Evaluation Model of Modern Network Teaching Quality Based on Artificial Intelligence E-Learning

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ABSTRACT

Modern e-learning system is a representative service form in innovative service industry. This paper designs a personalized service domain system, optimizes various parameters and can be applied to different education quality evaluation, and proposes a decision tree recommendation algorithm. Information gain is carried out through many existing principles of improved decision tree algorithm, and the information gain of the algorithm determines the inheritance of information. The process of modern e-learning system is based on personalized teaching and humanized intelligent interaction. This paper theoretically analyzes the improvement performance of the existing e-learning system in teaching quality evaluation and shows a good classification effect. This model provides reference materials for the expansion of education and teaching and provides a feasible practical model for personalized teaching in online schools. The authors provide good educational conditions and environment for students and cultivate all-around talents for the society.

KEYWORDS

Artificial Psychology, Model Building, Online Education, Teaching Quality

INTRODUCTION

With the development of the country's "Modern Distance Education Project", various networked and distance education systems have emerged. Distance education, as a one-way broadcasting mode, lacks two-way interactivity (Wang et al., 2016). The third generation is a distance education system that requires humanized and intelligent interaction capabilities. The research makes a practical prediction and evaluation of the development direction of communication technology. The interaction between teachers and students is analyzed and evaluated. The personalized computer-intelligent teaching process is added. So, a new education and learning method—E-learning has emerged as the times require.

At present, there is no universally recognized definition of E-learning, and there are different opinions about the definition of "E-learning" at home and abroad (Taylor & Taylor, 2021). E-learning is a rapidly developing industry.

Presently, many online learning models are not clear. Basically, it is still in a wild period and can only move the existing offline methods to the online. There is no mature mode based on the use scenario of the online itself. The content organization is relatively messy. The online behavior of the Internet makes the traditional knowledge content precipitate. Therefore, the information in the knowledge base grows exponentially with respect to the offline (González-González et al., 2020). The knowledge base contains all kinds of knowledge on the Internet, such as entertainment, finance, government affairs, publishing and distribution, and biomedicine, providing a better solution for people to use the web more intelligently. However, since any institution or organization can create a knowledge base according to its own needs and design concepts, the data in the knowledge base are also full of diversity and heterogeneity, and there are many mutual duplications or complementations. However, the lack of an effective organization and sorting business model is immature. The definition of online education is unclear. The demand points that need to be solved first should be positioned. The significance of the current online education slogan is greater than the actual significance (Sadiku et al., 2018).

The innovation of this paper: In the traditional classroom dominated by lectures, the teacher's own knowledge structure is consolidated, and the channels for obtaining data are also limited, becoming a closed classroom. Likewise, students gain very limited knowledge in closed classrooms. The intelligent E-learning of artificial psychology can conduct statistical analysis on massive data through the Internet to build an open classroom, which not only provides massive data resources for learners to use but also provides personalized services for learners. This paper breaks the framework of traditional online education methods, combines intelligent E-learning of artificial psychology with online education system technology, combines the characteristics of online education resources, learner characteristics, behavioral preferences, integrates specific education situations, and forms a closed-loop big data construction surrounding. This model provides reference materials for the expansion and application of big data in education and teaching and provides a feasible practical model for personalized teaching in online schools.

E-learning is a modern e-learning system that provides innovative services. However, traditional distance education systems lack two-way interactivity and humanized intelligent interaction capabilities. Therefore, the E-learning system based on artificial psychology intelligent e-learning has been proposed to provide personalized services and optimize various parameters for different educational quality evaluations. Moreover, a decision tree recommendation algorithm has been introduced, which utilizes information gain to determine the inheritance of information. The use of a personalized computer-intelligent teaching process helps to improve teaching quality evaluation in online education. This paper aims to analyze the performance of existing electronic learning systems in teaching quality evaluations and shows good classification results. The proposed model can provide reference materials for the expansion of big data in education and teaching and a feasible, practical model for personalized teaching in online schools.

LITERATURE REVIEW

Development Trends of Online Learning

There are currently three different translation methods for E-learning in China: network learning, E-learning, and digital learning (Sun et al., 2021). The current education reform in our country has taken the degree of education informatization as an important symbol, and an important criterion for judging the actual level of education is to evaluate its application level to development (Gurung, 2021). There are many virtual simulation software- or program-aided instructions in the market. It is very important for teachers to conduct application analysis reasonably.

Therefore, it is very important to strengthen the level of modern student interaction and improve the education index in teaching applications. Students need to learn to use the website resources of excellent courses to realize self-learning in online classes so as to support independent learning after class (Tartavulea et al., 2020). A system should be established for mutual communication between online learning and other forms of learning to promote the construction of digital campuses in colleges and universities and to promote the development of online colleges (Peterson, 2007). E-learning eliminates time and space barriers and reduces learning costs. However, it is difficult to "E-ify" people's feelings at present, which is precisely the research content in the field of artificial psychology and affective computing.

Application of Artificial Intelligence in Online Learning

According to the demand analysis, the evaluation plan should be based on the artificial intelligence analysis system, with the purpose of accelerating the construction of education informatization and smart education classroom quality (Lou, 2022). The system should be able to normalize, accompany the collection and real-time analysis of classroom data, convert the unstructured data of students' classrooms into structured data, and finally present the analysis results to users intuitively (Chang et al., 2022). At the same time, the system should be able to deeply mine the basic classroom analysis data of multiple classrooms and form a variety of chart data through multidimensional and multilevel comparative analysis, which is suitable for parents, students, teachers, and other education stakeholders and decision-makers (Behkam et al., 2022).

Emotional analysis refers to the process of using artificial intelligence technology to identify and analyze human emotions. Its application in electronic learning is mainly to understand the learners' emotional states and motivations, thereby providing personalized and adaptive teaching support. For example, Soui et al. (2023) proposed an emotion recognition model based on deep neural networks, which accurately recognizes seven basic emotions (anger, disgust, fear, happiness, neutrality, sadness, and surprise) by analyzing the learners' facial expressions, speech, and text. This model can be used on online education platforms to help teachers monitor and regulate learners' emotions.

Natural language processing (NLP) refers to the process of processing and analyzing natural language data using artificial intelligence technology. Its application in E-learning is mainly to achieve a natural interaction with learners and improve teaching quality and efficiency. For example, Zhang et al. (2020) proposed an online education question-answering system based on NLP, which utilizes technologies such as knowledge graphs, semantic analysis, and deep learning to achieve intelligent answers to various types of questions posed by the learners, such as definitions, principles, examples. This system can be used on online education platforms to help learners solve problems they encounter during learning.

Computer vision refers to the process of using artificial intelligence technology to process and analyze image and video data. Its application in electronic learning is mainly aimed at monitoring and evaluating the learners' behavior and performance, improving teaching effectiveness and feedback (Li et al., 2019).

In the learning environment, different from the traditional learning management platform, which mainly focuses on management and recording, intelligent E-learning software can provide personalized feedback for learners (Cho et al., 2022). Through online tests, the learners can better understand their weaknesses, further obtain relevant learning resources, and propose future learning paths.

In conclusion, intelligent assistance systems can provide task performers with personalized and appropriate content in real-time according to the attributes of roles or processes. It can act as a coach to speed up problem-solving and improve work performance (Bini et al., 2022).

In the intelligent E-learning software, the content search will be more intelligent and accurate, and learners can quickly narrow the search scope by building a knowledge map. The intelligent training system is able to better understand the information that the learner is searching for and summarize the content related to the searched topic. Through search, the learners can learn new knowledge or

new connections, allowing the learners to make unexpected discoveries, inspiring them to conduct a series of new searches and learning, and then better stimulate their enthusiasm for learning. Smart E-learning software provides a diverse and personalized learning process, thereby abandoning the parallel curriculum planning of the past. Through learning elements or knowledge elements, content resources can have attributes such as the learners' abilities, roles, work scenarios, and business processes on the tags of metadata (Zhou, 2021).

Entering the Internet era, the E-learning platform is favored by more and more enterprises, and it is becoming standard equipment for enterprise training (Sanusi, 2021). The core of the E-learning platform is content knowledge, but some companies like to purchase courses from outside. Those courses that are bought and used seem to save a lot of time for training managers, but they are often ineffective (Hu, 2019).

In fact, according to the real training needs of enterprise employees and the pain points in employees' work, mining the hidden experience of business experts through case development, micro-lecture production, knowledge extraction, and extraction into standardized methodologies that can be disseminated are the main sources of content on the E-learning platform and also the content that employees really need to train. In addition, the operation of the E-learning platform is also very critical (Ma et al., 2021).

It is difficult to take on the heavy responsibility of corporate learning by purely online learning. The "blooming" of enterprise online learning platforms seems to make this industry usher in new vitality, but, in fact, the utilization rate of internal learning platforms of most enterprises is not high. Some enterprises have tens of thousands of employees, but according to statistics, the utilization rate of internal online learning platforms of these enterprises is extremely low. Therefore, it is the correct way to adopt the form of online + offline. Online learning can be used as offline training (Bourman et al., 2022). In addition, diversified learning methods are an important measure for enterprises to break through training barriers.

MATERIALS AND METHODS

Theoretical Basis of the Improved Algorithm

Many modern information transmissions do not have certain information gain value. Because the information values of multiple attributes need to be divided, different inheritance methods need to be adopted in many basic value statistics. The information gain, when understood by name, is the difference between the front and rear information. In the decision tree classification problem, it is the difference between the information before and after the attribute selection division of the decision tree. Different attribute analysis is needed in future research and development (Otia & Bracci, 2022).

Algorithm Process

In decision tree analysis, there are many coincidences under different probability real columns. A decision tree is a top-down tree classification process for sample data, which is composed of nodes and directed edges. Nodes are divided into internal nodes and leaf nodes. Each internal node represents a feature or attribute, leaf nodes represent categories, and edges represent conditions for division. Starting from the top node, all samples are gathered. After the root node is divided, the samples are divided into different sub nodes, and then further divided according to the characteristics of the sub nodes until all samples are classified into a certain category. The classification probability of any instance may have the same result as that of the positive example and the negative example.

$$I(p,n) = \frac{p}{p+n} \log \frac{p}{p+n} + \frac{n}{p+n} \log \frac{n}{p+n} \qquad (1)$$

If the attribute A is the root of the decision tree, A with V, a value $\{V_1, V_2, V_3, ..., V_V\}$, it will be E divided into V subsets $\{E_1, E_2, E_3, ..., E_V\}$, assuming that E there is P_i a positive and N a counterexample, then the subset E. The desired information required is $I(P_i, N_i)$ that the A desired property is rooted, as shown in Equation (2).

$$E(A) = \sum_i^V \frac{P_i + N_i}{P + N} I(P_i + N_i) \tag{2}$$

$$gain(A) = I(p, n) - E(A) \tag{3}$$

ID3(Iterative Dichotomiser 3) $gain(A)$ selects $E(A)$ the largest, that is, $A*$ smallest, property $A*$ as the root node, E and recursively calls V the subnode generated by the above procedure on the subset E corresponding to the different values $A*$. ID3 is a representative that takes the information descendants as the evaluation function of the separated goal and adopts the top-down divide and rule strategy. Decision trees built using the ID3 algorithm have smaller average depths and faster classification rates (Dou et al., 2018).One can intuitively and accurately obtain classification rules and make objective and accurate classification judgments on unknown data through decision trees.

Overcome the Bias of the Selection Attribute

New attribute selection criteria can be found by transforming the information gain formula. The properties selected in this new standard not only overcome the drawbacks of E-learning's tendency to choose more valued properties as test properties but also significantly reduce the computational cost (Qu, 2021). As can be seen by Equation (3), there is a quantification $I(p, n)$ on each node, the A entropy value of the attribute can be selected $E(A)$ as the criterion for comparison between nodes, as shown in Equation (4).

$$E(A) = \sum_i^V \frac{1}{(p+n)\ln 2}\left(-p_i \ln \frac{p_i}{p_i + n_i}\right) \tag{4}$$

Since $(p + n)\ln 2$ is a constant in the training set, we can assume that the function $e(A)$ satisfies Equation (5).

$$e(A) = \sum_i^V -p_i \ln \frac{p_i}{p_i + n_i} \tag{5}$$

Bring Equation (4) into Equation (5) to get Equation (6).

$$e(A) = \sum_i^V \left(p_i \frac{n_i}{p_i + n_i} + n_i \frac{p_i}{p_i + n_i}\right) \tag{6}$$

One assumes that the number of values of each property is a function in Equation (7).

$$e(A) = (\sum_{i}^{V} \frac{2p_i n_i}{p_i + n_i})N \tag{7}$$

It is clear that in $e(A)$ there are only addition, multiplication, and division operations, and the time of the operation is certainly shorter than in $E(A)$ than that of operations with multiple logarithmic terms in it. Therefore, the selected function is $e(A)$ to calculate the value of each attribute for comparison, and the leaf node with the smallest value, that is, the property value. This impact on the overall performance of the data classification from the classifier is small.

RESULTS

Improved Algorithm Verification

When selecting eigenvalues, the algorithm tends to be biased towards problems with more attributes, so the selected features may not be the best choice (Zheng et al., 2019). Since this problem is related to the selected sample data, there is no control over the sample data, and some data have a certain amount of sporadic noise (Zhang, 2020). If you encounter these problems, you can use the concept of user interest to solve them. The feature information gain value is adjusted by removing the weight of prior knowledge when calculating the information gain to achieve the ability to correct some erroneous branches (Liu, 2017). In this paper, we choose test scores as the root node and select the characteristics of internal nodes for class management and teacher assignment. The improved decision tree is shown in Figure 1.

Figure 1. Improved decision tree
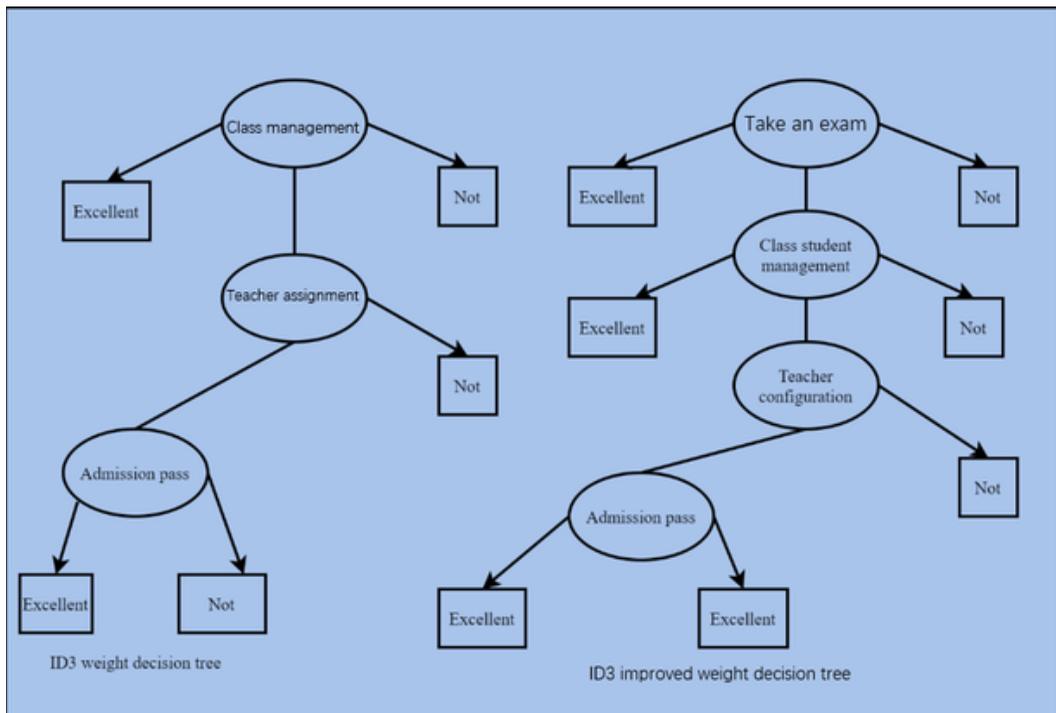
Data Preprocessing

Data collection is an integral part of a decision tree system and is the first link in a decision tree. Data collection for a typical decision tree system should include structured and semistructured data. This paper mainly focuses on structured data, and some mainly contain basic information of students. It is semistructured data structured according to features while extracting common parts and eliminating inaccuracies. In addition, this paper designs a student information questionnaire to be filled out by students, which contains the basic information of students as comprehensively as possible. Finally, this information is manually entered into the educational information mining database to form a subsequent decision tree. Here, we use the dimensionality reduction method. In other words, it is a way to find really useful attributes among the initial attribute attributes, the attributes of the subject types (A, B, C, D) that are highly correlated with the scores, and selects the test difficulty (high, medium, low), delivery time (normal, short), and test scores (excellent, good, poor) to create a basic data table to classify how good or bad the scores are. The training set of student test scores is shown in Table 1.

The training set selects the test type as the test attribute, and the values for the test type are: t1 = A, t2 = B, t3 = C, and t4 = D.

When t1 = A, p1 = 2, n1 = 2, this can be obtained:

$$e(t1) = \sum_{1}^{N} \frac{1}{(p+n)\ln 2} - p_1 \ln \frac{2p_1 n_1}{p_1 + n_1} = 2.2 .$$

When t2 = B, p2 = 1, n2 = 2, this can be obtained:

$$e(t2) = \sum_{2}^{N} \frac{1}{(p+n)\ln 2} - p_3 \ln \frac{2p_2 n_2}{p_2 + n_2} = 1.666$$

When t3 = C, p3 = 3, n3 = 2, this can be obtained:

$$e(t3) = \sum_{3}^{N} \frac{1}{(p+n)\ln 2} - p_3 \ln \frac{2p_3 n_3}{p_3 + n_3} = 2.512 .$$

When t4 = D, p4 = 2, n4 = 2, this can be obtained:

$$e(t4) = \sum_{4}^{N} \frac{1}{(p+n)\ln 2} - p_4 \ln \frac{2p_4 n_4}{p_4 + n_4} = 1.387 .$$

Table 1. Training set of student test scores

Student ID	Course Type	Exam Difficulty	Turn-In Time	Exam Results	Overall
1	C	middle	normal	excellent	Yes
2	A	high	short	good	Yes
3	A	low	normal	difference	Yes
4	B	middle	normal	excellent	No
5	B	low	normal	difference	Yes
6	C	middle	normal	good	Yes
7	D	high	normal	excellent	Yes
8	B	middle	normal	excellent	No
9	C	middle	normal	good	Yes
10	D	high	short	good	Yes

From this, the gain (test score) obtained is the largest, that is, the information of the test score is the most helpful for classification, so the test score is selected to partition the structure of the decision tree for the first time.

Classification Performance Analysis

In this section, the existing general algorithm and the improved decision tree algorithm are used for testing, and four data sets are selected for comparison. We further generalize the experimental data by performing 20 experiments on each data set and then computing the mean. And through the analysis of the above experimental data, the differences between the decision tree algorithm and the improved decision tree algorithm in the above four aspects are compared and analyzed. And all experiments are performed on machines with the same configuration and the same operating system.

- Dset1: There are 874 instances in total, five condition attributes, and one category attribute. All attribute values are discrete values, and the category attribute has three different values.
- Dset2: There are 968 instances in total, six condition attributes, and one category attribute. All attribute values are discrete values, and the category attribute has three different values.
- Dset3: There are a total of 1,282 instances, seven conditional attributes, and one category attribute. One conditional attribute is a continuous attribute, and the category attribute has three different values.
- Dset4: There are 1,548 instances in total, 24 conditional attributes, and one category attribute. Three conditional attributes are continuous attributes, and the category attribute has three different values.

The decision tree ID3 and the improved ID3 are used for learning, respectively, and the comparison results are shown in Table 2 and Figure 2.

The larger the instance set and the more attribute sets, the more obvious this advantage is. A comparison of the number of rules is shown in Table 3 and Figure 3.

Figure 3 shows that the number of decision tree rules composed of improved algorithms is far less than the number of decision-making tree rules. The number of rules corresponds to the number of leaf nodes. The fewer the number of leaf nodes, the less the number of rules, and the larger the example set, the more attributes, the more obvious these advantages. See Table 4 and Figure 4 for accuracy.

Classification accuracy is an important evaluation criterion for classification models. Figure 4 compares the accuracy obtained before. It can be seen from the figure that the improved decision tree is more accurate than the existing decision tree. And as the amount of data increases, the time difference increases linearly, but as the amount of data increases, the trend of the improved decision tree is slightly lower than that of the decision tree, and this downward trend is similar to the following. The comparison of the time to build the decision tree is shown in Table 5 and Figure 5.

Figure 5 compares the time-consuming before and after and shows the improved decision tree is less time-consuming than the existing one. The time difference increases linearly, which is also

Table 2. Comparison of the number of nodes

Data Set	The Number of Records	Decision Tree Leaf Nodes	Improves the Leaf Nodes of Decision Trees
Dset1	874	15	7
Dset2	968	26	16
Dset3	1,282	36	22
Dset4	1,548	43	28

**Figure 2. Comparison of the number of nodes**
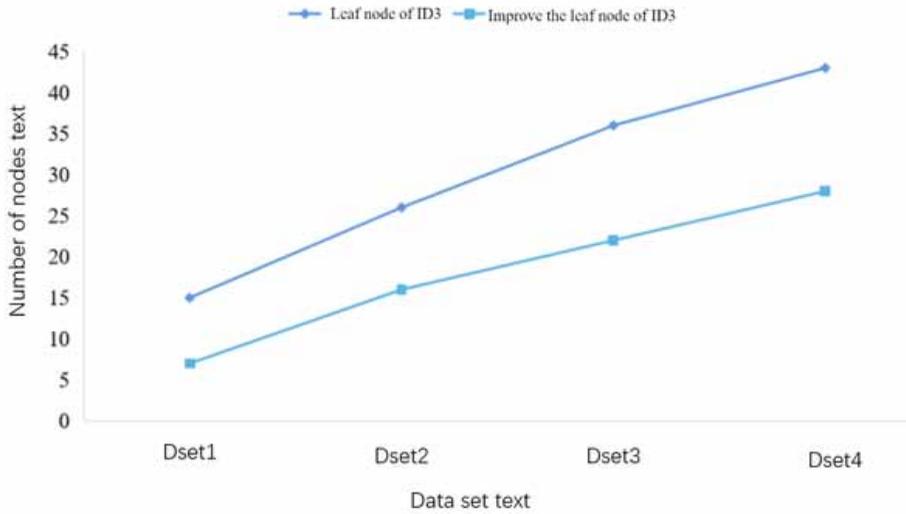
Table 3. Comparison of rule numbers

Data Set	The Number of Records	The Number of Rules in the Decision Tree	Improves the Number of Rules for the Decision Tree
Dset1	874	55	44
Dset2	968	85	68
Dset3	1,282	104	84
Dset4	1,548	124	102

Figure 3. Comparison of rule numbers
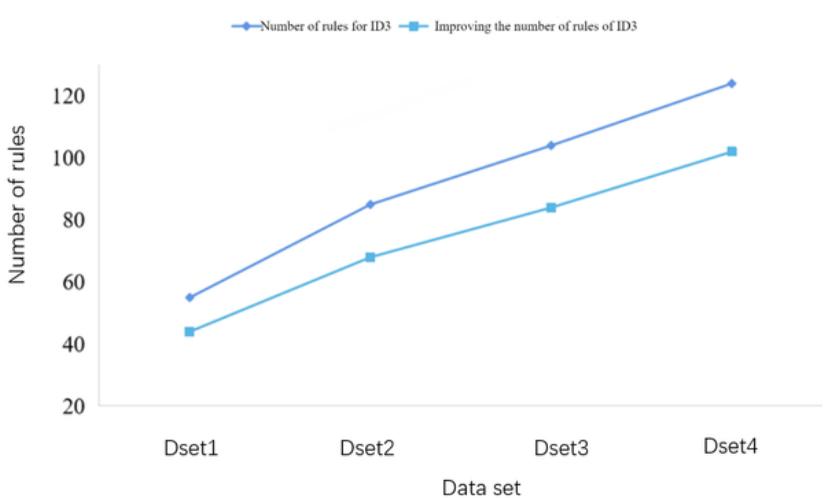
Table 4. Intelligent localization assisted comparison of accuracy rates

Data Set	The Number of Records	The Accuracy of the Decision Tree (%)	Improves the Accuracy of Decision Trees (%)
Dset1	874	67.7	73.5
Dset2	968	72.6	75.7
Dset3	1,282	80.5	84.3
Dset4	1,548	85.3	88.5

Figure 4. Comparison of accuracy
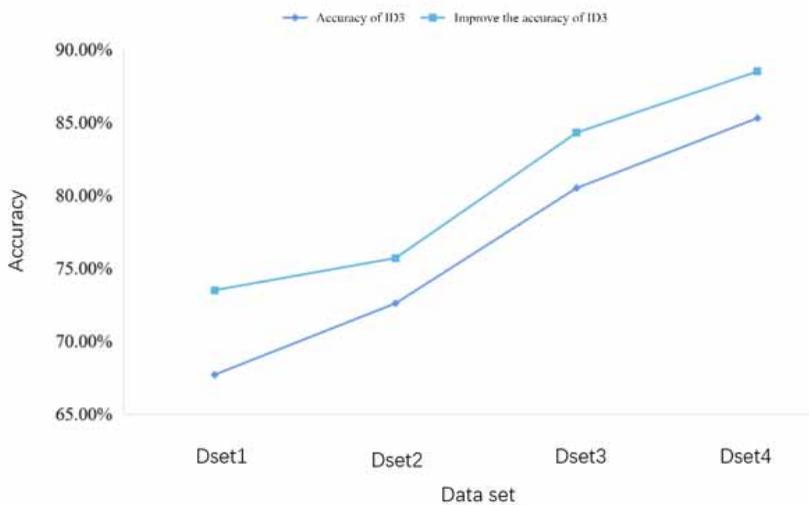
Table 5. The comparison of the time to build a decision tree

Data Set	The Number of Records	Average Time(s) Taken by ID3	Average Time Taken to Improve ID3(s)
Dset1	874	153.9	124.7
Dset2	968	252.6	200.5
Dset3	1,282	351.4	261.1
Dset4	1,548	420.3	308.5

related to the distribution of data features in the data set. This fully shows that the improved E-learning has greater efficiency and performance advantages than the original E-learning in the decision tree construction process for larger data sets (Cohen & McKeachie, 1980). E-learning is only a modern technical means to assist teaching and does not replace or weaken teachers' classroom teaching and practical teaching. Taking the course "Social Theory, Social Welfare and Social Work" as an example, the teaching methods and classroom organization forms adopted include classroom lectures, discussions, case studies, homework presentations, lectures by well-known experts, student practice, which are flexible and diverse.

Figure 5. Comparison of the time to build a decision tree
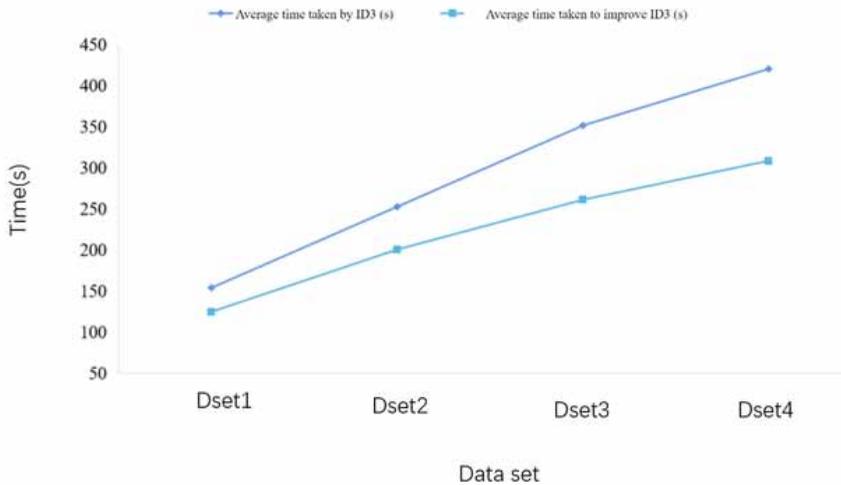
DISCUSSION

This study used multiple data sets and analyzed and compared them separately for different data sets. In terms of data preprocessing, in addition to using dimensionality reduction methods, a student information questionnaire has also been specially designed to provide more comprehensive student information and better construct a decision tree model. In terms of analysis methods, this paper used a decision tree algorithm and an improved decision tree algorithm for comparison, selected 20 experiments and calculated the average value, obtained experimental data, and analyzed their differences. At the same time, this paper also focused on time complexity, accuracy, and the time required to create a decision tree, evaluating the performance and effectiveness of the algorithm from multiple perspectives.

This study proposes an online education and teaching quality evaluation model based on artificial intelligence psychology, which achieves quantitative evaluation of teaching quality by constructing an improved decision tree algorithm and personalized service system. This model can be used for education quality evaluation in different fields and purposes.

In terms of data preprocessing, we used dimensionality reduction methods to select truly useful attributes from the initial attributes and create a basic data table to classify the quality of scores. In terms of classification performance, we tested and compared the performance of existing universal algorithms and improved decision tree algorithms on four data sets. The results showed that the improved decision tree algorithm outperformed existing decision tree algorithms in terms of node count, rule count, classification accuracy, and construction time.

In addition, we also discussed the diversity of teacher teaching methods and classroom organization forms, pointing out that online educational technology is only an auxiliary means of teaching and cannot replace traditional practical teaching and classroom teaching. Therefore, this model can provide a reference for the expansion of education and personalized teaching in online schools and provide better educational environments and conditions for students, making contributions to the cultivation of all-round talents in society.

CONCLUSION

This paper proposes an intelligent electronic learning model based on artificial psychology for online education and teaching quality evaluation, and, based on this, proposes a decision tree recommendation

algorithm. This algorithm fully considers the noise and uncertainty present in the sample data by introducing information gain, thereby improving classification performance and prediction accuracy.

Meanwhile, in terms of data preprocessing, this article adopts a dimensionality reduction method to further improve the efficiency and performance advantages of the algorithm. This research method not only has high application value in practice, but also provides new ideas and technologies for future education and teaching fields, with important theoretical and practical significance. Experiments have shown that compared to the original E-learning, the improved algorithm can establish a more concise decision tree classification model and is superior to the ID3 decision in terms of algorithm time complexity, accuracy, and time required to create a decision tree. As the amount of data increases, the time difference increases linearly, but as the amount of data increases, the trend of improving the decision tree is slightly lower than that of the decision tree, and this downward trend is similar to the following. In the process of constructing decision trees for larger data sets, the improved E-learning in this paper has higher efficiency and performance advantages compared to the original E-learning.

Afterward, we can further explore the relevant technologies and application scenarios of artificial psychological intelligence education and teaching and strengthen research on data preprocessing and algorithm optimization to improve the efficiency and performance advantages of algorithms and better apply them to the field of education and teaching. Future research can investigate additional parameters to further improve decision tree algorithms.

AUTHOR NOTE

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