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Practical Evaluation Analysis of Intelligent Product Design Using Decision Tree Algorithm

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ABSTRACT

The decision tree algorithm is an efficient machine learning technique that can help us better assess the practicality of intelligent products. This paper explores the basic principles of the decision tree algorithm and proposes a series of effective evaluation methods combined with practical applications to achieve better results. Through experimental verification, the decision tree algorithm performs well in the practicality evaluation of intelligent products (using clothing design as an example) and effectively addresses challenges in real-world applications. Therefore, the decision tree algorithm can serve as an effective tool to enhance the quality and competitiveness of product design for businesses.

Keywords: Decision Tree, Intelligent Product Design, Practicality Analysis, Gini Index, CART Algorithm

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1. Introduction

In today's world, the design of intelligent products has become increasingly important as it directly impacts consumers' experience. In this rapidly changing era, how to meet consumers' needs through thoughtful design and gain advantages in a competitive market has gained increasing attention. Practical evaluation should be conducted from multiple perspectives, including but not limited to functionality, ease of operation, stability, safety, durability, aesthetics, and appearance. To make the evaluation results more accurate and objective, a comprehensive and effective evaluation system must be adopted [1]. The decision tree algorithm is an effective machine learning method that constructs a complete and accurate decision tree model by analyzing user needs, technological trends, and changes in the market environment, thus improving the practicality of intelligent products [2]. The decision tree algorithm is a machine learning technique that uses a tree-like structure and adopts supervised learning methods, effectively solving complex problems such as classification and regression.

It constructs a decision tree as a model, starting with a single node and gradually expanding to better solve problems [3]. The decision tree algorithm aims to use its unique algorithm framework to quickly and accurately identify and deal with various complexity models. Its basic principle is to first divide the model into several independent branches, and then arrange these branches in sequence to obtain the optimal model. Moreover, it can be used to predict the accuracy of the model, thus better forecasting the model's representation. Due to its simplicity, ease of use, and fast computation speed, the decision tree algorithm has been widely applied in machine learning [4]. Its basic principle is to divide repetitive tasks into several sub-tasks and use recursive methods to form a tree-like model to achieve the final goal. Through the use of the decision tree algorithm, we found that the technology effectively evaluates the practicality of intelligent products. Firstly, the algorithm has various features, such as numeric patterns, image patterns, and image aggregation patterns, making it suitable for various complex practical needs. Secondly, the algorithm has good readability, making it convenient to execute strategies for different needs. Finally, the algorithm has high analytical accuracy, making it a very effective means to rapidly and finely evaluate the practicality of intelligent products. Through the decision tree algorithm, valuable information can be extracted from massive data, organized, and summarized, thus better identifying important trends and more accurately predicting future development trends. Therefore, the decision tree algorithm can be widely used in the practicality evaluation of intelligent product design. Its specific operational process can be as follows: firstly, from massive data sources, such as user needs, technological development, and market competitiveness, search for the optimal decision tree model, such as C4.5, ID3, and CART; then, use the decision tree model to construct a complete model to better identify future trends and promote future development. With well-designed schemes, we can more effectively improve and perfect our models. After rigorous testing and verification, we can more accurately measure its reliability. Through systematic research, we found that the decision tree algorithm is a very effective method for measuring the practical application of intelligent products. Especially in the field of smart homes, it can not only help designers better understand customer needs but also help them accurately judge market competitors, thereby better grasping consumer expectations and better serving consumers. Although the decision tree algorithm performs well in the practicality evaluation of intelligent product design, it also faces some challenges, such as lack of sufficient datasets, lack of reasonable feature selection, and other potential issues. Therefore, we need to seek more refined algorithms to overcome these challenges and improve efficiency. Due to the lack of large-scale data, the performance of the decision tree algorithm is often affected. Moreover, in the decision tree algorithm, correct feature selection is also important, as it will determine whether the decision tree's results have good accuracy. To improve this situation, future research should focus on optimizing the decision tree algorithm to achieve better results. The decision tree algorithm is a very effective tool that not only helps us better assess the practicality of intelligent products but also helps us improve the quality of products. However, it will also face many challenges, such as insufficient accuracy and unstable results. In the future, we will continue to conduct in-depth research to optimize the decision tree algorithm, making it more accurate and trustworthy. Through continuous improvement and optimization, we will help enhance the efficacy of intelligent products and promote innovation, providing consumers with a more comfortable, convenient, safe, and efficient lifestyle.

2. Related Work

For intelligent product design, practicality evaluation is undoubtedly a crucial task to better meet consumers' expectations and enhance features such as functionality, convenience, stability, safety, durability, and aesthetics. Therefore, many scholars have actively explored effective means of practicality evaluation to improve its application effectiveness. The decision tree algorithm has become an important tool in machine learning and has been widely applied in the development of various intelligent products. It can provide personalized solutions to meet various complex functions in smart homes, smart transportation, smart health management, etc. To better meet different application environments, the most suitable decision tree algorithm model and corresponding metrics should be carefully selected for a more accurate evaluation of its application effectiveness. Researchers have thoroughly explored the important role of the decision tree algorithm in practicality evaluation for intelligent product design. They pointed out that the decision tree algorithm can not only effectively address complex practicality issues but also provide reliable results. Furthermore, they discussed how to select the best model and evaluation metrics [5]. Through their research on the decision tree algorithm, Deborah and others found that it can effectively solve key issues like data quality, feature selection, and model optimization, significantly improving the algorithm's prediction accuracy and reliability [6]. Additionally, they conducted in-depth analyses of the decision tree algorithm's applications in various intelligent product design fields and provided detailed explanations of its strengths and limitations. In the future, we will explore more effective decision tree algorithm models to improve prediction accuracy and reliability and seek more feasible solutions. Scholars have conducted a series of practical cases to thoroughly explore the effectiveness of the decision tree algorithm and its performance in various intelligent product design environments, thus better understanding the features, functions, reliability, and other relevant factors of the decision tree algorithm [7]. Regarding current decision tree algorithms, Han et al. conducted in-depth analyses and pointed out that they contribute to the development of customized solutions tailored to specific environmental requirements, significantly improving the efficiency and quality of practical use [8]. They also highlighted that the future development of decision tree algorithms will move towards more advanced directions. Scholars have thoroughly explored the potential of the decision tree algorithm, closely integrating it with cutting-edge technologies such as artificial intelligence and machine learning. They provided a systematic review of various functions, features, performance, and its impact on various environments, with the aim of improving the use of the decision tree algorithm [9]. Through the analysis of multiple exemplary cases and their relevant application environments, this study deeply researched the optimization of decision tree algorithm models and their contributions to improving the effectiveness and quality in practice. The purpose of this research is to conduct an in-depth analysis of the use of the decision tree algorithm and its impact on intelligent product design. Based on multiple typical cases, we elaborate on the features, functions, feasibility, and future trends of the decision tree algorithm. In conclusion, the decision tree algorithm has become an important tool for intelligent product design and has significant development potential. Despite achieving many successes, it still faces various challenges, such as optimizing the algorithm's structure, improving computational efficiency and accuracy. In the design process, personalized solutions should be adopted based on specific application environments and the functionalities they bring, thereby enhancing system efficiency, accuracy, and reliability [10].

3. Decision Tree Algorithm Design

3.1 Intelligent Clothing Design Process Flowchart

In recent years, with the rapid development of technology, the clothing industry is moving towards a new direction. The application of technologies such as big data, cloud computing, intelligent manufacturing, and e-commerce has shifted clothing production from traditional high-end tailoring to more personalized mass production. This transformation not only promotes the digitalization of the clothing industry but also changes the traditional mindset of manufacturing, allowing consumers to participate more directly in the design and production of clothing. As consumers increasingly value personalization, the clothing industry has witnessed unprecedented vitality and is continuously optimizing its industrial structure. In the future, large-scale personalized tailoring will become a major development direction in the clothing industry, and intelligent clothing design will be an important component of it. Typically, the entire process includes three steps: identifying target audiences, conceptualizing ideas, and implementing production.

In the first step, it is essential to thoroughly understand the needs of the target audience and develop design proposals that cater to them. In addition to researching relevant materials, adjustments should be made based on the audience's height characteristics. According to the designer's creativity, various modifications can be made using original data to create unique patterns. Apart from basic geometric elements, three key factors - lines, colors, and fabrics - along with piecing and sewing, are used to perfectly present the clothing's silhouette, structure, and details. By employing advanced digital technologies and precise model analysis, clothing's appearance, functionality, aesthetics, and other information can be effectively transformed into three-dimensional, accurate images. This facilitates better recognition, modification, enhancement, optimization, etc., during the design process to meet customer demands effectively.

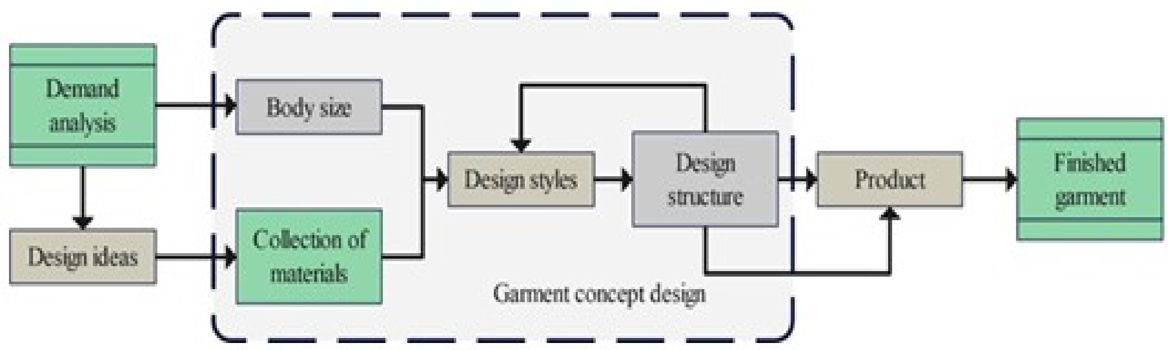

Figure 1. Intelligent Clothing Design Process

3.2 Feature Selection Framework

The main purpose of feature selection is to eliminate features with interference coefficients and find a subset of informative features with lower dimensions but higher discriminability. With the rapid increase in data volume and the number of samples, the feature dimensions are also continuously increasing. Additionally, irrelevant features and noise data are also growing rapidly, causing a gradual decline in algorithm performance. Therefore, feature selection is an important task, and based on Equation 1, the optimal features can be selected from the original data, thereby reducing the dimensionality of the dataset and improving the performance of the learning algorithm.

$$P\left(k^{i} / d\right) = \frac{P\left(k^{i} / d\right) \times P\left(k^{i}\right)}{P(d)} \tag{1}$$

3.3 C4.5 Algorithm and CART Algorithm

The CART algorithm is widely regarded as an effective numerical model capable of capturing and solving complex mathematical problems efficiently. It measures the accuracy of mathematical models using the Gini coefficient, which can be represented by Equation 2. The decision trees generated by the CART algorithm exhibit high accuracy. However, when the complexity of the decision tree reaches a critical value, its accuracy significantly decreases. Therefore, when dealing with continuous data, it is advisable to sort attributes based on their features and then split them into two different subsets according to their characteristics. By employing appropriate techniques for weighted impurity of sub-partitions and setting them to their optimal values, it becomes possible to effectively reduce various numerical values, resulting in improved classification performance.

An increase in $\Delta g(A)$ will contribute to a more efficient reduction of various numerical values, leading to better classification performance.

Building on the ID3 algorithm, an improved algorithm known as the C4.5 algorithm has been introduced, as seen in Equation 3. The C4.5 algorithm overcomes the attribute bias issue in the ID3 algorithm and handles continuity by discretizing and pruning, thereby mitigating the problem of "overfitting" to some extent. However, when the algorithm discretizes continuous features, it must traverse all values within that feature, which reduces efficiency.

$$Y(X) = \sum_{i=1}^{m} \frac{d_{1i} + d_{2i} + \ldots + d_{mi}}{D} \times I\left(d_1, d_2, \ldots, d_a\right) \quad (2)$$

$$\Delta b(t) = \alpha \, \Delta b(t-1) - \eta \frac{\partial \, err(t-1)}{\partial \, b(t-1)} \quad (3)$$

4. Experimental Design and Analysis

4.1 Experimental Design

Using the Analytic Hierarchy Process (AHP), we established a usability evaluation index system for intelligent clothing design, consisting of three parts: first, A, which represents the reliability of the entire intelligent clothing design; followed by Am, representing the reliability of appearance, operation, and sensory aspects; and finally, Amn, representing the comprehensive consideration of reliability for each component. In the end, a comprehensive assessment is made for each part's reliability. By creating an evaluation matrix comprising A11A13, R1, R2, and A31A35, we can determine the corresponding weights for each indicator of this smart product. These evaluation matrices help us better understand the characteristics of this product and provide more effective decision support. In this sentence, we divided the decision tree into two parts in an 8:2 ratio. We used Python's sklearn software to build the decision tree and trained it using these trees. We will adjust the parameters for each part of the decision tree, as these parameters may affect the performance of the decision tree and thus the decision tree model. Based on clothing styles and human-computer interaction as an essential means of innovative clothing design, we conducted in-depth analysis of user needs to precisely describe clothing styles and meet user requirements. Furthermore, to better embody the design characteristics of men's suits, we also adopted the decision tree algorithm to design suits in a more accurate way. By using the algorithm model, we can express the genes of clothing styles and identify their main components. Next, we can propose a new gene definition through analyzing these features and study their impact on clothing design. Finally, we can optimize these parameters through parametric design to obtain better results.

4.2 Experimental Results Analysis

As shown in Figure 2, with the increase in the number of Assembly processes in the model, we can observe changes in the model's prediction accuracy. In the stage where the number of Assembly processes is from 0 to 5, the prediction accuracy significantly increases from 0.6 to 0.76 and remains stable at this level. This indicates that adding Assembly processes at the initial stage of the model can significantly improve the prediction accuracy. However, when the number of Assembly processes increases to around 14, the prediction accuracy suddenly drops to around 0.6. This may indicate that at this stage, the model might face overfitting or other issues, leading to a significant decrease in prediction accuracy. Subsequently, as the number of Assembly processes continues to increase, the prediction accuracy gradually rises to around 0.77, suggesting that the model recovers and achieves better prediction results after some adjustments. In the later stages, although there is a slight fluctuation in prediction accuracy, it ultimately decreases slowly to around 0.7. This may be due to the increasing complexity of the model as the number of Assembly processes increases, leading to a decline in prediction performance.

Through practical evaluation, we found that using the decision tree algorithm to improve the efficiency of intelligent decision systems is more effective and can significantly reduce the training cycle, thus achieving the desired results faster. On the other hand, we can also verify the effectiveness of this algorithm through practical examples and assess its reliability based on real instances. The prediction results of the optimized decision tree algorithm model are significantly lower than the original reference points, indicating that both its accuracy and efficiency are excellent. From Figure 3, we can also see that this gap is smaller than before, indicating that this new intelligent decision algorithm is more refined, flexible, and better than the previous one.

Due to scientific advancement and increasingly fierce competition, new products are rapidly being launched to meet consumers' expectations for more efficient and specific services. Considering the diversity of various product categories in the current market, the scalability of the database can also be affected. Therefore, it is urgent to adjust the parameters of the decision tree algorithm so that it can withstand multiple rounds of training and maintain good accuracy and reliability. To test this, we evaluated the standard deviation of the results from the 8 training sessions of the established decision tree algorithm to demonstrate its reliability. Through multiple tests, we found that the standard deviation of the optimized intelligent decision model based on the decision tree algorithm is significantly reduced, far superior to the original model. Therefore, we can confidently conclude that this model can effectively meet the needs of intelligent products and maximize its effectiveness.

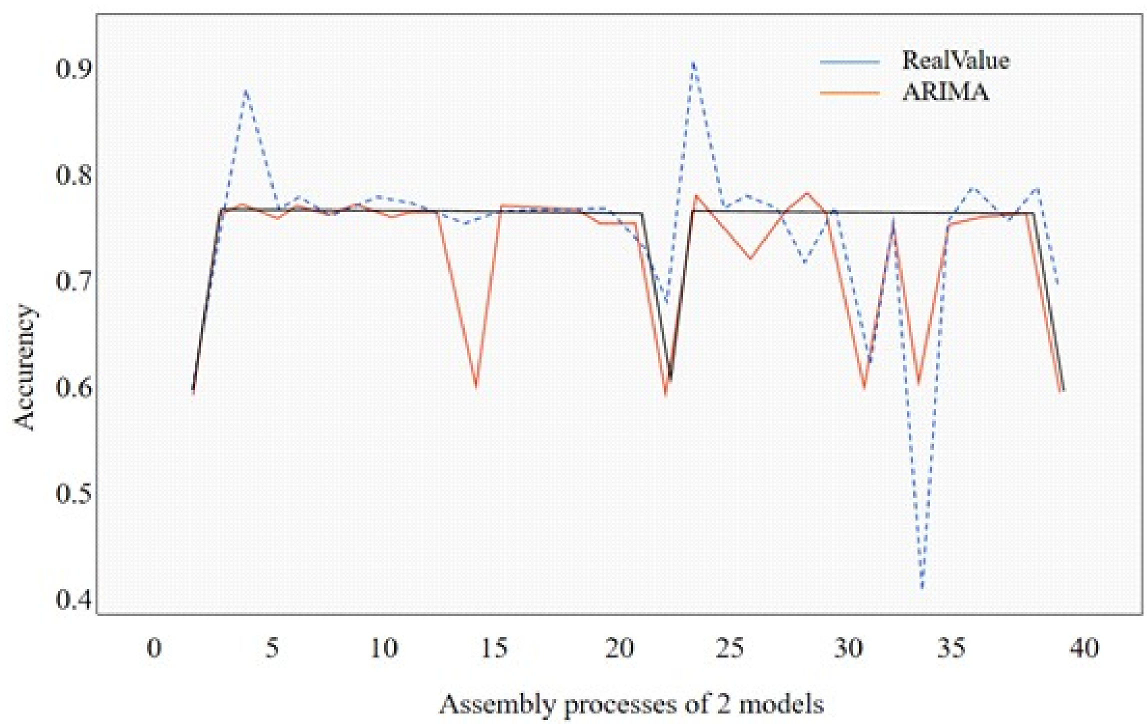

Figure 2. Comparison of output results of decision Tree model

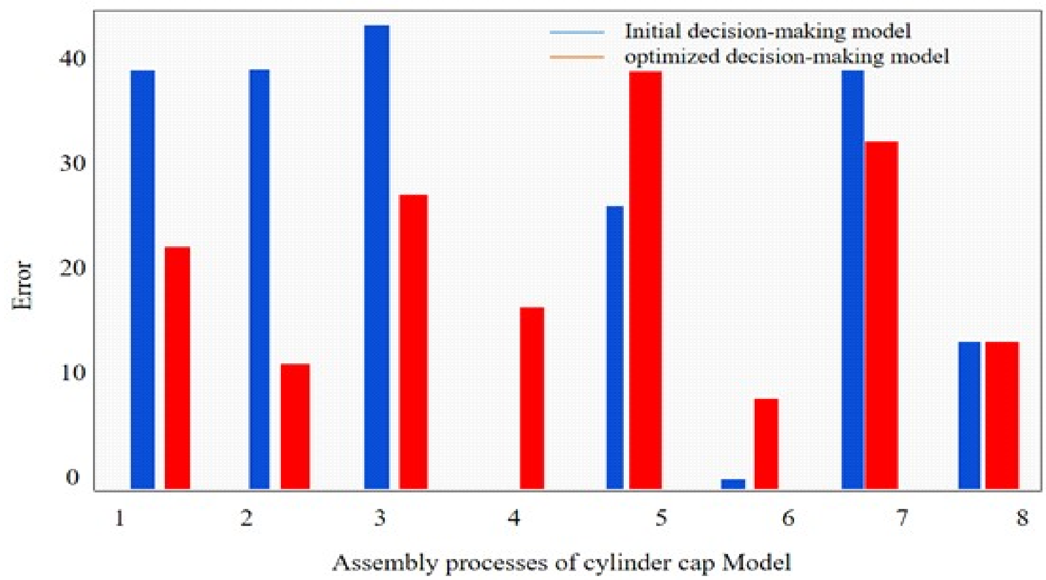

Figure 3. Comparison of Percentage Errors in Decision Tree Algorithm Models

5. Conclusions

The focus of this paper is on how the decision tree algorithm is widely applied in the practical usage of intelligent products. It not only helps to deeply understand customers' needs but also facilitates the identification of product deficiencies, enabling targeted adjustments or improvements. In addition, the decision tree algorithm greatly enhances the accuracy and speed of evaluations, thereby driving research and innovation in intelligent products. The decision tree algorithm is a highly effective method for evaluating the practical usage of intelligent products. This algorithm predicts vast amounts of data and provides decision-makers with a more accurate and comprehensive approach for unified judgment. However, the decision tree algorithm still has some challenges. The system requires us to provide precise and complete information strictly. The decision tree algorithm is an essential tool that helps us adjust parameters and optimize models to improve their accuracy and stability. To better evaluate the practicality of intelligent products, continuous exploration and experimentation are needed, along with efforts to improve the algorithm and enhance data processing capabilities. The decision tree algorithm plays a crucial role in intelligent product design, not only providing accurate practicality assessments but also offering strong support for the development of intelligent product design, thereby promoting continuous progress.

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