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Research Article

Research on the Decision Model of Product Design Based on a Deep Residual Network

Licheng Zong [1] and Nana Wang [2]

[1] *School of Art, Northwest University, Xi'an 710127, China*
[2] *School of Cultural Heritage, Northwest University, Xi'an 710127, China*

Correspondence should be addressed to Licheng Zong; zonglicheng@nwu.edu.cn

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An artificial intelligence (AI) design decision model is constructed to improve the efficiency of design decision evaluation and avoid the influence of the decision preference on product design and development. Using the concept of AI, the proposed model is based on a data set of product modeling design schemes, and the data set is marked with product modeling semantics. The deep learning residual network (ResNet) algorithm is used to train the data set to improve the accuracy of design decisions, transform the general design decision problem into the semantic recognition problem of design scheme images, and eliminate the design decision preference to the greatest extent. The validity and the feasibility of the proposed AI design decision-making method based on the ResNet algorithm are verified via an example of motorcycle modeling design decision-making.

1. Introduction

Modern product design integrates multiple elements such as technology, humanities, art, culture, and commerce. Design is characterized by apparent multi-disciplinary and multi-field intersection [1]. Product innovation design includes three functional units, namely, the problem, solution, and decision [2], and Analysis–Synthesis–Evaluation (ASE) is one of the typical design processes [3]. Design evaluation and decision-making are important components of modern product innovation design [4]. In part, design decisions will be directly related to the success or failure of product design and development.

The decision-making process of modern product design is usually completed by the cooperation of engineers, sales staff, consumers, designers, and enterprise managers. Differences in the cognitive backgrounds, subjective preferences, and experiences of decision-making groups cause the decision-making process to be complicated, vague, and full of uncertainty. Therefore, efficient and accurate design decisions that do not involve the personal preferences of the decision-maker are critical to successful product development [5].

Design decision-making is based on the design evaluation. There are currently three types of design evaluation, namely, experimental, mathematical, and online evaluation. Experimental evaluation primarily analyzes physical and psychological data, such as the visual perception of participants, the way to use the product, and the functional experience of the product, and then explores the product attributes. Common experimental evaluation methods include eye movement experiments [6], EEG experiments [7], and comprehensive experiments including these two methods [8]. Mathematical evaluation mainly involves the setting of evaluation indicators, the construction of evaluation models for quantitative calculation, and the scoring and evaluation of the design schemes. Common mathematical evaluation methods include the analytic hierarchy process [9], the rough set evaluation method [10], neural networks [11], and deep learning models [12]. In online evaluation, data mining technology is mainly used to acquire, cluster, analyze, and mine online user data, and is an inevitable trend in the development of network informatization. Related research methods include the use of big data [13], natural language processing [14], and text mining [15].

Deep learning is a new field of machine learning research, the core of which is a neural network that simulates the information analysis and processing of the human brain. In recent years, it has achieved great success in the fields of image and language recognition, autonomous driving, and medical care [16]. Based on the basic concepts of artificial intelligence (AI), in this study, a product group data set with product design semantics is constructed, and the data set is artificially labeled. The data set is continuously trained by deep learning algorithms, and the product design decisions are realized by AI methods. This improves the design decision accuracy and efficiency, and eliminates the decision bias.

2. Related Theories

The product design process begins with the input of the user's needs. Designers and engineers comprehensively deduce relevant design resources, design strategies, design constraints, and design methods to promote the execution of the design behaviors and the solidification of the design results. The final output is user satisfaction. When designing products, designers must analyze the user's needs based on their own knowledge reserves and experience, propose solutions and conduct comprehensive evaluations, and realize the conversion between design processes via design decisions. Design decisions are constantly iterated to finalize the design for the market.

2.1. Product Design Semantics and Design Decisions. Each product has or conveys different product semantics, via which the image characteristics of products in different usage scenarios are studied. Semantic communication between people and products is achieved through continuous iteration in the design process [17]. Via a communication method built between people and products, the product connotation, form, structure, color, and other elements are transmitted to users so that they can form a certain cognitive image of the product. Generally, in the early stage of product design, the design entrusting party or design developer will propose specific development tasks according to the product positioning, user needs, brand strategy, marketing strategy, etc. The semantic vocabulary of product design is a specific description provided before new product design and development. For example, the client will use a clear semantic vocabulary of shape and color to semantically describe the expectations of the new product, and the design team will use this semantic vocabulary as an important design input to guide the design process until a satisfactory design solution is obtained.

During the product design process, the product design plan will be analyzed, communicated, and evaluated many times, and the final design plan will be obtained via the selection and design decisions of Party A and the design expert team. Throughout this process, product design semantics are an important basis for design decisions. According to the product design process, product design semantics are proposed at the beginning of product design and development, and are communicated to designers via a

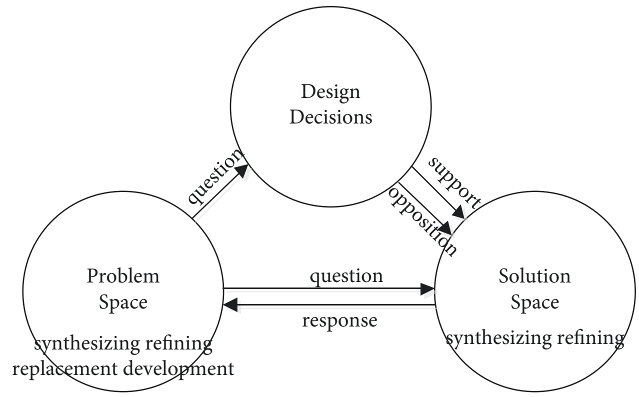


Figure 1: The semantic model of the problem space–design decision–solution space.

design semantic vocabulary. The design team parses and expresses the design semantic information based on their design knowledge, experience, and tools. Design brainstorming, conceptual design optimization, and detailed design proposals are then used to interpret the scheme, and the decision-making evaluation of the design scheme is carried out via the semantic matching degree between the design scheme and the design goal [18].

2.2. Semantic Model of Product Design Decisions. The process of product design is accompanied by solutions to different design problems. The solution process includes the initial state of the problem, the target state, and the solution strategy [19], and roughly undergoes the stages of sketch conception, conceptual design, scheme design, detailed design, and design refinement. Constant revision and adjustment are required to form a satisfactory solution for users. This process is the co-progression of design problems and design solutions with a basis on design decisions [20], which links the problem space and the solution space. Based on the principle of semantic models, the interrelationships between the design problem space, design decision space, and solution space were constructed (Figure 1), as were nine semantic connections used to describe the product design decision problems, namely, synthesis, refinement, substitution, expansion, questioning, support, opposition, prompt, and response.

(i) Problem space. The problem space is used to reflect on the user needs. When user needs are not met, the problem space questions the solution space and design decisions.

(ii) Design decisions. The design decision is the screening of the solution of the design problem, and the solution space is formed by supporting or opposing one or multiple solutions.

(iii) Solution space. A solution space is a collection of solutions designed by designers for user needs. For any problem in the design process, the solution space must respond to it. The elements in the solution space can be further refined and synthesized to form a new solution set.

2.3. AI and Image Recognition. In the field of image recognition and processing, AI technology, including graphic preprocessing, graphic segmentation, graphic feature extraction, and judgment matching, has become relatively mature. Machines can preprocess, analyze, and judge a target image to identify various objects or targets. The field of deep learning mainly includes the use of convolutional neural networks (CNNs) and generative adversarial networks (GANs). Neural network research originated from the field of biology. In 1998, Fukushima [21] constructed a neural cognitive machine composed of alternating simple and complex cell layers, which was considered to be the first engineering implementation of CNNs. A GAN is a generative model proposed by Kim et al. [22] in 2014. For neural networks, with the increase in the number of network layers, the training difficulty of learning algorithms such as CNNs and deep neural networks (DNNs) increases, and ideal model training results cannot be obtained. Using the residual learning framework, He et al. [23] proposed the residual neural network (ResNet) algorithm, which overcomes the increase of the training difficulty of the network with the deepening of the network, thereby allowing the number of network layers to reach new heights.

In the product design stage, the analysis, communication, display, and evaluation of the design scheme are usually carried out in the form of renderings. The images of design renderings are direct carriers for conveying the information of the design language. In the evaluation of design decisions, images of design renderings can be processed by AI to obtain algorithms implementing classification, understanding, and semantic feature evaluation [24]. Therefore, the image of the rendering of the design scheme is used as the output, the resulting image is preprocessed, semantic image segmentation is performed on the key modeling areas according to the designer's requirements, and the semantic features are extracted for judgment. Finally, according to the score of algorithm reasoning and the pre-evaluation of the design scheme, the purposes of the evaluation, optimization, and decision-making of the design scheme set are achieved.

3. Method of Product Design Decision-Making Based on AI

The loss of traditional deep learning algorithms will increase with the increase of the depth beyond a certain level. The unique structure of the ResNet algorithm can accelerate the training of deeper neural networks without losing speed. The detection and segmentation effects of the ResNet algorithm are better than those of other algorithms, and its accuracy is also greatly improved. In this study, the residual unit module of the ResNet algorithm is used to study the deep learning and semantic segmentation of the design scheme, and AI design decision-making is realized via the machine learning method.

3.1. Decision-Making Framework of AI Product Design Based on a Deep Learning Algorithm. According to the general product design process, the semantics of the target product design are used as the input, and AI design decisions are made based on the design scheme renderings of each round. A deep residual network-based AI design decision-making method is constructed, and the overall framework of which is shown in Figure 2.

After the design semantics of the target product are determined, a large amount of design proposal data of the same type are collected. These design proposals are preprocessed and semantically labeled, and a basic design proposal data set available to the machine is constructed. According to the design scheme images in these data sets, the modeling of key areas and semantic feature extraction are performed, and the data are continuously trained through the ResNet core algorithm. The deep residual network consists of three fully connected layers and 10 convolutional layers. After the first convolutional layer, the network is divided into three residual modules, each of which is divided into a main path and a shortcut. Three convolutional layers are located on the main path to extract the deep features and the features of design semantic annotation in the image features of the design scheme. To facilitate the upward propagation of residuals during training, the shortcut contains a convolutional layer. At the end of the residual module, the key features obtained from the main path and the shortcut are restacked and integrated to classify the previously obtained convolution features. The convolution features obtained previously are classified via restacking integration. During the intelligent decision-making of product design, users can set target semantics, input the design scheme images of the intermediate process into the trained deep residual network, and evaluate different design schemes via image semantic decoding.

3.2. Data Set Construction and Feature Extraction. In the field of AI, data sets are used to train and test proposed algorithms [25]. The goal of AI design decision-making is to evaluate the design and modeling semantics of the corresponding area via the semantic segmentation of the product modeling area; thus, the general outline of the target area must be given. As an example, a subject collected a large number of side views of gas motorcycles in domestic and foreign markets as the main image data, and a basic data set was constructed, as shown in Figure 3. After the completion of the basic data set, it is necessary to perform segmentation and semantic annotation on the modeling area of the basic image to further improve the evaluation efficiency and accuracy. For the image evaluation of the design scheme in combination with AI algorithms, it is necessary to segment and extract the contour lines of the image modeling area, and to combine the Kansei engineering method to extract and label the main modeling semantic parts in the images. Due to the huge data set, multi-user participation was adopted, and professional designers performed artificial semantic annotation on the feature areas of the data images.

3.3. AI Product Design Decision Model. The advantage of the ResNet algorithm is that it can quickly accelerate the training process of the neural networks [26]. The original input of the

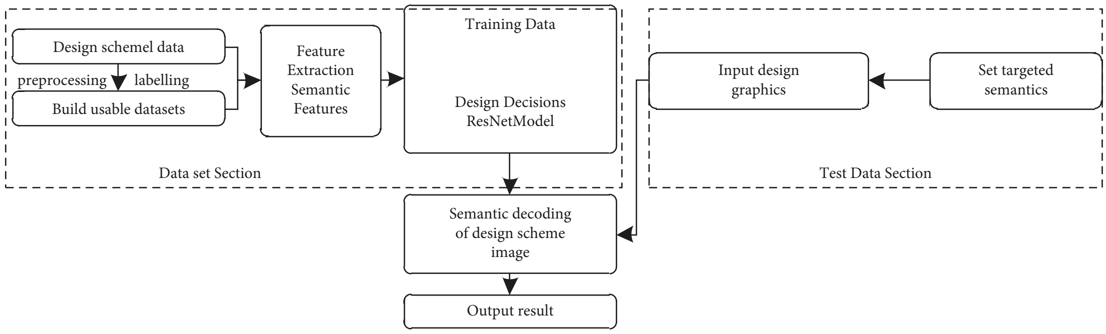


Figure 2: The AI design decision-making framework.

Figure 3: A section of the design decision data set.

entire deep network of ResNet is x, and the output is $F(x)$, which is obtained through a Conv-ReLU-Conv combination layer. By adding the output and the original output, i.e., $H(x) = F(x) + x$, the identity activation function of the original input result is superimposed on the convolution output, the stacking layer is used to fit $H(x) - x$, and the re-superposition of x will help to obtain $H(x)$ (Figure 4). To ensure that the accuracy rate decreases after the network is deepened, stochastic gradient descent can be used to propagate the response, and chain derivation can be used to obtain a faster convergence speed [27].

$$y = F(x, w_i) + x, \quad (1)$$

where x is the input, y is the output, and $F(x, w_i)$ is the residual mapping. Moreover, W_i is a linear convolution operation, in which the dimensions of x and F must be consistent. If they are inconsistent, linear mapping can be used to match the dimensions, as follows.

$$y = F(x, W_i) + W_s x_{\circ}. \quad (2)$$

The design plan image is input and scaled proportionally according to its short side, normalization (resize) processing is performed, and a cropped area with a size of 600×480 is then sampled from the image. After convolution operation with a 4×4 convolution kernel, the extracted image features include the contour features of three main regions. In the AI design decision model, the default step size of all max-pooling layers is 2, and the default step size of the convolution operation is 1. If the sizes of the output key features are different, it is usually filled with zeros; if they are the same, the result will be used as the final output [28]. The final data of the convolution layer are converted into a 13-layer fully connected network, and the key features of the image are superimposed and merged in the residual module. The previously obtained convolution features are classified, and the recognition results are output via the softmax classifier.

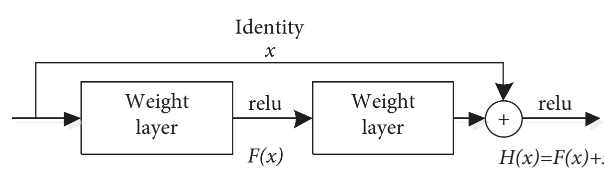


Figure 4: The algorithm flow of a single residual module in the ResNet algorithm.

4. Verification of the Decision-Making Model of AI Products

The TensorFlow deep learning framework [29] was used to implement the ResNet algorithm for AI design decisions based on the Python programming language, and the gas motorcycle design case was used as the basic data set to verify the performance of the ResNet algorithm in design decisions.

4.1. Experimental Data. In the experiment, the side view of motorcycles was used as the main image data. To ensure sufficient experimental samples, the image data of domestic and foreign motorcycles were obtained via a web crawler to construct the basic data set.

4.2. Data Preprocessing. Via web crawling, a large amount of basic image data was obtained. The basic data set was screened to eliminate the invalid samples. The basic preprocessing process and methods were as follows.

Step 1. Images with a side view or approximate side view were kept, and images taken from other perspectives were deleted.

Step 2. The image modeling area was segmented. In the styling design of gas motorcycles, the handles, wheels, and lights of the motorcycle are basically standard parts, and no additional design is required. Therefore, in the process of extracting the contour lines or boundary lines of the products in the data set, the FCN (fully convolutional network) open-source code of the UC Berkeley team was used for graph segmentation and contour extraction. Figure 5 shows the key areas of motorcycle styling design. The area marked No. 1 is the motorcycle oil tank, the area marked No. 2 is the motorcycle seat, and the area marked No. 3 is the motorcycle engine. The modeling design of these three parts forms the overall design semantics of the motorcycle. Areas No. 1 and No. 2 area are two key design areas in the motorcycle modeling design. The design of areas No. 1, No. 2, and No. 3 accounts for more than 85% of the motorcycle styling design, so they are the most important for people's visual perception and influence.

Step 3. The semantic annotation of image modeling was conducted. In current product design image research, statistical analysis and perceptual engineering methods are the most often used. The product image mainly reflects the product's design features, color, layout, structure, and other psychological perceptions of consumers. The usual product image vocabulary is "male-female, solemn-frivolous, future-past, solid-fragile, technology-conservative, rational-sensual." [30] Building on the current research progress of product modeling design images, relevant research was conducted on product modeling semantics. The research objects were designers, consumers, and enterprise managers. A total of 108 survey questionnaires were distributed, after which another three pairs of image vocabulary were included, namely, "introverted-publicized, complete-fragmented, and dynamic-stable." These nine image vocabulary pairs correspond to the semantic annotation of modeling design, as shown in Table 1.

The modeling semantics and decision-making scores were manually labeled by five design experts and obtained after conducting confidence statistics, after which images of 3000 pieces of motorcycle modeling metadata were randomly selected as the training set. After data preprocessing, a total of 3843 motorcycle images were obtained. The metadata of each image included four modeling semantic channels and two score channels, respectively, representing the modeling semantics and overall decision score of the image.

4.3. Experimental Process. The experimental process of AI design decision-making included the input layer, residual module, batch regularization layer, pooling layer, and activation function.

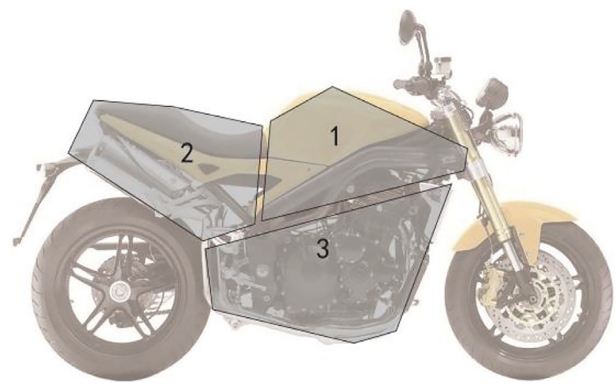


Figure 5: The key labeling areas of motorcycle styling design.

Step 1: Image metadata was used as a data set for the input layer, and included the resulting preprocessed images, semantic labels, and scoring data.

Step 2: The final data were converted via the convolutional layer to the output of a 13-layer fully connected network. The first convolutional layer was divided into three main residual modules after the operation.

Step 3: On the main path, the deep features of the design scheme image were extracted through three convolution layers. The size of the first two layers was the same as that of the convolution kernel of the previous layer, and the size of the convolution kernel on the shortcut was doubled after the third layer.

Step 4: The shortcut controlled the number of features via a convolution layer, thus directly doubling the convolution kernel and speeding up the upward propagation of the residual during training. The main path and shortcut of each residual module obtained the key features of the design image. The numbers of feature layers and feature dimensions of the main path were kept consistent with those obtained by the shortcut, and the two were superimposed and converged at the end of the residual module.

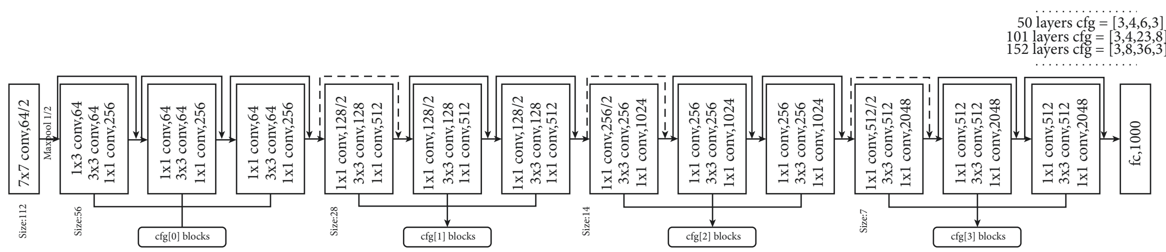
Step 5: For the three fully connected layers, the previously obtained convolutional features were classified. The process continued to the next stage after adding and fusing at the end of the module.

In the experimental process, to speed up the training effect, the batch normalization method proposed by Ioffe and Szegedy [31] was adopted. Thus, the mean value of the features after convolution extraction was 0, the variance was 1, and each convolution layer and pooling layer was processed by batch normalization. The softmax classifier was used in the last layer to output the intelligent decision recognition results [32]. A depiction of the motorcycle shape obtained by the ResNet algorithm in the training phase is shown in Figure 6.

4.4. Experimental Results. To verify the validity and decision-making satisfaction of the proposed AI design decision-

Table 1: The semantic annotation of data set modeling.

Numbering	Semantic description	Modeling semantic description			Realizability (1–10)	Overall evaluation (1–10)
		First part	second part	Third part		
1	Solid male restrained	Sensual female	Rational solemnity	Rational and stable	6	7
2	Technology sensibility publicity	Sensual fragmented sensual pieces	Rational tech rational technology	Solid	5	7
3	Steady restrained female	Male tech	Future solemn	Full dynamic	7	6
4	Robust complete restrained	Rational and stable	Future complete	Technology	8	5
N	. . . .	. . . .	. . . . . .	. . . . . .	. . .	. . .



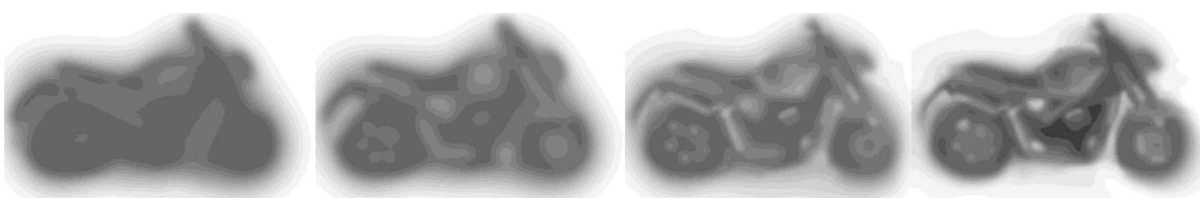


Figure 6: Semantic recognition at different training stages.

making model, two groups of modeling semantic input vocabulary were set. The first group included the semantic vocabulary of "future, stability, and dynamic," and the second group included the semantic vocabulary of "technology, sensibility, and integrity"; these vocabularies represent the semantic vocabulary of motorcycle product styling design. Also, Party A and five design experts jointly participated in making design decisions about three motorcycle design schemes. Based on Party A's scoring results of the design scheme, the full score was 10 points, and the proposed ResNet AI design decision-making model and design experts, respectively, scored the comprehensive satisfaction of the design scheme. During the experiment, the subject used the design decision accuracy curve as an indicator to analyze the experimental results. The design decision accuracy refers to the degree of fit between the scores of the proposed ResNet AI design decision model or the design expert and the score given by Party A. The higher the degree of fit, the higher the effectiveness of the tested model. In Figure 7, the abscissa of the design decision accuracy curve indicates the number of iterations, and the ordinate indicates the degree of fit.

5. Discussion

Figure 7(a) presents the change curve of the decision accuracy rate of Party A, the design experts, and the ResNet design decision model after using the three modeling image words of "future, stability, and dynamic" as the design semantic labels and inputting the renderings of such design schemes as images. With the increase in the number of iterations, the design decision accuracy of the ResNet AI design decision model gradually increased. When the number of iterations was about 160, the decision accuracy tended to be stable. The design decision accuracies of the three design schemes were, respectively, 0.83, 0.78, and 0.75, and the design decision accuracies of the design experts for the three schemes were, respectively, 0.78, 0.66, and 0.63.

Figure 7(b) shows the change curve of the decision-making accuracy rate of Party A, the design experts, and the ResNet design decision-making model after the three modeling image words of "technology, sensibility, and integrity" were used as design semantic labels. When the number of iterations was about 165, the accuracies of the design schemes obtained by the ResNet AI design decision

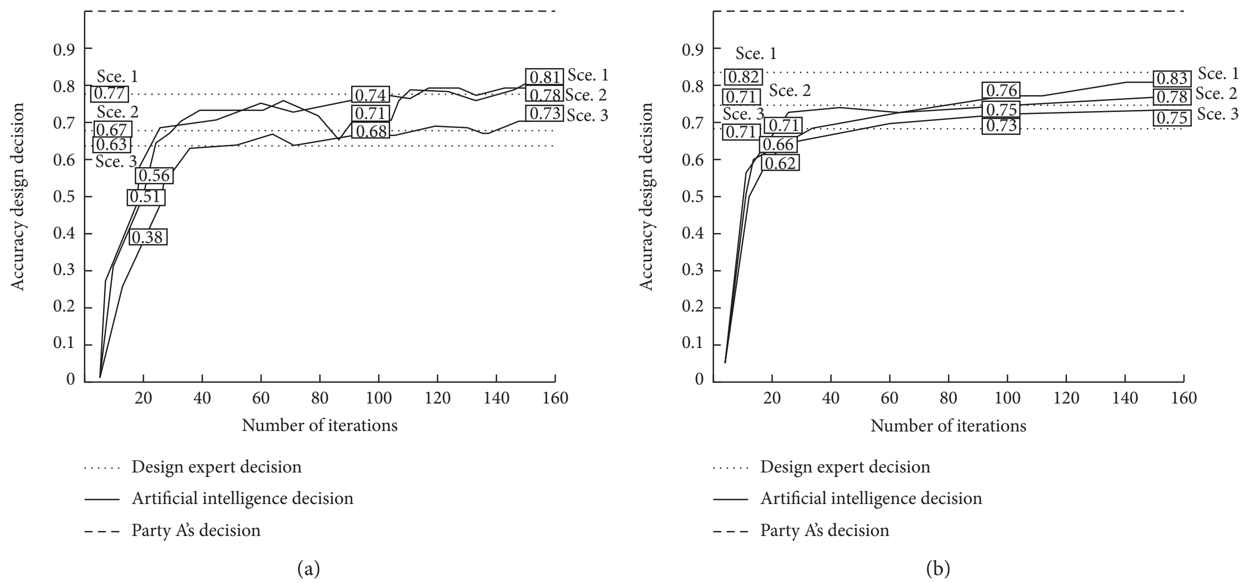


Figure 7: The comparison of the decision satisfaction of the (a) first and (b) second groups of modeling semantic vocabulary.

Table 2: The comparison of design evaluation satisfaction.

Method	Average satisfaction (%)	Average recall (%)
CNN	54.3 ± 3.4	44
DNN	57.8 ± 2.6	61
ResNet	77.6 ± 5.3	65

model were, respectively, 0.83, 0.78, and 0.77, while the design decision accuracies of the design experts for the three schemes were, respectively, 0.84, 0.76, and 0.71.

Thus, the satisfaction of the ResNet AI design decision was found to be higher than the average decision satisfaction of the design experts for both schemes.

To further verify the effectiveness of the proposed ResNet AI design decision-making model, a judgment was made based on the original data set, and the traditional CNN [33] and DNN [34] deep learning algorithms were, respectively, compared (Table 2). The average decision satisfaction and the average recall rate of the ResNet AI design decision model were found to be higher than those of the two other algorithms. The proposed ResNet AI design decision-making model performed stably in two rounds of design decision-making, and the design decision-making time was greatly shortened as compared with that of manual decision-making.

6. Conclusion

Building on the design scheme data set of product modeling semantics, this work was based on the concept of AI in combination with the characteristics of design decision-making. The data set was semantically annotated, and an AI evaluation decision model was constructed with the deep ResNet algorithm. The design decision problem was transformed into the semantic recognition problem of design scheme images, and the product design decision was realized via the AI design decision method. Finally, the effectiveness of the proposed method was verified by a case of motorcycle modeling design decision-making. The analysis of the experimental results revealed that the proposed ResNet AI design decision-making model exhibited higher decision-making satisfaction and decision-making efficiency than traditional manual design decision-making and the CNN and DNN algorithms.

Future research will focus on the following aspects. (1) Deep residual networks have good learning performance, but in the field of design decision-making, a smaller amount of data will lead to less effective training effects. While the crawler method was used to obtain graphic data in this study, there was a large amount of irrelevant data, which increased the data preprocessing and screening time. The acquisition and preprocessing process and methods of design data will be further studied in future research. (2) A general model for product design decision-making will be constructed based on a multi-level ResNet, the general method of ResNet-based product design decision-making will be investigated, and further experimental analysis will be conducted for other types of product design.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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