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Computer-Aided Design AND APPLICATIONS

The Usage of Random Forest Algorithm in Evaluating the Effect of Art Illustration Interactive Design

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Abstract. Art illustration interactive design is an important way to attract user attention, convey information vividly and intuitively, and enhance emotional resonance among users. However, issues such as homogenization of design elements, lack of cultural value, and limitations of traditional evaluation methods limit the comprehensive evaluation of design and cannot effectively promote its development. Therefore, this article adopts the random forest algorithm to construct an art illustration interactive design evaluation model and deeply analyzes the contribution rate of evaluation indicators to select key indicators. Experimental results have shown that compared to traditional methods, our model exhibits higher evaluation accuracy and stability. The error between the evaluation results and actual results is smaller, and the adaptation range is wider. It can provide effectiveness and reliability; the model presented in this article can complete effect evaluation from multiple perspectives and comprehensively display the evaluation results of primary and secondary indicators, helping designers to have a deep and multi-dimensional understanding of design effects, optimize design schemes, and visually compare the advantages and disadvantages of different designs.

Keywords: Random Forest; Art Illustration; Interaction Design; Design Effect; Design Evaluation
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1 INTRODUCTION

Art illustration, as a visual element that is intuitive and easy to understand, can effectively assist in conveying information. In digital interfaces, illustrations can enable users to quickly and directly obtain information, and make decisions on what to do next. Compared to pure text or graphic design, illustrations can more accurately express the designer's intentions and improve the efficiency of information transmission [1]. Art illustration interactive design enhances the visual appeal of products by introducing vivid and vivid illustration elements and interesting interactive methods. This design can reduce the cognitive burden and operational difficulties of users, enable them to easily complete tasks, and enhance their satisfaction and desire to use the product. It can inject personality

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and style into the product through unique illustration style and creativity, helping the product stand out in the fiercely competitive market [2]. This design can enhance the differentiated competitiveness of the product, and increase brand value and market share. In terms of design, artistic illustration interactive design focuses on creating fun and interactivity, which can stimulate emotional resonance among users. Illustration can present information humorously and exaggeratedly, making users feel relaxed and happy. This design can attract visual attention from users while making it easier for them to establish emotional connections with the product, increasing user stickiness and desire to reuse the product. However, due to the timeliness, diversity, and intensity of market competition, some products blindly imitate successful art illustrations and interactive designs in order to obtain more benefits in a short time and achieve the goal of visually attracting users through the superposition of similar elements [3]. Therefore, these artistic illustration interactive designs lack uniqueness and innovation, ignoring the personalized needs and habits of users. The layout arrangement of stacked visual elements does not reach a balanced state, and the correlation and harmony between design elements are low, which makes users feel confused visually and reduces their sense of pleasure.

Many image problems are not only seen as an image to image translation tasks but also incorporate elements of artistic illustration interaction, bringing richer application scenarios and user experiences to these technologies. In the image-to-image translation technology based on the GAN algorithm and its variants, the application of interactive art illustrations is particularly prominent [4]. For image-to-image translation techniques with multimodal and multi-domain representations, artistic illustration interaction is also of great significance. Effective Image Content Analysis (AICA) in the field of emotional computing and abstract image art recognition is a challenging branch of AICA. Abstract images are composed, and humans cannot recognize the objective subject they depict. Artistic recognition of abstract images can not only promote research progress in the fields of art and psychology. In previous studies, traditional methods have struggled to bridge the emotional semantic gap, while neural network-based methods have been limited by the difficulty of training on small datasets. To classify abstract images in art, it is necessary to establish a connection between low-level visual information of images and human cognitive artistic semantics and to cross deeper artistic semantic gaps [5]. Moreover, it can expand the application scenarios of abstract images and visual elements in daily life and assist in the creative work of generative AI. The concept of style transfer has been introduced into the problem of abstract image art recognition, and a new solution has been proposed, which includes two modules: style transfer data enhancement and a classification model that integrates style features. Universal image art recognition methods often focus too much on high-level semantics and overlook the characteristics of abstract images themselves, lacking differentiation from large-scale AICA tasks in terms of thinking. The image style concept in the style transfer task defines the low-level visual information contained in the image, which is semantically similar to abstract images. This data augmentation method not only alleviates the problem of small sample size in the dataset but also enables deep neural networks to be directly trained and improved. Some scholars have proposed a new generative data augmentation method to expand the content semantics of abstract image art recognition datasets [6].

Through this method, research has improved the performance of abstract image art recognition, providing references for related issues. Moreover, the introduction of advanced semantic information as interference helps the model learn the mapping relationship between low-level visual features and emotional labels of images during training, thereby improving classification performance [7]. Extract content images from the FI dataset using the original dataset as style images, and perform style transfer based on MetaStyle for data augmentation. Propose a neural network model that integrates style features. On the one hand, relevant methods are used to extract feature maps at different levels of the neural network, which are processed as style features of the image. On the other hand, based on residual convolutional neural networks and SE attention mechanism, advanced semantics, and the two features are fused for sentiment recognition [8].

To improve the interactive design effect of art illustration, some scholars have proposed to effectively evaluate its design effect through a systematic and scientific approach. The demand for simple image recognition can be effectively solved through algorithms proposed in recent years. Due

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to the demand driving the solution of traditional image recognition problems, current research on this problem is no longer challenging. However, it is not easy to find one's favourite style of artwork from numerous art exhibitions and a vast collection of art pieces. Appreciate artworks through online cultural exhibitions or online museums [9]. In theory, the difficulty coefficient of style classification research is higher than the other two. This article first introduces the current research progress of image classification, laying the foundation for the emergence and development of visual art image style classification, and then elucidates the relevant research background and specific significance of visual art image style classification. This has accelerated the research of experts and scholars in the field of computer science on the style classification of visual artworks [10]. As the material life of the masses gradually became prosperous, they began to pursue spiritual enjoyment. Enhance oneself by visiting museums, admiring exhibitions of famous artists, and other means.

2 RELATED WORK

Chang et al. [11] introduced advanced interactive technologies and algorithms to enable artists to interact with their works in real-time during the creative process, thereby more intuitively expressing their creative intentions and enhancing the artistic effect of their works. This system is based on machine learning and big data analysis and can intelligently recommend color combinations, pattern combinations, etc., providing artists with creative inspiration and guidance. The system supports a user feedback mechanism, allowing artists to evaluate their works. Based on feedback, the system iteratively optimizes and continuously improves design quality. This system covers the computer-aided design functions of traditional art graphics. During the creative process, artists can preview the effects of their design works in real-time and make adjustments as needed. This real-time feedback interaction greatly improves the flexibility and efficiency of the design. In terms of system structure, functional structure, database design, etc., special emphasis is placed on the integration of artistic illustration interaction. The system provides various interactive tools, such as stroke simulation, colour adjustment, layer management, etc. These tools not only help artists control their works more finely but also inspire their creative inspiration. The functional illustration interaction not only significantly shortens the development cycle of art and design works but also improves work efficiency. It also enriches the creative process and enhances the artistic effect of works through real-time previews, various interactive tools, and intelligent recommendations.

With the continuous virtual reality, artistic illustration interaction will present a more diverse and personalized trend. Liow et al. [12] conducted in-depth scenarios, with a particular focus on the field of artistic illustration interaction, and explored the application of computer-aided interaction technology in it. Especially in the field of artistic illustration interaction, digital technology provides artists and designers with rich creative means and interaction methods. Image art recognition is a challenging sub-problem, and studying it has both theoretical and practical significance. Traditional machine learning methods cannot bridge the emotional semantic gap. Noticing the conceptual similarity between abstract images and image styles in style transition tasks, a new method is proposed to address the issue of emotion recognition in abstract images. It is divided into two modules: style transfer data expansion and neural network model design for integrating style features to solve the above two problems. Due to the small sample size of the dataset, advanced neural network algorithms cannot be fully trained directly. Using a MetaStyle style transfer method with multiple styles and contents, randomly select samples from the FI dataset as content images for data augmentation in the abstract image sentiment recognition dataset. This method also introduces rich high-level semantic information as interference to the training set, enhancing the model's ability to learn from style to emotion mapping. By combining traditional enhancement methods, the training set can be expanded to 198 times, allowing for direct training and improvement of large-scale convolutional neural networks on the expanded dataset. Wang [13] proposed an abstract image emotion recognition neural network model that integrates style features. Implement a neural network based on residual convolution module and SE attention mechanism, extract high-level semantic features that may be included in the image, and fuse the two for emotion recognition of abstract images. Divide the pre-trained VGG model into different levels of feature space and extract

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the style features of the image. Conduct experiments on the abstract image emotion recognition dataset represented by the MART dataset for the above work modules and their key components. Based on the proposed model, the neural network structure has been improved, and a new abstract image emotion recognition network model has been proposed. Based on the convolutional neural network design criteria proposed by ConvNeXt, advanced architecture ideas and macro and microstructure design methods from works such as ResNeXt and SwinTransformer are introduced to implement basic modules such as anti-bottleneck residual convolution blocks, dry blocks, and independent downsampling blocks. The results show that the proposed solution achieves the best performance in abstract image emotion recognition problems. Compare with other existing methods to verify the effectiveness of the proposed method in this paper.

Nowadays, the popularity of graphic design has never faded. Whether in logo design, packaging design, poster design, or illustration design, graphics are one of the most important elements in design works. From interface design to logo design and packaging design, graphic design has emerged in various design fields. It not only reflects people's aesthetic changes but also reflects the transformation of contemporary designers' design thinking and language. In order to better integrate graphic design into graphic design works, Zhou et al. [14] sought a perfect fusion of functional beauty and formal beauty. Graphic design attracts public attention with concise and concise graphic symbols, clear information layers, and bold colours, and is favoured by designers. Graphic design of graphics is highly praised and favoured by designers, which naturally has its advantages, but it does not mean that it is suitable for application in all designs. Deeply explore how to transform graphics from 3D to 2D, from concrete to abstract, and how to choose colour tones and colour combinations in graphic design. By combining graphic flattening design cases, and applying and analyzing the methods and principles summarized, the theoretical research results of the article are more convincing and credible. The systematic study of graphic design methods will provide a theoretical basis for future research on the application of graphic design from the perspective of visual communication and has certain academic and practical significance. Zou [15] delved into the origin, development process, and stylistic characteristics of graphic design styles. Discuss three aspects: functional principles of graphic design, visual language principles, and the audience's emotional needs. Summarize the principles that graphic design should follow in the field of visual communication. This system can not only accurately identify the visual elements of artistic illustrations but also understand the interactive behavior of users. And deeply interpret the connotations of artistic works, providing users with a richer and more personalized interactive experience of artistic illustrations.

3 CONSTRUCTION OF AN EVALUATION MODEL

3.1 Effect Evaluation Model Based on Random Forest Algorithm

The CART classification tree structure in the random forest model is quite similar to the growth pattern of trees in nature. It mainly consists of three major parts: root nodes, internal nodes, and leaf nodes. These input sample data each contain a series of identical indicator attributes, which constitute the candidate set for our segmentation. That is to say, once we choose a certain attribute to segment the data, this attribute will no longer be considered in the subsequent growth process of the tree. Firstly, let's take a look at the root node, which is like the foundation of a tree, serving as the starting point for all sample data. All data will start their journey from here. When we arrive at the internal node, it is like a branch of a tree, and the CART tree selects the best classification attribute and corresponding value based on a principle called the Gini coefficient. Finally, we arrived at the leaf node, which is like the leaves of a tree, the endpoint of the data journey. The Gini coefficient is actually an indicator of data purity, and the smaller its value, the higher the purity of the data. In the growth process of CART trees, there is an interesting rule: each indicator attribute has only one chance to be selected. When the samples in the leaf nodes belong to the same category, we can say that these samples have been well classified. By using the CART tree growth method, we can achieve more precise partitioning of data at each node of the tree, thereby improving the accuracy of our classification. By continuously selecting the best attributes and values for segmentation, the CART

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tree is like carefully pruning its branches, gradually dividing the data into smaller subsets. The leaf node no longer needs to be further segmented, and the candidate indicator set becomes an empty set, at which point the segmentation process stops. Through this approach, CART trees can gradually construct a hierarchical classification model for predicting the classification of new sample data. In a random forest, integrating multiple such CART trees and using their prediction results for voting or averaging can further improve the accuracy and stability of classification.

$$Gini(t_m) = 1 - \sum_{n=1}^{2} [P(Y_n | t_m)]^2 \tag{1}$$

When the samples of a node belong to the same category, the Gini index will reach its minimum value, which is 0, indicating that the data has reached the highest purity at that node. On the contrary, when the samples in a node are divided into different types with the same proportion, the Gini index will reach its maximum value, which usually means that the purity of the data is the lowest. To quantify this impurity or impurity, we can use the Gini index to calculate the purity level of any given node. The calculation of the Gini index involves the proportion of samples of different categories in nodes, and the specific calculation formula may be similar to that shown in (5).

$$Gini(T) = \sum_{m=1}^{2} \frac{i_m}{i} Gini(t_m) \tag{2}$$

The number of samples in the split nodes refers to the number of samples used for segmentation on these nodes. This means that after a sample is selected during each sampling, it is still possible for it to be selected again in subsequent sampling. Autonomous sampling (also known as bootstrap sampling) in CART classification trees is a random sampling technique with substitution. For those samples that were not selected in the EEE (I guess you might mean "out of the bag," that is, out of the bag) sampling, their probabilities can be calculated using a specific formula. The total number of these samples, which we refer to as the total number of samples in a node, is the sum of all data points considered when constructing the decision tree. The calculation method of this probability is similar to the mathematical expression shown in (6), but here, we no longer directly reference specific formulas but emphasize the concepts and logic behind them.

$$P = (1 - \frac{1}{i})^i \tag{3}$$

$$Q_m(x,y) = \frac{\sum_{m=1}^{k} I(h_m(x) = y, (x,y) \in O_m(x))}{\sum_{m=1}^{k} I(h_m(x), (x,y) \in O_m(x))} \tag{4}$$

When evaluating the predictive performance of CART classification trees, we usually focus on samples that have not been selected for model training (also known as out-of-bag samples). This ratio provides us with an intuitive measure of the model's generalization ability, as it measures the model's performance on unprecedented data. This usually manifests as a type of voting. The final prediction result of a random forest is determined based on the voting results of all classification trees.

$$Y_f = \arg\max_y \sum_{k=1}^{ntree} \delta(h(x, \theta_k) = y) \tag{5}$$

A notable feature of random forests is their ability to utilize out-of-bag (OOB) samples for model evaluation. To more accurately quantify the performance of the model, we can use interval functions to evaluate the confidence interval of generalization errors. By inputting these OOB samples into the random forest model, we can obtain an effective generalization error estimate, which provides us with an indicator to measure the classification performance of the model. In addition, the generalization error itself also has a mathematical expression, which may resemble the form of (9) or (10), but here we focus more on explaining the concepts behind it.

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$$mg(x,y) = ave_k \delta(h_k(x) = y) - \max_{n \neq y} ave_k \delta(h_k(x) = n) \tag{6}$$

$$Pe^* = P_{x,y}(mg(x,y) < 0) \tag{7}$$

The interval function form can be defined for its edge function as shown in (8):

$$mr(x,y) = P(h_m(x) = y) - \max_{n \neq y}\{P(h_m(x) = n)\} \tag{8}$$

The accuracy of random forest is calculated using formula (9):

$$precision = TP/(TP + FP) \tag{9}$$

The accuracy calculation is shown in (10):

$$ACC = (TP + TN) / (TP + FN + TN + FP) \tag{10}$$

The formula for calculating the error rate is (11):

$$E = 1 - ACC \tag{11}$$

$$DIFF_m = ACC - \sum_{k=1}^{ntree} ACC_{km} / ntree \tag{12}$$

The formula ACC_{km} represents the accuracy of the k classification tree OOB estimation after all out-of-bag sample values of the m indicator attribute in random order.

3.2 Selection of Evaluation Model Indicators

The evaluation of artistic illustration interactive design includes two aspects: artistic illustration design and interactive design. There are many dimensions to consider in the evaluation process, so there are many influencing factors in the selection of indicators. In order to comprehensively and multi-dimensionally evaluate the effectiveness of art illustration interactive design, this article constructs a multi-level evaluation index from four dimensions, as shown in Figure 1.

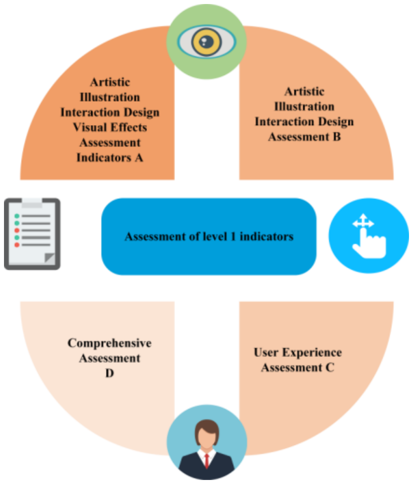

Figure 1: Primary indicator for evaluating the effectiveness of interactive design in art illustration.

The first level indicator A in the figure is the visual effect evaluation indicator for artistic illustration interactive design, which includes secondary indicators such as the degree of theme and target conformity A1, colour matching A2, visual element attractiveness A3, detail processing level A4, style harmony A5, style expressiveness A6, overall picture structure layout A7, and overall visual effect harmony A8. The first level, indicator B, is the evaluation of art illustration interactive design, which

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includes second-level indicators such as usability B1, friendliness B2, operability B3, consistency B4, timeliness B5, feedback B6, stability B7, reliability B8, accessibility B9, controllability B10, etc. The first level indicator C is user experience evaluation, and its second level indicators include user satisfaction C1, emotional resonance C2, personalized needs C3, user pleasure C4, interaction efficiency C5, practicality C6, etc. The first level indicator D refers to comprehensive evaluation, while the second level indicator includes innovation D1, cultural value D2, uniqueness D3, market competitiveness D4, sustainability D5, etc. in art illustration interactive design. Some of these secondary evaluation indicators have a certain scope and specificity, which does not apply to the evaluation of all artistic illustration interactive design effects and can be supplemented as special indicators. Therefore, in order to improve the effectiveness and efficiency of indicator selection, this paper constructs an indicator contribution rate evaluation model based on the random forest algorithm. By analyzing the contribution rates of each secondary indicator, the indicators with higher contribution rates are selected to form the final rating indicator system. The schematic diagram of the indicator contribution rate evaluation method based on the random forest algorithm is shown in Figure 2.

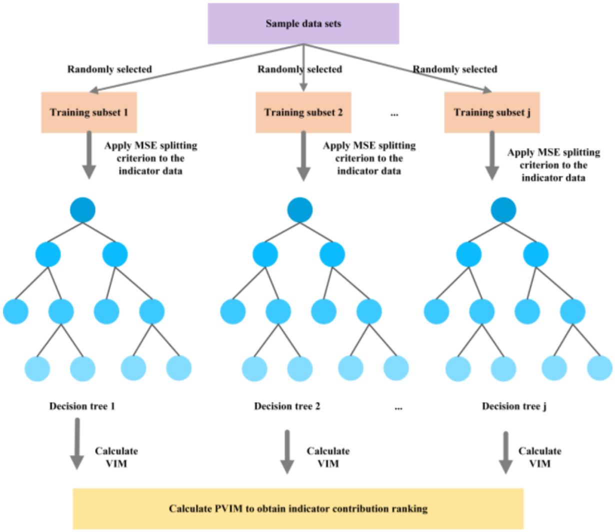

Figure 2: Schematic diagram of indicator contribution rate evaluation method based on random forest algorithm.

The number of secondary indicators is N, represented as $x_1, x_2, ..., x_i, i = 1, 2, ..., N$. After the indicator data is changed, its performance evaluation frequency is I, and the corresponding evaluation result is represented as $y_1, y_2, ..., y_i, i = 1, 2, ..., I$. All the above variables together constitute the sample dataset. H. Randomly select a training subset with the number of j from the H dataset, denoted as $H_g, g = 1, 2, ..., j$, and the corresponding scale is represented as K_g, as shown in formula (13):

$$H_g = (x_i^{(g)}, y_i^{(g)}) \tag{13}$$

Among them. $i = 1, 2, ..., K_g, g = 1, 2, ..., j$ If the sample size of the model is sufficient, there is a negative correlation between the number of decision trees in the model and the impact of its individual decision trees on the results, which can to some extent reduce the probability of accidental error data affecting the results.

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During the generation process of each decision tree in the model, the corresponding variable importance measurement can be calculated based on the decrease in node uncertainty. After the model is constructed, the contribution rate score of each indicator can be obtained by calculating the average importance measurement results of all decision trees. The contribution rate evaluation results of each secondary indicator are shown in Figure 3.

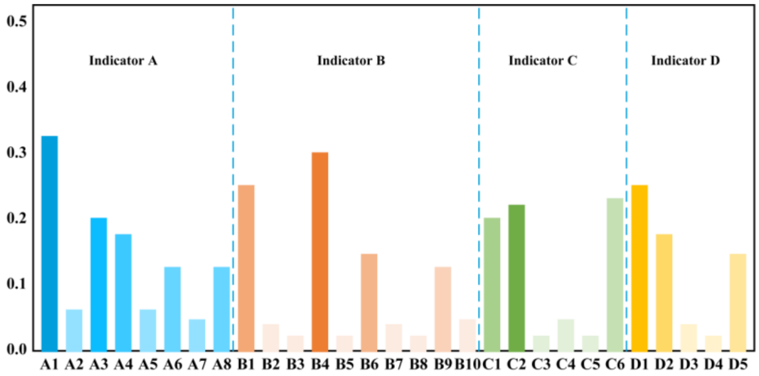

Figure 3: Evaluation results of contribution rates of each secondary indicator.

According to the results in Figure 3, effective secondary indicators for evaluating the effectiveness of artistic illustration interactive design can be selected, as shown in Table 1.

Primary indicators	*Secondary indicators*
Visual evaluation index A for artistic illustration interactive design	A1 Theme and Objective Compliance: Evaluate whether the illustration accurately reflects the design theme and objectives and whether it effectively conveys the creative intention
	A3 Visual Element Attraction: Evaluate whether it has sufficient attractiveness and whether it can generate a strong visual impact
	A4 level of detail handling: Evaluate the level of detail handling in illustration works
	A6 Style Expressiveness: Evaluate whether the illustrations fully demonstrate the expressive power of the artistic style and whether the audience can feel the author's personality and emotions
	A8 Overall Visual Harmony: Evaluate whether the overall visual effect of the illustration work is harmonious and unified
Art Illustration Interactive Design Evaluation B	B1 Usability: Evaluate the usability of illustration works in interactive design
	B4 Consistency: Evaluate whether the design style and operation methods of each part of the design are consistent to provide a good user experience
	B6 Feedback: Evaluate whether the design provides timely feedback to users, informing them of the current status and progress of completion and enhancing the interaction

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	experience between users and the product
	B8 Reliability: Evaluate whether the design is stable and reliable
	B9 Accessibility: Evaluate whether the design can make it easy for all users to use
User Experience Assessment C	C1 Satisfaction: Evaluate the overall satisfaction level of users when using illustration works
	C2 Emotional Resonance: Evaluate whether illustrations can evoke emotional resonance among users
	C6 Practicality: Evaluate whether illustrations have practical application value and whether they can meet the actual needs of users
Comprehensive evaluation D	D1 Innovation: Evaluate whether illustrations are innovative in visual and interaction design and whether they can bring freshness and surprise to users
	D2 Cultural Value: Evaluate whether illustrations have cultural value, whether they can inherit and promote traditional culture, or showcase contemporary cultural characteristics
	D5 Sustainability: Assessing whether sustainability factors have been considered in the design and production process of illustration works

Table 1: Evaluation indicators for the effect of interactive design in art illustration.

4 EXPERIMENTAL RESULTS

4.1 Experimental Results of Performance Evaluation Model Based on Random Forest Algorithm

The random forest model contains numerous parameters, and different parameter settings and combinations will have different impacts on the final results. In order to reduce the interference of subjective factors during parameter setting and with a fixed number of model features, we have decided to explore the relationship between the number of decision trees and out-of-bag (OOB) errors through experiments. Specifically, when the number of decision trees is set to 50, the fluctuation of OOB error becomes particularly significant, and there is a significant increase in subsequent stages. However, when we delve deeper into the experimental results of each decision tree with different numbers, we can discover some interesting details. The results of the experiment are shown in Figure 4, revealing the close relationship between the two. Observing the curve in the graph, we can observe that there seems to be a positive correlation between the total number of decision trees and the OOB error. This indicates that when the number of decision trees is small, the stability of the model may be affected, leading to significant fluctuations in the prediction results. This indicates that increasing the number of decision trees within an appropriate range can effectively improve the stability of the model and reduce the fluctuation of prediction results. However, when we increase the number of decision trees to 100 and 300, the OOB error performance in these two cases is similar, and the fluctuation range is relatively small. The overall OOB error performance is the lowest and the volatility is the smallest, demonstrating good stability and providing accurate experimental results for future application experiments. Therefore, the number of decision trees in the random forest model is set to 150 in this paper.

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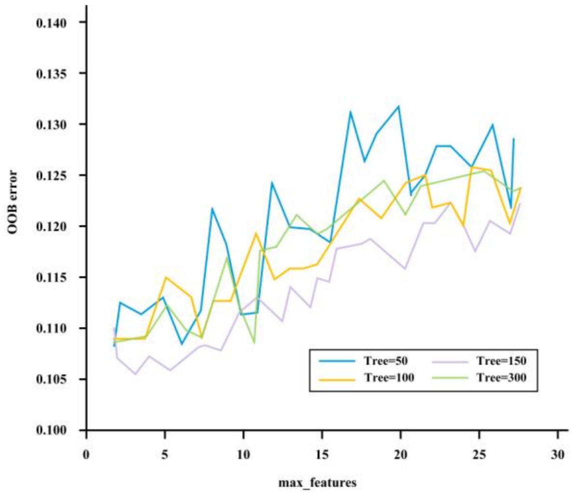

Figure 4: The relationship between the number of decisions in a random forest evaluation model and the OOB error.

This article randomly divides the dataset into 7:3 parts, of which seven parts are used as performance training data for the model, and the rest are test datasets. After training, this article randomly selected ten sets of test data, each containing five different art illustration interaction designs. Ten sets of art illustration interactive design effects were evaluated through expert evaluation and this article's evaluation method and compared with actual effects. The difference between the expert evaluation results and the actual effect is relatively small in most cases, and there is a significant error between some evaluation results and the actual effect. The evaluation results of this article's evaluation method are basically in line with the actual effect; that is, the difference between the two is relatively small. Through the comparison of errors, it can be seen that the error of the evaluation method in this article is smaller, and the range of error variation is relatively small. This indicates that the method not only has good evaluation accuracy but also exhibits good stability, which can adapt to different evaluation environments and objects. Figure 5 shows the evaluation test results and error results of two art illustration interactive design evaluation models.

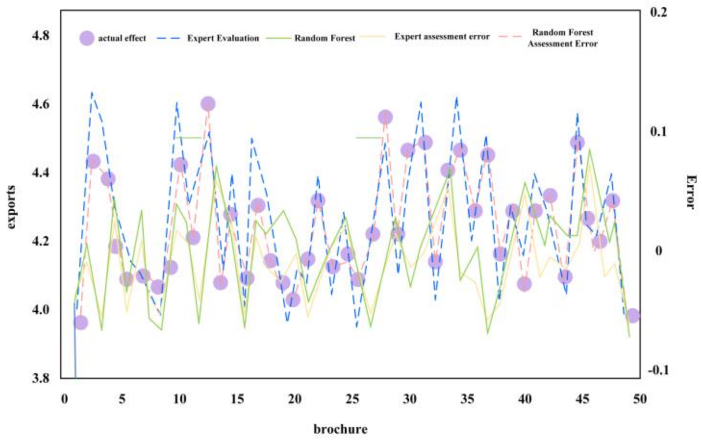

Figure 5: Evaluation test results and error results of two art illustration interactive design evaluation models.

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4.2 Experimental Results of Applying a Random Forest Algorithm-Based Performance Evaluation Model

In order to verify the effectiveness of the performance evaluation model based on the random forest algorithm, this paper selected the art illustration interaction design in a certain game scene for performance evaluation. The evaluation results are shown in Figure 6. The evaluation results in the figure are secondary indicator evaluation results, with evaluation scores of 0-60 indicating poor performance, 61-80 indicating average performance, 81-90 indicating good performance, and 91-100 indicating good performance. The results in the figure show that the evaluation scores of the secondary indicators in all aspects of Scenario A have all reached 80 points or above, and some indicators have evaluation scores above 90 points. In scenario B, most of the secondary indicators are evaluated in the range of 81-90, and some indicators have evaluation scores in the range of 61-80. The comprehensive indicator evaluation results show that the interaction design of scenario A is based on scenario B, which can bring users a better experience.

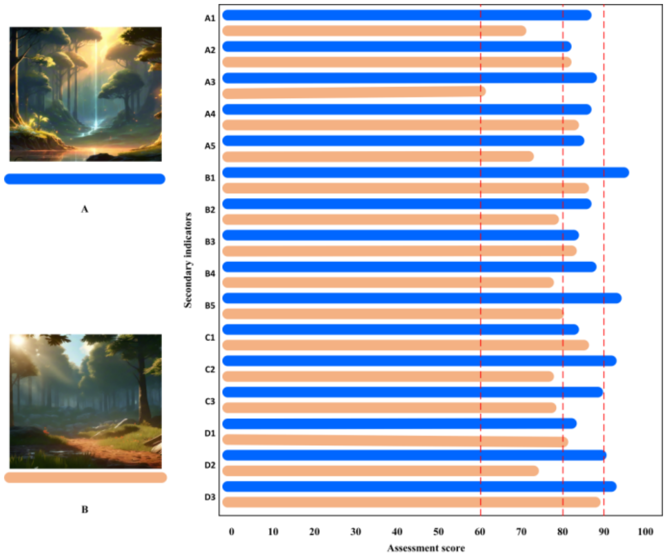

Figure 6: Evaluation results of artistic illustration interaction design effects in-game scenes.

As shown in Figure 7, the evaluation results of the first-level indicators for the effectiveness of artistic illustration interaction design in-game scenes are obtained based on the evaluation results. Designers can have a more intuitive understanding of the weak points in illustration interaction design. The results show that although the overall interaction design effect of scenario A is good, it is relatively weak in terms of visual effects and comprehensive evaluation, and further optimization is needed. Scenario B performs the worst in visual effect design, with relatively weak user experience and comprehensive evaluation.

5 CONCLUSIONS

Art illustration interactive design can help products attract the attention of users and express more information more vividly and intuitively, allowing users to have emotional resonance and deepen the correlation between the two. However, there are problems with the homogenization of design elements and the lack of cultural value in the interactive design of art illustrations. Moreover, traditional evaluation methods have single evaluation indicators, making it difficult to effectively make a comprehensive and systematic evaluation of the effects of art illustration design.

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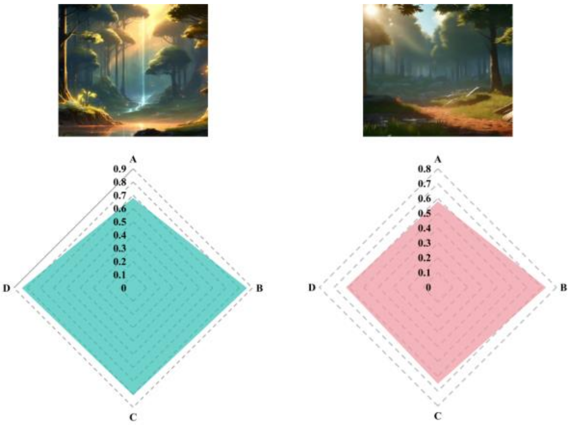

Figure 7: The evaluation results of the first level indicator of artistic illustration interaction design effect in-game scenes.

This article delves into the field of interactive design evaluation in art illustration and constructs a comprehensive evaluation model based on the random forest algorithm. Through a series of performance experiments, this model has demonstrated excellent accuracy, error control efficiency, and stability. In the application experiment, the model also successfully demonstrated its effectiveness in evaluating the effectiveness of interactive design for artistic illustration. Compared with traditional evaluation methods, the evaluation results of the model are closer to reality, providing more effective and reliable basic data for subsequent application experiments. This achievement not only brings new perspectives to the field of interactive design in art illustration but also provides powerful tool support for designers and researchers. The evaluation results include both primary and secondary indicators. Designers can have a more comprehensive and detailed understanding of the problems in interactive design effects and make further adjustments. Meanwhile, the evaluation results can more intuitively demonstrate the advantages and disadvantages of the interaction design between the two art illustrations. There are still many issues in this article that need to be further optimized in future research. Considering the many influencing factors of illustration interaction design, the evaluation index dimension should be expanded and more index factors should be introduced in future research.

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