Brushwork Segmentation Method for Ink Painting Based on Digital Culture Entropy Regression

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Abstract: *As a traditional form of Chinese art painting, Ink painting is the most important type of art painting research. However, due to differences in color and strokes, ink painting often faces issues in brushwork analysis, such as poor segmentation results and insufficient accuracy in segmentation and localization. Therefore, in order to achieve segmentation of brushwork in ink painting and improve the segmentation effect of ink painting, a digital cultural entropy regression based brushwork segmentation method for ink painting is proposed. The new method uses a digital cultural entropy regression model to locate the information entropy of ink painting. Meanwhile, the new model uses an improved mask area Convolutional Neural Network (CNN)to achieve image segmentation and contour localization of ink painting brushwork. Finally, a brand new segmentation system is built based on actual application situations. In the intersection to union ratio test, the digital cultural entropy model achieves the highest pixel accuracy of 92.34% and 94.64% in position and pixel analysis, respectively. Finally, in terms of system efficiency, the digital cultural entropy system can achieve a maximum of 88IPS, reducing instruction time by 0.91ms compared to other models. The response time is also shortened by 1.7ms. Therefore, the model developed in this study can more effectively achieve the segmentation of ink painting brushwork. This has great application value in improving the segmentation effect of brushwork in ink painting.*

Keywords: *Digital culture entropy regression, ink painting, painting technique, brushwork, segmentation.*

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1. Introduction

With the rapid development of digital image processing technology, the digital protection and research of traditional Chinese painting art have gradually become a hot topic in academia and industry [10]. As an important genre of traditional Chinese painting, ink painting not only carries rich cultural connotations, but also demonstrates unique artistic charm. However, due to the differences in ink, color, and brushstrokes among these ink painting styles, automatic recognition and image segmentation of ink paintings have become the most important tasks at present [19]. Digital cultural entropy, as an emerging image analysis tool, can effectively measure the complexity and uncertainty of image information, providing a new perspective for image segmentation [11, 29]. In recent years, although clustering and semantic segmentation algorithms have been applied to some extent, their performance in complex ink scenes varies. Among them, clustering algorithms have low accuracy in segmenting ink gradient areas due to their dependence on color distribution similarity, and cannot effectively handle meticulous details. However, Although Mask Region Convolutional Neural Network (Mask R-CNN) performs well in instance segmentation, its segmentation accuracy in specific scenes is low due to the lack of cultural feature modeling [26, 17].in addition, existing methods still have bottlenecks in cross scale object segmentation and operational efficiency, making it difficult to meet the real-time requirements of high-resolution digitization. Riefard *et al*.'s [20] study, in order to enhance the visual appeal and user engagement of 3D video game character design, a comprehensive survey was conducted on video game players' preferences for 35 non-realistic rendering art styles, covering six major categories such as style lines and cross patterns. The research results indicated that players with different genders, age groups, and game type preferences had significantly different preferences for NPR style segmentation, which provided valuable insights for customizing style segmentation based on specific user groups. Although Riefard *et al*.'s [20] method could achieve style segmentation of animated images, further exploration is needed for the segmentation effect of painted images. In Yang et al.'s [28] study, in order to address the complexity of managing instance mask permutation invariance in ubiquitous and instance segmentation networks, a latent diffusion method based on stable diffusion was proposed for ubiquitous segmentation. This method omits specialized object detection modules, complex loss functions, and ad-hoc post-processing steps.

The research results indicated that by training shallow auto-encoders and diffusion models, the new method achieved excellent segmentation results on Common Objects in Context (COCO) and ADE20k, and demonstrated exploration potential for mask completion or repair. Additionally, the model is adaptable to multiple tasks although this method could segment and manage images, further exploration is needed for the segmentation effect of brushwork in ink painting. In order to improve the accuracy of document layout analysis in Chinese document and image segmentation, [28] proposed a layout analysis framework that integrates blank smear cutting and swin transformer in their research. The research used Whitespace Smear Cutting (WSC) algorithm for unsupervised image segmentation in the first stage; In the second stage, swin transformer was used for pixel level classification, and a continuous training paradigm was designed. The research results indicated that the fusion framework effectively integrated pixel level semantic information, improved semantic classification accuracy, and verified its feasibility and effectiveness on Chinese document datasets and Page Object Detection (POD) datasets [5]. Although research could achieve semantic segmentation of images, further exploration is needed to apply it to the segmentation effect of brushwork in ink painting. Yelizaveta *et al*. [30] developed an innovative framework for explicit annotation of paintings using stroke categories. This framework regarded stroke categories as meta level semantic concepts that connect artists, styles, and periods, effectively promoting the integration of ontology in specific domains. Its research ultimately showed that the multi-expert semi-supervised framework surpassed traditional classification methods in stroke pattern annotation and laid the technical foundation for achieving higher-level ontology annotation [30].

In summary, although most models currently used in research can achieve semantic segmentation of images, existing models still suffer from insufficient accuracy and efficiency in ink painting stroke segmentation tasks. Therefore, an innovative stroke segmentation method based on digital cultural entropy regression is proposed in this study. This method combines the digital cultural entropy regression model with an improved Mask R-CNN algorithm to achieve precise localization of ink painting areas and pixel level segmentation of brushstrokes. By constructing a complete stroke segmentation system, the research has provided a new technological path for digital art analysis while improving the traditional ink painting stroke segmentation effect.

2. Methods and Materials

2.1. Digital Culture Entropy Regression Model Based on Brushwork Segmentation

The brushwork segmentation method for ink painting mainly divides the image into multiple different ink painting regions based on its different grayscale, color, and other characteristics. In the segmentation of ink painting, ink painting belongs to the type of painting that uses lines and structures to shape on the canvas. Meanwhile, ink painting presents different light and shadow changes and texture changes in color through the transition from light to dark and changes in dryness and wetness. Based on the actual characteristics of ink painting, the instance position change relationship of ink painting is determined by dividing the information entropy region of ink painting. Information entropy typically represents the expected value of information in areas where ink painting segmentation may occur, as shown in Equation (1) [12].

$$A(x) = -\sum_{i-1}^{n} p(x_i)\, log\, p(x_i) \tag{1}$$

In Equation (1), where $A(x)$ indicates the information entropy of a random variable and $p(x_i)$ indicates the probability of event x_i occurring. For the information entropy change of ink painting, one-dimensional information entropy is generally used. The one-dimensional information entropy change is expressed by calculating the expected change value of pixel information of ink painting, as shown in Equation (2) [4, 32].

$$A = -\sum_{0}^{255} P(i)\, log\, P(i) \tag{2}$$

In Equation (2), A indicates the grayscale entropy of the image, $P(i)$ indicates the proportion of pixels with grayscale value i in the image, and the range of grayscale values is 0-255, which is processed according to commonly used image processing techniques in computers. The binary value converted to decimal is 255. The one-dimensional grayscale value variation can reflect the pixel characteristics of ink paintings, but in order to cover more image information features, it is necessary to ensure that all ink paintings have different color tone differences. Therefore, in the brushwork segmentation of ink paintings, multi-dimensional numerical values are used to determine the color tone of ink paintings. Therefore, a formula is used to calculate the color tone ratio of ink paintings as shown in Equation (3) [7].

$$N = \frac{max(m)}{S} \tag{3}$$

In Equation (3), N indicates the proportion of pixels representing color tones to the total number of pixels in the image, m indicates the number of color tone pixels in the ink painting image area, and S indicates the total number of pixels in the image. The change in the proportion of color tones in ink painting is calculated through the variation of color tone pixels in the color space channel of ink painting, as shown in Equation (4).

$$T_L = * \frac{N_L * H_L}{N_L + H_L} \tag{4}$$

In Equation (4), T_L the proportion of image features calculated in the color space channel, N_L indicates the proportion of pixels with color tones in the color space channel to the total number of pixels in the image, and

H_L indicates the information entropy of the image in the color space channel. The study fuses the features of ink painting images to a quarter size, then inputs them into the Position branch and divides them into multiple regions. The feature space is then fused with the image space and the variance of the regions is calculated to obtain the result shown in Equation (5) [6, 24].

$$R = \lambda(T_L^{a,b} - T_L^{a^*,b^*})^2 + \gamma(T_B^{a,b} - T_B^{a^*b^*}) + \chi(T_c^{a,b} - T_c^{a^*,b^*})^2 \qquad (5)$$

In Equation (5), R indicates the weighted sum of squares of variance. λ, γ, and χ represent weight parameters. (a^*,b^*) indicates the coordinates of the adjacent region of pixel (a, b) $T_L{}^{a,b}$ is the brightness spatial component of the image. $T_B{}^{a,\,b}$ is the component of the image color from light to dark. $T_C{}^{a,\,b}$ is the component of the image color from dry to wet. $T_B{}^{a^*,\,b^*}$ indicates the brightness spatial component of the image in the adjacent region (a^*,b^*), $T_B{}^{a^*,\,b^*}$ indicates the component of the image from light to dark in the adjacent region (a^*,b^*), and $T_c{}^{a^*,\,b^*}$ indicates the component of the image from dry to wet in the adjacent region (a^*,b^*) When there are multiple image information in the ink painting image area, the color tone representation and color information entropy of different areas are calculated through formulas. Then, the calculated area information entropy changes are used to calculate the confidence change of the ink painting image through algorithms and activation functions. The algorithm model used in the study is shown in Figure 1.

As shown in Figure 1, the position algorithm used in the image confidence calculation process first divides the ink painting image into multiple different information regions, and then distinguishes and calculates the new region information entropy based on the color tone of the information regions. The new information entropy is input into the classifier to build a new hierarchical network, and then the image size distance of the region is calculated based on the feature parameters of the image.

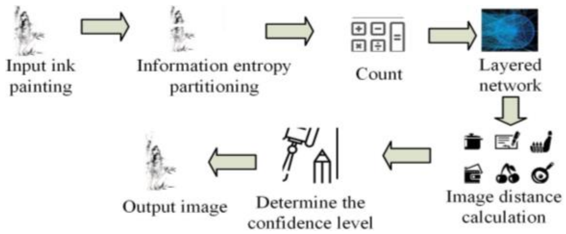


Figure 1. Algorithm model used in the study.

Finally, a fully connected layer is used to calculate the new confidence change magnitude. The confidence level should be checked to see if it falls within the range of 0 to 1. If it does fall within this range, it can be confirmed that the current area is the same. If not, the area should be reassessed and recalculated to ensure that all output image areas belong to the same area. The final loss function calculated by the algorithm is shown in Equation (6) [16, 21].

$$L_O = \sum_{i=1}^{n*n} \tau L_c + L_k \qquad (6)$$

In Equation (6), L_o indicates the total loss function of the algorithm, τ indicates the weight parameters of the Position algorithm, L_c indicates the classification loss function of the algorithm, and L_k indicates the structural loss function of the algorithm. After dividing the ink painting image into regions, the contour regression method is used to generate an image detection box, and then the center of the image is located. The offset of the center point coordinates is calculated to obtain the initial contour change [15]. The process of image contour generation algorithm is shown in Figure 2.

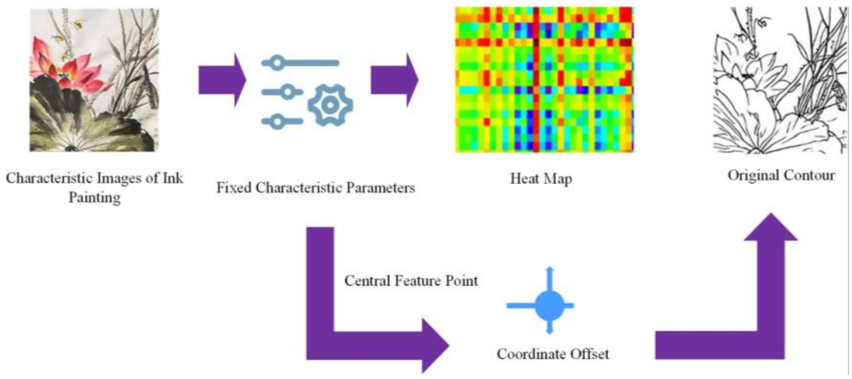


Figure 2. Image contour generation algorithm flow.

As shown in Figure 2, the image contour generation algorithm first inputs the feature image of the ink painting, then fixes the feature parameters of the image and corresponds them one-to-one. Through feature extraction, it inputs the corresponding branches and generates a heat map. The coordinate offset of the contour points is calculated based on the central feature points in the feature map, and the original contour is obtained based on the offset. According to the changes in the initial contour, coordinate positioning is performed to obtain the initial contour point expression as shown in Equation (7) [13, 14]

$$V_{init} = \frac{1}{M}\sum_{i=1}^{M} smooth\left(x_i^{init} - x_i^{gt}\right) \qquad (7)$$

In Equation (7), V_{init} indicates the initial contour point.

M indicates the total number of contour points. x_i^{init} indicates the predicted i-th initial contour point, and x_i^{gt} indicates the actual i-th contour point. $smooth$ indicates the smoothing function. By segmenting contour points and generating results, the algorithm samples the initial contour and determines the relative position of the sample. Based on the generated relative position, the normal map of the ink painting image is updated as shown in Equation (8).

$$q^{gt} = q + w \tag{8}$$

In equation (8), q^{gt} indicates the updated predicted image position of the ink painting, q indicates the current predicted position, s indicates the direction of movement, and w indicates the distance of movement. The formula for the change in movement distance is shown in Equation (9) [22, 31].

$$w = \sqrt{S}|P(q) - 0.5| \tag{9}$$

In Equation (9), z indicates the proportionality coefficient, S represents the area, $P(q)$ represents the multi-layer perceptron, and 0.5 is the range of relative position change of the image obtained by predicting the contour point position based on the ink painting image, where 0.5 is the contour point position on the image boundary, 1 represents the contour point position outside the image, and 0 represents the contour point position inside the image. After confirming the position information of the contour points, the initial state of the brushwork of the ink painting is masked through multi-channel linear changes, that is, the brushwork segmentation is performed. First, the position of the brushwork segmentation is determined through the Position algorithm, and then the brushwork of the ink painting is quantified and position perceived, and the composition of the brushwork is predicted. Finally, the change in the number of regions in the image brushwork is output based on the quantization result, as shown in Equation (10).

$$out = \sum_{i=1}^{num} \sum_{j=1}^{count} v_j \, m_j \tag{10}$$

In equation (10), out represents the number of output brushwork regions, m represents the prediction of brushwork channels, $num - count$ represents the number of each brushwork segmentation channel, and v_j represents the weight of brushwork segmentation prediction. The final total loss value is shown in Equation (11) [8, 27].

$$L = L_m + L_p \tag{11}$$

In equation (11), L represents the total loss value, L_m represents the predicted loss value of the brushwork segmentation, and L_p represents the pixel loss value of the brushwork style image.

2.2. Improving the Entropy Regression Model of Digital Culture and Brushwork Segmentation System

Due to the inability of a single digital cultural entropy regression model to segment the background and semantics of ink painting brushwork during the segmentation process, research uses semantic segmentation algorithms based on the digital cultural entropy regression model to segment the semantics of ink painting images [2]. The Mask R-CNN algorithm is an algorithm that can predict the mask of each target and achieve pixel level segmentation. To improve the segmentation performance of the regression model, the Mask R-CNN algorithm is used to improve the model. The running framework of Mask R-CNN algorithm is shown in Figure 3.

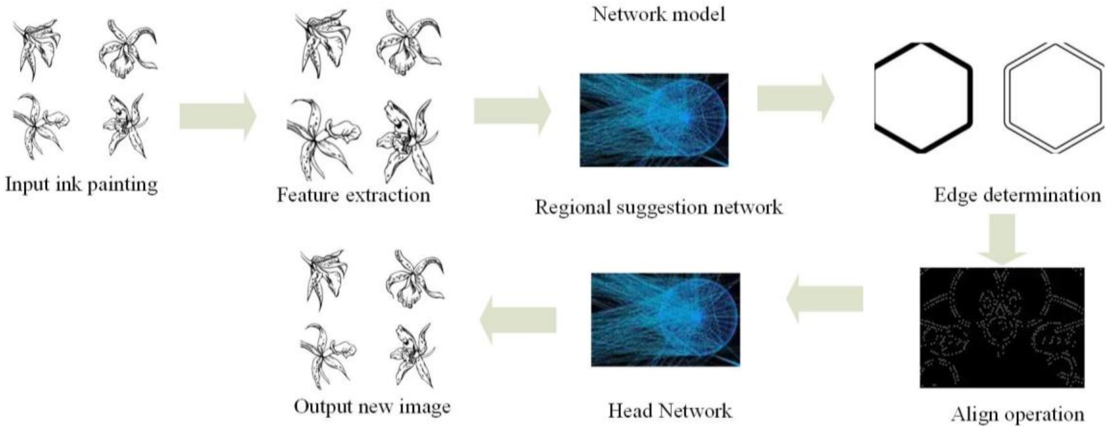


Figure 3. Running process of mask R-CNN Algorithm.

As shown in Figure 3, the Mask R-CNN algorithm first extracts features from the input ink wash painting image using the ResNet-50 network. After obtaining the feature extraction image, the region recommendation network is used to convolve the feature regions and determine the image edges for preliminary image target determination. Secondly, the algorithm model accurately extracts regional features through Region of Interest (RoI) Align operation, and improves the overall image accuracy by solving the problem of parameter quantization error in the network. Finally, the feature extracted image is input into the head network. The boundary box position is refined through convolutional networks and fully connected layers, and the refined and precision improved image is finally output. The Mask R-CNN algorithm can achieve precise localization and segmentation of the target in the image. In the Mask R-CNN algorithm, the RoI Align operation can improve the pixel matching of the image and thus enhance the accuracy of the image. Figure 4 shows the framework structure of the RoI Align operation.

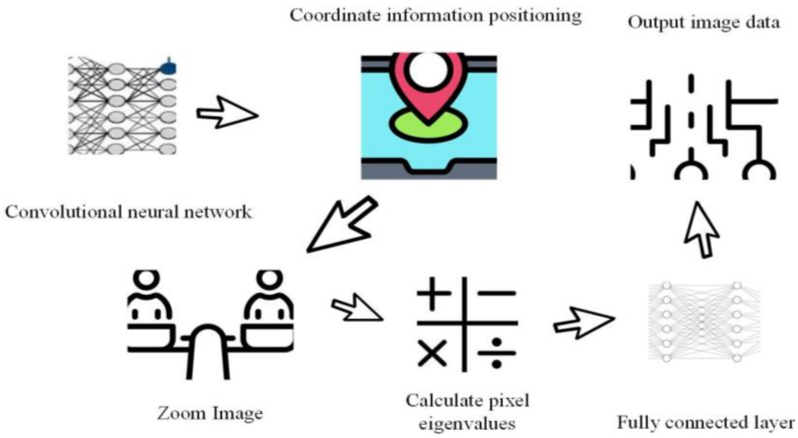


Figure 4. Running process of RoI align operation.

As shown in Figure 4, the model first locates candidate regions onto feature maps via coordinate mapping and uniformly divides them into grid cells of fixed size. Subsequently, it performs refined sampling within each cell, calculating feature values at sampling points using bilinear interpolation to prevent pixel misalignment caused by quantization errors. Finally, it generates uniformly sized output features through aggregation operations [25]. By using the Mask R-CNN algorithm to improve the regression model, the localization effect and segmentation accuracy of ink painting brushwork can be effectively enhanced. The improved model structure is shown in Figure 5.

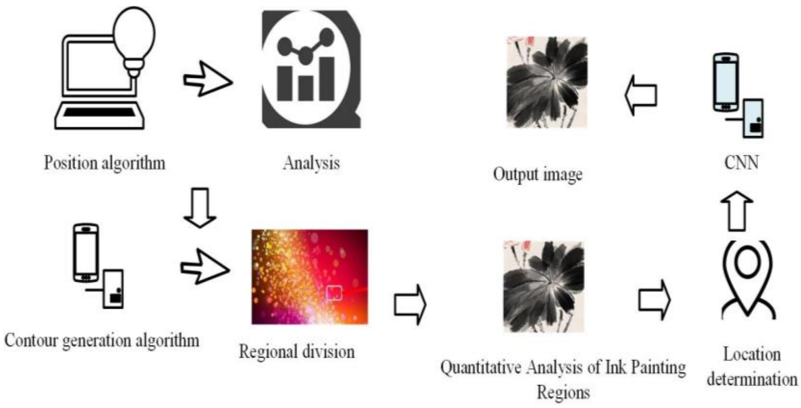


Figure 5. Improved model structure.

As shown in Figure 5, the improved regression model first uses the position algorithm to predict and analyze the image confidence of the ink painting after inputting image information. Then, based on the generated image confidence, the image contour generation algorithm is used to calculate and analyze the initial contour size of the segmentation area of the ink painting's brushwork. The brushwork area of the ink painting is then quantified and positioned. Finally, the Mask R-CNN algorithm is used to extract features from the final output image data, improving the overall segmentation accuracy of the region. After building a complete regression model, a new ink painting brushwork segmentation system is designed based on actual application situations. The system is designed based on user usage, including functional and non-functional design. Functional design mainly analyzes user business, and its core functions include user ink painting data transmission, ink painting classification, and ink painting label labeling [18, 23]. User functionalities are simultaneously considered, including user login, user data retrieval, and backend data maintenance. The non-functional aspects mainly include user experience, user security, and system scalability, among which user experience ensures that users can easily view the segmentation effect of ink painting brushwork. Security needs to ensure that the data transmitted and used by users cannot be leaked while encrypting the data [1, 3, 9]. Scalability mainly ensures that data can be stored and expanded. The system framework is built based on the actual usage requirements of the system as shown in Figure 6.

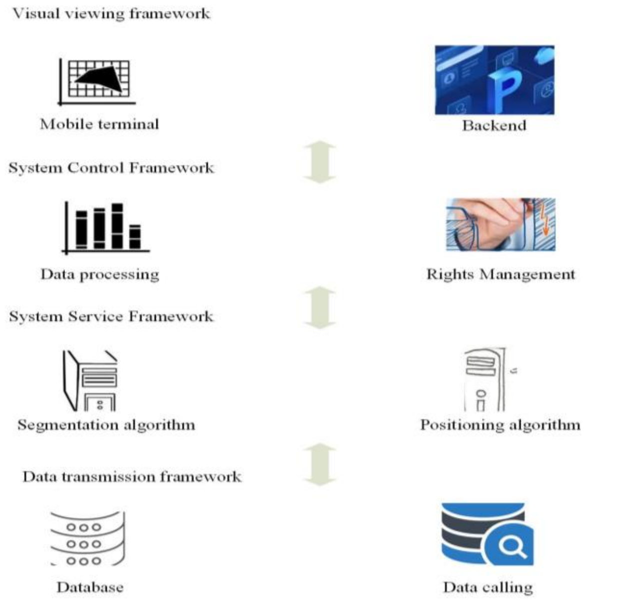


Figure 6. System framework.

Note: The arrows in the diagram indicate: bidirectional interaction.

As shown in Figure 6, the ink painting brushwork system mainly consists of four main frameworks: visual viewing framework, system control framework, system service framework, and data transmission framework. The visual viewing framework includes system task management, visual viewing network, and data mobile visual viewing module. The system control framework includes three modules: data calling, user permission management, and function control. The system service framework mainly manages and divides ink painting data through the brushwork segmentation algorithm. The final data transmission framework mainly stores and calls data through database modules, using PostgreSQL database. All framework data can be transmitted to each other to ensure the stable operation of the system. The main process of system operation is shown in Figure 7.

As shown in Figure 7, the system will first upload user demand data during operation, and then perform permission checks on user information after entering the system control framework. Regardless of whether the user is registered, the system directly executes their commands. after registering user information. During the process of receiving user instruction requests and making system function calls, the functions and data that need to be called are returned and stored in real-time. Finally, the system returns the final call and usage results to the visual viewing framework for users to view, and saves the entire usage process as data.

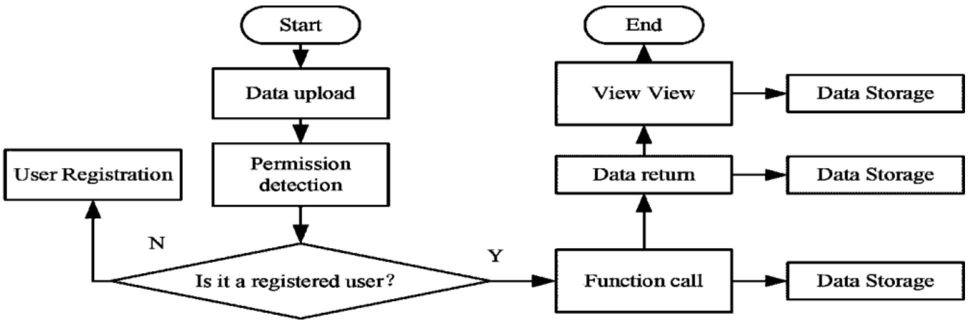
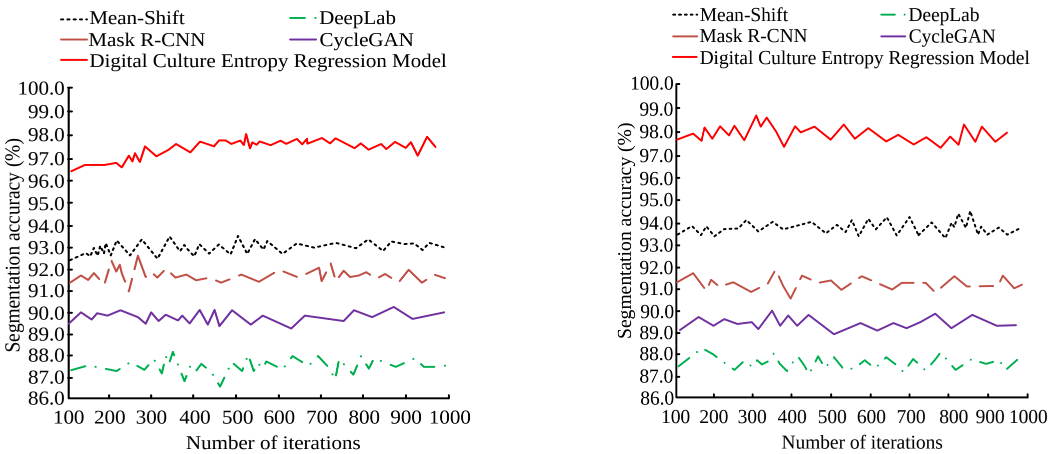


Figure 7. Main process of system operation.

3. Results

3.1. Analysis of the Actual Effectiveness of the Entropy Regression Model for Digital Culture

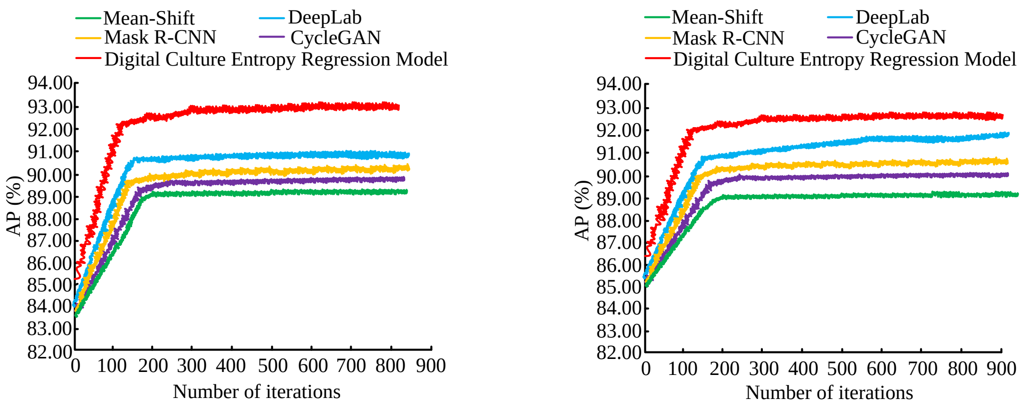
The system development environment included both hardware and software aspects. In terms of hardware environment, there were two different configurations: one was a machine running Windows 10 operating system, equipped with Intel i5-6400 CPU, with a clock speed of 2.7GHz, 8GB DDR4 memory, and 1TB SSD Solid State Drive. The other was a machine running Ubuntu 18.0 operating system, equipped with AMD Ryzen 7 5800X processor, running at a frequency of 3.8GHz, 16GB DDR4 memory, and 1TB SSD. In terms of software environment, the research used PyTorch 1.9.1 as a deep learning framework and relied on Compute Unified Device Architecture 11.1 and CUDA Deep Neural Network Library 8.0.4 for deep learning operations. The backend development languages included Java 1.8 and Python 3.8, while the frontend development languages included HTML, Cascading Style Sheets, and JavaScript. In addition, the study also used IntelliJ Integrated Development Environment for Applications, pycharm, and Navicat as development tools. The study set the algorithm learning rate to 0.003, momentum to 0.95, batch_2 to 4, iteration count to 11000, pre training count to 1100, and pre training learning rate to 0.02. The research's dataset integrated publicly available digital collections from authoritative institutions such as the Palace Museum in Beijing and the shanghai museum. It also included professionally licensed paintings from partner art academies and artist studios, encompassing a total of 1,200 high-quality ink wash painting images. Systematically categorized by subject matter, the dataset comprised three major categories: 650 landscape paintings, 350 flower-and-bird paintings, and 200 figure paintings. This comprehensive collection fully covered the primary themes and brushstroke techniques characteristic of Chinese ink wash painting. The study aimed to test the actual brushwork segmentation performance of different algorithms under the same ink painting conditions. The segmentation accuracy was compared using algorithms including mean shift, deeplab network, Mask R-CNN, and Cycle Consistent Generative Adversarial Network (CycleGAN), as shown in Figure 8. The segmentation accuracy refers to the accuracy of the algorithm in identifying and classifying these different regions. mean shift is an unsupervised clustering algorithm based on density estimation, achieving region segmentation by iteratively locating density extrema points in feature space. DeepLab network employs a semantic segmentation model with a dilated convolutional architecture, preserving resolution by expanding the receptive field. Mask R-CNN is an instance segmentation algorithm based on the faster R-CNN framework, achieving pixel-level object segmentation by adding a mask head branch. CycleGAN is a generative model for cross-domain image transformation via cyclic consistency loss, applicablesegmentation tasks in stylized images.



a)Landscape painting. b)Flower and bird painting.

Figure 8. Comparison of segmentation accuracy of different algorithms.

As shown in Figure 8-a), the digital cultural entropy regression model used in the testing of ink and landscape painting types had the highest segmentation accuracy, reaching up to 97.8%. The segmentation accuracy of the DeepLab algorithm was the worst among several model comparisons, with the highest accuracy of 87.8%, which was 10.0% lower than the digital cultural entropy regression model. This due to the addition of Mask R-CNN to the digital cultural entropy regression model, which improved the detection and segmentation performance of ink painting images. From Figure 8-b), in the comparison of the segmentation effects of ink painting flower and bird painting brushwork, the digital cultural entropy regression model showed the highest segmentation accuracy, with an accuracy rate of up to 98.7%. At the same time, the DeepLab algorithm also showed poor accuracy in flower and bird painting brushwork segmentation, with the highest segmentation accuracy of only 88.1%, which was 10.6% lower than the segmentation accuracy of the digital cultural entropy regression model. The digital cultural entropy regression model exhibited the highest segmentation accuracy and the best segmentation effect in different ink painting brushwork segmentation. The study tested the actual segmentation effect of the model under different ink painting image pixels, and compared the pixel ratio size of the ink painting test to obtain the results shown in Figure 9. The Accuracy of Pixel (AP) represents the proportion of correctly predicted category pixels to the total number of pixels.



a) Landscape painting. b) Flower and bird painting.

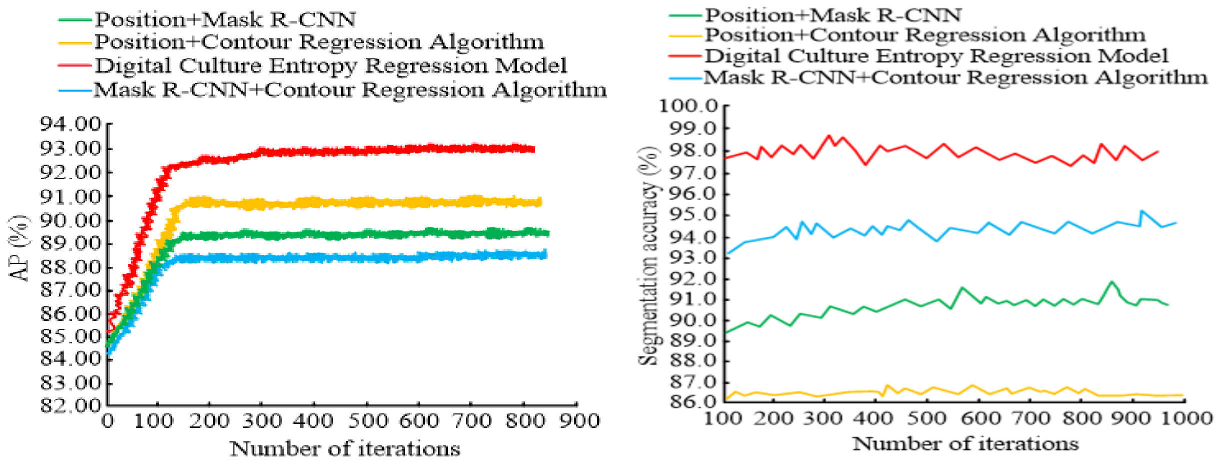
Figure 9. Comparison of AP between different algorithms.

As shown in Figure 9-a), among the Average Precision comparisons of different algorithms, the digital culture entropy regression model had the highest AP and its accuracy could reach up to 93.15%. At the same time, the highest AP of the mean shift algorithm was only 89.25%, which was 3.90% lower than the digital cultural entropy regression model. This indicated that the digital cultural entropy regression model performed better in correct pixel segmentation and recognition. From Figure 9-b), the recognition accuracy of different models in pixel recognition of flower and bird paintings was significantly lower compared to landscape paintings. This due to the fact that recognizing more elements in flower and bird paintings was more difficult. At the same time, the AP value of the digital culture entropy regression model could reach up to 92.74%, while the highest AP value of the Mean Shift algorithm was only 88.89%, which was 3.85% lower than that of the digital culture entropy regression model. From this, the digital cultural entropy regression model had the best recognition effect in pixel recognition of different ink paintings, and could be used to identify and analyze different ink paintings. To analyze the testing effects of different types of ink paintings in different models, the AP of different ink paintings was tested and shown in Table 1.

Table 1. Comparison results of AP recognition for different types of ink paintings.

Model	AP recognition in different ink paintings(AP/%)					
	Person	Horse	Bird	Flower	Dog	Shrimp
Mask R-CNN	85.62	86.48	87.52	88.35	85.49	86.48
CycleGAN	87.26	89.42	90.24	90.35	90.48	90.11
DeepLab	88.63	89.67	89.33	90.11	91.05	89.75
Mean-Shift	85.46	85.23	84.16	84.22	85.69	87.62
Digital culture entropy regression model	92.65	93.68	92.48	93.48	93.22	93.47

As shown in Table 1, in the comparison of ink painting pixel recognition among different models, the digital cultural entropy regression model showed good recognition performance in different types of ink painting pixel recognition. Among them, the highest accuracy could reach 93.68% in the recognition of ink painting horses, while the Mean Shift algorithm had the lowest recognition accuracy of only 85.23% in the recognition of the same ink painting horses, which was 8.45% lower than the digital cultural entropy regression model. In the recognition of ink painting dogs, the mean shift algorithm had the best recognition effect than the Mask R-CNN. This due to the fact that the less brushwork required for ink painting dogs allowed the mean-shift algorithm to better recognize and segment them. Using the digital cultural entropy regression model for segmentation and recognition of ink paintings had good recognition and segmentation effects. To analyze the actual performance of the model after adding different networks, the study conducted a melting experiment on the digital cultural entropy regression model, as shown in Figure 10.



a) AP.

b) Flower and bird painting.

Figure 10. Comparison of segmentation effects of models with different modules added

As shown in Figure 10-a), the AP value of the digital cultural entropy regression model was the highest after adding different modules, but the AP value of the Mask R-CNN+Contour Regression Algorithm was the lowest, only 88.22%, which was 4.52% lower than that of the digital cultural entropy regression model. This due to the poor recognition accuracy of the Mask R-CNN+contour regression algorithm model for the pixels in the ink painting area. From Figure 10-b), the segmentation accuracy of the digital cultural entropy regression model was the highest after introducing different modules, while the segmentation accuracy of the Position+corpus regression algorithm model was the lowest, only 86.5%, which was 12.2% lower than that of the digital cultural entropy regression model. Introducing different models could improve the segmentation performance of the model in different aspects. The study analyzed the actual model performance of position prediction and contour localization under different image intersection and union ratios, where the intersection and union ratios included AP (AP50) calculated at a threshold of 0.50, AP (AP75) calculated at a threshold of 0.75, Average precision for small objects (APs) for small objects, AP (APm) for medium-sized objects, and AP (APl) for large objects, as shown in Table 2.

Table 2. Comparison results of different intersection and union ratio tests for different models.

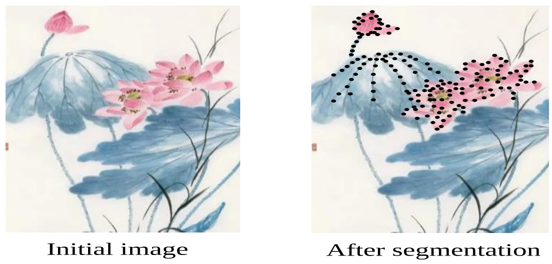
Model	Image analysis type	Different AP values (%)				
		AP50	AP75	APs	APm	APl
Mask R-CNN	Predict location	88.34	87.21	86.48	86.44	85.15
	Pixel regression	89.64	88.48	86.48	87.48	86.58
CycleGAN	Predict location	87.35	86.49	87.54	86.57	87.59
	Pixel regression	88.26	86.59	87.42	86.25	86.72
DeepLab	Predict location	84.62	85.94	86.25	84.93	84.68
	Pixel regression	84.68	85.69	84.16	85.64	85.64
Mean-Shift	Predict location	82.15	81.68	82.46	80.48	81.95
	Pixel regression	81.26	82.16	81.06	80.36	83.48
Digital culture entropy regression model	Predict location	92.34	90.21	93.48	92.44	93.15
	Pixel regression	94.64	92.48	92.48	93.48	94.58

As shown in Table 2, the AP value of the digital cultural entropy regression model was the best among several models when the intersection to union ratio was 50. The model's position prediction value could reach 92.34%, and the pixel regression value could reach 94.64%. Meanwhile, the AP value of Mean Shift algorithm was the lowest among several models, only 82.15% and 81.26%, respectively. After changing the aspect ratio and image size of ink painting images, the digital cultural entropy regression model still had a high AP value among different models. This indicated that the digital cultural entropy regression model still had good brushwork segmentation performance after changing the image size and aspect ratio, and had good performance in image position localization and prediction. When the threshold was set to 0.50, the model achieved an AP50 of 94.64% in the pixel regression task, surpassing the best-performing comparison algorithm, CycleGAN, by 6.38%. Particularly in the segmentation task for large-sized targets (APl), the model achieved an accuracy of 94.58%, significantly outperforming Mask R-CNN's 86.58%. This demonstrated that our method maintained stable segmentation performance when handling brushstrokes of varying scales.

3.2. System Operation Effect Test Results

To analyze the actual segmentation effect of the system on the brushwork of ink paintings, the study conducted brushwork segmentation tests on different types of ink paintings and obtained the results shown in Figure 11.

The midpoint in the Figure (11) represents the segmentation area of brushwork, and each point represents a pixel area. Due to the differences in image segmentation effects among different ink paintings, only the segmentation of some of the main content was displayed. As shown in Figure 11-a) and b), in landscape painting segmentation, the system mainly performed pixel segmentation on the main brushwork of ink painting. Through a single segmentation result, the brushwork situation of the entire image could be judged and analyzed. At the same time, from the perspective of the segmentation effect of the system, it could segment the complete brushwork of ink paintings and achieve segmentation of ink paintings. Based on the actual operation of the system, the ink painting brushwork segmentation process is shown in Figure 12.



a) Landscape painting.

b) Animal painting.

Figure 11. Comparison of segmentation effects of ink paintings.

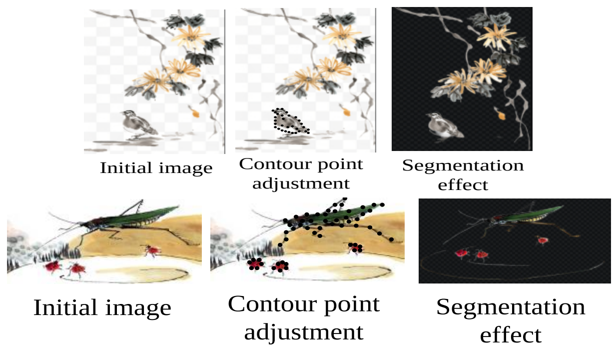


Figure 12. Display of segmentation effects of different ink paintings.

As shown in Figure 12, for the ink painting based on the initial image, the system first divided the main object contour area in the ink painting. In the figure, the contour and border of the main object were determined by the segmentation points, and then the system extracted the overall division area, as shown in the ink painting display effect image obtained in Figure 12. As shown in Figure 12, the overall rendering could clearly display all the main images, which contained the entire brushwork area of the ink painting. This indicated that the system could effectively segment the brushwork of the ink painting. To test the actual operational performance of the current system, the study tested the operational indicators after adding different modules, as shown in Table 3. IPS stands for instruction execution speed per second, with higher values indicating faster running speed.

Table 3. Comparison results of operational indicators of different modules.

Model	Operating speed (IPS)	Running time (ms)	Use parameter quantity	Response time (ms)
Mask R-CNN	54	1.85	12645	1.2
CycleGAN	56	1.78	26171	0.6
DeepLab	68	1.47	23584	0.8
Mean-Shift	49	2.04	36158	1.9
Digital Culture Entropy Regression Model	88	1.13	10264	0.2

As shown in Table 3, the digital cultural entropy regression model system had the fastest running speed of 88IPS, which was 39IPS higher than the Mean-Shift system. At the same time, the digital cultural entropy regression model system improved the instruction running time by 0.91ms compared to the Mean-Shift system. In addition, the parameter usage and response time of the system were compared, and the digital cultural entropy regression model system improved by 25894 and 1.7ms respectively compared to the mean-shift system. This showed that the digital cultural entropy regression system built in the study had better performance in comparing system operating indicators. The digital cultural entropy regression system achieved an operating speed of 88 IPS, representing an approximately 29.4% improvement over the second-fastest DeepLab system. In terms of parameter usage, the research system required only 10,264 parameters, reducing the number by 18.9% compared to the minimalist Mask R-CNN system, demonstrating the model's outstanding computational efficiency.

4. Discussion and Conclusions

This study addressed the challenge of accurately segmenting brushstrokes during the digitization of traditional ink paintings. To this end, an innovative approach based on digital cultural entropy regression and an enhanced Mask R-CNN model was proposed, establishing a comprehensive brushstroke segmentation system. The primary contribution lied in applying information entropy theory to quantify the cultural characteristics of ink paintings. Through key techniques such as RoI align, the localization accuracy of the segmentation model was optimized, providing a novel technical pathway for computational analysis of traditional art. Experimental results demonstrated the proposed model's significant advantages across multiple dimensions. In segmentation accuracy, the model achieved 97.8% and 98.7% precision on landscape and flower-bird paintings respectively, surpassing the traditional Mean Shift algorithm by over 10%. For pixel-level recognition, its average precision reached up to 93.15%, significantly outperforming comparison models. These quantitative results fully validated the effectiveness of the digital cultural entropy regression model in capturing the complex textures and hierarchical variations of ink wash painting brushstrokes. Additionally, the constructed system achieved an efficient operation speed of 88 IPS with a response time reduced to 0.2ms, demonstrating the method's practical applicability. Despite achieving expected outcomes, certain limitations remain. First, experimental data primarily focused on freehand-style ink paintings, and the generalization capability for other important genres such as meticulous brushwork requires further validation. Second, the segmentation stability of the model in extreme ink-color scenarios requires enhancement. Building upon this work, future research will expand the diversity and complexity of the dataset by incorporating works from more genres and styles. Concurrently, cross-modal learning approaches will be explored, integrating semantic information such as painting-related texts to deepen the model's understanding of artistic intent. This will ultimately advance the deep integration of digital preservation and research in cultural heritage.

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