Image Style Recognition and Intelligent Design of Oiled Paper Bamboo Umbrella Based on Deep Learning

Yixiang Wu[1] and Hongyang Zhang[2]

[1] Yiwu Industrial and Commercial College, Yiwu 322000, Zhejiang, China, 3316162376@qq.com
[2] Jiangsu Tourism Vocational College, Yangzhou 225000, Jiangsu, China, 786212917@qq.com

Corresponding author: Yixiang Wu, 3316162376@qq.com

Abstract. The intelligent design of cultural and creative products has become the research hot spot in the field of computer aided design. Aiming at the disadvantages of low recognition accuracy and manual feature extraction of the early product image recognition model, this research uses the image recognition model for cultural and creative products constructed with deep convolutional neural network. In this research, the classical oiled paper umbrella is taken as the example, and an image recognition experiment on the umbrella has been carried out with a kind of Residual Network (ResNet-50) that is based on convolutional neural network. The experimental result shows that the ResNet-50 convolutional neural network is effective and accurate for product image recognition, with a accuracy rate reaching 94.3%. On the basis of the image recognition of oiled paper umbrella, an experiment has also been carried out on the conditional generative adversarial network (Deep Convolutional GAN, DCCAN), with both generator and discriminator adopt deep neural network. The input of generator is Gaussian noise, which generates a series of classical oiled paper umbrella through Deep Convolutional GAN, and the experimental result is the product creative design scheme. The experimental result shows that the sample images generated by conditional generative adversarial network are feasible and effective, and that the model can generate some shallow classical oiled paper umbrellas, which assists the inspiration design of oiled paper umbrella. This research provides a new idea for modeling of product image recognition, and overcomes the disadvantages of the traditional product design, such as too much reliance on designers, complicated process and low design efficiency.

Keywords: Convolutional neural network; cultural and creative products; Deep Convolutional GAN; Residual Network; product images.
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1 INTRODUCTION

The intelligent design of product appearance is one of the major trends of industrial design development in the future. In recent years, the design creativity based on artificial intelligence is being promoted from the theoretical level to the practical level. The design architecture of artificial intelligence is constructed through the combined application of multiple algorithms of Kansei Engineering[12; 13], Genetic Algorithm (GA)[20], Rough Set Theory[7], Refine Kano Model[9] and artificial neural network[8; 19]. Reviewing the literature for the design of auxiliary products of artificial intelligence, we can find that the application of artificial intelligent technology in the field of product design has gradually achieved some results, but artificial intelligence is in urgent need to develop the technology in creative design of auxiliary products. The research on the intersection of product creative design and artificial intelligence technology is still in its infancy, and the main problems it is faced with are as follows:

Generally, Kansei Engineering determines the emotional response of key design variables to users through Quantitative Theory I[13]. However, the accuracy of Quantitative Theory I will be reduced if the prediction relationship is nonlinear. Some researchers have used models of artificial neural network, support vector machine (SVM) and GA to fit the nonlinear relationship between consumer emotional response and product form design variables. The technologies of artificial neural network and SVM[21] have been proved to be suitable for building the relationship model between product form design variables and user emotional response. The disadvantage is that the data set of user perceptual characteristic of these prediction models is established manually. Due to the subjectivity in the perceptual image of users in the products, it is difficult to effectively build the relationship model between the product form design variables and user emotional response based on the traditional methods. In order to solve the problem of information loss of original data caused by manual operation, it may be considered from the aspect of automatically extracting features from the original data for modeling to improve the reliability of the prediction model of emotional response, which brings greater challenges to the new method of building the mapping relationship model between user emotional preference and product form design variables. In product creative design, the design of product appearance is limited to the thinking frame of the designers. The intelligent design for product appearance based on machine learning has become a research hot spot. However, the training data of the machine learning algorithm used at present has great limitations, and it cannot learn good, extensive and deep features from the large-scale training data that is not constrained by thinking patterns, so as to generate a variety of more creative products.

According to the above analysis, there are many problems existing in the traditional machine learning algorithm relying on domain knowledge for manual feature extraction and selection. In recent years, the deep learning, such as Deep Convolutional Neural Networks (DCNN)[11] has made great breakthroughs in the realization of creative tasks, has been widely used, including image generation, image synthesis, and image generation and inpainting through text. In view of the fact that the Deep Convolutional Neural Network Model can generate the photo-like and vivid image samples through unsupervised learning in computer vision environment, this research considers that when a large number of known images of the specific products are used as the training data, the Generative Adversarial Networks (GAN) of DCNN may learn the favorable immediate features from a large number of unmarked images through deep learning of the training data, so as to generate the clear and vivid images with similar features as the known product images, and to generate the new creative design. According to this, this research develops the research on image identification of product appearance and product creative design based on DCNN.

2 LITERATURE REVIEW

2.1 Kansei Engineering and Artificial Neural Network

With the development of machine learning technology, the intelligence of product design based on machine learning algorithm has gradually become a trend, mainly including Genetic Algorithm (GA), artificial neural network and Support Vector Machine (SVM). The combination of artificial neural network and Kansei Engineering is applied for product form design. Based on artificial neural network model, Fu Guo et al [4].built the relationship model between phone form design variables and perceptual image. Yuhazri et al[22].quantified the perceptual images of users' preference for the car forms, providing the basis for the design of the car in line with the users' expected feelings. Artificial neural network shows good performance in perceptual evaluation, and it has been proved to be very suitable for building the relationship model between product features, emotional response and user preferences[4]. However, users' evaluation on perceptual image of the product is subjective, and with the constant development of machine learning technology, the product design based on Kansei Engineering and artificial neural network will be more effective. Whereas for the limitation of hardware and times, the traditional artificial neural network has few layers and weak expression ability, and it has not surpassed the traditional machine learning method in learning ability. As the deep learning technology gradually evolves from the artificial neural network, it has made great progress in recognition accuracy and robustness.

2.2 Deep Learning and Its Application in Computer Aided Design

The essence of deep learning is artificial neural network with deeper layers. Inspired by neurobiology, artificial neural network (ANN) puts forward the neural network with multiple layers, hoping to make computer achieve the high intelligence of human by simulating the biological neural system. During more than 30 years from 1980 to 2010, many different neural network layers, construction and initialization methods have been developed. For example, Yarn LeCun et al.[11] put forward the gradient-based back propagation algorithm and trained the LeNet-5, the convolutional neural network model. After 2010, various new deep learning models have been proposed. For example, Krizhevsky et al.[10] proposed AlexNet, a convolutional neural network, based on LeNet-5. Simonyan et al.[16] proposed the VGGNet, with a depth of 16 to 19 layers, through exploring the depth of convolutional neural network, and found that deepening the depth could improve the accuracy of object recognition. Szegedy et al.[18] designed the VGGNet, a deep convolutional neural network with 22 layers, by deepening and widening the network structure. And Kaiming He[5] evaluated the network with a depth of 152 layers (8 times deeper than VGGNet), and proposed a learning framework for residual, which improved the accuracy of Image Recognition, and the result was much better than the previous network. On the application of deep learning in computer aided design, Date et al.[1] constructed a fashion design method based on convolutional neural network, which could customize new clothes according to users' preference. The powerful self-learning feature extraction ability of deep convolutional neural network is very suitable for fashion design industry. However, in the field of industrial product design, the product image recognition and classification researches based on deep neural network are few. In view of the strong abilities of self-learning feature extraction and nonlinear classification of deep convolutional neural network, the author thinks that the deep convolutional network is suitable for the research of product image recognition.

2.3 Generative Adversarial Network and the Research Status of Its Application

The Generative Adversarial Network (GAN) is a deep neural network model. Goodfellow et al.[3] proposed the generative adversarial network model composed of a generator and a discriminator. And afterwards, a variety of derivative models based on adversarial network have been proposed constantly. Mirza et al.[12] proposed conditional generative adversarial network. Gatys et al.[2] put forward neural-style transfer algorithm, which used convolutional neural network to reappear the style of painting. Chintala et al.[15] presented the deep convolutional adversarial neural network, introducing convolutional neural network into adversarial network, to enhance the stability of adversarial network training. Isola et al.[6] proposed a method to realize the conversion of image to image by using conditional generative adversarial network model. And Lingyun Sun et al.[17] developed a man-machine collaborative painting system based on generative adversarial network. In view of the fact that the generative adversarial network may generate the vivid image sample in facing a large number of image information, the author thinks that when a large number of known images of the specific products are being as the training data, the generative adversarial network may learn the favorable immediate features from the large number of unmarked images through deep learning of training data, so as to generate the new product design scheme.

3 METHOD

3.1 The Proposed Integrative Method

The purpose of this paper is to develop an intelligent recognition and design system for the image of Oiled Paper Umbrella and to provide designers with an intelligent aided design system. It needs to build a database of umbrellas, and screen the Oiled Paper Umbrella from the large-scale umbrellas, so as to study the image recognition model of Oiled Paper Umbrella. The traditional product image recognition model is lack of ability in dealing with nonlinear problems. This paper chooses the residual network (ResNet-50) to study the product image recognition model. This model is high in accuracy and is competent for the task of screening the Oiled Paper Umbrella from the large-scale umbrellas, so as to build the database of Oiled Paper Umbrella. The database is for the learning of generative model (GAN). By learning the image of Oiled Paper Umbrella, GAN will intelligently generate the new Oiled Paper Umbrella, and finally serve the designers, giving them the new design inspiration for Oiled Paper Umbrella. Based on the above process, the model is to generate new umbrella products in the style of Oiled Paper Umbrella, which serves the industrial design of umbrella.

Construct the image recognition on oiled paper umbrella based on deep convolutional neural network, and the technical route is shown in Fig. 1.

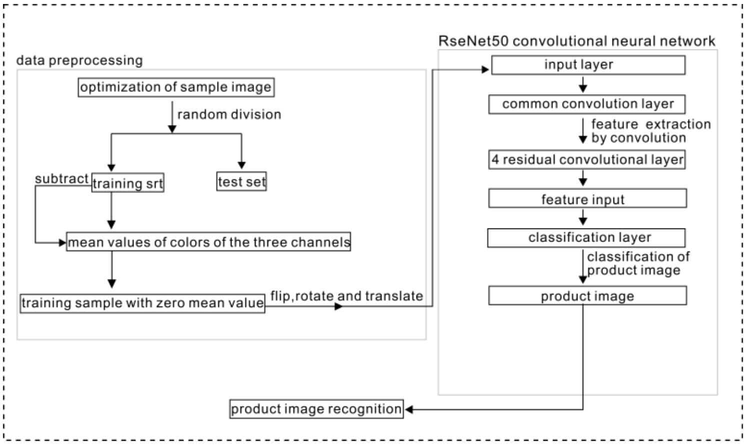


Figure 1: Product Image Recognition based on Convolutional Neural Network of ResNet50.

3.1.1 Data pre-processing

In this paper, the size of each sample in the data set of umbrellas is different, but is roughly square. This paper needs to build an umbrella database, and the large-scale umbrella database is a mixture of 1200 umbrella pictures of oiled paper umbrellas and modern style umbrellas. Because it cannot display all the samples, this paper selects some of them from the data set, as shown in the following figure.

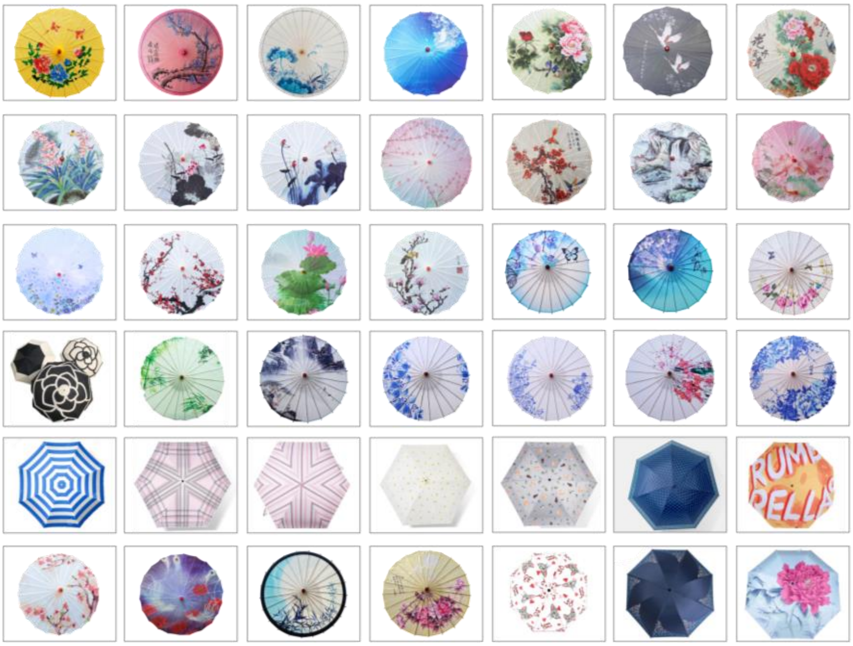


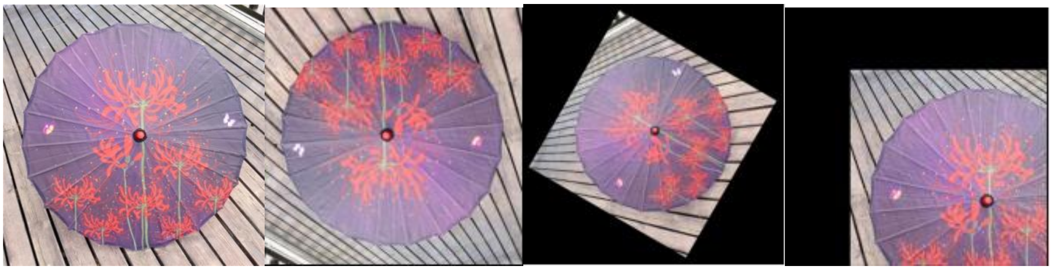
Figure 2: Some Samples of Umbrella Database.

The convolutional neural network needs the same length and width input sample data. In order to make the length and width of the image meet the training of convolutional neural network, the sample image is scaled to 224 * 224 by bilinear interpolation. As shown in Fig. 3, Picture (1) is the sample image of the umbrella, with the size of 402 * 390. Picture (2) is the sample image scaled by bilinear interpolation, whose size is 224 * 224.

(1) (2)

Figure 3: Image Sample Scaling.

Based on the training set samples, the color mean values of R, G and B channels are calculated respectively, and then the color mean values of each training sample are subtracted to get the zero mean training sample. In addition, in order to reduce the risk of over fitting of convolutional neural network training, this paper uses operations of translation, rotation and flipping to make full use of date set and expand the diversity of date set, so as to improve the generalization ability of convolutional neural network. As shown in Fig. 4, Picture (1) is the original image. Picture (2) is the flipped image. Picture (3) is the rotated image. And Picture (4) is the translated image.



(1) (2) (3) (4)

Figure 4: Preprocessing of Image Sample.

The whole data set of umbrella is randomly divided into the training set and test set, accounting for 70% and 30% respectively. Table 1 shows the data distribution of training samples and test samples of each umbrella.

Umbrella Types	*Total Samples*	*Training Sets*	*Test Sets*
Classical Oiled Paper Umbrella	650	455	195
Modern Umbrella	600	420	180

Table 1: Distribution of Umbrella Samples.

3.1.2 Structure of product image recognition of convolutional neural network

ResNet is the Residual Network, which is easier to be optimized and can improve the accuracy by increasing the depth. The core is to deal with the side effect (the degeneration problem) caused by increasing the depth, which may improve the performance of the network by increasing the network depth.

With the deepening of the network, the richer features the neural network can calculate, and the betters results it can achieve. The disadvantage of the deeper neural network is only that the parameters you need to train are large, which leads to a need for a lot of computing resources. But in fact, as the network deepens, the size (norm) of the gradient drops sharply, which is called gradient disappearance, and will result in a very slow learning rate. In rare cases, the gradient will rise sharply, that is the gradient explosion phenomenon, when the accuracy manifested in the training set does not improve compared with the that in the shallow network, but will decline. The Residual Network is a network proposed to solve the phenomenon of gradient disappearance in network deepening.

In view of the great success of ResNet50 in the field of image recognition, this paper uses ResNet50 for fine-tuning training of umbrella recognition, with the network structure shown in Fig. 5. The ResNet50 contains 49 convolutional layers and 1 full-connected layer, among which, the ID BLOCK (Identity Block) *2 in Stage 2 to 5 represents two residual blocks with unchanged size, and CONV BLOCK (Convolution Block) represents the residual block with added scale. Each residual block contains 3 convolutional layers, so there are 1+3*(3+4+6+3)=49 convolutional layers.

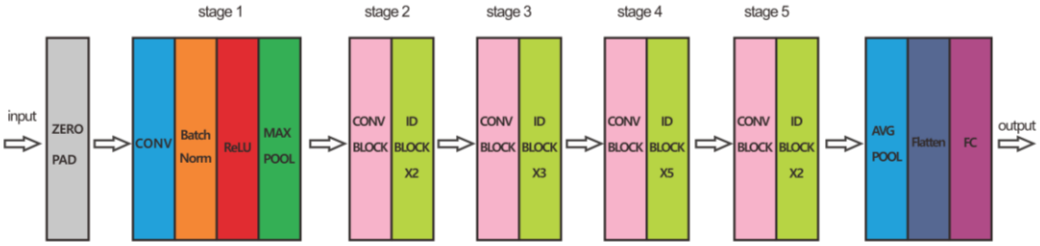


Figure 5: Overall Structure of ResNet50 Network Model (Source: Reference [14]).

CONV in Fig. 5 is the convolutional layers of convolutional operation; BN (Batch Norm) is the batch regularization processing; Relu is activation function; MAX POOL represents the maximum pooling operation; AVG POOL represents the overall average pooling layer operation; and stage 2 to stage 5 are the residual blocks.

ResNet50 is composed of 5 stages and a full-connected classification layer. The network input is umbrella sample image after data preprocessing. And the features of the umbrella sample are extracted after image input of convolutional layer and convolutional operation of convolution kernel. Convolution is the main operation of feature extraction.

Stage 1 is a convolutional block of the common CONV + BN + ReLU + MAXPOOL, and Stage 2 to 5 are residual convolutional blocks, which is the reason for ResNet50 to achieve such deep layers. The output of the last full-connected layer FC is two-dimensional vector, representing the classical umbrella and the modern umbrella.

Each convolutional layer is followed by a ReLU activation function, which increases the nonlinearity of the network and possessed the advantages of high calculational efficiency, no gradient saturation and fast convergence compared with the traditional activation functions of sigmoid and tanh. Its formula is:

$$f(x)=\max(0,x) \tag{1}$$

The output formula of Neuron in Layer is:

$$h_{i,j}=ReLU(\sum_{k=1}^{n}W_{i-1,k}X_{i-1,k}+b_{i-1}) \tag{2}$$

Among it, $W_{i-1,k}$ represents Weight k in Layer $i-1$. $X_{i-1,k}$ represents input of Neuron k in Layer $i-1$. b_{i-1} represents input of Neuron k in Layer $i-1$. And b_{i-1} represents the offset top of Layer $i-1$.

$$J(W)=-\frac{1}{m}[\sum_{1}^{m}y^{(i)}\log h_w(x^{(i)})+(1-y^{(i)})\log(1-h_w(x^{(i)}))] \tag{3}$$

Among it, Point $(x^{(i)},y^{(i)})$ represents Sample i. m represents the number of training samples and $h_w(x)$ represents the pseudo function.

In fact, the whole process of network training is the process to finding the minimum parameters of softmax loss function $J(W)$, which involves two processes: forward propagation and backward propagation. First of all, take the experimental sample in data set as the input, and carry out forward propagation through network to calculate the loss function $J(W)$. And then, use stochastic gradient descent algorithm for backward propagation to calculate the derivative of the loss function on the weight of each layer: $\frac{\partial J(W)}{\partial W_i}$. Among it, i represents the layers of the network. Update the weight of each layer, and the formulate is:

$$W_{i+1} = W_i - \alpha \frac{\partial J(W)}{\partial W_i} \tag{4}$$

Among it, α is the super parameter learning rate, which will constantly reduce the loss function $J(W)$ and minimize the error of product image recognition.

3.1.3 Parameter design

For ResNet50, this paper uses the pre-training model of classification task under large-scale date set of ImageNet, which speed up the network convergence rate. The training phase is divided into two parts to get a better result. The first part is to freeze all parameters except for that of the full-connected classification network, adjust the parameters of the backbone network, use Adam optimizer, set the maximum learning rate as 0.0001 and the Batch size as 8, and train 5 epoches. The second part is to release all the network parameters, use Adam optimizer, and set the maximum learning rate as 0.0001 and the Batch size as 4.

3.2 The Design Model of Oiled Paper Umbrella based on Conditional Generative Adversarial Network with the Technical Route Shown in Fig. 6.

The generative adversarial network has not been widely concerned in product design. With conditional generative adversarial network, this paper makes a preliminary exploration on emotional intelligent design of products based on the image recognition model of classical oiled paper umbrella. The goal of the model is to generate the design scheme conforming to the product according to the product image given by users, so as to save cost for the enterprise and speed up the iterative process of classical oiled paper umbrella.

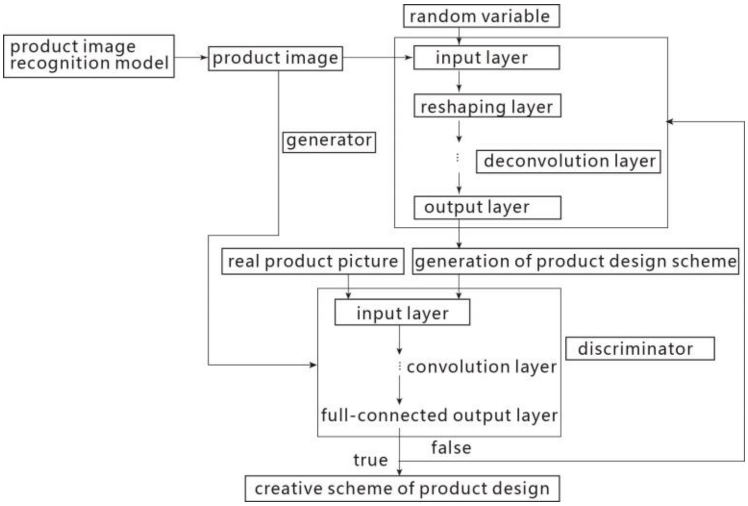


Figure 6: Generation Diagram of the Generative Structure of Conditional Generative Adversarial Network.

3.2.1 Structure of conditional generative adversarial network

The structure of the conditional generative adversarial network is shown in Fig. 7 and Fig. 8, which is consisted of generation model and discrimination model. The input of generative model is random variable and image of classical oiled paper umbrella, and the output is the generation of design scheme for the classical oiled paper umbrella. While for the discrimination model, the input is the generation of product design picture and the real product picture, and the output is the probability value to judge whether the input is the real design picture or the generated design picture. As an instructional condition, the image of classical oiled paper umbrella makes the network generate the design scheme of the product sample that meets the requirements.

DCGAN is proved to be with a certain robustness and stability in practice. Both the generation model and the discrimination model design based on DCGAN. The structure of the generation model is shown in Fig. 7.

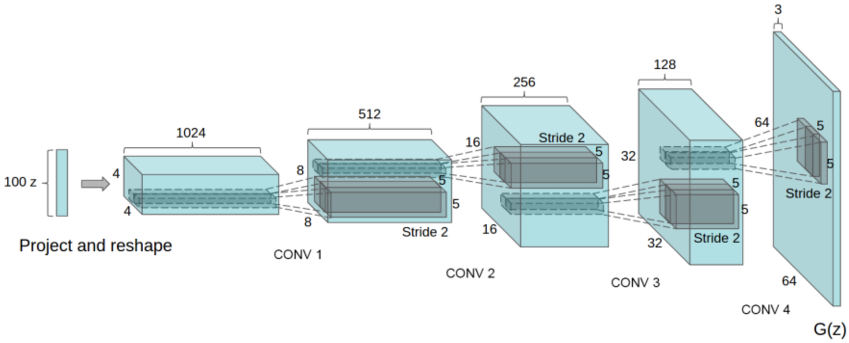


Figure 7: Structure of Generation Model (Source: Reference[15]).

The generation model includes a input layer, a reshaping layer and 4 deconvolution layers. The input layer is a 100-dimension Gaussian noise Z. Z is the one-dimension vector satisfying Gaussian distribution. The Gaussian Function is shown in formula (6).

$$Z(x)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{5}$$

Among them, take 0 for μ and take 1 for σ. Put the 100-dimension noise vector conforming to Gaussian distribution in to the generative network.

The input layer gets the output of 4*4*1024 through projection and reshaping, which is the input of the 4 deconvolution layers. With the deconvolution operation, the length and width of the output increase constantly while the depth gradually decreases. The dimensions outputted by deconvolution layers of conv1, conv2, conv3 and conv4 are 8*8*512, 16*16*256, 32*32*128 and 64*64*3 respectively. The output of conv4, the lase deconvolution layer, is the output of generation model, that is the generation of the design scheme for classical oiled paper umbrella.

The structure of the discrimination model is shown in Fig. 8. It includes a input layer, 4 convolution layers and one full-connected output layer. The input layer is followed by 4 continuous convolution layers. With the convolution operation, the length and width of the output decrease constantly while the depth gradually increases. It receives the image with the dimension of 64*64*3, while the dimensions outputted by convolution layers of conv1, conv2, conv3 and conv4 are 32*32*64, 16*16*128, 8*8*256 and 4*4*512 respectively. Finally, they are transmitted to the full-connected layer for classification. The output value would be 0 or 1, with 1 indicating that the image received by discrimination network is true, while 0 indicating that the image is false. In this research, the output of the discrimination model is the probability value to judge whether it is real sample or generative sample to satisfy the set product image.

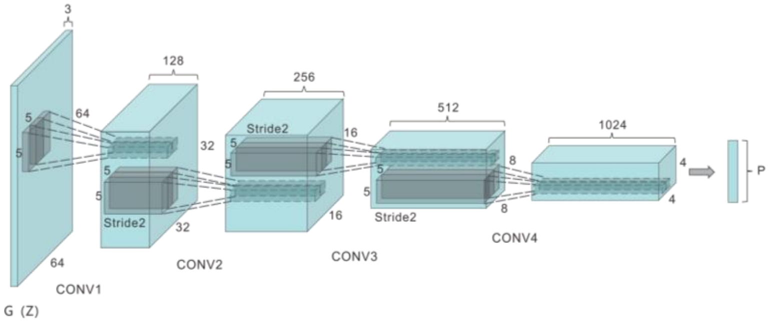


Figure 8: Structure of Discrimination (Source: Fig. 6 and Reference [15]).

3.2.2 Parameter design

The whole model is optimized by stochastic gradient descent algorithm, with the batch size being set as 8 to generate the data set of the experiment, and one round of experiment needs 400 times of iterative training. All parameters of the generator and the discriminator are initialized by Gaussian distribution with mean value of 0 and standard deviation of 0.02. The loss function of the whole model is:

$$\min_{G}\max_{G} V(D,G) = E_{x\sim p_{data}(x)}[\log D(x\mid y)] + E_{z\sim p_z(z)}[1 - D(G(z\mid y)] \tag{6}$$

Among it, x is subject to the real data distribution $p_{data}(x)$, and the noise is subject to the prior distribution $p_z(z)$. E represents the expectation, D represents the generation model and G represents the discrimination model.

In the training process, the generator and the discriminator are updated alternatively. In one iteration, fix the generator and update twice the discriminator, and then fix the discriminator and update once the generator.

4 RESULTS AND ANALYSIS

4.1 Experiment Results of Image Recognition of Oiled Paper Umbrella

After fine-tuning training of ResNet50 on umbrella product image, the product image recognition model is obtained, and the product image is classified. As shown in Fig. 9 Accuracy Curve and Fig. 10 Loss Curve, we can see that the network converges more and more with the deepening of training epoch, and the Loss value of both training set and test set is more and more close to 0. The whole recognition network has learned the distinguish between classical oiled paper umbrella and the modern umbrella, and it completes the convergence basically in the 12th epoch. Because that the training data set and the test data set are incoherent, the loss and accuracy of all test data sets are lagged, but they tend to be consistent on convergence completion. The best recognition rate of ResNet50 for the whole data set of umbrella product image is 94.3%. The recognition rate for classical oiled paper umbrella is 94.8% while for the modern umbrella, it is 93.8%. The experimental results show that ResNet50 is competent for the task of image recognition of classical oiled paper umbrella and modern umbrella products.

4.2 Feature Visualization

The learning of convolutional neural network is an end-to-end learning process. The feature learned inside the network is like a black box. The learning process is not transparent and interpretable. In order to further understand the learning process of product image recognition model, the feature mapping of the convolution layer in ResNet50 middle layer is visualized to observe the changes of features in the deep layers with the deepening of layers, so as to understand the feature extraction process of ResNet50.

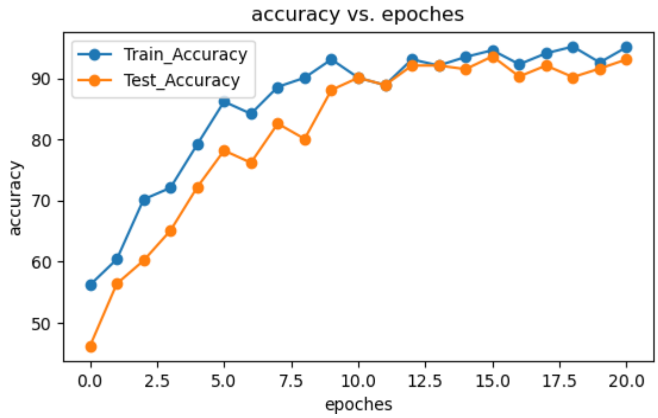


Figure 9: Accuracy Curve.

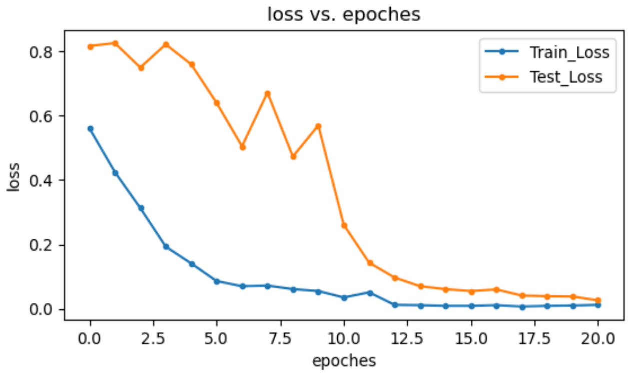
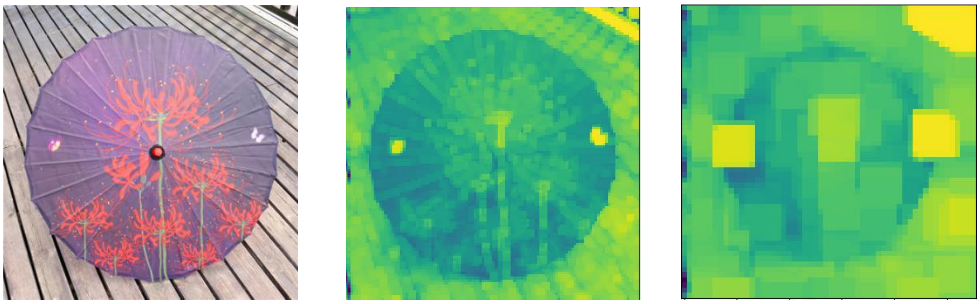
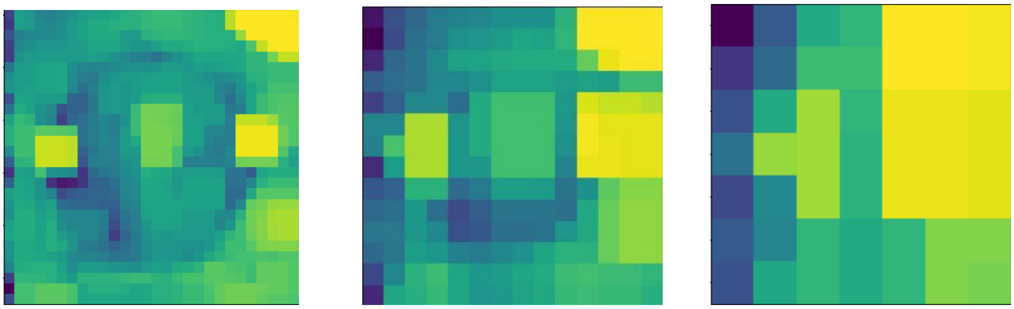


Figure 10: Loss Curve.

As shown in Fig. 11, it shows the change process of convolution features from the input of the original umbrella sample data to the last stage, including the feature mapping of the five stages of layers with different depth.



Input Sample stage 1 stage 2



stage 3 stage 4 stage 5

Figure 11: Changes of Convolution Features with Depth.

From Fig. 11, it can be seen that convolution feature mapping has a trend from bottom to top and from concrete to abstract. In Stage 1 to 3, the umbrella shape and the edge features can be seen, while they are abstract features rather than concrete features in Stage 4 and 5.

4.3 Analysis of Design Results for Oiled Paper Umbrella based on Conditional Generative Adversarial Network

After 400 rounds of iterative training, DCGAN gets the final experimental results, which are shown in Fig. 12.

Figure 12: Results Display of Classical Oiled Paper Umbrella.

After 400 rounds of iteration, DCGAN converges at last. It may generate some shallow classical oiled paper umbrellas. It can be seen that the generated classical oiled paper umbrellas are similar to the real ones in color distribution and graphics. Although they are not as vivid and bright as the real ones, they may inspire the production and manufacturing. Compared with the real classical oiled paper umbrella, the production image is relatively low in clarity, whose reasons may be as follows: (1) The background and color of the classical oiled paper umbrella are complex, and DCGAN can only learn the rough feeling rather than the profound details. All the production images are vague and the color is not bright enough, so the details can't be seen. (2) The original image size is about 600*600, and the network can only generate the image of 64*64, so we can't see more details.

The experimental results of DCGAN show that the shallow classical oiled paper umbrellas generated by DCGAN are meaningful for production and manufacturing. There is room for the improvement of conditional generative adversarial network, and the high-quality classical oiled paper umbrellas can be further generated by using larger network models.

To verify the effectiveness of this method, 100 product designers are asked to give the perceptual evaluation on the above 6 images. Results are shown in Table 2. The average score of all Classical Oiled Paper Umbrella was 3.52, and the highest score was 3.71, which shows the effectiveness of the model constructed in this paper.

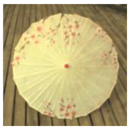
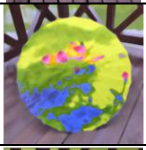
Classical Oiled Paper Umbrella	People of the Scores					Average Scores
	1	2	3	4	5	
	4	10	42	31	13	3.39
	2	8	26	45	19	3.71
	5	15	32	38	10	3.33
	10	17	45	22	6	2.97
	12	12	35	32	9	3.14
	3	8	32	42	15	3.58
Remarks: 5: very strong in sense of classical style; 4: strong in sense of classical style; 3: general in sense of classical style; 4: poor in sense of classical style; 1: no sense of classical style.						

Table 2: Perceptual Evaluation Results of Product Designers.

5 CONCLUSIONS

This paper mainly introduces the construction and analysis of umbrella image recognition model based on convolutional neural network. The product image recognition experiment has been carried out by using deep convolutional neural network, ResNet50. The experimental results show the effectiveness and accuracy of ResNet50 on product image recognition, and the accuracy is as high as 94.3%. At the same time, to further explore the learning process of product image recognition model, the feature mapping of the convolutional layer is visualized, and the change trends of the convolutional feature mapping from bottom to top and from concrete to abstract has been observed. The conditional generative adversarial network is guided in the generation through umbrella product images. First of all, the structure of conditional generative adversarial network is described. The convolutional neural network is used in both generator and discriminator. The input of the generator is the Gaussian noise and product image, and the final output is the generation of sample image by deconvolution operation. Secondly, the details of the experiment design and the parameter design are introduced, and the experimental results are analyzed and verified. The feasibility and effectiveness of conditional generation of sample image based on umbrella product image has been proved. The model can generate some shallow classical oiled paper umbrellas to assist the inspiration design of oiled paper umbrellas. The features and innovations of the project are as follows: (1) Aiming at the shortcomings of low recognition precision and manual feature extraction of the early product image recognition model, the product image recognition model constructed by deep convolutional neural network not only has the ability of self-learning feature extraction, but also greatly improves the accuracy of product image recognition. At the same time, it overcomes the disadvantages of being easy to fall into local optimal solution and poor robustness of constructing product image recognition model by using artificial neural network in recent years. This project uses the deep convolutional neural network, ResNet50, to construct the product image recognition model. In the field of product design, there is no case of using the convolutional neural network to construct the product image recognition model, which provides a new idea and method for product image modeling. (2) On the basis of product image recognition model, aiming at defects of the algorithm of shallow neural network that is limited to optimize the combination of similar products to form the design scheme, this project proposes a product creative design model constructed by generative adversarial network. The generative adversarial network is with strong stability in the face of big data image. The model is fast in iterative speed and it can well deal with the edge details of products. What's more, it overcomes the disadvantages of the traditional product design, such as too much reliance on designers, cumbersome process and low design efficiency. This research has explored the feasibility of the inspiration on product design creativity of generative adversarial network.

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Yixiang Wu, https://orcid.org/0000-0001-7521-7288
Hongyang Zhang, https://orcid.org/0000-0002-5637-9449

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