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Retraction

Retracted: Design of Packaging Design Evaluation Architecture Based on Deep Learning

Scientific Programming

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Shi, "Design of Packaging Design Evaluation Architecture Based on Deep Learning," *Scientific Programming*, vol. 2022, Article ID 4469495, 8 pages, 2022.

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Research Article

Design of Packaging Design Evaluation Architecture Based on Deep Learning

Lei Shi

Dalian Polytechnic University, Dalian 161034, Liaoning, China

Correspondence should be addressed to Lei Shi; shilei@dlpu.edu.cn

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Most researchers use visual communication symbols to achieve the purpose of information dissemination, which is also a very important marketing tool for the current era of packaging design. And the use of visual communication technology to make better product packaging design has become one of most the important means for major enterprises to sell their products and construct a good brand image. In this paper, we use a deep CNN-based aesthetic classification method for splash screens and a deep learning-based NIMA neural network to predict the aesthetic evaluation distribution of splash screen images, respectively. The connotation of visual communication and packaging design and the impact of the role of visual communication technology on packaging design are analyzed.

1. Introduction

In essence, packaging design is a kind of visual symbol transmission. It not only gives products a better aesthetic effect but is also an important means of product promotion, with both instrumental and rational characteristics. In this day and age, visual communication techniques are highly valued and are gradually showing diversified development. Packaging design is also an important means of product marketing [1]. As people's pursuit of material wealth continues, consumers' view of consumption has become more and more open, and how major enterprises can attract consumers' attention and capture their hearts, packaging design has become an important marketing tool for products [2]. Therefore, the application of visual communication technology in product packaging design is particularly important, and visual communication can be directly and effectively shown to have the effect of visual information transmission, which also determines the first impression of consumers of the product [3].

Visual communication is the direct purpose of visual communication design, is through the logo, typography, painting, graphic design, illustration, color, electronic devices, and other two-dimensional image performance to the public to convey a variety of visual information. Visual communication is more inclined to interactive design, focusing on interactive experiences and interactive feelings. Its focus is on functionality, but it also has a graphic design, color matching, and so visual communication also covers the visual aesthetics of the content [4, 5].

Packaging is a complete reflection of the brand concept, product characteristics, consumer psychology, and meeting the consumer's desire to buy [6]. Therefore, packaging design is a combination of art and natural science, applied to the protection and beautification of product packaging. Packaging design is not a broad sense of "art", nor is it just decoration, but contains a multifunctional embodiment of science, art, materials, economics, psychology, and market and other comprehensive elements. Packaging design includes the following three aspects: packaging design, packaging structure design, and packaging decoration design.

Excellent packaging design is the organic unification of the above three. Only the organic unification of the three can give full play to the role of packaging design, and packaging design not only involves two fields of technology and art, but it also involves other related disciplines in their respective fields. Therefore, to design good packaging [7]. We should apply visual communication to package design and grasp consumer psychology for design [8].

Based on the existence of such a consensus tendency, an emerging field of computer vision, computable image aesthetics, has emerged, whose research aims to enable computers to simulate human vision and aesthetic thinking, thereby making aesthetic decisions about images and building a bridge between computers and visual artworks [9]. Through the calculation and evaluation of image aesthetics, it can predict the aesthetic feelings of users when using visual interactive systems and then help designers to judge and obtain aesthetic expressions that match users' psychological feelings, which are important for achieving positive human-computer interaction. In this paper, we take splash screen images as the research object, use the user's subjective aesthetic rating of splash screen images as the basis and use a deep learning method to simulate the user's aesthetic perception of images and verify the feasibility of evaluating the aesthetics of works through computer image aesthetics evaluation to assist designers.

1.1. The Importance of Visual Communication Technology in Packaging Design. Nowadays, in order to highlight the freshness and personalized features of the products, most of them will choose some colors related to the product development trend as the main color and show the characteristics of the products through the main colors related to the products, while adding some other colors as auxiliary colors so as to set off the freshness of the products. Monotonous and uniform color schemes make it difficult for consumers to be impressed by the product, and it is easy for people to ignore the cultural elements conveyed by the product and produce visual fatigue. Thus packaging color will have a greater impact on the development of the product [10]. Therefore, the color design of the packaging is a prerequisite for consumers to see the superiority of the product. The current product packaging design needs to be more bold and innovative in color matching, and designers should continue to inspire themselves and broaden their creative thinking to capture consumers' emotional tendencies through packaging color and improve the rendering power of the product [11].

The graphic design of the package is the most prominent design in the whole package design. Now many products in the market will be carefully considered before the product packaging pattern design. At the same time, this aspect of the excellent designer is also relatively scarce. Not only in the packaging graphics and patterns, but also in the overall LOGO of the product, is a major focus. The visual communication design will use LOGO and product patterns and the combination of the entire cover with more personalized and visually appealing graphics to highlight the theme of the product. The use of LOGO and packaging patterns will show some specific things in order to attract consumers' attention, so that people associate and deepen the impression of the product [12, 13].

2. Research Status

Among mainstream methods for image aesthetic quality assessment, they can be divided into traditional aesthetic assessment methods based on artificial design features and the currently popular aesthetic assessment methods based on deep learning.

In the method of evaluating aesthetics based on artificial design features, image aesthetics are mainly evaluated by expert manual design of low-level visual features, high-level aesthetic features, and composition aesthetic features (see Figure 1(a)). As a pioneer first proposed the relationship between computer vision features and image aesthetics, based on the basic aesthetic principles such as color matching and contrast of images, images were classified into two categories of high and low aesthetics by methods such as support vector machine and regression. Wu et al. [14] used low-level features to learn classification models to distinguish photographic images of professional photographers from those of ordinary users. Han et al. [15] developed a method to assess the aesthetic quality of images based on color coordination. Kumar [16] selected high-quality images based on image layout, scene, and natural lighting conditions. Domestic scholars have also made many contributions to image aesthetics assessment. Liu et al. [17] extracted low-level visual features, high-level aesthetic features, and visual area features from the overall area and visually critical areas of an image and established an image aesthetic classifier and an aesthetic score assessment model.

In such evaluation methods, which usually involve training and test sets consisting of high-quality and low-quality images, regression analysis of the extracted features against a human aesthetic quality score is required to distinguish high-quality images [18]. However, this requires the researcher to have expertise in photographic aesthetics such as composition and color.

In recent years, with the rise of deep learning techniques, researchers have introduced convolutional neural networks (CNN) to solve the related problems in image aesthetic evaluation tasks. Due to its powerful automatic learning capability, it can automatically extract high-level abstract features from a large amount of image data without requiring researchers to have specialized aesthetic knowledge (see Figure 1(b)), and has become a mainstream approach to solve image aesthetic evaluation problems [19]. They adapted convolutional neural networks to make them applicable to solving different image aesthetic evaluation problems [20] and proposed a deep convolutional neural network with RS-CJS. Fudan University proposed an aesthetic image reviewer model, NAIR, based on CNN and recurrent neural network (RNN), which not only predicts aesthetic ratings but also generates semantic evaluations. These studies have shown good performance in image aesthetic evaluation.

Previous research has mostly focused on photographic images as the main object of aesthetic evaluation, and researchers have developed various algorithms and programs to improve the accuracy of evaluation and help users filter and optimize photographic images. However, for designers,

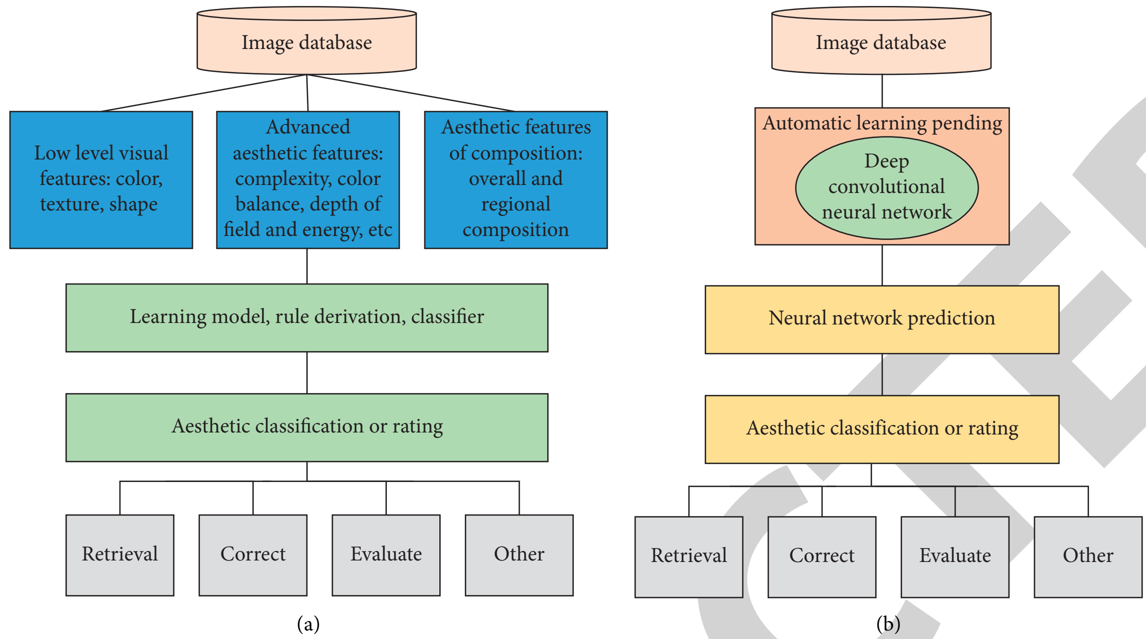

Figure 1: Two aesthetic quality assessment methods: (a) aesthetic evaluation method based on artificial design feature and (b) aesthetic evaluation method based on deep learning.

it is more meaningful to understand the precise aesthetic tendencies of user groups than to get an image aesthetic classification or rating. The method used in this paper differs from other methods in that instead of simply determining the image aesthetics as high or low, the statistical distribution of human ratings is used as the prediction result, so that the prediction result has a higher correlation with human ratings. In addition, other studies mainly use AVA as the mainstream dataset, and the evaluation results mainly represent the aesthetics of Westerners [21].

3. Aesthetic Evaluation Experiment of Splash Screen Design Based on Deep Learning

3.1. Splash Screen Image Data Acquisition. A total of 1002 samples of APP splash screen image data were collected through various methods, including screenshots and Internet downloads. The participants were recruited through a WeChat group, taking into account their age, gender, educational background, and APP usage experience. A total of nine participants were recruited, including five females and four males, aged 17 to 37 years old. These participants used more than ten different APPs on a daily basis and had knowledge of aesthetics such as color and composition [22]. No compensation or fees were provided to the participants for this study. Each participant was scored independently on a 5-point Likert scale (5 for very good looking, 4 for good looking, 3 for average, 2 for bad looking, and 1 for very bad looking) [23].

The data distribution of the aesthetic evaluation of splash screen images is shown in Figure 2. From Figure 2, it can be seen that the data samples for each rank are uneven, and most of the labeled data falls between rank 2 and rank 3, with less data in the high and low ranks and an overall Gaussian distribution. Therefore, 90% of the sample data in each rank is randomly sampled as the training data set, and the remaining 10% are used as the test data set. Finally, 903 training data sets and 99 test data sets were obtained. The data distribution of training and test sets is shown in Figure 3.

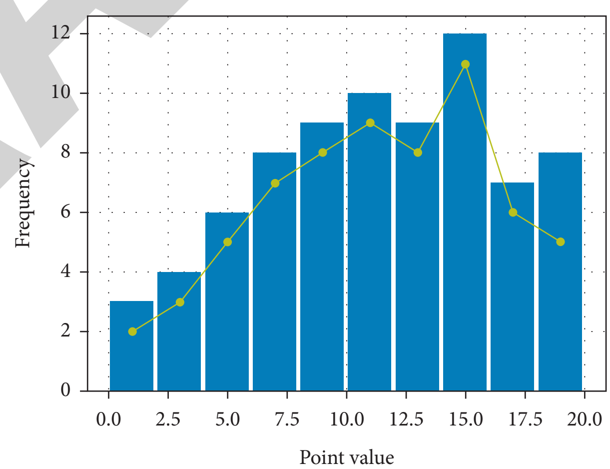

Figure 2: Data distribution of aesthetic evaluation.

The method is to classify the aesthetic quality of the splash screen image into good and poor grades. Those with an average score greater than or equal to 2.6 are judged to be of “good” aesthetic quality, and those with less than 2.6 are judged to be of “poor” aesthetic quality. The rules for classifying the aesthetic quality of splash screens are as follows:

$$\begin{cases} 1.0 \leq \text{socre} < 2.6, & \text{difference}\,(482), \\ 2.6 \leq \text{socre} \leq 5.0, & \text{good}\,(421). \end{cases} \tag{1}$$

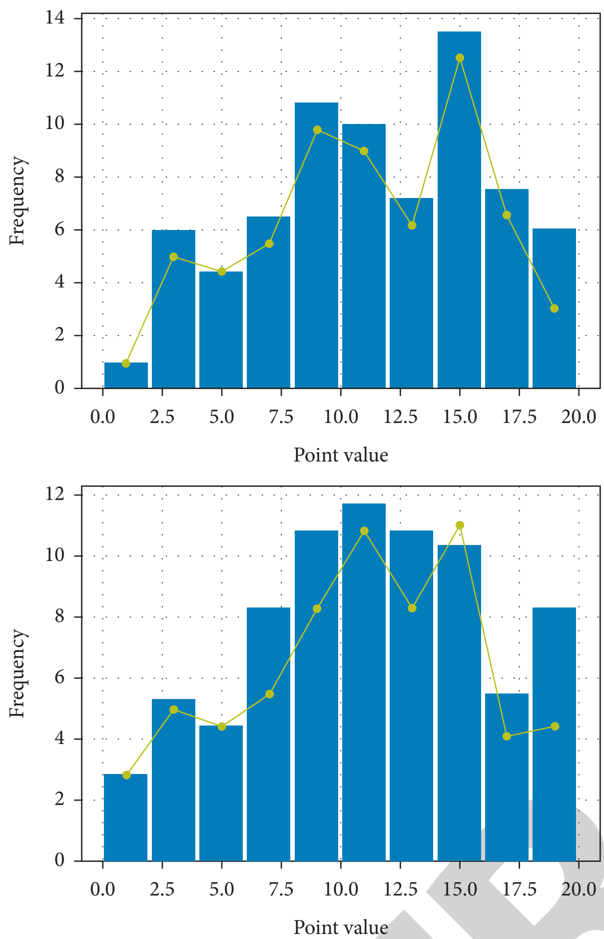

Figure 3: Data distribution of the training and test sets. Aesthetic classification of splash screens based on deep convolutional neural networks.

That is, the average score of a splash screen image rating is counted as

$$\text{score} = \frac{1}{n}\sum_{i=1}^{n} \text{person}_i. \tag{2}$$

Then, a deep neural network is designed to perform binary classification learning on the splash screen image data, and the neural network structure of the model is shown in Figure 4. A splash screen image is input, and the model obtained by pretraining the inception-ResNet-v2 CNN on the ImageNet dataset [24] is used to perform migration learning on the splash screen image to extract high-level abstract aesthetic features, and then the classifier network is passed through the final fully connected layer of the classifier network outputs two-dimensional probabilities (good/bad probabilities) for aesthetic binary classification.

The inception-ResNet-v2 CNN utilizes residual connections and convolutional operations with a large number of small kernels to make the network deeper and smaller, achieving the best current performance in the ILSVRC image classification benchmark test [25]. Therefore, the powerful feature extraction ability of the inception-ResNet-v2 convolutional neural network is utilized to achieve the aesthetic quality classification of splash screen images. The overall recognition rate of the experimental results reaches 64.7% (see Figure 5), and the overall recognition rate of the splash screen aesthetic classification is shown in Table 1.

4. Aesthetic Distribution Prediction Method for Splash Screens Based on Deep Learning NIMA

The difference between the aesthetic evaluation method NIMA proposed by Google and the above aesthetic classification method is that the above aesthetic classification method is to classify aesthetics into good and poor, and the predicted grade is to represent the average level of this image, which is displayed as the result of the predicted classification category. While the NIMA method [26] is to predict the probability distribution of a human's aesthetic evaluation of an image by CNN, the obtained probability distribution map can more accurately understand the concentration trend of a user's evaluation of an image and can more accurately guide how many people in the population find an image good looking to what degree. The distribution of splash screen aesthetic evaluation is shown in Figure 6.

From the distribution, it can be seen that 44% of people think this splash screen poster has an aesthetic rating of 3, and 11% think this splash screen poster has a poor aesthetic design and it has an aesthetic rating of 1. NIMA is designed to generate a histogram of the probability distribution of rating, i.e., the probability value of each rating, for any one image by predicting this probability distribution of human assessment of image aesthetics, which is similar to the human aesthetic rating system generates a histogram of aesthetic probability distributions that is formally compatible with the histogram of aesthetic probability distributions generated by the human aesthetic rating system. Therefore, the prediction results of NIMA [27] are closer to those of human evaluation and more representative of the aesthetics of the public.

The true distribution of human ratings for an image can be expressed as an empirical probability mass distribution function:

$$p = \left[p_{s_1}, p_{s_2}, \ldots, p_{s_i}, \ldots, p_{s_N}\right]. \tag{3}$$

where p_{s_i} represents the probability of level S_i. The goal of the NIMA method is to predict the probability distribution of the aesthetic rating of a given image.

The structure of the deep learning NIMA-based method for predicting the aesthetic distribution of splash screens is shown in Figure 7 [28]. The probability distribution of the aesthetic evaluation of the splash screen with five levels is obtained.

If we obtain the probability distribution of the aesthetic rating of the splash screen p [29], then the mean value of the aesthetic quality rating of the splash screen can be defined as

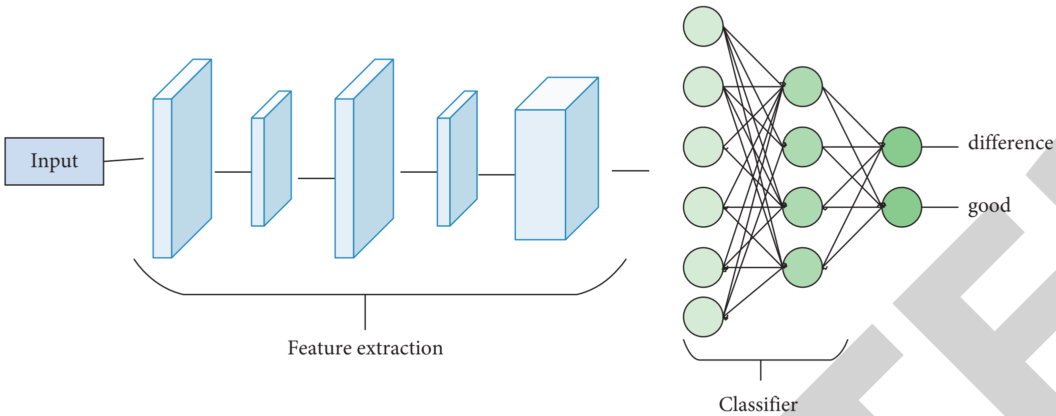

Figure 4: Aesthetic classification structure of splash screen based on CNN.

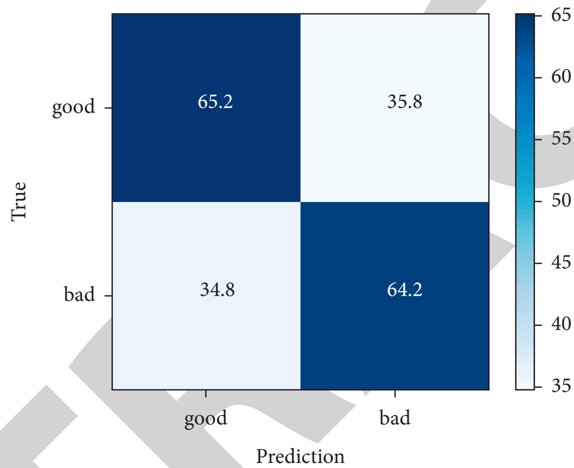

Figure 5: Confusion matrix of experimental results.

Table 1: Overall recognition rate of splash screen aesthetic classification.

Grade	Predicted as "poor" level	Predicted as "good" level
"Poor" level	30	16
"Good" level	19	34
Average overall recognition rate	64.7	

$$\mu_{\text{score}} = \sum_{i=1}^{N} s_i \times p_{s_i}. \tag{4}$$

The standard deviation of the aesthetic quality rating of the splash screen is

$$\sigma_{\text{score}} = \sqrt{\sum_{i=1}^{N} \left(s_i - \mu_{\text{score}}\right)^2 \times p_{s_i}}. \tag{5}$$

The aesthetic quality of the splash screens could then be compared qualitatively by the mean and standard variance of the splash screen aesthetic quality ratings. To compare the correlation between the predicted quality rating distribution p and the participants' labeled quality rating distribution q, the Pearson correlation coefficient was used to measure the correlation between two variables X and Y with values between −1 and 1, calculated as follows:

$$r = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}}. \tag{6}$$

The final results showed that the Pearson correlation coefficient value on the 99 test sets, trained by learning from the training data, was 0.516, with a moderate correlation agreement between its predicted and participant-labeled values. The predicted aesthetic data are shown in Figure 8. The mean value of participants' ratings for Figure 8(a) was 2.888 and the machine predicted 2.257, with a difference of 1.053; the mean value of participants' ratings for Figure 8(b) was 2.667 and the machine predicted 2.495, with a difference of 0.919. The two values differed but showed a moderate

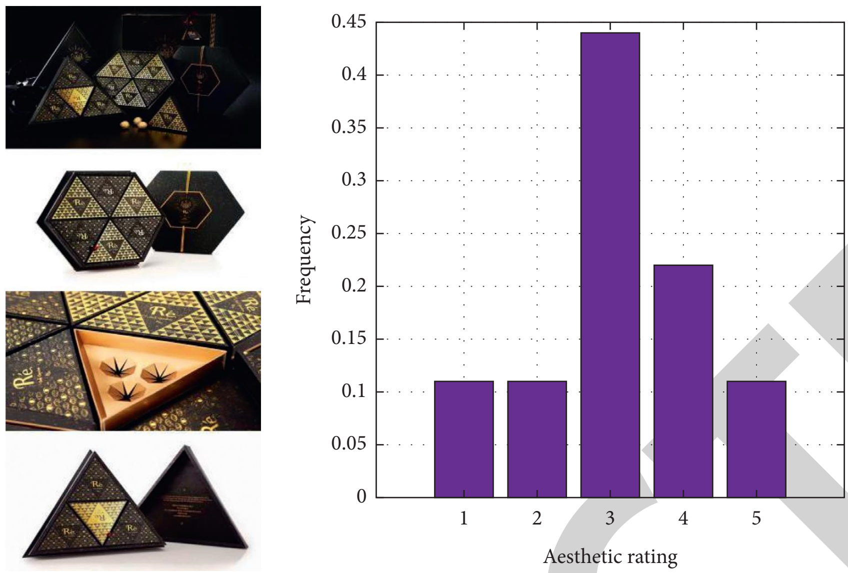

Figure 6: Distribution of splash screen aesthetics evaluation.

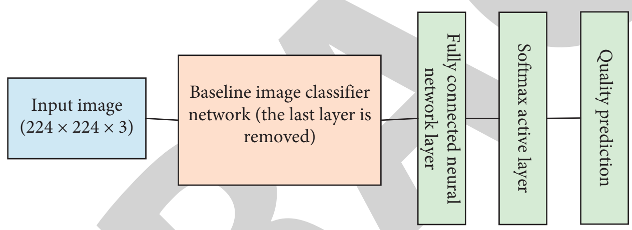

Figure 7: Structure of the flash screen aesthetic distribution prediction method is based on deep learning NIMA.

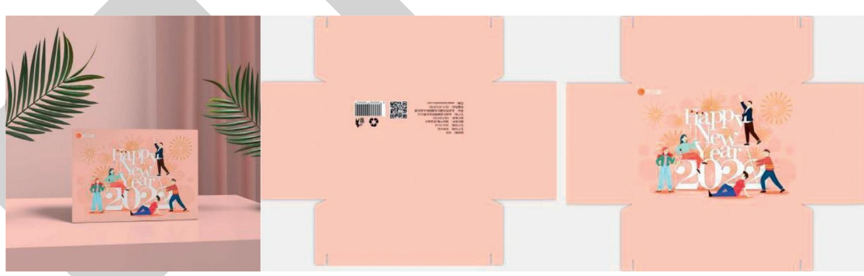

Figure 8: Predicted aesthetic data: (a) participant: 2.888 machine: 2.257 (± 1.053) and (b) participant: 2.667 machine: 2495 (± 0.919).

correlation. Due to the limited amount of data and labeled data in the "domestic mobile splash screen image aesthetics dataset," if there are enough training data, the Pearson correlation of the deep learning NIMA-based splash screen aesthetics distribution prediction method on the test set will reach a strong correlation, and the predicted results will be more representative of human aesthetic standards.

5. Experiment

Nowadays, when consumers buy products, they also pay attention to the external image of the products, which means that consumers will get different emotional experiences from them. In this way, the external image of the product is enhanced, and even the external image of the product itself becomes a consumer product. The external image of a product must be expressed through a series of graphic elements, which gives rise to certain functional and artistic visual communication techniques in the consumer field [30].

The evaluation method and results were provided to three visual designers with more than ten years of work experience, who felt that presenting the distributed evaluation results would provide a clearer view of the public's concentration on the image ratings and could be used as important supporting evidence for the evaluation of visual works within the team.

It is found that deep learning-based image aesthetic evaluation distribution can help designers and companies in

Figure 9: Two images with an aesthetic score of 3.

two dimensions [31]. First, the splash screen aesthetic distribution prediction method can help designers predict the user aesthetic evaluation distribution of their design work and establish an objective aesthetic evaluation. Based on this, future design teams can develop aesthetic parameter evaluation standards as a reference for visual evaluation and reduce the subjectivity of evaluation. Secondly, through the constructed "splash screen image aesthetics dataset," designers can more accurately understand the aesthetic characteristics perceived by users, obtain the aesthetic tendency of target users, and make forward-looking visual designs to provide users with a pleasant experience and realize precise marketing for enterprises, as shown in Figure 9.

The application of visual communication technology in packaging design is extremely important. The importance of color and pattern to package design was analyzed above, and the application strategy of these elements is now analyzed. The designer has to present the cultural connotation in the product packaging design through some artistic visual symbols or words to achieve a better information transfer effect. In general, most of the visual symbols people choose are design graphics or symbols in two-dimensional space, and these visual symbols are different from the traditional visual symbols. Based on this premise, designers have to realize that whatever visual design and whatever colors are used, they have to make it easy to understand for ordinary consumers. Color, graphics, and text are the basic elements of packaging design. Therefore, the aesthetic quality is evaluated as shown in Figure 10.

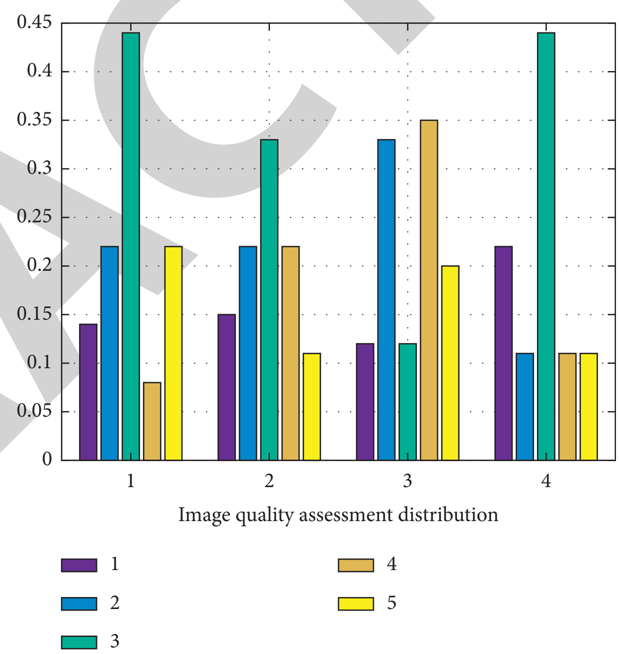

Figure 10: Distribution of aesthetic quality evaluation.

6. Conclusions

This study investigates the creative and emotional splash screen images designed by designers and uses NIMA as the main evaluation method to effectively predict the aesthetic evaluation distribution of splash screen images. The feasibility and effectiveness of applying deep convolutional neural networks to the aesthetic evaluation of interface design are verified. We could choose the visual symbols that can attract consumers' attention and enhance their desire to purchase, and then carry out a series of packaging designs so as to create a win-win situation in which quality design and healthy consumption promote each other.

Data Availability

The data used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work.

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