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Article

Algorithm for simulating calligrapher's stroke features using neural networks

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Abstract: In the field of calligraphy art, simulating the stroke features of calligraphers has always been a challenging task. Traditional methods often rely on manually designed rules or feature extraction algorithms, which are difficult to accurately capture calligraphy details and time-consuming. This article aimed to explore a more effective method to simulate the stroke features of calligraphers using neural network technology. This article mainly explored the simulation algorithm of calligrapher stroke features based on neural networks, including calligrapher stroke feature statistics, calligrapher stroke feature abstraction, and calligrapher stroke feature extraction. By using Convolutional Neural Network (CNN) to learn and analyze calligraphy works, a better performance neural network model was established to achieve automatic recognition and classification of calligrapher stroke features. By continuously optimizing model parameters, the accuracy of calligrapher stroke feature simulation can be improved. The average similarity rates for imitating stroke features of five calligraphers (regular script, cursive script, clerical script, seal script, and running script) using Artificial Neural Network (ANN) were 0.72, 0.62, 0.40, 0.33, and 0.53, respectively. The average similarity rates for imitating stroke features of 5 calligraphers (regular script, cursive script, clerical script, seal script, and running script) using CNN were 0.93, 0.78, 0.87, 0.67, and 0.80, respectively. The research results of this article promoted the inheritance and innovation of calligraphy art, and expanded the expression forms and application fields of calligraphy art.

Keywords: artificial neural network; Chinese character stroke features; similarity rate; fluency rate; convolutional neural network

1. Introduction

This article provides a novel technical approach that can help understand and simulate the stroke features of calligraphers, providing a new strategy for the digitization, automation, and intelligence of calligraphy art. By conducting in-depth research on the application of neural networks in simulating calligraphy stroke features, the aim is to promote the development and application of computer vision and artificial intelligence in art and expand the application of neural networks in cultural heritage protection and inheritance. In addition, this study also helps to improve the digital reconstruction and simulation level of calligraphy artworks, providing new ideas and methods for cultural inheritance and innovation.

This article provides an in-depth analysis of the algorithm for simulating calligrapher stroke features using neural networks, including details on calligrapher stroke feature statistics, calligrapher stroke feature abstraction, and calligrapher stroke feature extraction. It provides a detailed description of the process of neural network modeling and how to train the model. The performance and effectiveness of the CNN algorithm are evaluated through experimental verification and result analysis, and compared and discussed with ANN. The article has a rigorous structure, clear hierarchy, and both theoretical depth and practical guidance, providing effective guidance and reference for readers to comprehensively and deeply understand the algorithm research of neural network simulation of calligrapher's stroke features.

2. Related work

At present, there has been some progress in the algorithm research on the stroke features of calligraphers. Calligraphy aesthetics is a branch of Chinese aesthetics gradually formed under the integration of Chinese and Western cultures. Wang Luya believed that constructing the aesthetics of inscriptions is of great significance for contemporary calligraphy appreciation, creation, and aesthetics. It is an essential perspective and element in calligraphy appreciation [1]. Yang Lijie explored solutions for calligraphy text sequence recognition, which is a challenging task as traditional text recognition algorithms rarely achieve satisfactory results [2]. Yifan Zhang proposed that calligraphy art is an art defined by characters, which is not only reflected in the form of Chinese characters, but more importantly, in the meaning of Chinese characters [3]. Tang Xingjia proposed spectral imaging as an information acquisition method for synchronous perception of attributes and vision, which can be used for calligraphy and painting identification. Especially through hyperspectral imaging and data analysis, it is possible to identify the pigments and inks used in painting and determine printing features [4]. Guo Dongmei found that due to the large number of strokes collected by the robotic arm for learning and training, there is a lack of operability. The simulated stroke model can replace the real samples collected by the robot as the training dataset source for deep learning and training [5].

With the continuous development of artificial intelligence and machine learning, neural networks have become a research hotspot in more and more fields. Among them, using neural networks to simulate and analyze the stroke features of calligraphers has become a highly concerning topic. Luo Guoliang proposed a novel and simple method of presenting tactile feedback of Chinese calligraphy in VR (virtual reality) by using a soft and deformable sponge as a medium between the handheld controller and the writing surface, and generating a realistic user experience [6]. Si Huihui used the rapid development of computer-assisted technology and deep learning algorithms to promote the digitization of Chinese calligraphy and painting. Chinese calligraphy samples were collected and improved through digitization, preprocessing, noise reduction and resizing. The system can reliably identify and classify different calligraphy styles, breaking through the limitations of traditional recognition technology [7]. Chinese calligraphy, as a famous form of performance art, occupies an important position in China's intangible cultural heritage. Li Rui used brain functional network analysis to study the aesthetic experience of Chinese cursive calligraphy [8]. Lyu Ruimin designed two experiments to measure velocity and trace sensation, which are instantaneous representations and cumulative representations of the same content - the dynamic sensation of strokes. Different visualization designs were applied to these two experimental data as artistic recreation of traditional artworks [9]. Cui Wenyi used a multi-label convolutional neural network to create and train a recognition model to simultaneously identify the text content and font of a single Chinese character. The results showed that the system can recognize calligraphy features well [10].

Neural network simulation can enhance the application level of calligraphy automatic writing technology, enabling computers to automatically simulate and learn the brushwork features of calligraphers, bringing new opportunities and challenges to the inheritance and development of calligraphy art. Neural network simulation technology also has important application value in calligraphy teaching.

3. Methods

Calligraphy is an indispensable part of Chinese culture and has been highly respected since ancient times. The charm of calligraphy lies in its freedom and novelty. It is not just a way of writing, but also a form of artistic expression. The stroke features of a calligrapher are the core elements of calligraphy art, which determine the style and features of calligraphy, and are also an important indicator of the calligrapher's level and style. Therefore, the study of simulation algorithms for calligrapher stroke features is of great significance [11]. With the development and application of digital technology, a large number of digital calligraphy works are presented to people, providing a more convenient and extensive data source for the study of calligraphy writing features. At the same time, the proposal and application of neural network algorithms also provide new avenues for solving this problem. Therefore, conducting neural network simulation research on the brush features of calligraphers has great practical significance and value.

3.1. Fundamentals of neural networks

Neural networks are based on neurons, simulate the human nervous system, and through continuous learning and training, can obtain features and perform classification, prediction, and other operations on them. Taking calligraphy as an example, neural networks are used to simulate the stroke features of calligraphers, enabling computers to learn and simulate calligraphers, and improving the application level of calligraphy automation technology.

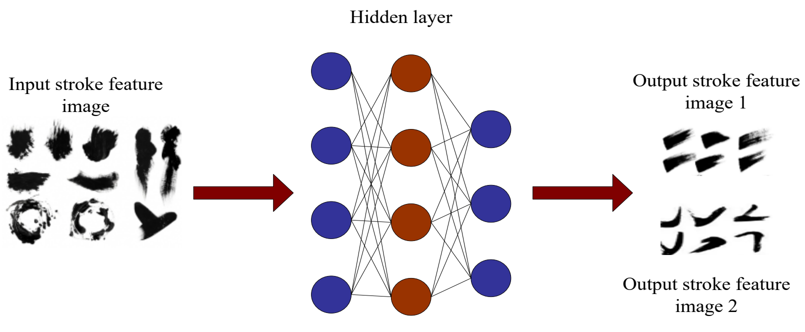

Figure 1. Structural model of neural network.

Neural networks are generally divided into an input layer, a hidden layer, and an output layer. Some neural networks do not have hidden layers, while others have multiple hidden layers. Neural networks use neurons as the basic processing unit, usually consisting of multiple input and single output units. The structural model is shown in **Figure 1**.

As shown in **Figure 1**, the general structure of a neural network consists of an input layer (input stroke feature image), a hidden layer, and an output layer (stroke feature image 1 and image 2).

A feedforward neural network is a supervised learning method that requires three parts of information for forward propagation: input, network connection structure, and neuron parameters.

The training of neural networks is to train the training data and adjust the weights and biases of the network, to achieve accurate fitting of the training data and prediction of unknown data. The commonly used training methods include stochastic gradient descent, backward propagation, Adam optimizer, etc. Stochastic gradient descent is a basic optimization algorithm that iteratively updates the weights and biases to make the network output close to the labels of the training set samples:

$$\theta_{t+1} = \theta_t - \alpha \nabla J\left(\theta_t; x^{(i)}, y^{(i)}\right) \tag{1}$$

In the t-th iteration, the model parameter (including weights and biases) is represented by θ_t, and the step size for each update is controlled by the learning rate, represented by α.

Underfitting refers to the phenomenon where a model performs poorly on both the training and testing sets, due to its low complexity and difficulty in expressing the features of the training data. In practical applications, in order to avoid overfitting and other issues, methods such as cross-validation and regularization are often needed.

3.2. Calligrapher's stroke features based on CNN

Calligraphy, as an important art form of traditional Chinese culture, has a long history. The stroke style of calligraphers has its unique features, such as being broad, thick, steady, sparse, elegant, and smooth. These features are not only a concentrated reflection of the aesthetic character and artistic style of calligraphers, but also an important basis for identifying calligraphy works. Therefore, analyzing the stroke features of calligraphers is an important aspect of computer-aided calligraphy research [12,13].

(1) Statistics on the stroke features of calligraphers:

The statistics of stroke features in calligraphy works mainly study the stroke features of calligraphy works in calligraphy works. The common stroke features in calligraphy works include stroke length, stroke curvature, starting direction, stroke speed, etc. The stroke features of different calligraphers vary, so it is necessary to conduct statistical analysis on these features.

In order to further improve the performance of neural network models, it is also possible to consider using deep learning models such as CNN, and using end-to-end learning methods to automatically learn and extract the best feature expressions. This method can effectively reduce the cost of manually designing feature engineering and better adapt to the requirements of different data and tasks for feature expression.

CNN also has the function of feedforward neural networks, which use methods such as local connections and weight allocation. This algorithm uses local connections instead of fully connected ones, reducing the number of weights in each layer and making the network easy to optimize; on the other hand, sharing parameters at the same level can reduce the number of parameters. Compared with ANN, CNN has advantages in processing high-dimensional data information, such as speed, fault tolerance, and strong adaptability, especially in areas where inference rules are not yet clear and have advantages such as high resolution.

The length and width features can be obtained by calculating the length and width of the stroke, using the length and width information of the calculated stroke contour. The stroke length is calculated as:

$$L = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (2)$$

The length of the stroke is represented by L; the number of nodes in a stroke is represented by n; $t$ihe x-axis and y-axis of the i-th node on the stroke are represented by x_i and y_i.

CNN is a neural network based on perceptual fields, which is a variant of multi-layer perceptrons with features of perceptual fields. It understands the image from local to overall, outputs the underlying input data in a hierarchical structure based on local perceptual regions, and sorts out the various prominent features of the data through forward propagation.

For the feature description of a stroke, it is divided into several equally divided segments, which are used as the basic units for feature extraction and can capture various features of the stroke in more detail. The formula for calculating stroke width:

$$W = \max_{i-1}^{n}(w_i) - \min_{i=1}^{n}(w_i) \quad (3)$$

The width of the stroke is represented by W, and the width of the node is represented by w_i.

The starting and ending coordinates of each small segment can accurately describe the shape and trajectory of the stroke. These coordinate values can be used to calculate the length, width, angle and other features of small segments, and help accurately locate the positions of various parts. Therefore, designing effective neural network input features is crucial for simulating the strokes of calligraphers. On this basis, the shape, direction, angle, length, width and other features of the strokes are comprehensively considered, and a comprehensive feature vector is constructed as the input of the neural network to improve the recognition accuracy and ability of the model, achieving simulation of calligrapher's stroke features.

(2) Abstract stroke features of calligraphers:

CNN evolved from neural network structures, where each node is a neuron. There are significant differences in structure between fully connected neural networks and CNNs, but the overall structure, input, output, and training process are very similar. Feedforward neural networks are completely connected, while artificial neural networks only have some inputs connected to the network. The first level of this neural network is the interactive connection between a convolutional neural network and a pool, each layer containing the features of multiple neurons. This method preserves basic geometric transformations such as translation, scaling, and rotation, and effectively processes the image. It has a wide range of applications in fields such as character recognition, facial recognition, human pose estimation, and object detection.

By simulating the stroke features of calligraphers, a feedforward neural network is used to learn the stroke features of calligraphers, thereby simulating their strokes. However, in order to achieve better simulation results, it is necessary to design reasonable factors such as the number of neurons and hidden layers in the neural network.

Starting from the input layer, the network structure takes the output of that layer as the output matrix, until the entire connected layer. CNN only responds to the local region input in the previous layer and extracts high-order features from the input. Convolutional operations are utilized to enhance the features of the original signal and reduce noise:

$$y_{mn} = f\left(\sum_{j=0 i=0}^{J-1 I-1} x_{m+i,n+j}\, w_{ij} + b\right), (0 \leq m < M, 0 \leq n < N) \tag{4}$$

Among them, x is the input vector; w is a convolutional kernel; b is bias; y is the output; function f is the activation function.

(3) Calligrapher's stroke feature extraction method:

The calligrapher's stroke feature extraction method is a method of analyzing and abstracting the calligrapher's strokes to obtain the calligrapher's stroke features. The stroke features of calligraphers are shown in **Figure 2**:

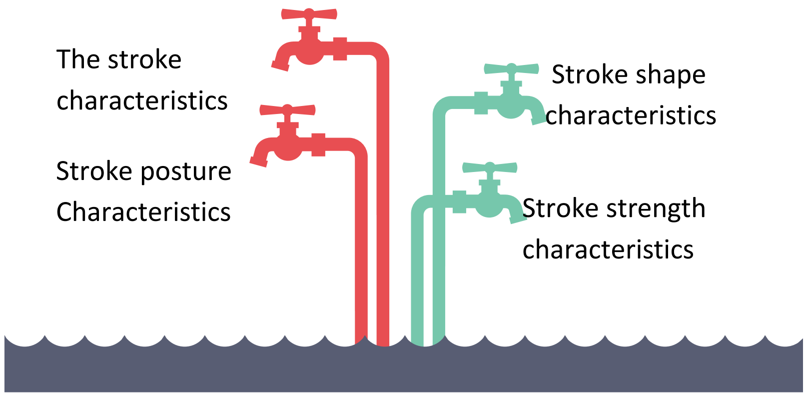

Figure 2. Calligrapher's stroke features.

As shown in **Figure 2**, common stroke features of calligraphers include Chinese character stroke features, Chinese character stroke shape features, Chinese character stroke posture features, Chinese character stroke strength features, etc.

The pooling layer is a function transformation of the non-overlapping regions of the upper feature map, with its depth remaining unchanged but its size changing.

Pooling operation can be seen as dimensionality reduction of feature maps, reducing sensitivity to transformations such as tilting and shifting, and improving generalization ability. Based on the principle of local correlation in images, while maintaining image rotation, subsampling can reduce computational complexity. This secondary feature extraction structure involves performing sampling operations on each feature map obtained in the previous layer, thereby reducing the required optimization parameters. The operations are:

$$y_{mn} = \frac{1}{S_1 S_2} \sum_{j=1}^{S_2-1} \sum_{i=0}^{S_1-1} x_{m \times S_{1+i}, n \times S_{2+J}} \tag{5}$$

Because neuron y_{mn} cannot rely on other specific neurons, it can only learn robust connections from random neurons to reduce weight connections and enhance the model's robustness against missing connection information.

The feature extraction of calligrapher strokes based on CNN has always been a highly concerning but challenging topic. The use of CNN technology can effectively capture the subtle strokes and structural features in calligraphy, and accurately extract and understand the personalized stroke style of calligraphers. The challenge lies in its complex and varied handling of calligraphy works. However, with the powerful expressive power of CNN, more in-depth research can be conducted on calligraphy art.

Although CNN has achieved good results in stroke feature extraction for calligraphers, it still faces some challenges. For example, there may be certain limitations in collecting and annotating data on calligraphy works, which can affect the model's promotional ability. In addition, calligraphy works have diverse and complex forms, posing higher challenges to feature extraction. It is necessary to design more complex network structures and loss functions to better explore the information contained in calligraphy works.

4. Imitation effect of calligrapher's stroke features

4.1. Handwriting similarity

To improve the accuracy of the experiment, 155 Chinese characters were randomly selected from the works of each calligrapher (a total of 5), scanned, and converted into image format. Five different fonts including regular script, cursive script, official script, seal script, and running script, and five different styles of text including rigid, elegant, rigorous, bold, and modern simplicity were analyzed. The data contains the vast majority of samples and is representative. These fonts were analyzed for similarity, fluency, detail accuracy, and style consistency.

When calculating the similarity, the stroke features of each Chinese character are extracted, including the starting and ending points, stroke length, angle, curvature, etc., and the feature points of the two Chinese characters are compared to calculate the similarity score. In terms of fluency, the speed change of the stroke during writing is calculated, and the stability of the speed can reflect fluency. The ratio of stroke writing time and stroke length is used. For detail accuracy, shape context or other feature matching methods are used to evaluate the accuracy of details, especially the matching of key parts (pen folds, intersections).

ANN was used to imitate the stroke features of calligraphers in regular script, cursive script, clerical script, seal script, and running script. The similarity rate of handwriting is shown in **Table 1**:

Table 1. Handwriting similarity rate based on ANN imitation.

Calligrapher and average	Regular script	Cursive Script	Clerical script	Seal Script	Running Script
Calligrapher 1	0.76	0.67	0.44	0.35	0.67
Calligrapher 2	0.7	0.65	0.36	0.35	0.65
Calligrapher 3	0.73	0.67	0.54	0.3	0.46
Calligrapher 4	0.71	0.52	0.34	0.28	0.35
Calligrapher 5	0.72	0.6	0.34	0.36	0.54
Average	0.72	0.62	0.40	0.33	0.53

As shown in **Table 1**, ANN was used to imitate the stroke features of calligraphers in regular script, cursive script, clerical script, seal script, and running script. The average similarity rates of the stroke features imitated by five calligraphers were 0.72, 0.62, 0.40, 0.33, and 0.53, respectively.

The average similarity rate of handwriting in regular script (0.72) was the highest, because regular script is one of the basic fonts in Chinese calligraphy, and it is also the most common and standardized font. The characters of regular script are dignified and neat, with concise and bright stroke structures. The main features are straight and horizontal strokes, and the shapes are stable, making it a model of calligraphy art.

The average similarity rate of seal script was the lowest (0.33), because seal script is an ancient font in Chinese calligraphy and one of the oldest fonts, originating from the Shang Dynasty. The font of seal script is square and powerful, with even strokes and crisscrossing strokes. It has a simple and heavy artistic style and is often used to distinguish calligraphy, seal cutting, and other aspects.

CNN was used to imitate the stroke features of calligraphers in regular script, cursive script, clerical script, seal script, and running script. The similarity rate of handwriting (the highest is 1, the closer it is to 1, the higher the similarity) is shown in **Table 2**:

Table 2. CNN-based handwriting similarity rate.

Calligrapher and average	Regular script	Cursive Script	Clerical Script	Seal Script	Running Script
Calligrapher 1	0.93	0.79	0.89	0.69	0.85
Calligrapher 2	0.91	0.75	0.86	0.61	0.85
Calligrapher 3	0.91	0.78	0.88	0.65	0.75
Calligrapher 4	0.97	0.72	0.83	0.6	0.8
Calligrapher 5	0.94	0.85	0.87	0.78	0.74
Average	0.93	0.78	0.87	0.67	0.80

As shown in **Table 2**, CNN was used to imitate the stroke features of calligraphers in regular script, cursive script, clerical script, seal script, and running script. The average similarity rates of the stroke features imitated by the five calligraphers were 0.93, 0.78, 0.87, 0.67, and 0.80, respectively.

Compared to traditional ANN, it can better capture the local features and spatial structure of images. The reason is that traditional ANNs typically require manual design of feature extractors when processing image data, and then use multi-layer perceptrons for feature learning and pattern recognition. CNN has strong feature extraction and image processing capabilities, so it has high similarity. CNN uses convolution and pooling operations to extract features from images, which can automatically extract low-level features (such as edges, textures, etc.) in the image. Based on this, it gradually extracts more abstract and higher-level features using methods such as multi-level convolution and pooling. This method can effectively preserve the handwriting details and structural features of the image, thereby obtaining recognition results that are closer to real handwriting.

CNN can also process calligraphy font data of different sizes and styles, and adaptively adjust them based on the differences between samples, thereby further improving the similarity of calligraphy works. Traditional ANN requires manual adjustment of network structure and parameters, often encountering difficulties in processing complex handwritten data.

4.2. Fluency rate

The fluency rate of ANN and CNN imitating 151 Chinese characters is shown in **Figure 3**.

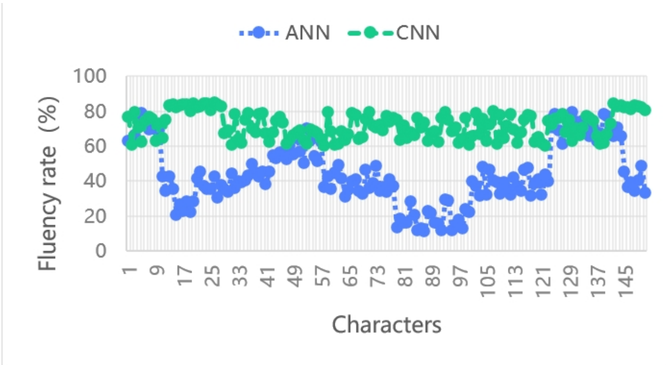

Figure 3. Smoothness rate of ANN and CNN imitation.

From the curve trend in **Figure 3**, it can be observed that the fluency rate of ANN imitating Chinese characters fluctuated greatly and was very unstable, with the lowest point being below 20%; the fluency rate of CNN imitating Chinese characters was relatively stable, with an overall rate of over 60%.

Compared to traditional ANN, CNN has significant advantages in smoothness. By observing the overall trend and connectivity of handwriting, combined with pixel level comparison methods or deep learning methods, the simulation ability of CNN on the fluency of calligrapher calligraphy is further evaluated.

Traditional ANN may have certain limitations in handling fluency and coherence due to its unique network structure and training methods. CNN is a method that combines convolution and pooling to extract layer-by-layer features from images, preserving both the spatial structure and local information of the image. This structure enables CNN to better grasp the overall trend and connectivity while maintaining image continuity, enabling it to better handle coherence and fluency issues. CNN has stronger contextual awareness and can grasp the content and structure of images as a whole. This allows CNN to consider the logical relationship and coherence between the front and back strokes when generating handwriting, ensuring that the generated handwriting looks more natural and smooth overall.

4.3. Detail accuracy

To ensure that the generated handwriting can accurately simulate the detailed features of real calligraphers, the accuracy of the details imitated by ANN and CNN was recorded separately, as shown in **Figure 4**:

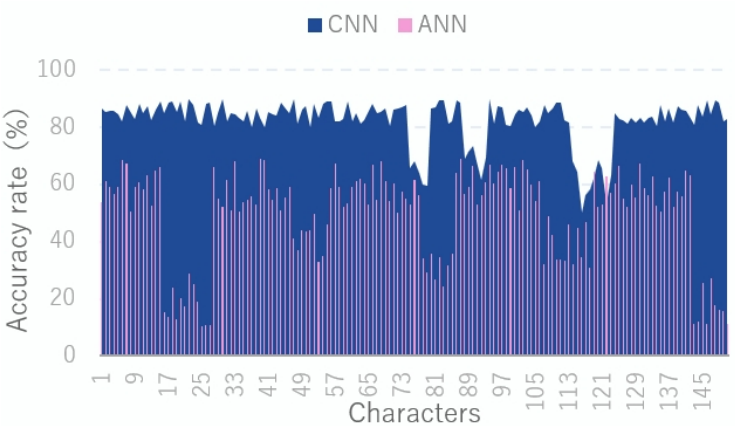

Figure 4. Accuracy of details imitated by ANN and CNN.

As shown in **Figure 4**, compared to traditional ANN (up to around 70%), CNN (up to around 90%) had higher detail accuracy, mainly due to its powerful feature extraction and image processing capabilities.

CNN combines convolutional and pooling layers to extract image features layer by layer, which can better capture the local structure and details of the image. This structure enables CNN to better preserve image details and accurately recognize subtle differences and changes in calligraphers' handwriting, resulting in more accurate handwriting. This method does not require manual design of feature extractors, and only requires training on the image to automatically learn image detail features. This method enables CNN to have stronger adaptability to writing data with different styles and structures, further improving the accuracy of writing details. In addition, the network model can adaptively adjust according to the differences between samples, thereby further improving the accuracy of details during the training process.

4.4. Style consistency

Using ANN to imitate the calligrapher's style (rigidity, elegance, rigor, boldness, and modern simplicity), calligraphers were asked to rate the consistency of ANN's imitation style, as shown in **Table 3**:

Table 3. Style consistency score based on ANN.

Style and average	Calligrapher 1	Calligrapher 2	Calligrapher 3	Calligrapher 4	Calligrapher 5
Rigidity	73.5	66.05	66.76	69.38	62.44
Elegance	72.71	67.34	74.96	63.14	60.04
Rigor	60.07	74.77	72.39	67.52	65.81
Boldness	60.91	64.97	66.93	65.5	68.93
Modern simplicity	70.11	69.09	71.37	69.23	61.15
Average	67.46	68.44	70.48	66.95	63.67

As shown in **Table 3**, calligraphers rated the consistency of ANN's imitation style. The average scores of the five calligraphers for rigidity, elegance, rigor, boldness, and modern simplicity were 67.46, 68.44, 70.48, 66.95, and 63.67, respectively.

Using CNN for imitation again, the style consistency score is shown in **Table 4**:

Table 4. Style consistency score based on CNN.

Style and average	Calligrapher 1	Calligrapher 2	Calligrapher 3	Calligrapher 4	Calligrapher 5
Rigidity	86.56	82.47	80.76	83.84	83.91
Elegance	82.85	84.18	86.49	87.6	89.66
Rigor	82.85	85.21	82.94	81.57	88.51
Boldness	84.63	80.78	81.19	86.89	89.72
Modern simplicity	81.9	82.31	82.79	83.35	89.32
Average	83.76	82.99	82.83	84.65	88.22

As shown in **Table 4**, the average score of calligraphers for CNN-based imitation was between 80 and 90 points, which was rigid, elegant, rigorous, bond, and modern minimalist.

CNN combines convolution and pooling layers to extract image features layer by layer, which can better reflect the overall structural features of the image. This structure enables CNN to better address the issue of style consistency while maintaining image style features. CNN has strong advantages in image understanding, context awareness, and can grasp the content and structure of images as a whole. In this way, CNN can better capture the calligraphy style features of calligraphers, including the shape, structure, and lines of strokes, to ensure that the generated calligraphy works are close to the true calligrapher in overall style.

CNN has strong generalization ability in processing large-scale image data, and can handle calligrapher's handwriting data of different sizes and styles. This method can more accurately simulate the stroke features of calligraphers and improve the consistency of the writing style.

4.5. Generating stroke restoration degree

The strokes generated by ANN and CNN were displayed and compared with the works of the original calligraphers. The highest similarity is 1, and the closer it is to 1, the higher the similarity, as shown in **Figure 5**:

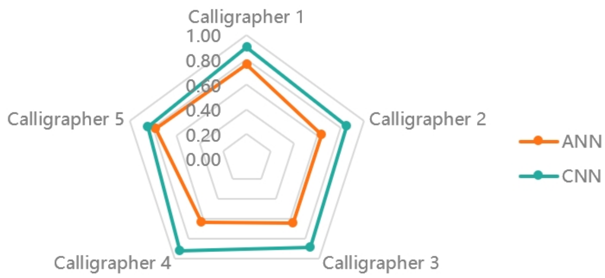

Figure 5. Stroke similarity generated by ANN and CNN.

As shown in **Figure 5**, the strokes generated by CNN were very similar to the works of the original calligraphers, both above 0.8. Especially in terms of the structure of Chinese characters, the thickness of strokes, and the tactile feel of the strokes, they were very close to the original works. This indicates that the algorithm can successfully simulate the stroke features of calligraphers.

CNN can gradually extract stroke features from calligraphy works through multi-layer convolution and pooling operations, such as stroke thickness, direction, and connection methods. By extracting local features, the structure and form of calligraphy can be better understood. By utilizing fully connected layers and feature mapping techniques, CNN can effectively integrate local features and reproduce the unique brushwork style of calligraphers. The combination of these three features not only enables accurate identification of calligraphy creators, but also reveals the stylistic differences and creative features of different calligraphers. This article takes calligraphy works as the research object, and through training big datasets, learns rich and accurate stroke feature expressions, providing strong support for calligraphy identification, calligraphy style analysis and other applications.

5. Conclusions

This article simulates the stroke features of calligraphers through neural network algorithms and trains the corresponding neural network model to convert the stroke features of calligraphers into digital features, thereby generating strokes similar to their style. This study provides new ideas for the promotion and inheritance of calligraphy art, and opens up new directions for the application and exploration of artificial intelligence in the field of art. In the future, 3D printing and virtual reality technology can be combined to combine neural network simulation with calligraphy art to create a more realistic calligraphy simulation and interactive experience. In addition, neural network technology can be used to evaluate calligraphy art, and by comparing and analyzing the stroke features of calligraphers, the precise division of calligraphy style and creative style can be achieved.

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Conflict of interest: The author declares no conflict of interest.

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