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A Design of Apparel Appearance: Recognition and Evaluation of Clothing Pattern Styles under Deep Learning

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ABSTRACT
Designing the appearance of clothing can effectively enhance its attractiveness and expand its marketability. This paper briefly introduces the Convolutional Neural Network (CNN) and applies it to the recognition and evaluation of clothing pattern styles to assist in evaluating clothing appearance design. A case analysis was then conducted. Firstly, the CNN algorithm was compared with the traditional Back-Propagation Neural Network (BPNN) algorithm, and then the design scheme proposed in this paper, called "Sanduo and Jiuru", was evaluated. The results showed that, compared to the BPNN algorithm, the CNN algorithm not only converged faster during training but also demonstrated superiority after the convergence became stable. In addition, the test set also verified the accuracy of the CNN algorithm in recognizing and evaluating clothing pattern styles. The evaluation of the "Sanduo and Jiuru" design was also very similar to human evaluation, and its excellence was analyzed accordingly.

KEYWORDS
apparel appearance, deep learning, pattern style recognition, scoring

INTRODUCTION

In the early stages of the clothing industry’s development, due to low social productivity and economic levels, clothing was mostly produced through manual customization, resulting in different clothing designs for different individuals. When society's productivity increased, the capacity to produce garments also grew significantly. As a result, standard sizes of garments were established to streamline the mass production process [1]. The mass production of clothing greatly reduces production costs and provides consumers with a variety of clothing styles to choose from. Nevertheless, it remains essential for clothing manufacturers to provide personalized clothing designs to meet the increasing demand for diverse clothing styles from consumers [2]. The design of clothing appearance can further enhance the variety of clothing styles, and excellent clothing appearance design can greatly attract consumers. The design of clothing appearance is not only based on the structure of the garments themselves but also the pattern design on their surface. Excellent clothing pattern designs cannot be created out of thin air. Designers typically combine various pattern elements, and recognizing different clothing pattern styles in this process is not only advantageous for designing clothing patterns but also for evaluating design schemes later [3]. When designing clothing image schemes, multiple schemes will be generated. Therefore, it is necessary to evaluate these schemes and choose the best one. Although relying solely on manual evaluation can capture people's subjective feelings, it can also lead to one-sided evaluation results due to excessive subjectivity. The emergence of intelligent algorithms provides a new method for evaluating clothing pattern design schemes. Intelligent algorithms are trained on a large number of clothing pattern design schemes that have been evaluated manually. This allows them to uncover hidden rules and accurately recognize and score different clothing pattern styles within the design scheme. Relevant studies are as follows. Zhan et al. proposed a new development mode for double-layer full-fashioned knitted clothing and fake two-piece knitted clothing [4]. They achieved double-layer clothing patterns in their research, providing effective references for the design of fake two-piece knitted clothing. Jankoska used Computer-Aided Design (CAD) methods to design 3D clothing and 2D patterns for a men's shirt efficiently and accurately [5]. Kulsum improved the quality of learning by enhancing students' learning outcomes and their ability to grade women's fashion patterns using CAD pattern systems [6]. The researcher found that students' learning outcomes and their ability to grade women's fashion patterns improved. This article briefly introduces the Convolutional Neural Network (CNN) and applies it to the recognition and scoring of clothing pattern styles to assist in the evaluation of clothing appearance design, followed by a case analysis. This article proposes using deep learning algorithms, such as a CNN, to recognize and rate the pattern styles of clothing to assist in designing clothing appearance. Since evaluating clothing patterns is a subjective task, the labels of training samples used to train the CNN algorithm were manually marked based on evaluations from multiple professionals. The effectiveness of the CNN algorithm in recognizing clothing patterns was verified by comparing it with the BPNN algorithm. Subsequently, the trained CNN algorithm was utilized to evaluate the 'Sanduo and Jiuru' scheme proposed in this paper and compared with the results of manual evaluation. The final results confirmed that the evaluation provided by the CNN algorithm closely approximated manual evaluation, thus demonstrating its potential for assisting in clothing pattern design and evaluation.

BASED ON DEEP LEARNING ALGORITHMS FOR CLOTHING PATTERN RECOGNITION AND SCORING

Convolutional Neural Network

In deep learning algorithms, the Back-Propagation Neural Network (BPNN) is the most fundamental and classical algorithm, consisting of an input layer, hidden layers, and an output layer. When used for clothing pattern recognition and rating, image feature extraction algorithms need to be used first to obtain the image features of clothing patterns, which are then input into the BPNN for calculation [7]. Although the BPNN can also uncover hidden patterns, it is difficult to fully describe image features using image feature extraction algorithms, which leads to information loss during the training of the BPNN and affects the accuracy of recognition and evaluation [8]. The CNN is more suitable for processing image data compared to the BPNN. The basic structure of the CNN, as shown in Figure 1, comprises an input layer, convolutional layers, pooling layers, a fully connected layer, and an output layer. The input layer receives the image data to be processed. The convolutional layer and the pooling layer perform convolutional feature extraction and compression on the image. The fully connected layer calculates the extracted and compressed convolutional features, outputting the desired target results in the output layer, which represents the relevant rating of pattern styles and designs.

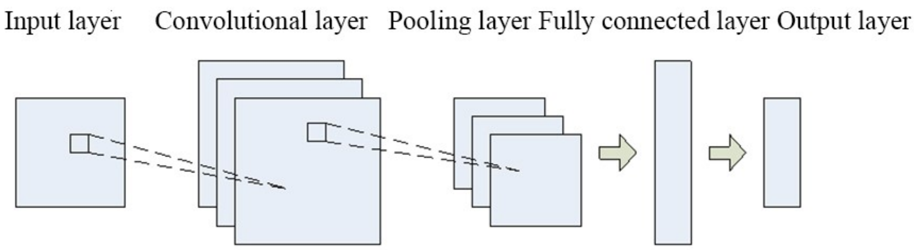

Figure 1. The basic structure of a CNN

In practical CNN applications, the number and structure of convolutional and pooling layers will be adjusted according to specific needs. The convolutional layer uses convolution kernels to extract convolutional features from the image [9], and the formula is:

$$y_j^l = f\left(\sum_{i=1}^{N_j^{l-1}} w_{i,j} \otimes x_i^{l-1} + b_j^l\right), j = 1,2,\cdots,m, \tag{1}$$

where l represents the current number of layers, w is the convolutional kernel weighting matrix, x_i^{l-1} stands for the output feature map matrix, f stands for the activation function, $\otimes$ stands for convolutional operation, and b_j^l is the bias of the j-th feature map in the l-th layer. The role of the pooling layer is to compress the convolutional feature map and reduce the amount of computation afterwards. In this structural layer, the pooling frame is used to slide on the feature map with a specified step length. During the sliding process, the feature data within the pooling frame is compressed using either mean compression or maximum compression.

After the forward calculation of the feature map undergoing multiple convolutions and pooling in the fully connected layer, the results are outputted in the output layer. If it is during the training process, the output of the output layer is compared with the labelled result. Then, the gradient descent method is used to backpropagate the error, adjusting the weights and biases in the CNN [10]. The corresponding formula is:

$$\begin{cases} \omega_i' = \omega_i - \dfrac{\eta \cdot \partial e}{\partial \omega_i} \\ b_i' = b_i - \dfrac{\eta \cdot \partial e}{\partial b_i} \end{cases}, \tag{2}$$

where e stands for the error between the output result and the label result and η stands for the learning rate [11].

Process of Clothing Pattern Recognition and Scoring Based on CNN

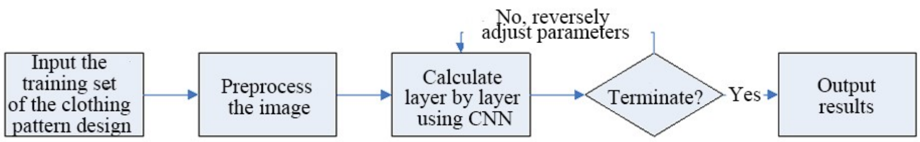

Figure 2. The training process of CNN-based clothing pattern recognition and scoring

The previous section provides a brief introduction to CNN. When using it for clothing pattern recognition and scoring, the basic training process of the entire algorithm is shown in Figure 2.

① Clothing pattern design schemes are collected to form a training set and a test set. In addition to the images of the design schemes, both sets also include corresponding labels that not only contain the style of the clothing pattern in the design scheme but also provide ratings for different aspects of the clothing pattern [12]. The clothing pattern styles in the dataset can be marked directly; when scoring the clothing pattern, it is divided into different evaluation levels using the analytic hierarchy process (AHP) method. Multiple professionals evaluated the patterns, and the weights of different-level projects were determined to obtain the score.

② The design images in the training set are preprocessed.

③ The preprocessed images are input into the CNN for layer-by-layer computation, including convolution calculation and pooling compression. The formulas for convolution calculation and pooling compression as described in the previous section [13]. After multiple rounds of convolution and pooling computations, the convolution features of the image are calculated in the fully connected layer to obtain the pattern style and evaluation score of the design.

④ Whether the algorithm meets the termination conditions is determined. The termination conditions include: (1) the number of training iterations reaches the set value; (2) the error between the computed result and the labelled result of the training set stably converges. Either of the two termination conditions being met indicates the termination of the algorithm.

⑤ If the algorithm satisfies the termination conditions, training is stopped and the results are outputted. If the algorithm does not meet the termination conditions, the error is used to adjust the hyperparameters in the CNN in a reverse manner, as described in the previous section.

CASE ANALYSIS

Object of Analysis

The clothing pattern design used for recognition and in-depth evaluation in this study was named "Sanduo and Jiuru". The basic design process is shown in Figure 3, drawing inspiration from the Riparia kite. In the design process, Ebru materials were initially created by imitating the pattern prototype of the Riparia kite. Then, the lines and configuration elements were extracted from the Ebru materials. Local patterns were created using these extracted elements, and these patterns were then combined and applied to the clothing. When conducting style recognition and in-depth evaluation of the "Sanduo and Jiuru" clothing pattern design in Figure 3, this article used CNN for assistance. Firstly, a CNN algorithm was used to recognize the clothing pattern style of the design and give initial ratings. Subsequently, an in-depth evaluation analysis was conducted based on the recognition results and ratings provided by CNN.

a) b) c)

d) e)

Figure 3. The basic design flow of the pattern of the "Sanduo and Jiuru" clothing pattern design: a) Make Ebru materials, b) Extract elements, c) Make local patterns, d) Combine patterns, e) Clothing pattern design

Before using the CNN for assistance, it was trained using the training data. This article sampled a variety of clothing designs from the market, collecting a total of 1,500 sets of clothing designs. Among them, 1,000 sets were used as the training set, and the remaining 500 sets were used as the test set. The clothing designs in the dataset were presented as .jpg images with dimensions of 3000 x 2000 pixels. The focus of these images was mainly on pattern decorations of the clothing. Figure 4 shows some of the clothing pattern styles.

Figure 4. Some clothing pattern styles

Analysis Methods

The CNN algorithm was initially used for preliminary style recognition and scoring, and then an in-depth evaluation analysis based on the results given by the CNN was conducted. Table 1 presents the basic structural parameters of the CNN during the training process, which consists of four convolutional layers and two pooling layers. Max pooling was used in the pooling layers, and the sigmoid activation function was used in the convolutional layers [13]. During the training process, the gradient descent method was used to adjust the hyperparameters in the algorithm, and the learning rate was set at 0.01. In addition to validating the effectiveness of the CNN algorithm using the test set, it was also compared with the traditional BPNN, which used scale-invariant feature transform features for pattern extraction.

Table 1. The basic structural parameters of the CNN

Name of structure	Parameter setting	Name of structure	Parameter setting
Convolutional layer 1	32 convolution kernels in a size of 2 x 2	Convolutional layer 3	16 convolution kernels in a size of 2 x 2
Convolutional layer 2	32 convolution kernels in a size of 2 x 2	Convolutional layer 4	16 convolution kernels in a size of 2 x 2
Pooling layer 1	3 x3 pooling frame	Pooling layer 2	3 x 3 pooling frame

The labels in the training samples used during training were manually annotated. To ensure that the evaluation criteria, i.e., the "way of thinking," were as close as possible to human evaluation, this article used the AHP method to annotate the evaluation results of the training samples [14]. The specific hierarchy division and weights are shown in the results section below. In the AHP method, the survey content was designed based on the target layer project. Ten experts who have been engaged in fashion design for more than five years were asked to rate the graphic design scheme using a ten-point scale. The final result adopted the average score, and then the score of the intermediate layer project was calculated based on the score and corresponding weight of each target layer. Based on the weight of the intermediate layer project, the final score of the design, i.e., the top layer, was further calculated.

Experimental Results

Figure 5 illustrates the trend of recognition accuracy and score error for clothing pattern styles during the training process of the BPNN and CNN as the number of iterations increased. As shown in Figure 5 the recognition accuracy of both algorithms for clothing pattern styles gradually increased and eventually stabilized with the increase of training iterations. Throughout this process, the CNN consistently exhibited higher recognition accuracy than the BPNN. The scoring error of both algorithms for clothing patterns initially decreased and eventually stabilized. Throughout this process, the CNN consistently had a lower error score than the BPNN. In addition, Figure 5 also shows that the recognition accuracy and score error of the CNN converged to stability after approximately 140 iterations, whereas the BPNN converged to stability after around 200 iterations.

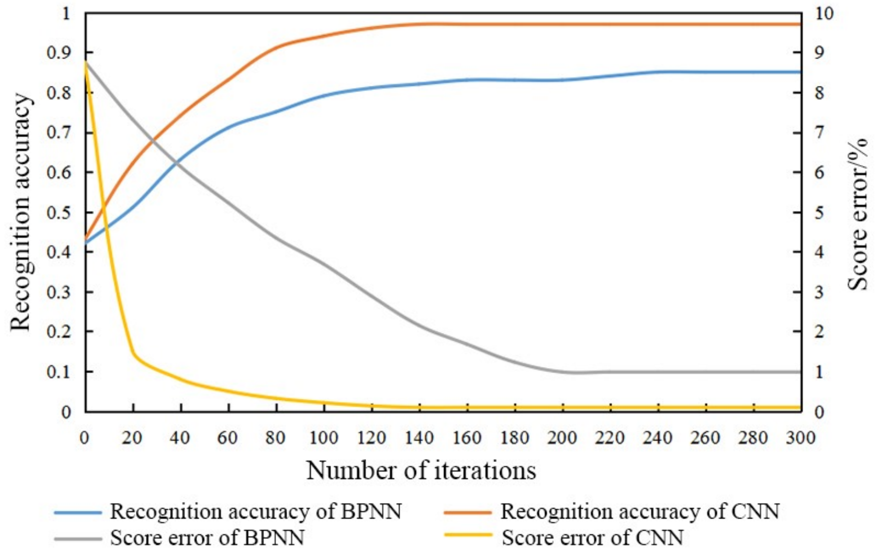

Figure 5. Changes in style recognition accuracy and score error of the BPNN and CNN in the training process

After training the BPNN and CNN, they were tested on the test set, and the results are shown in Figure 6. The recognition accuracy of the BPNN for clothing pattern styles in the test set was 0.76, with a score error of 1.02%; while the recognition accuracy of the CNN for clothing pattern styles in the test set was 0.98, with a score error of 0.09%. Figure 6 intuitively shows that compared to the BPNN, the CNN achieved higher recognition accuracy for clothing pattern styles and lower score error.

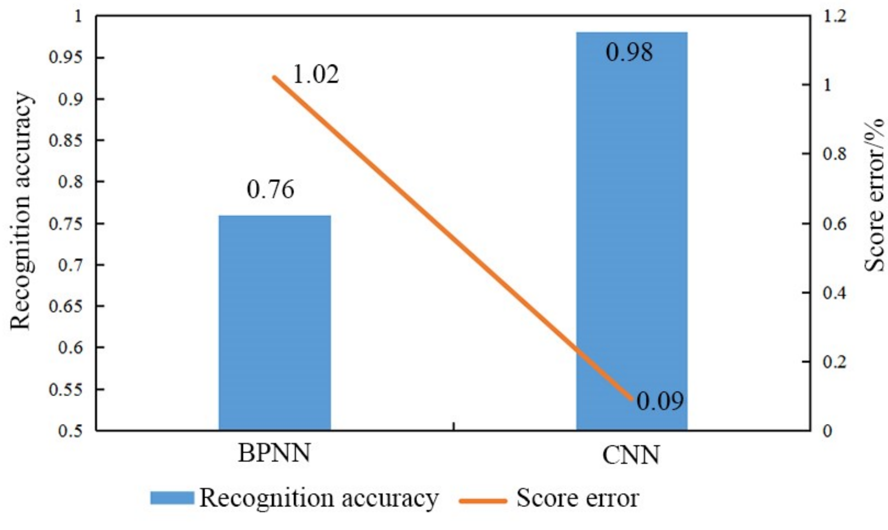

Figure 6. Style recognition accuracy and scoring error of the BPNN and CNN for the test set

After conducting comparative experiments with the BPNN to verify the accuracy of the CNN algorithm in recognizing fashion patterns and scoring, the CNN algorithm was applied to the evaluation of the "Sanduo and Jiuru" fashion design shown in Figure 3. The style recognition result of this design by the

CNN algorithm was "animal-based composition," and the scoring result for the design is presented in Table 2. It was seen from Table 2 that the scoring of each target layer by the CNN algorithm was generally consistent with the manual scoring, with only one or two items showing slight differences. However, the scores generated by the BPNN algorithm differed from the manual ratings for each target project. After calculation, the comprehensive score of manual evaluation for the design was 7.87 points, the comprehensive score of the CNN algorithm was 7.90 points, and the comprehensive score of the BPNN algorithm was 7.65 points.

Table 2. Manual scoring results and CNN scoring results for the "Sanduo and Jiuru" design

Middle layer	Weight	Target layer	Weight	Manual scoring	CNN scoring	BPNN scoring
Pattern configuration	0.52	Degree of novelty	0.65	8.5	8.5	8.2
		Degree of suitability	0.35	8.5	8.6	8.3
Colour design	0.48	Degree of sharpness	0.25	7.8	7.8	7.4
		Reasonable degree	0.20	8.6	8.7	8.5
		Degree of innovation	0.55	6.4	6.4	6.3

Discussion

Designing fashion patterns can not only enhance consumer attraction but also increase the variety of clothing styles, enrich consumers' shopping choices, and benefit the expansion of clothing sales markets. Multiple design schemes may be generated during the process of designing fashion patterns. Selecting a relatively superior scheme from these design schemes is also an important aspect of fashion appearance design. Zhang et al. proposed a sketch generation model to replace the traditional preprocessing step of roughly extracting image edges [16]. They then constructed a fine-grained sketch-based image retrieval model using a deformable CNN and conducted experiments on a clothing sketch dataset to validate the retrieval accuracy of this model. Zhang et al. focused on clothing style images and established a sample library for collar styles [17]. They compared and analyzed the advantages and disadvantages of commonly used image processing methods, such as grayscale conversion, sharpen detection, morphological operations, and image segmentation. They developed corresponding image preprocessing schemes, providing new ideas for automatic pattern recognition, software development, and application. This article used the CNN algorithm in deep learning to assist in recognizing and evaluating fashion pattern styles. The CNN algorithm was used to recognize the pattern style of a design and provide an initial assessment of its quality by assigning a score to the fashion pattern. Further evaluation was then carried out based on this preliminary assessment.

In the above case analysis, the CNN algorithm was first compared with the traditional BPNN algorithm to verify the accuracy of the CNN algorithm in recognizing clothing patterns and scoring them. Then, the CNN algorithm was used to recognize and evaluate the "Sanduo and Jiuru" design scheme, and the final results are shown in the previous text. Further analysis was conducted on both manual evaluation and CNN evaluation results.

The "Sanduo and Jiuru" design in Figure 3 references the Shouyan kite with the "Sanduo and Jiuru" design and incorporates the texture painting style of Ebru. The smooth texture in Ebru complements the streamlined shape of the Riparia kite, resulting in a novel combination. In addition, the prototype of the "Riparia" referred to in this design is Feiyan Zhao, a beautiful woman with a slender figure from the Han Dynasty. This pattern represents a woman with a slim figure, versatile charm, and graceful dancing posture. The clothing style used in this design refers to the curve-bottom clothes of the Han Dynasty, which perfectly reflect a woman's slender figure, making their combination very appropriate. In terms of colour design, the "red pot bottom" style from Riparia Kite was chosen. This colour is bright and implies auspiciousness and female charm. The colour design was reasonable, but the use of red, a colour with auspicious meaning, was relatively common in terms of innovation; therefore, the degree of innovation was not too high. The contribution of this article lies in utilizing the CNN algorithm to recognize patterns in clothing designs and provide valuable references for the field of clothing design. The limitation of this article lies in solely using the CNN algorithm for recognizing clothing pattern designs. When the CNN is employed to recognize patterns, it can still be influenced by background or noise present in the images, resulting in a decline in recognition accuracy. Hence, preprocessing the images becomes essential. The future research direction will concentrate on image preprocessing and prior extraction of line features from clothing patterns.

CONCLUSION

This article introduces CNN and its application in recognizing and scoring clothing patterns, to assist in evaluating clothing appearance design. A case analysis was conducted on the application of CNN. The CNN was first compared with the traditional BPNN algorithm. Then, the "Sanduo and Jiuru" design was evaluated and analyzed. During the training, as the number of iterations increased, the recognition accuracy of the BPNN and CNN algorithms increased first and then stabilized, and the scoring error decreased first and then stabilized. However, the CNN algorithm consistently achieved higher recognition accuracy and lower score errors compared to the BPNN algorithm, and both algorithms reached stable states faster. For the test set, the CNN algorithm had higher accuracy in recognizing clothing pattern styles and lower score errors compared to the BPNN algorithm. For the "Sanduo and Jiuru" design, the CNN algorithm's scores for each target layer were generally consistent with manual evaluation, with only one or two items showing slight differences. The comprehensive score given by the manual evaluation was 7.87 points, the score given by the CNN algorithm was 7.90 points, and the score given by the BPNN algorithm was 7.65 points.

Conflicts of Interest

The author declares no conflict of interest.

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