Convolutional Neural Network in Computer Aided Ceramic Art Design

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Abstract. On the basis of practicality, ceramic art design constantly increases its aesthetic artistry, bringing renewal and enjoyment to human life. Ceramic art is a complex art form, and the aesthetic feeling of its works is highlighted. It is need to fully collect the technology and innovative design ideas of skilled craftsmen. Only by fully exerting the utility function and spiritual function of the products themselves can the design beauty be highlighted. In this paper, taking ceramic art design as the breakthrough point, the characteristics and influencing factors of its design beauty are analyzed, a three-dimensional modeling algorithm of ceramic art products based on convolutional neural network (CNN) is proposed, and the computer-aided ceramic art design strategy under the influence of artificial intelligence is explored. Compared with the traditional support vector machine (SVM) algorithm, the algorithm in this paper improves the accuracy of ceramic art image recognition by 28.64% and the recall by 19.68%, and the digital image processing effect of SVM algorithm takes longer. The computer-aided design (CAD) method of ceramic image based on deep learning (DL) proposed in this paper can effectively solve the problem of unclear image and insufficient stereo, and at the same time keep the definition of ceramic image, and can accurately locate the edge contour of ceramic artwork.

Keywords: Ceramic Art Design; Deep Learning; Computer Aided Design; Convolutional Neural Network.
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1 INTRODUCTION

Due to the rapid development of the world economy and the great progress of science and technology, social products are greatly enriched, and people's material and cultural living standards have been greatly improved. When consumers buy products, they no longer regard the function of products as the first essence of purchase, but begin to pay more attention to the spiritual feelings brought by products [1]. Ceramic is an invention with great cultural background, and the birth of each personalized ceramic product contains a unique meaning and connotation. Porcelain, as one of the earliest global commodities in the world, is a bridge and link to promote the exchange and mutual learning of world civilizations and continuous progress. Ceramic art is a complex art form, and the aesthetic feeling of its works is highlighted, which requires a full collection of skilled craftsmen's technology and innovative design ideas. Only by fully exerting the utility function and spiritual function of the product itself can its design beauty be highlighted [2]. At present, computer vision technology has been applied to different degrees in different industries, but it has not been specifically applied in pattern recognition of ceramic products. The reason may be that the decorative patterns of ceramic products are interlaced with each other, and the same type may have different sizes, so the ceramic products cannot be identified by a single feature [3]. If designers can master consumers' psychology with the help of modern intelligent algorithms and deeply explore consumers' feelings and needs, they can successfully develop good ceramic art products, thus improving the market competitiveness of enterprises.

Ceramic art design requires not only determining the appearance quality of ceramic products, but also considering the structure, function and materials that affect the interests of producers and users. Its basic contents include ergonomics design, shape design, color design and other designs of products [4]. The traditional product-oriented design mode has changed, and the consumer demand-oriented product development mode will gradually follow the mainstream. For product art designers, how to find and master the spiritual needs of consumers, how to shape the product's personality characteristics and how to give the product an emotional shape are all very important issues. ANN is a mathematical model that imitates the structure and function of biological nerves. By imitating the human brain, a large number of simple neurons are connected to each other at first, and then the data samples are repeatedly trained and the network algorithm is feedback-learned, so that the parameters can be automatically adjusted to achieve high accuracy. In this study, a computer-aided ceramic art design model based on DL is constructed, and its main innovations are as follows:

(1) In this paper, the feature extraction and modeling of ceramic art product images are carried out by CNN, which avoids the processing of sample blocks with a large number of unknown pixels and reduces the continuous accumulation of errors caused by matching errors.

(2) In this paper, a method of ceramic image recognition based on DL is proposed, which uses morphological gradient operation to remove most of the noise background and obtain the edge boundary of ceramic image.

(3) The DL-based CAD method for ceramic art products can effectively solve the problem of unclear image and insufficient stereo, and keep the clarity of ceramic art products' images.

2 RELATED WORK

DL is an important part of ANN and plays a major driving role in AI. Deep ANN belongs to deep network structure and is the earliest network model proposed in the development of DL. Wang et al. proposed a hybrid component model, which uses smaller components to describe the 3D model, so that it cannot only more accurately represent the shape of the object, but also overcome the deformation caused by perspective and out of plane rotation that cannot be handled by large components. Kuzin et al. described the basic framework of computer aided engineering for polished ceramic surface layers. The framework is based on two computational models, a mathematical model and various algorithms for steady-state and unsteady thermos-elasticity. An automatic thermal stability calculation system and a method for calculating horizontal and vertical movement, temperature, stress and stress intensity using the test point method [5]. Lee et al. [6] determined the mechanical properties of computer aided design/computer aided manufacturing (CAD/CAM) resin composites for dental restorations, assuming a perfect coupling of silane. The results show that the CAD/CAM resin composite model is successfully reconstructed from the frozen EM images. This shows that the image processing method is useful for the production of dental restorative materials containing nano fillers and the prediction of homogenized mechanical properties. Moussally et al. [7] described the use of the chair side CAD and CAM. The results show that the sequela of AI can be treated conservatively and timely through the CAD/CAM on the side of the operating chair to obtain aesthetic and functional effects. In order to meet the needs of aesthetics and functions, ceramic restorations should be compatible with the existing occlusion, and should not have any negative impact on oral dynamics. Muric et al. [8] compared the accuracy of occlusal design formed by conventional wax sample method and computer aided design (CAD) to understand the similarity with natural tooth morphology. Sun et al. [9] used calculation tools to analyze the design of ceramic products, and used three-dimensional methods to deal with the design. On this basis, the application of 3D printing technology in ceramic field is discussed. Secondly, through personal design and experiments, the principle of using machines in the 3D printing process of ceramics and the characteristics of 3D printing ceramic modeling are summarized. Finally, according to the characteristics of ceramic 3D printing technology, combined with the principles of aesthetics and modeling design, ceramic 3D printing technology is applied to the design and production of ceramic modeling. Instead of the growing demand for total knee arthroplasty (TKA), Tumulus and Sarkar [10] proposed an effective method to establish TKA material model optimization. In this study, we proposed different computer aided design models of knee prosthesis combining metals, ceramics and polymers, and explained the best material models for work and life.

With the extensive application of DL in image recognition, the image technology becomes more and more mature. But the application of image technology in ceramic art design is relatively small. This paper takes ceramic art design as the starting point, and uses CNN to extract features and model ceramic art product images, so as to avoid a large number of sample blocks with unknown pixels being processed, thus providing technical support for computer-aided ceramic art design under the influence of artificial intelligence.

3 METHODOLOGY

3.1 Visual Aesthetic Feeling of Ceramic Product Modeling Image and Color

Each kind of object has its own unique characteristics. These objects with different shapes constitute people's living environment and enrich our lives. Product shape design, that is, shape design, is an important content of modern industrial design research. It refers to the synthesis of materials, processes, functions, visual effects and market relations related to product shape to design products in line with the times.

The contrast of ceramic colors is different in the same area, but when the ceramic area increases, the color area will also increase, and the visual impact of color to viewers will be stronger. On the contrary, when the area is reduced, the impact of color is correspondingly reduced. With the same size, area, color and other elements of ceramic works, different shapes will show different aggregation and dispersion states. People's cognitive process of product modeling image is the same, but the cognitive result will be ever-changing, and different people's cognition of the same product modeling image will be slightly different. The whole process of cognition is an activity of actively explaining external information, which will change with the development of social culture, value orientation and social environment. Figure 1 shows the structure of ceramic product image recognition system.

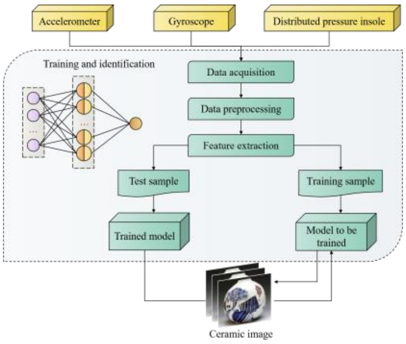

Figure 1: Structure of ceramic product image recognition system.

Therefore, the application of color in ceramic works will affect the aesthetics and appreciation of ceramic works. In ceramic art design and creation, scientific selection and rational use of colors can effectively create a unique and harmonious artistic atmosphere, and bring unique, pleasant and impressive visual and psychological experience to viewers. In order to effectively create this harmonious artistic atmosphere, designers often choose different materials and colors for integration and coordination, such as organically combining different glaze colors with ceramic pigments.

3.2 3D Modeling of Ceramic Art Image Based on CNN

The combination of computer technology and ceramic design enhances the modern aesthetics of ceramic art. The so-called modern aesthetics is in line with the popular aesthetic concept of modern society. Ceramic industry can't just stay on the aesthetic vision of traditional Chinese culture or western culture. Whether it's artistic ceramics or practical ceramics, aesthetic innovation should be carried out with the development of social culture and the promotion of aesthetics. Figure 2 shows the convolution operation process of ceramic image fast recognition model.

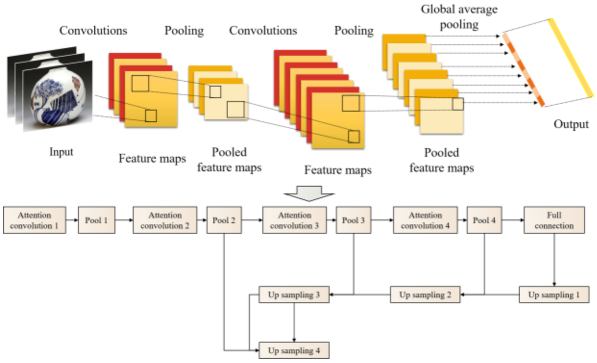

Figure 2: Fast recognition model of ceramic image.

ANN is put forward by imitating people's thinking mode, but in reality, we don't deal with things alone, and we will deal with related things together. If there are some problems in task-based learning, such as small amount of data, high data dimension and serious noise, it will be very difficult to distinguish irrelevant features of the model. Multi-task learning can make the model focus on the influential features, because it can provide additional evidence for irrelevant features through other tasks.

Let X_i^k represent the sum of inputs of neurons i in k layer, and Y_i^k is the output. The weights of neurons j in layer $k-1$ to i in layer k are W_{ij}, so there is the following functional relationship:

$$Y_i^k = f\left(X_i^k\right) \tag{1}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{2}$$

Generally, f is an asymmetric Sigmoid function:

$$f\left(x_i^k\right) = \frac{1}{1+\exp\left(-X_i^k\right)} \tag{3}$$

If the output layer is the m layer, the actual output of the i neuron in the output layer is Y_i^m. Let the corresponding human body signal be Y_i, and define the error function e as:

$$e = \frac{1}{2}\sum_i \left(Y_i^m - Y_i\right)^2 \tag{4}$$

Let the gray value range of the original ceramic image $f(x,y)$ be $\left(g_{\min}, g_{\max}\right)$, select an appropriate threshold T, and:

$$g_{\min} \le T \le g_{\max} \tag{5}$$

Image segmentation with single threshold can be represented by the following formula:

$$g(x,y) = \begin{cases} 1, & f(x,y) \ge T \\ 0, & f(x,y) < T \end{cases} \tag{6}$$

$g(x,y)$ is a binary image. The object can be easily exposed from the background through binarization. The key to binarizing ceramic images is the reasonable selection of threshold T.

Scan the bitmap pixel matrix from left to right and from bottom to top, and find the bottom left boundary point. Starting from the first boundary point, the initial search direction is defined as along the upper left, and if the upper left point is a black point, it is the boundary point. Assuming that the ceramic product image is represented as an d -dimensional feature vector, the features of two given images are:

$$x = \left(x_1, x_2, \ldots, x_d\right)^T \tag{7}$$

$$y = \left(y_1, y_2, \ldots, y_d\right)^T \tag{8}$$

The cosine of the angle between them can be used as a similarity measure:

$$Sin_t(x,y) = \frac{x \cdot y}{\|x\|\|y\|} \tag{9}$$

The distance between two histograms can be measured by histogram subtraction:

$$D_h(x,y)=\frac{\sum_i^d \min(x_i,y_i)}{\min\left(\sum_i^d x_i,\sum_i^d y_i\right)} \tag{10}$$

Minkowski distance is defined as:

$$D_p(x,y)=\left(\sum_{i=1}^d |x_i-y_i|^p\right)^{1/p} \tag{11}$$

In order to distinguish the functions of different feature components in similarity measurement, they are often weighted:

$$D_1(x,y,w)=\sum_{i=1}^d w_i|x_i y_i| \tag{12}$$

The detection model uses multi-frame input through CNN technology, which can better distinguish the gradual change process frame and the non-shot boundary frame of the candidate boundary frame in the process of detecting video shot cut. This method is convenient to classify multiple types of videos at the same time, thus improving the efficiency.

The input signal $I(X,t)$ is compared with N distribution models, and then the matching model is updated. If:

$$|I_j(X,t)-\mu_{ij}(X,t)|<\tau D_{ij}(X,t) \tag{13}$$

The $I(X,t)$ matches the model p_i . Where τ is a global threshold, and i represents the i distribution model. The subscript j represents the component in (s,r,g) space.

If $I(X,t)$ matches more than one p_i at the same time, the distribution model with high probability, small variance and small difference from $I(X,t)$ is selected for updating. That is, the distribution model satisfying the minimum similarity distance $d_i(X,t)$ is updated. $d_i(X,t)$ is defined as:

$$d_i(X,t)=\sum_{j=s,r,g}\frac{|I_j(X,t)-\mu_{ij}(X,t)|D_{ij}(X,t)}{h_{ij}(X,t)} \tag{14}$$

Update the matching p_i according to the following formula:

$$\mu_{ij}(X,t+1)=(1-\alpha)\mu_{ij}(X,t)\alpha I(X,t) \tag{15}$$

$$D_{ij}(X,t+1)=\min\left\{\left[(1-\beta)D_{ij}^2(X,t)+\beta\left(I(X,t)-\mu_{ij}(X,t)\right)_2\right]^{1/2},D_{\max}\right\} \tag{16}$$

$\alpha\in(0,1)$ is the update factor of mean, which determines the update rate of mean, $\beta\in(0,1)$ is the update factor of variance, which determines the update rate of variance, and $D_{\max}$ is the estimated value of the largest variance in all models, which is the global upper limit of variance.

4 RESULT ANALYSIS AND DISCUSSION

The prominence of design beauty in ceramic art design is influenced by two factors, namely, ceramic artists' own ability and accomplishment and the level of modern ceramic production technology. The application of computer technology promotes the systematization of ceramics, and the ultimate goal of ceramic design art is ceramic production, which turns fictitious paper models into reality. Then ceramic production also belongs to a step of ceramic design art, that is, the final link. For the systematic guarantee of this final link, computer technology can contribute to a more scientific process arrangement.

In order to verify the effectiveness and practicability of the ceramic image modeling method in this paper, this section tests and analyzes the performance of the system. In the experiment, the time required for three-dimensional modeling of ceramics with different numbers of pictures and nodes was tested. The experimental results are shown in Figure 3.

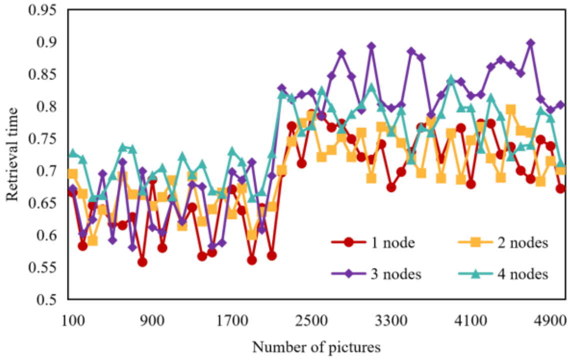

Figure 3: Time consumption of image recognition.

It can be seen from Figure 3 that when the number of ceramic product images is small, the more nodes there are, the more time it takes for image recognition. With the increasing number, the advantages of multiple nodes can be revealed.

When the input image is received, the model is directly opened for feature comparison, and it is not need to extract the features of the images in the image database every time the image is recognized. Compared with database image feature extraction, the feature extraction of input image is relatively simple. Although the image is unknown before each input, it cannot be preprocessed too much. However, the background information in the image is effectively deleted by ceramic positioning, which makes the image data smaller. The detection effect of the operator is evaluated by the number and accuracy of edge pixels, as shown in Table 1. The misjudged points in the table indicate that the non-edge points are judged as edge points.

	Original image	*Robert*	*Sobel*	*Prewitt*	*LOG*
Edge points	725	589	551	529	561
Detection ratio	-	81.5%	82.6%	79.5%	82.1%
Misjudgment point	-	None	Basic none	None	None

Table 1: Comparison of detection effects without noise.

In practice, most of the processed ceramic three-dimensional images are polluted by noise, even if smooth denoising is done before processing. Table 2 shows the comparison results of detection effect when Gaussian noise is added.

	Original image	Robert	Sobel	Prewitt	LOG
Edge points	725	542	545	522	545
Detection ratio	-	78.9%	80.1%	75.2%	80.3%
Misjudgment point	-	Basic none	Have	Have	Basic none

Table 2: Comparison of detection effects when adding Gaussian noise.

As far as ceramic art itself is concerned, the color technology it uses embodies the cultural idea and artistic spirit of a specific period. Therefore, when people watch a certain ceramic art, they can know its production period and social background from its color matching. Subjective assessment refers to judging the design effect of ceramic products from the perspective of visual psychology. Table 3 and Figure 4 show the subjective assessment results of ceramic art design based on the modeling method in this paper.

Sample set	*SVM*	*Proposed method*
1	9.5	8.6
2	9.3	7.5
3	8.6	6.9
4	8.9	8.1
5	9.1	7.1
6	8.4	7.6
7	9.2	7.1
8	8.5	7.8
9	8.8	7.4
10	8.5	7.3

Table 3: Subjective assessment of ceramic art design given by observers.

It can be seen that the ceramic 3D image modeling method in this paper can obtain higher subjective scoring results than the traditional CAD method.

Ceramic type classification can distinguish different ceramic types, which reduces the range of ceramic pattern retrieval. Small-range retrieval can speed up the retrieval speed and increase the retrieval accuracy, and can better distinguish different ceramic types with the same pattern. In order to find out the same ceramic products, the input images need to compare the images in the ceramic image database one by one, so when the number of matching objects is reduced, the number of matching times can be reduced. In the computer operation, the time required for each match is the same, so reducing the number of matches can reduce the time required for image recognition and make the recognition result display faster. Comparing and enhancing the image processing effect by different methods takes time for comparative analysis, as shown in Figure 5.

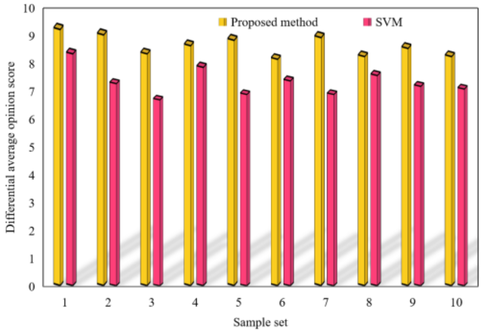

Figure 4: Subjective assessment of ceramic images given by observers.

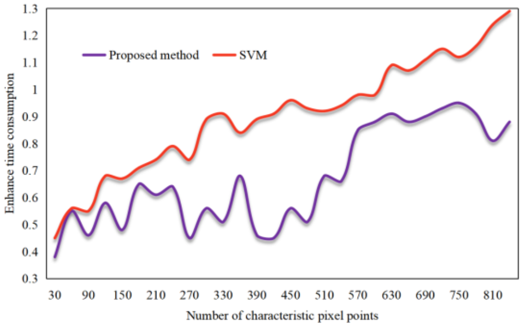

Figure 5: Time-consuming comparison results of enhanced image processing effects of different methods.

As can be seen from Figure 5, the effect of digital image processing of ceramic images by SVM algorithm takes longer. Feature extraction is only the dimensionality reduction of image data, which extracts the discriminative features in an image and reduces the dimensions of the image into a vector. However, whether the features are the same or not is not the only index to test whether the two images are similar. Whether the two images are similar or not also needs to determine the positional relationship between features and whether there is excessive deviation, which is another important index of image recognition. Ceramic ware is rich in shape and color, and its manufacturing techniques are diverse, which makes ceramics diverse and complex. When the number of images in the image database is quite large, the image retrieval speed will slow down. In order to improve the effect of ceramic image retrieval, this paper puts forward the method of ceramic type classification and location cutting to improve the speed and accuracy of image recognition. Figure 6 shows the precision results of different algorithms.

It can be seen from Figure 6 that the accuracy of this algorithm is 28.64% higher than that of traditional SVM. Any object is made up of components, and the components are combined into a whole, finally forming the functions and characteristics of the product. As mentioned earlier, people's image cognition is a process from the whole to the division, and then from the division to the whole. ANN with pre-input function realizes that the input image is divided into parts at first, and then integrated into a whole input image. Generally, there is only one image, and the feature extraction of the input image can be directly extracted by CNN, and then compared with the database image. Compare the recall of the algorithm for ceramic artwork image recognition, as shown in Figure 7.

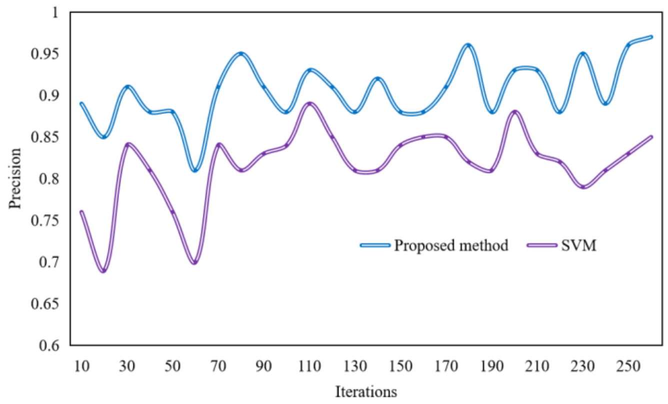

Figure 6: Accuracy results of different algorithms.

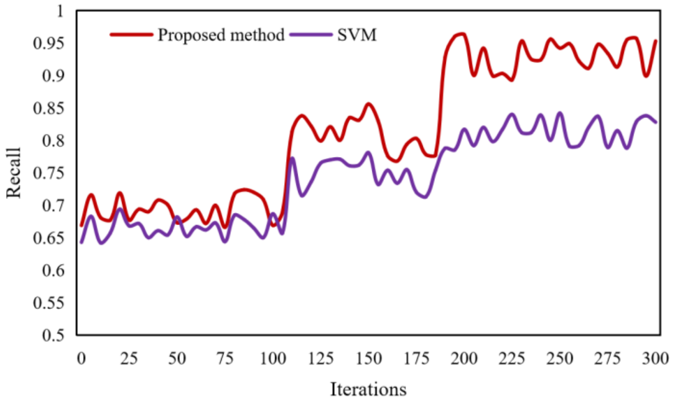

Figure 7: Comparison of recall of ceramic artwork image recognition.

The test results show that the recall of ceramic art image recognition by this algorithm is increased by 19.68%. Therefore, the proposed DL-based ceramic image CAD method can effectively solve the problem that the image is not clear and stereoscopic, while maintaining the clarity of the ceramic image, and can accurately locate the edge contour of the ceramic artwork. When designing ceramic art, designers should select from many colors according to the theme and spiritual connotation of ceramic art, which can not only produce ideal visual impact effect, but also show the spirit of ceramic art quality. In addition, if we want to ensure the effect of ceramic art design, we should master certain matching methods when choosing and matching colors, so as to ensure the full play of color functions.

5 CONCLUSIONS

This paper takes ceramic art design as the breakthrough point, analyzes the characteristics and influencing factors of its design beauty, puts forward a 3D modeling algorithm of ceramic art products based on DL, and explores the computer-aided ceramic art design strategy under the influence of artificial intelligence. The experimental results show that the accuracy of ceramic art image recognition by this algorithm is improved by 28.64% and the recall is improved by 19.68% compared with the traditional SVM, and the processing effect of ceramic image digitization by SVM algorithm takes longer. The proposed DL-based ceramic image CAD method can effectively solve the problem of unclear image and insufficient stereo, and at the same time keep the definition of ceramic image, and can accurately locate the edge contour of ceramic artwork. Aiming at ceramic image retrieval in the concurrent environment, and combining with the retrieval characteristics of this system, we can increase the message queue, increase Map Reduce, increase cache strategy, etc. to improve the access and computing ability in the concurrent environment, and further improve the system.

6 ACKNOWLEDGEMENTS

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