compared with decision trees, based on the advantages of fuzzy decision trees in solving the ambiguity of customer data, genetic algorithms are used to optimize two important parameters in the fuzzy decision trees. Then, a method based on optimized fuzzy decision-making to analyze the crisis of customer forfeiture is proposed. The experimental results show that the method is feasible and effective. It provides new ideas for analyzing and predicting customer confiscation crises and helps managers make better decisions in business strategies. However, the overall research lacks data support and needs more data support its conclusion [2]. Jang and Kim can identify different types of soil through these characteristics. Good soil classification is very important for better use of soil. The opinions of experts may be very different. It is not easy for experts to manually classify soil. In addition, different types of soil cannot be defined deterministically. In order to explore alternative methods to solve this problem, the application of using an automatic program to generate a soil classifier from data using a fuzzy decision tree induction algorithm is studied. In order to compare the results obtained by the fuzzy decision tree classifier, we used two well-known classifier generation methods: the classic decision tree induction algorithm C4.5 and the fuzzy rule induction algorithm named FURIA. The experimental results lack more data support. As a result, the results obtained by the fuzzy decision tree classifier are still doubtful [3, 4].

Based on the analysis of the fuzziness of customer data characteristics, this paper compares the two inductive learning algorithms of decision trees and fuzzy decision trees and then uses mobile computing to optimize two important parameters involved in the establishment of fuzzy decision trees. And use the optimized fuzzy decision tree for customer churn analysis. According to the relevant data elements of member management, the spatial data of the sample area is selected, and the ID3 algorithm in the decision tree algorithm

is combined with the fuzzy algorithm based on mobile computing to realize the program establishment of the sample area, and the classification model of the decision tree in the member management is established, and through the established classification prediction model, whether users will be lost was analyzed and predicted, and the correctness of the three schemes was evaluated at the same time.

2. Application of Fuzzy Decision Tree Algorithm in the Management of Sports Fitness Members

2.1. Decision Tree Model Design and Algorithm

2.1.1. Decision Tree Construction. In the process of building a decision tree, we must first have data samples. This is the database for the construction. People do feature tests and sort this data through the test features to form a tree structure with nodes and branches. This is the basic idea of the decision tree. The decision tree sort algorithm is performed from top to bottom. Characteristics with good classification results are selected at each node to classify the samples. The process continues to execute, and finally, all training sets are classified by this tree, or all attributes have been used [5, 6]. To build a decision tree, first, select the best test attribute, and then, use the selected attribute to divide the sample set, and at the same time, build the next level of nodes. In the end, the result of the division is only the same sample. This division is pure.

The following description is for the general process of constructing a decision tree: a sample set and an empty tree form the initial state. For a node, use the test attribute of this node to divide the node; if all the samples of the node are contained in the same category, a leaf node with the imprint of this category will be created, and the creation will stop; otherwise, use the best measurement to calculate each possible division of each set; if a test is the best category selected as the node in the test, a child node with as many outputs as the number of outputs different from the division will be established; when marking the boundary between the parent and the child, the output result of this classification is used, and finally, the sample set is divided into the child nodes. As the current node, the child node will stop the classification when it cannot be classified again [7–9].

2.1.2. Simplification of Decision Tree. The data of a decision tree is quite complex, so it is difficult for users to understand, so the meaning of this decision tree is not so important. Therefore, if there are fewer branches and leaves that constitute a decision tree, the classification process is relatively simple, and the space for storing data is relatively small, so when constructing the tree, pay attention to as simple as possible, and do not build the tree's branches and leaves too large [10–12]. Therefore, the decision tree needs to be simplified. For decision trees, a technique that effectively targets noise is called pruning technique. This technique enables people to better understand and simplify a tree. The decision tree is relatively simple and good, but the pruning technology is not a panacea. If there is too little data and we still use the pruning technology, the information of the tree will be

seriously insufficient. Therefore, pruning technology is not an absolute technology. It can achieve better results when it is applied at an appropriate time. Of course, it is necessary to prevent it from being applied when it is not needed.

2.1.3. Prepruning. Before a tree is built, pruning the tree data as soon as possible to stop the growth of the tree. Regarding the prepruning method, when to stop is a key issue. There are many methods to study the prepruning and choose the appropriate time. A more concise method is to specify the height of a tree, choose to stop the growth of the tree when it reaches this height, and no longer continue to test the data with attributes [13, 14]. This method is a double-edged sword. Sometimes checking the height of the tree can have good results, but stopping the growth of the tree too early will cause incomplete data classification, which will cause the results to be inaccurate. Set an appropriate feature value for the data attribute. When categorizing data, when the attribute value of a node is this operating value, the tree does not stop growing and does not split. This method can avoid data fragmentation very well and also avoid data conflicts caused by excessive data classification.

Set a limit value, which can be called a threshold. This value means the number of nodes. As the tree continues to grow, when reaching a certain node, the number of nodes is less than this value; then, the growth of the tree can be forcibly stopped [15, 16]. This method is also an important means to limit the excessive growth of the tree, but its application is limited to the small amount of data; processing with this method will affect the accuracy of the results. When building a tree, it will affect the performance of the model. A tree that is too large will affect the speed of the model, and a tree that is too small will not be able to fully classify the data. Therefore, there must be a value for the benefit of the model, and the growth will stop when the benefit value is less than the limit value as the tree grows.

2.1.4. Postpruning

(1) REP (Reduced Error Pruning) Method. For pruning, every point on the decision tree may be processed. Because the construction of the decision tree is from top to bottom, the coordinated pruning process is also such a sequential process. This method does not deal with each node one by one. It is an abstract and concise way of thinking. The decision tree T is divided into many subtrees S , and the number of subtrees is regarded as leaf nodes, so that a simple tree is formed first [17, 18]. It has S leaf nodes. For a leaf node, it covers N samples, and there are E errors. Then, the misjudgment rate of the subtree is estimated as:

$$p = \frac{\sum_{i=1}^S E_i + 0.5S}{\sum_{i=1}^S N_i}. \quad (1)$$

We assume that the misjudgment of each sample in the subtree obeys a binomial distribution, where N represents the number of all samples contained in the subtree. Therefore, before pruning, the expected number of misjudgments is:

$$E = N * p. \quad (2)$$

If the error rate caused by the classification of the new tree is very low and the properties of the subtrees in the construction of the number of subtrees S are different, replace S with leaf nodes. This process is done continuously, and finally, the number of children of the decision tree T is replaced by leaf nodes. This processing method will get the ideal tree [7, 19]. The advantage of this method is that a decision tree with higher accuracy can be obtained, and the tree will not be too large.

(2) PEP (Pessimistic Error Pruning) Method. Assuming that the initial decision tree is T and a certain child node has a branch of number $n(t)$, there are $e(t)$ misclassifications in the results of these cases, and the error rate of the data set is:

$$r(t) = \frac{e(t)}{n(t)}. \quad (3)$$

The error rate is biased, because the training data is used to generate the tree while also pruning the tree, so the degree of pruning of this method is not accurate enough. In order to improve the evaluation of this method for accuracy, the error rate can be corrected to:

$$r'(t) = \frac{[e(t) + 1]}{n(t)}. \quad (4)$$

The number of children $T(t)$ of tree T is set to S ; the number of leaves in this tree is $L(S)$; then, the classification error of $T(t)$ is:

$$r'(T_1) = \frac{\sum_S [e(s) + 1/2]}{\sum_S n(s)} = \frac{\sum e(s) + (L(s)/2)}{\sum n(s)}. \quad (5)$$

When the samples in the training set conflict, this result will be invalid. The PEP method introduces a continuous correction mechanism in the error estimation. This correction method has a better effect on the situation where the data is more troublesome. If the data simply introduces this mechanism, the result will be inaccurate [20, 21]. If the classification method is applied to classify the data of all sample sets, then:

$$e'(T_1) + SE[e'(T_1)] = \frac{1}{2} [L(T_1) + \sqrt{L(T_1)}]. \quad (6)$$

If the leaf node for correcting classification errors in subtree T_1 is large enough, pruning it.

2.1.5. Performance Evaluation of Decision Tree. For decision trees, high complexity does not mean accuracy. In this sense, accuracy is not related to the complexity of the tree. Of course, complexity is not an evaluation criterion for accuracy. For a decision tree, people usually have many evaluation criteria as follows:

According to this rule, unknown data is processed. Such a process can help people discover unknown knowledge information. The accuracy of the information obtained from the data can determine the accuracy of staff decision-making. Even if a model is accurately classified, its understanding is complex and cannot be considered a good method. A good classification model can present a classification method with a description that is easy for people to understand and uncomplicated [22, 23]. For decision-makers, a concise model description is more conducive to understanding and more conducive to widespread application. The amount of data that a model can bear is also a factor in whether people use this model. When the amount of data is very large, a good model can still show good accuracy, and this model is worth applying.

2.2. Classical Decision Tree Algorithm

2.2.1. ID3 Algorithm. The ID3 algorithm is characterized by first calculating the information entropy of the attributes of the sample set and selecting the optimal attributes for splitting by comparing these values. Use this attribute to divide the nodes to form a decision tree [24, 25]. If the element included in member management Y is $\{x_1, x_2, \dots, x_n\}$, and the occurrence probability of each element is $\{p_1, p_2, \dots, p_n\}$, respectively, then the entropy of member management Y is defined as follows:

$$\text{info}(Y) = - \sum_{i=1}^n p_i \log_2 p_i. \quad (7)$$

The probability that an instance can be classified into category i is:

$$p(c_i) = \frac{c_i}{|Y|}. \quad (8)$$

At this time, the entropy of member management Y is:

$$\text{info}(Y) = - \sum_{i=1}^n p(c_i) \log_2 p(c_i). \quad (9)$$

If the attribute A is selected as the splitting attribute, the value is $\{a_1, a_2, \dots, a_m\}$, and the data set is divided into m class through A , where the conditional information entropy is expressed as:

$$\text{Info}(Y | A) = - \sum_{i=1}^n \sum_{j=1}^m p(c_i, a_j) \log_2 p(c_i, a_j), \quad (10)$$

$$\text{Info}(Y | A) = \sum_{j=1}^m p(a_j) \sum_{i=1}^n p(c_i | a_j) \log_2 p(c_i | a_j).$$

Then, the information gain brought by attribute A is:

$$\text{Gain}(X, A) = \text{Info}(X) - \text{Info}(X | A). \quad (11)$$

When building a decision model through the ID3 algorithm, it is necessary to traverse each decision attribute and use the attribute with the largest information gain to divide the data set, so the decision tree obtained in this way is more accurate. The ID3 algorithm is shown in Algorithm 1.

2.2.2. C4.5 Algorithm. In order to calculate the efficiency of member management, the definition of its split information is as follows [26, 27]:

$$\text{Split}(Y, A) = - \sum_{i=1}^m p(a_i) \log_2 p(a_i), \quad (12)$$

$$\text{Split}(Y, A) = - \sum_{i=1}^m \frac{n_i}{n} \log_2 \frac{n_i}{n}.$$

Split information represents the information generated by dividing data set Y into subsets according to the value of decision attribute A , so there is a definition of membership management efficiency:

$$\text{GainRatio}(Y, A) = \frac{\text{Gain}(Y, A)}{\text{Split}(Y, A)}. \quad (13)$$

2.2.3. Comparison and Analysis of Decision Tree Algorithms. There are many decision tree algorithms. There are many differences in the scalability, execution speed, comprehensibility of the results, and accuracy of classification and prediction. A summary comparison of these algorithms is shown in Table 1.

3. Experimental Design of Fuzzy Decision Tree Algorithm in Sports Fitness Member Management

3.1. Model Realization. In order to complete the comparative experiment of the three decision tree schemes and realize a fuzzy decision model, it has the functions of data importing, data fuzzification, generating decision tree model, model testing, and instructions for use. The main business flowchart of the sports fitness membership management model is shown in Figure 1.

3.2. Test Subject. In order to obtain accurate and reliable experimental results to complete the analysis of the algorithm, we must first select the appropriate experimental data set. This article selects the 7 most commonly used data sets from the UCI data set as the initial experimental data to conduct model training on three different schemes. The specific description of the data set used is shown in Table 2. After training, apply the model to the analysis of customer churn and then use the data of a certain club to conduct experiments. Customer data consists mainly of basic information, geographic distribution information, and service information. Use statistical sampling to extract 1500 records from customer data in a given year. The characteristics of the customer in the database include customer age, residential area, profitability, period of service, and type of contract, and customers are divided into YES (churn) and NO (no churn) two

```

BuildID3(Y, T)
Input:
X: Training samples;
T: Root node, initially empty;
Output:
T: Decision tree root node
Begin
  Create node T with Y
  if Y all belong to the same class C
    return T
  end if
  if Y is empty or less than the given threshold
    return T
  end if
  Let n be the number of candidates attributes in node T
  for i=1:n
    Calculate Gain (Y, A) and find the attribute A that maximize the value
  end for
  Use A to divide Y into k subsets
  for i=1:k
    T. add(BuildID3(Yi, Ti))
  end for
End
    
```

ALGORITHM 1: ID3 algorithm diagram.

TABLE 1: Comparison of typical decision tree algorithms.

	Attribute selection metrics	Dealing with continuous attributes	Pruning method	Do you need an independent test sample	Decision tree structure
ID3	Information gain rate	Discretization	Misclassification	Yes	Polytree
C4.5	Information gain rate	Presort	Misclassification	No	Polytree
CART	CINI coefficient	Presort	MDL	No	Binary tree

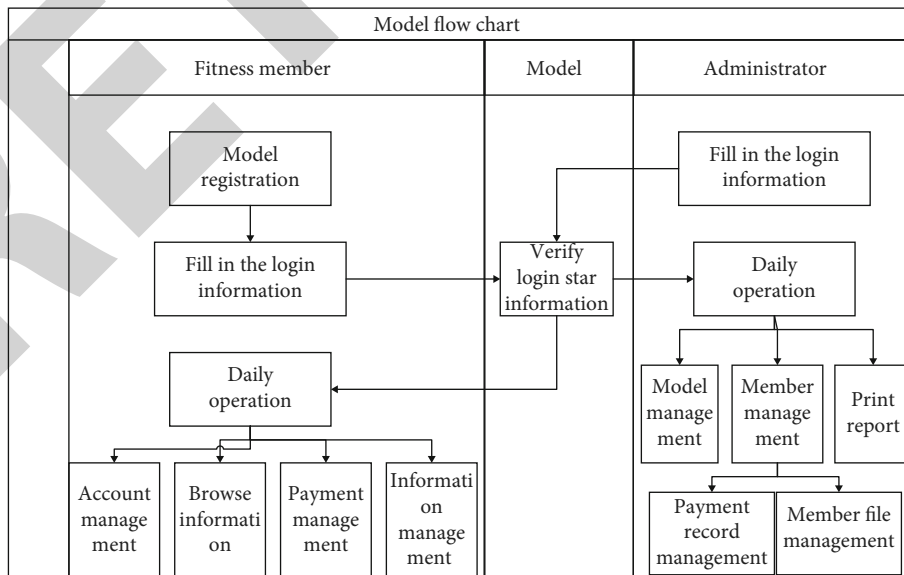


FIGURE 1: The main business flow chart of the sports fitness membership management model.

TABLE 2: Data set introduction.

S.no	Data sets	Instances	Number of classes (k)	Number of features (d)	Size of class
1	Iris	150	3	4	50, 50, 50
2	Wine	178	3	13	59, 74, 48
3	Glass	214	5	9	29, 76, 70, 17, 22
4	Diabetes	768	2	8	268, 500
5	Heartstatlog	270	2	13	150, 120
6	Ionosphere	351	2	34	126, 225
7	Sonar	208	2	60	97, 111

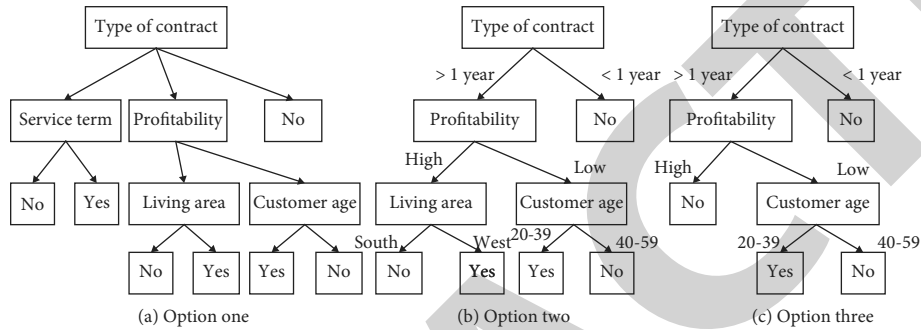


FIGURE 2: Decision tree built by three options.

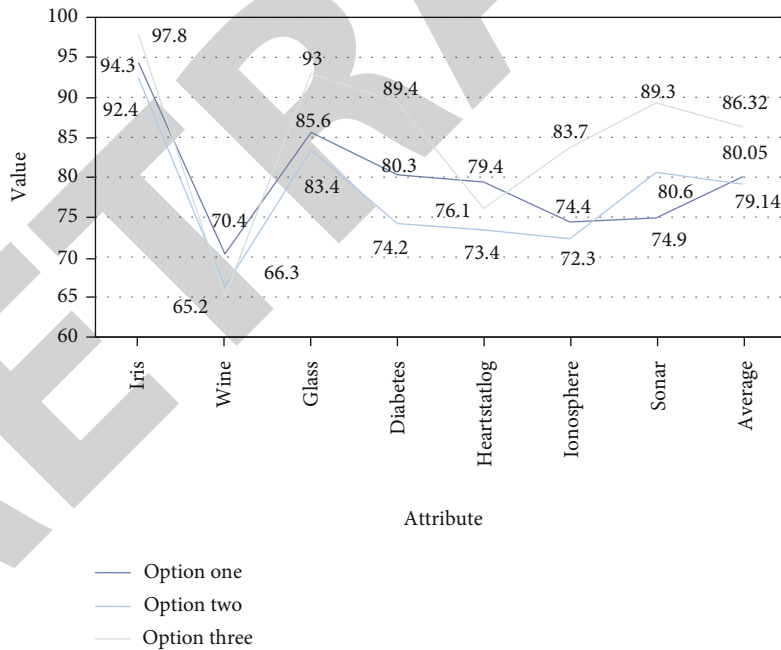


FIGURE 3: Comparison diagram of classification accuracy of three schemes.

types. Use these data files as training samples to create a vague decision tree for customer analysis and analyze the key factors of customer change [28].

3.3. Experiment Procedure. The experiment compared the three schemes. The first plan is to use the traditional decision tree ID3 algorithm to build a decision tree; the second plan is to use the fuzzy decision tree ID3 algorithm to build a deci-

sion tree, and the third plan is to build a decision tree based on the fuzzy decision tree ID3 algorithm of mobile computing. Figure 2 shows the decision tree established by the three schemes.

3.4. Statistical Processing. Statistical analysis was performed with the SPSS 13.0 statistical software. The significance test of the difference was performed by one-way analysis of

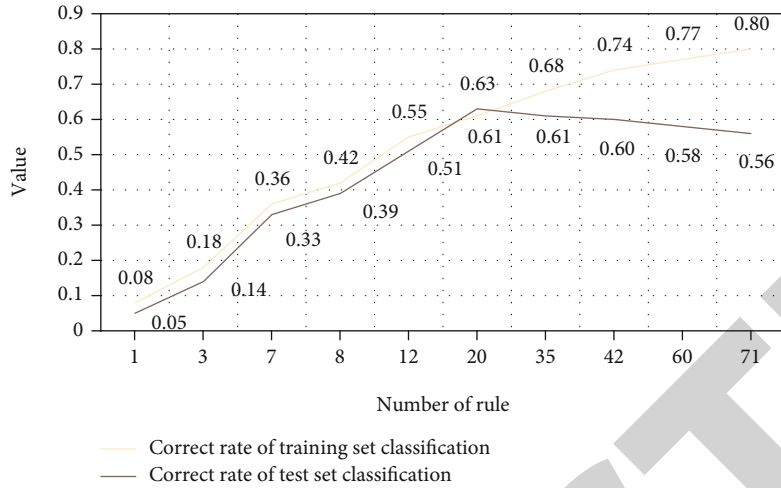


FIGURE 4: Schematic diagram of comparison of classification accuracy of training and test data sets under different rules of a decision tree.

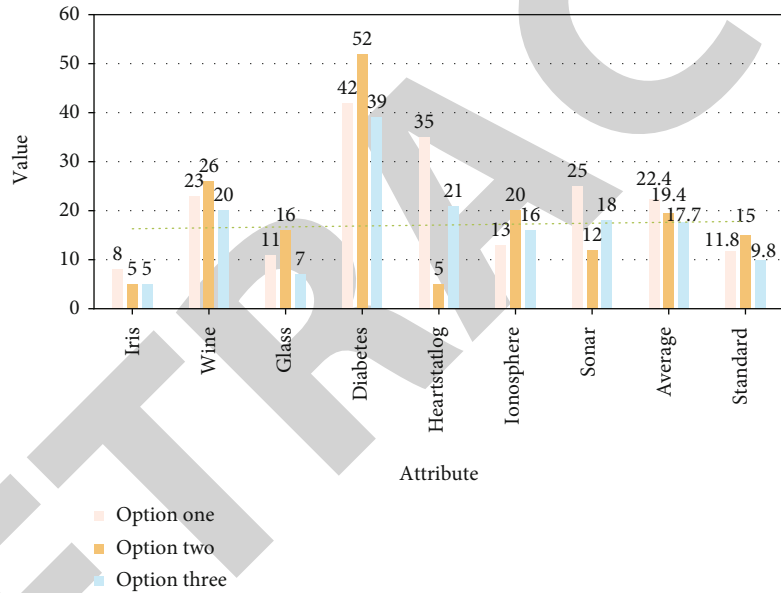


FIGURE 5: Comparison of the number of classification rules generated by the three schemes.

variance, the difference between the two groups was tested by LSD-t, and the statistics of the results of the application of the fuzzy decision tree algorithm in the management of sports and fitness members were performed by the group t test. $P < 0.05$ is considered to be significant and statistically significant.

4. Fuzzy Decision Tree Algorithm in the Management of Sports Fitness Members

4.1. Data Set Training Results

4.1.1. *Correct Rate Comparison.* By applying three different decision tree schemes to the seven preprocessed data sets, the correct rates of different algorithms in the classification of each data set can be obtained as shown in Figure 3.

It can be seen from Figure 3 that the fuzzy decision tree ID3 algorithm based on mobile computing has the highest

accuracy in the Iris data set, reaching 97.8%, and the accuracy rate in the Wine data set is the smallest, only 65.2%; the fuzzy decision tree ID3 algorithm is in the Iris data set; the accuracy rate is the highest, reaching 94.3%, and the accuracy rate in the Wine data set is the smallest, only 66.3%; the traditional decision tree ID3 algorithm has the highest accuracy rate in the Iris data set, reaching 92.4%, and the accuracy rate in the Wine data set is the smallest, only 70.4%. The mobile computing-based fuzzy decision tree ID3 algorithm proposed in this paper achieved the highest accuracy rate (86.32%), which shows that the fuzzy decision tree ID3 algorithm based on mobile computing can produce high accuracy when dealing with continuous attributes.

4.1.2. *Rule Number Comparison.* Figure 4 shows the classification accuracy of training and testing under the same scheme with different numbers of rules.

TABLE 3: Data table of the effect of authenticity on accuracy.

Correct rate (%)	0.50	0.56	0.64	0.70	0.76	0.82	0.88	0.94	0.96	0.98
Option one	86	87	87	87	89	90	94	89	85	79
Option two	86	87	87	87	90	92	95	90	85	80
Option three	86	87	87	87	92	98	91	88	87	83

Schematic diagram of the influence of authenticity on the number of rules

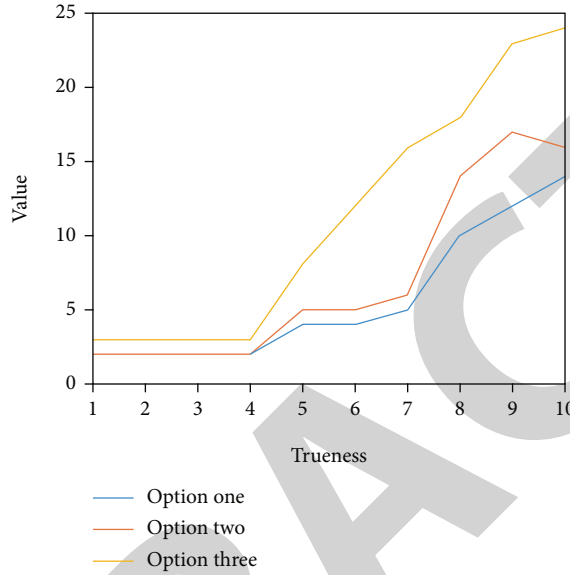


FIGURE 6: Schematic diagram of the influence of authenticity on the number of rules.

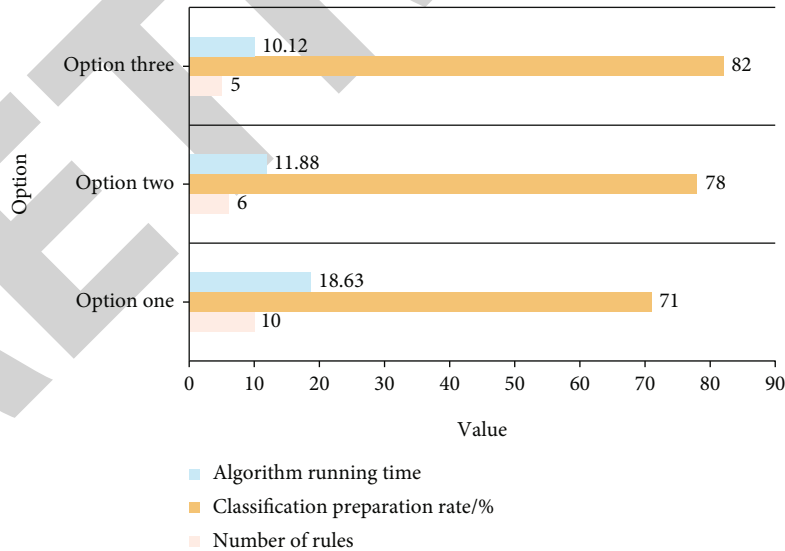


FIGURE 7: Comparison chart of the efficiency of the three algorithms.

As can be seen in Figure 4, too many rules tend to cause overfitting, which means that the classification effect on the training set will be better, but the prediction accuracy of the test set will decrease. It shows that the model can reasonably describe the volume expansion of the soil-soil mixture at low constraint pressure, the compression of the volume under

high constraint pressure, and the increase of the maximum strength of the soil-rock mixture with the increase of the constraint pressure, which confirms that the model simulates a soil-rock mixture.

It can be seen from Figure 5 that the fuzzy decision tree ID3 algorithm based on mobile computing produces the least

number of rules in each data set, indicating that its overall decision-making efficiency is higher than the traditional decision tree ID3 algorithm and the fuzzy decision tree ID3 algorithm. The fuzzy decision tree ID3 algorithm of mobile computing is more applicable than the other two schemes.

4.1.3. Authenticity Analysis. The degree of realism has a very close relationship with the scale of the decision tree. It is very important for the fuzzy decision tree algorithm to choose an appropriate degree of realism for different schemes. The results are shown in Table 3.

It can be seen from Table 3 that for fuzzy decision trees, as the degree of reality increases, the accuracy of classification first increases and then decreases, and the fuzzy decision tree ID3 algorithm based on mobile computing achieves the maximum accuracy around 0.82, and fuzzy decision-making the tree ID3 algorithm and the traditional decision tree ID3 algorithm achieve the maximum correct rate at 0.88, which shows that the fuzzy decision tree ID3 algorithm and the traditional decision tree algorithm need to obtain the maximum correct rate when the number of rules generated is more, and the efficiency is lower. Fuzzy decision tree ID3 algorithm is based on mobile computing.

It can be seen from Figure 6 that as the degree of reality increases, the number of rules generated by the model increases. This is because the greater the degree of truth, the more recursive times of each branch, so the scale of the spanning tree is the larger, the more rules can be obtained.

4.2. Application in the Management of Sports Fitness Members. After the training, the model is applied to the analysis of customer churn, and experiments are conducted with the data of a certain club member. The results are shown in Figure 7.

It can be seen from Figure 7 that the customer churn analysis model constructed by the fuzzy decision tree optimized by the genetic algorithm not only has fewer rules but also has obvious advantages in classification accuracy. This advantage can help club managers to provide targeted services to those customers with high churn rates in future marketing. At the same time, the running time of scheme 3 is short, which is particularly important in the analysis of the company's massive customer data.

5. Conclusions

Based on the analysis of the importance of the process of establishing the fuzzy decision tree, this paper uses mobile computing to optimize these two parameters, which provides a basis for the value of the parameters when the fuzzy decision tree solves specific problems. At the same time, the optimized fuzzy decision tree is used for the analysis and prediction of the customer churn crisis in sports and fitness, and the experiment is carried out with the customer data of a club. The experimental results show that the optimized fuzzy decision tree is used in customer churn crisis analysis, and the generated decision tree has fewer rules, simpler structure, and higher classification accuracy. These advantages can more effectively provide managers with a new research idea

and analysis method for the retention research of sports and fitness customers. The disadvantages of this research are that in this paper; when the decision tree algorithm is analyzed experimentally, the client data of a particular association is selected. In order to make the research more universal, the scope can be increased accordingly. At the same time, the fuzzy decision model designed in this document only supports one fuzzy decision algorithm, and more mainstream algorithms can be added. In addition, other algorithms related to data mining can be added to become a complete data mining tool.

Data Availability

No data were used to support this study.

Conflicts of Interest

There are no potential competing interests in our paper.

Authors' Contributions

All authors have seen the manuscript and approved to submit to your journal.

Acknowledgments

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