Evaluation model construction of automobile appearance design based on random forest algorithm

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Abstract. Random forest algorithm is a nonlinear supervised classification algorithm, which is based on the idea of ensemble learning and consists of multiple decision tree classifiers. The algorithm has strong generalization ability, fault tolerance ability and nonlinear fitting ability, and can learn the deep-seated laws in the sample system according to a small number of samples using information entropy as the criterion. In the form of questionnaire survey, this paper collects the main evaluation factors of automobile appearance modeling design for 100 consumers or potential consumers. After selecting the evaluation factors, 50 consumers or potential consumers score a car according to these evaluation factors, to collect the original data. Experimental results show that the accuracy of the algorithm is as high as 84%, which shows that the model has such a high accuracy that it can be applied to the evaluation of automobile appearance modeling design. At the same time, this method can also be transferred to the appearance modeling design of other models.

1. Introduction
"The fourteenth five year plan for national economic and social development of the people's Republic of China and the outline of long-term goals for 2035" clearly points out that it should "create new advantages of digital economy", promote the integration of digital innovation industry and real economy, enable the transformation and upgrading of traditional industries, nurturing new industries, new businesses and new models, and speed up the construction of digital economy, digital society and digital government, so as to promote the development of digital economy Digital transformation drives the transformation of production mode, life style and governance mode as a whole [1].

Under the background of digital earth and Internet of things, digital creative industry takes digital creative technology and innovative design as the important pillar, cultural creativity and content production as the development core, and drives the development of surrounding industries through integration and penetration. 3D modeling is one of the fields in which 3D digital technology plays an important role [2-3].

After 3D modeling, the entity must be evaluated in appearance to determine whether it can be put into production. At present, the commonly used evaluation method is manual evaluation, which brings a lot of time cost loss, subjective bias and other problems. Therefore, it is necessary to build an algorithm to evaluate the 3D model quickly, objectively and scientifically.

Random forest is a new machine learning model. The classic machine learning model is neural network algorithm. In 2018, Ma Hui established an evaluation model for aircraft appearance design...
based on BP neural network algorithm. Experts established evaluation indexes and collected data. The maximum relative error of the model after training is about 10% [4]. In January 2021, Li Yanlong et al. used BP neural network to evaluate the appearance of the car. While the average relative error is only 3.54% [5]. However, neural network algorithm is based on big data for fitting learning, with large amount of calculation and complicated programming process. It can get low error in small amount of data and may be over fitting, which may lead to low generalization ability of model, and it is difficult to collect large data samples. Therefore, BP neural network is not suitable for appearance design evaluation of 3D model. The random forest algorithm uses repeated binary data for classification, and combines the decision tree with the random forest to summarize the classification results. On the premise of reducing the amount of computation, it improves the prediction accuracy and generalization ability under only small amount of data, and maintains the high stability of the algorithm through the idea of ensemble learning [6-7].

Therefore, this paper takes 3D modeling of automobile as the research object, and proposes an evaluation method of vehicle appearance design based on random forest algorithm. The evaluation results are collected through questionnaire survey. The effectiveness of the algorithm is verified by comparing the evaluation results with the prediction results of the algorithm, which provides a reference for the appearance evaluation of other types of three-dimensional model modeling.

2. Principles

Random forest algorithm is the product of ensemble learning, which is another combination forecasting algorithm proposed by Breiman after Bagging algorithm. It constructs multiple decision trees by random splitting of nodes and bootstrap sampling, and outputs their prediction results as a whole, so as to effectively avoid the shortcomings of over fitting and low classification accuracy of single decision tree, and enhance the generalization ability of the algorithm. The structure of Random forest algorithm is shown as Figure 1.

![Figure 1. The structure chart of random forest algorithm.](image)

Random forest algorithm is essentially a greedy algorithm. It chooses an optimal value in each internal node to split, and then each branch generates an attribute value corresponding to it. Each leaf node along this path represents the category of the sample, and recurses the decision tree until the termination condition is reached. According to Formula 1, a series of randomly growing decision tree classifiers are randomly constructed as independent distribution random vectors.

\[
\{h(X, \theta_k), k = 1, 2, 3, \ldots, K\}, \{\theta_k, k = 1, 2, 3, \ldots, K\}
\]

(1)

Where K is the number of decision trees used for classification in the forest. Under the action of independent variable X, each decision tree will classify the samples in turn, and finally select the category with the highest frequency as the final result.

The decision tree learning adopts the top-down recursive method, and its basic idea is to build a tree with the fastest entropy decline through information entropy as a measure, and the entropy value at the leaf node is 0. The calculation formula of information entropy is as follows:

\[
H = -\sum_{i=1}^{k} p_i \log(p_i)
\]

(2)

Where, Pi refers to the proportion of each type of information i in the system.
Taking information gain as the feature to divide training data set, there is a problem that the feature with more values is preferred. This problem can be corrected by using information gain ratio. The information gain ratio of feature A to training dataset D is defined as the ratio of its information gain to the entropy of training dataset D about feature A. The formulas are shown in Formula 3, 4, 5.

\[ G_{R}(D, A) = \frac{G(D, A)}{H_{A}(D)} \]

\[ H_{A}(D) = -\sum_{i=1}^{n} \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|} \]

\[ G(D, A) = H(D) - (\sum_{i=1}^{n} \frac{|D_i|}{|D|} \sum_{k=1}^{K} \frac{D_{ik}}{D_i} \log \frac{D_{ik}}{D_i}) \]

**Algorithm flow as follows:**

Step 1. The training set S, test set T and feature dimension F are obtained by collecting data. Then the parameters are determined.

a. Number of decision trees used T.

b. Depth of each tree D.

c. The number of features used by each node F.

d. The least number of samples on each node S or the least information gain on each node M.

Step 2. The training set S(i) with the same size as S is extracted from the C in S as the sample of the root node, and the training starts from the root node.

Step 3. If the current node reaches the termination condition, the current node is set as the leaf node, and the prediction output is the average value of each sample value of the current node sample set. Then continue to train other nodes. If the current node does not reach the termination condition, the F-dimension features are randomly selected from the F-dimension features. Using this F-dimension feature, finding the best one-dimensional feature K and its threshold th. The samples whose k-dimension feature is less than th on the current node are divided into the left node, and the rest are divided into the right node. Then, continue to train other nodes.

Step 4. Repeat Step 2 and Step 3 until all nodes have been trained or marked as leaf nodes.

Step 5. Repeat Step 2, Step 3, Step 4 until all decision trees have been trained.

3. **Experimental design**

3.1. **Questionnaire investigation**

3.1.1. **Construction of evaluation index.** First of all, through the questionnaire survey, the car design factors that consumers pay more attention to are screened out. In this paper, 24 external components of the car are selected as the local evaluation factors, and then considering the visual impact of the overall sensory of the car, six overall evaluation factors are abstracted: length width ratio, weight, color matching, edge line smoothness, light and shadow effect, shape characteristics.

The main objects of this questionnaire are undergraduates and their families. Undergraduate students are potential consumers, and their families are often economic sources or car users, which has great reference value.

A total of 100 questionnaires are distributed, of which 87 are valid. By collecting the average score of each index of the questionnaire, 11 local components that consumers pay most attention to are selected as the final local evaluation factors, and 4 overall evaluation factors are selected as the final overall evaluation factors, so as to establish the final evaluation index (Table 1).
Table 1. 15 evaluation indexes of automobile 3D model.

| First level indicators | Number | Secondary indicators                  |
|------------------------|--------|---------------------------------------|
| Overall evaluation     | X1     | Length width ratio                    |
| factors                | X2     | Color matching                        |
|                        | X3     | Shape feature                         |
|                        | X4     | Light and shadow effect               |
|                        | X5     | Headlamp                               |
|                        | X6     | Upper air inlet                       |
|                        | X7     | Lower air inlet                       |
|                        | X8     | Car door                               |
| Local evaluation       | X9     | Side window                            |
| factors                | X10    | Waist line                             |
|                        | X11    | Shoulder line                          |
|                        | X12    | Taillight                              |
|                        | X13    | Exhaust pipe                           |
|                        | X14    | Rear bumper                            |
|                        | X15    | Front bumper                           |

For each secondary indicator, six score options are given: 5 points, 4 points, 3 points, 2 points, 1 point and 0 points to represent the satisfaction of the evaluation index. At the end, consumers give the final sensory evaluation score of the car appearance design.

After determining the evaluation index, select a model to 50 consumers to score each index of the car, and give the final score to get the original data of model training. The first 25 copies of the data are used as the training set, and the last 25 copies are used as the verification set.

3.1.2. Collection and processing of questionnaire data. Table 2 is the collected data of 50 consumers’ scores on various indicators of the car, with a total of 50 copies (Y is the overall liking degree of the consumer and the final evaluation).

Table 2. Data collected by 50 consumers on the questionnaire of scoring of automobile indicators.

| X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | X12 | X13 | X14 | X15 | Y   |
|----|----|----|----|----|----|----|----|----|-----|-----|-----|-----|-----|-----|-----|
| 4  | 3  | 4  | 5  | 3  | 3  | 5  | 0  | 5  | 5   | 5   | 3   | 3   | 5   | 4   | 4   | 88.79|
| 4  | 2  | 1  | 4  | 4  | 4  | 4  | 1  | 2  | 4   | 5   | 3   | 4   | 4   | 2   | 74.49|
| 3  | 4  | 4  | 4  | 3  | 5  | 3  | 3  | 4  | 3   | 5   | 2   | 3   | 3   | 5   | 89.46|
| 4  | 3  | 1  | 5  | 5  | 1  | 5  | 1  | 3  | 4   | 3   | 4   | 3   | 4   | 3   | 79.26|
| 2  | 5  | 5  | 4  | 3  | 2  | 3  | 2  | 2  | 4   | 5   | 2   | 4   | 4   | 4   | 81.72|
| 5  | 5  | 3  | 4  | 3  | 3  | 5  | 5  | 2  | 4   | 4   | 3   | 3   | 3   | 2   | 78.85|
|    |    |    |    |    |    |    |    |    |     |     |     |     |     |     |     | 81.67|
|    |    |    |    |    |    |    |    |    |     |     |     |     |     |     |     | 80.58|
|    |    |    |    |    |    |    |    |    |     |     |     |     |     |     |     | 92.55|

In fact, in the final evaluation scores of consumers, subtle score differences do not obviously show the overall feeling of this car in the hearts of consumers. Therefore, the final evaluation Y in Table 3 is classified and mapped into five grades: excellent, good, average, bad and very bad, and represented by five scores of 5, 4, 3, 2 and 1 (see Table 3).
Table 3. Classification mapping of final evaluation $Y$.

| Y value | $>90$ | $90~80$ | $80~70$ | $70~60$ | $<60$ |
|---------|-------|---------|---------|---------|-------|
| Overall sense | Excellent | Good | Average | bad | Very bad |
| Classification mapping | 5 | 4 | 3 | 2 | 1 |

In order to avoid the impact of outliers in scoring on the final prediction results, and because the sample size is small, Grubbs criterion is used to replace outliers.

$$G = \frac{|x - \bar{x}|}{S}$$  \hspace{1cm} (6)

In Formula 6, $X$ is a consumer's score of a certain index of the vehicle, $\bar{x}$ is the average of all the scores of the index, and $S$ is the standard deviation of the index. According to Grubbs critical value table (Table 4), if $G$ value is greater than $g(n, a)$ (where $n$ is the number of samples, $a = 5\%$, which is 95% confidence), so the value is considered to be an outlier and should be rounded off, and then replaced by an average value; otherwise, the value is considered to be a normal value and should be retained.

Table 4. Grubbs critical value test table.

| n     | 95%  | 99%  | 95%  | 99%  |
|-------|------|------|------|------|
| 3     | 1.15 | 1.15 | 15   | 2.55 | 2.81 |
| 4     | 1.48 | 1.50 | 16   | 2.59 | 2.85 |
| 5     | 1.71 | 1.76 | 17   | 2.62 | 2.89 |
| 6     | 1.89 | 1.97 | 18   | 2.65 | 2.93 |
| 7     | 2.02 | 2.14 | 19   | 2.68 | 2.97 |
| 8     | 2.13 | 2.27 | 20   | 2.71 | 3.00 |
| 9     | 2.21 | 2.39 | 21   | 2.74 | 3.03 |
| 10    | 2.29 | 2.48 | 22   | 2.76 | 3.06 |
| 11    | 2.36 | 2.56 | 23   | 2.78 | 3.09 |
| 12    | 2.41 | 2.64 | 24   | 2.80 | 3.11 |
| 13    | 2.46 | 2.70 | 25   | 2.82 | 3.14 |
| 14    | 2.51 | 2.76 |      |      |      |

In order to further reduce the risk of over fitting phenomenon in random forest algorithm, make two different data scale to the same data area and range, and reduce the impact of scale, characteristics and distribution differences on the model, the data in Table. 1 are normalized (Max - min normalization)

$$X_{km}^{'} = \frac{X_{km} - X_{min}}{X_{max} - X_{min}}, k = 1,2,\ldots,10, m = 1,2,\ldots,15$$  \hspace{1cm} (7)

$X_{km}^{'}$—Processed data;$X_{km}$—Data before processing;$X_{max}$—The maximum value of the secondary index before processing;$X_{min}$—The minimum value of the secondary index before processing.

3.1.3. Construction of random forest model. One of the characteristics of random forest algorithm is that it does not need too many samples to support, and it is a probability model rather than a statistical model, so it is still very accurate for the prediction of small sample size. In this paper, SKlearn library based on Python language is used to train the random forest model. Firstly, according to the Formula 6, 7, the data in Table. 1 are removed outliers and normalized by Max-Min, and the collected questionnaire data are imported by using Python pandas library. The first 25 pieces of data are used as...
the training set, and the last 25 pieces are used as the verification set. The random forest model set up 10 decision trees, and the information gain is used as the judgment standard.

```python
import numpy as np
import sklearn
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
import pandas
data=np.array(pd.read_excel(r'C:\Users\Ami\questionnaire_1.xlsx'))
xtrain=data[:25,:-1]
ytrain=data[:25,-1]
xtest=data[25:,:-1]
ytest=data[25:,-1]
clf=RandomForestClassifier(n_estimators=10,criterion='entropy')
clf=clf.fit(xtrain,ytrain.astype('int'))
pred=clf.predict(xtest)
score=clf.score(xtest,ytest)
print(score)
```

**Figure 2.** Random forest training code.

4. **Analysis of experimental results**

After the random forest is trained, the test set obtains the prediction results in Table 4, the training time is 0.78 s, and the prediction accuracy is ACC = 88%.

| Evaluation value(real) | 3 | 3 | 3 | 3 | 4 | 3 | 3 | 3 | 5 | 4 | 3 | 2 | 3 |
|------------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|
|                         | 3 | 4 | 3 | 3 | 2 | 3 | 3 | 3 | 3 | 4 | 4 | 5 |   |

| Estimate(pre) | 3 | 3 | 3 | 4 | 4 | 3 | 3 | 3 | 5 | 4 | 2 | 2 | 3 |
|---------------|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 4 | 3 | 3 | 2 | 3 | 3 | 3 | 3 | 4 | 3 | 5 | |

**Accuracy rate** 84%

It can be seen from Table 5 and Figure 3 that although the sample data is small, the teaching quality evaluation model based on random forest algorithm still has high prediction accuracy, good generalization ability, fast model training speed, easy data collection and simple training process, which is more suitable for evaluating the three-dimensional modeling model of automobile appearance. Therefore, the rapid evaluation of the car appearance model established by the designer can greatly reduce the cost of manpower evaluation and time cost, which is closer to the preferences of the market consumers. It has a guiding role for the modeling of the designer, provides a relatively objective method for the car appearance design, and has a certain reference value for other engineering applications.
Figure 3. Comparison between the predicted and real classification results of algorithm prediction data and real evaluation data.

In addition, according to the results of the questionnaire, the average scores of indexes X1 ~ X15 after excluding outliers are as follows:

Figure 4. Average score of each index after excluding abnormal value.

As can be seen from Figure 4, the average score of indicator X12, i.e. taillight, is very high, indicating that consumers are very satisfied with the taillight design of this car, with an average score of more than 4. The average score of index X3 is the lowest, between 2 and 3 points, which indicates that the shape feature design of this car does not fit the aesthetic characteristics of the majority of consumers. Designers should strengthen the study of the shape feature design of cars. On the whole, the average score of the overall evaluation factors (X1 ~ X4) is lower than that of the local evaluation factors (X5 ~ X15), and the scores of several local evaluation factors are about 4 points, which indicates that the designers design the local parts of the car very well and conform to the aesthetic of consumers, but the score of the local parts is lower when they combine into the whole vehicle, which is due to the lack of coordination and collocation ability of designers for multiple components, so it should strengthen the study in this aspect.
Figure 5. Correlation analysis between final evaluation and each index.

From Figure 5, it can find that the correlation of X4, X7, X9 and X10 is low. It shows that consumers don't pay much attention to the design of light and shadow effect, lower air inlet, side window and waistline of the car. The design in this aspect is not enough to affect consumers' final evaluation of the car. And X2, X12, X13, X14 and X15 are highly correlated, which reflects that consumers pay more attention to the color matching of vehicles and the structural modeling and functional design of taillights, exhaust pipes and front and rear bumper, with the safety and practicability of vehicles as the primary consideration.

5. Conclusions
It's a nonlinear supervised classification method for the application of random forest algorithm to the evaluation and classification of automobile appearance design. This paper proposes to train the random forest by collecting indicators and raw data through questionnaire survey. The test results show that the model has high accuracy and generalization ability, and the training is simple, rapid and suitable for small sample size. The random forest has achieved a good performance in the appearance evaluation of automobile modeling with its nonlinear fitting ability. Similarly, it can also be transferred to the appearance evaluation of other three-dimensional modeling models to provide assistance for "Digital economy".

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