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RESEARCH ARTICLE

Analysis And Research on the Composition and Line Characteristics of Chinese Meticulous Figure Painting Based on Deep Learning

Mo Huang*

Jingdezhen Ceramic University, Jingdezhen, 333000, China

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***Corresponding Author:**

huangmo89@126.com

ABSTRACT

Chinese meticulous figure painting, also known as gongbi style, emphasizes precision and detail. It features delicate brushstrokes, fine lines, and vibrant colors to portray realistic human figures. These works often depict elegance and grace, highlighting facial expressions, clothing textures, and intricate backgrounds with extraordinary accuracy.

Integrating traditional artistic principles with modern technology, this research will provide a more profound view and improvement of the intricate details involved in the digital representation of this art form.

The study begins with a data collection procedure, gathering a large dataset of high-quality Chinese meticulous figure paintings. Pre-processing techniques, such as z-score normalization, GF, and image resizing are applied to confirm the quality of the painting dataset. The HOG is utilized to extract edge and texture information, thereby improving the classification and recognition of painting styles and features. The ISOA-ARNN model has been formulated to efficiently analyze and predict patterns of composition and the characteristics of the lines. The ISOA algorithm is successful optimize the hyper parameters of ARNNs for further improvement of their performance in capturing sequential and structural features of paintings.

The model achieves optimal accuracy through iterative experiments in replicating the delicate linework and complicated compositions of the art form. The ISOA-ARNN model effectively enhances the digital reproduction of meticulous figure painting, as demonstrated by evaluation metrics such as accuracy (96.1%), precision (93.7%), recall (94.3%), F1-score (94.0%) and execution time metrics.

This study explores the association between traditional Chinese art and modern technology, suggesting distributed computing and synthetic data augmentation to address challenges in digitization and preservation.

NOMENCLATURE

Abbreviation	Full Form
DL	Deep Learning
GF	Gradient Filter
HOG	Histogram of Oriented Gradients
ISOA-ARNN	Intelligent Seagull Optimization Algorithm Adaptive Recurrent Neural Network
GPU	General Processing Unit

CPU	Central Processing Unit
AI	Artificial Intelligence
FLBP	Fuzzy-based Local Binary Pattern
VAE	Variational Autoencoder
ViT	Vision Transformer
MRF	Markov Random Fields
SVM	Support Vector Machine
MLP	Multi-layer Perceptron
TMQACNN	Trusted Multiscale Quadratic Attention-embedded CNN
KITTI	Karlsruhe Institute of Technology and Toyota Technological Institute
DNN	Deep Neural Network
YOLO	You Only Look Once
SEM	Structural Equation Modelling
HSV	Hue Saturation Value
CNN	Convolutional Neural Network
TL	Transfer Learning
YOLOv8	You Only Look Once version 8
UCI	University of California, Irvine
MA-MS1DCNN	Multiscale one-dimensional CNN with a multi-attention mechanism
HSV	Hue Saturation Value
SD	Standard deviation
BPTT	Backpropagation Through Time
TBPTT	Truncated Backpropagation Through Time
Θ	Network Parameters
X	Hidden-Hidden Influence Matrix
V	Input-Hidden Influence Matrix
U	Hidden-Output Influence Matrix
$\phi(.)$	Activation Function (Foundation Function)
$\Psi(.)$	Output Function
g[s]	Internal State of the Network at Time s
w[s]	Input Sequence Element at Time s
b[s]	Combined Influence Vector at Time s
JQ	Symbol Representing a Mathematical Space
ML	Machine learning
RNNs	Recurrent Neural Networks
GF	Gaussian filter
RAM	Random Access Memory
D_t	Position of the search agent that avoids collisions with others.
O_t	Current location of the search agent.
A	Representation of the crusade of a search agent
w	Current iteration of the algorithm.
B	Dynamic factor reducing linearly over iterations to balance exploration and exploitation.
e_a	Linearly decreasing control parameter from fc to 0.
N_t	Position update of the search agent relative to the best neighbor.

q	Randomized parameter for spiral turns in the seagull's whirling movement.
q^c	A random integer between 0 and 1, is used to control randomness in movement.
C_t	Combined position of the search agent, balancing avoidance and attraction.
l	Random angle between 0 and 2π2\pi2π, used in spiral movement calculations.
v, u	Constants control the shape and radius of the spiral path.
f	Frequency factor used to define the spiral path.
w', y', ze	Coordinates of the seagull's whirling movement in 3D space.
Ps	Position updates of search agents storing the best solution.
O_{at}	Best search agent position at the current iteration.
y	An individual observation of the attribute
$mean(Y)$	The average of the painting data
$std(Y)$	The standard deviation of the painting data
Z	The z-score normalized value of the attribute
$S(y)$	The value of the function at position y, such as the pixel position in the image
y	The input value or position, like a pixel in the painting image
μ	The mean of the Gaussian distribution, determining the center of the curve
σ	The standard deviation of the Gaussian distribution, controlling the spread
π	The mathematical constant Pi
e	The mathematical constant Euler's number
RNN	Recurrent Neural Networks
DNN	Deep Neural Network

INTRODUCTION

The Chinese meticulous figure painting, "gongbi" in Chinese, is a highly artistic form of painting that involves a high degree of accuracy in all brush strokes. Such a technique is applied to represent human figures, animals, flowers, and even sceneries in vivid realism [1]. The artists do this by fine linings and layers of colors to create realistic images that are culturally deep. This style requires a great deal of skill, time, and patience- years of practice, as each stroke is made up of complex images [2]. This discipline has been practiced from eras and time still changes, but the link between this craft and Chinese culture and aesthetics is still profound.

Line characteristics of Chinese meticulous figure painting

In murals, lines are an essential tool for painters to portray composition, subject matter, and emotion. Artists are utilized at various levels, continuously, and with a strong sense of rhythm, making them a model for the production of ancient frescoes [3]. Lines are employed in willow leaf painting and iron line drawing to depict various textures found in nature [4]. Clothing patterns are described by iron wire lines, whereas lines are softly floating depicted in willow leaf paintings [5]. In murals, lines are frequently depicted as virtual to near, light to light, and light to heavy. Table 1 details Chinese precision drawing and mural painting techniques, including lines used to enhance visual and emotional impact of images.

Table 1: Line expressions in mural art and meticulous figure painting

Line Expression	Description	Purpose
Outline	Fundamental technique for defining forms and limits.	Defines the external shape, adding 3D realism.
Gradient line	Line changing in width or grayscale.	Creates a soft transition effect, adding layers.
Parallel lines	Parallel paths point identically.	Shows texture, light/shadow effects, and movement.
Diagonal lines	Lines not parallel to horizontal/vertical.	Adds dynamic rhythm and liveliness.
Curves	Wavy or bent lines.	Expresses fluidity, softness, and elegance.
Cross, dotted, dashed lines.	Various line forms like cross and dotted.	Adds rich, diverse visual effects.
Soft, smooth contours	Delicate lines outlining the shape.	Enhances beauty, softness, and grace.
Fine line with a plump pen	Fine lines detailing features like the face.	Adds depth and dimension to subtle details.
Dynamic rich lines	Varying line thickness expressing motion.	Captures movement, posture, and vitality.
Alternating warm/cool lines	Warm and cool ink lines showing light/shadow.	Enhances depth and texture for 3D effect.
Non-physical lines	Invisible lines for fine details.	Subtly conveys details or dynamic movements.

The Significance and Exact Use of Lines in Chinese Meticulous Figure Paintings

The line is essential for expressing the contour, rhythm, and movement of figures in mural paintings, which are an significant structure of Chinese art. Different personalities can be represented by lines; for instance, the delicate position of young individuals can reveal their gentleness, while the harsh and vibrating lines of older people can reflect their power[6]. The form, attire, and movement are also be conveyed by line modifications. Clothing folds and textures are outlined with fine lines, which add delicacy and vibrancy to the image[7]. By defining the actors' surroundings and backdrop, such as trees, buildings, or landscapes, Artists provide an atmosphere that gives the image depth and a feeling of space[8].Figure 1 emphasizes this importance by pointing out the key functions of the line in Chinese highly skilled figure painting such as a depiction of form, demonstrating motion, emotional expression, composing the whole, and unifying the expressive content with emotions.

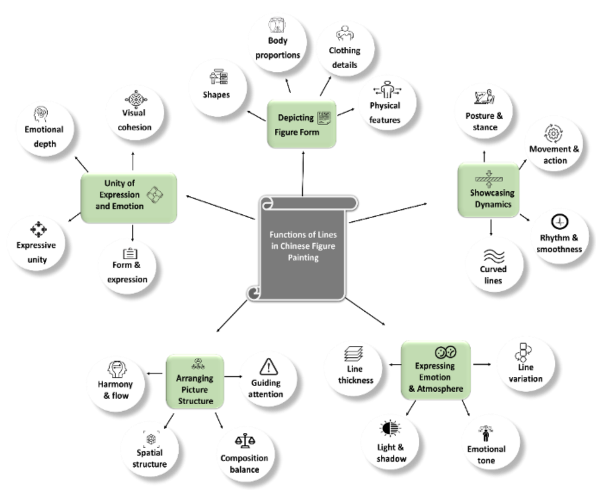


Figure 1: Roles of Lines in Chinese Figure Painting

The Visual and Emotional Impact of Lines in Chinese Mural Paintings

Lines have a major role in Chinese precise figure painting, especially in mural art, for composition, aesthetic enhancement, and emotional expression. Intricate details, such as garment textures, are depicted using antiquated techniques like Eighteen Strokes and tracing methods like iron line and willow leaf painting, maintaining traditional techniques while adding emotional depth [9]. Lines faithfully capture the physical characteristics of figures, using hair, skin texture, and wrinkles to convey emotions and energy [10]. The total visual effect is increased by the rhythm and movement produced by variations in line thickness, curvature, and direction. The fundamental function of painting is described in Table 2, with a focus on composition, emotion, texture, and movement.

Table 2: Essential Factors of Painting

Point	Description
Role of Lines	Lines are essential for composition, aesthetic enhancement, and emotional expression in Chinese figure painting.
Intricate Techniques	Techniques and tracing methods are used for detailed depictions, such as garment textures.
Traditional Methods with Emotional Depth	Traditional techniques are maintained while adding emotional depth.
Conveying Emotions and Energy	Lines capture physical characteristics (e.g., hair, skin texture, wrinkles) to express emotions and energy.
Realistic Texture and Light	Lines contribute to realistic texture, light, and shadow, enhancing the painting’s immersion.
Rhythm and Movement	Variations in line thickness, curvature, and direction create rhythm and movement, enhancing the visual effect.

Research objective: The research combines traditional Chinese art with modern technology to enhance the digital representation and analysis of intricate figure paintings.

Research contribution

- This research integrates the traditional Chinese art with modern technology for improving the digital representation and analysis of meticulous figure paintings
- The study utilizes Kaggle's Chinese meticulous painting dataset. Z-score normalization, gradient filter application, and image resizing are used to ensure dataset quality and consistency.
- HOG is applied to extract edge and texture information for better style recognition.
- The ISOA-ARNN model is developed, combining Seagull Optimization and RNN to analyze composition patterns and line characteristics.
- Evaluation metrics include accuracy, precision, recall, F1-score, line work replication, noise suppression, color palette match, and expert evaluation are utilize to evaluate the performance of the proposed method.

Research organization: Section 2 contains the study’s review of the literature, and **Section 3** illustrates the methodology. The results of the study are presented in **Section 4**. **Section 5** demonstrates the discussion, and the conclusion is established in **Section 6.**

LITERATURE REVIEW

Table 3 provides a comprehensive overview of literature on meticulous figure painting, outlining data, research objectives, and limitations of each study.

Table 3: Collection of various articles on the meticulous figure painting

Ref	Objective	Data	Proposed method	Drawbacks/Challenges
[11]	Enhance traditional Chinese paintings using AI-generated resources.	Traditional Chinese paintings dataset	FLBP + VAE	Challenges in preserving traditional characteristics and reducing image distortion.
[12]	Generate intermediate painting steps for Chinese painting with consistency to the real painting process.	Chinese painting dataset	ViT-based generator with adversarial learning	Balancing traditional aesthetics with modern elements and multimedia integration.
[13]	Integrate computer-aided design and multimedia display with DL for decorative art.	Traditional decorative art patterns	DL + computer graphics for pattern generation	Capturing the full complexity of aesthetic perception and generalizability across populations.
[14]	Develop an objective method for diagnosing aesthetic perception in students using AI.	A dataset of 2153 paintings from 675 students, annotated across 77 aesthetic dimensions.	A hybrid framework combining CNN and Transformer models	Difficulty in replicating traditional processes and ensuring applicability across styles.
[15]	Generate intermediate painting steps ensuring consistency with traditional techniques.	Chinese painting dataset	ViT-based generator with adversarial learning	Challenges in capturing all fine details, requiring high-quality input datasets.
[16]	Classify digital paintings by artist attribution using multi-scale pyramid representation and DL.	WikiArt and WGA datasets	Multi-scale CNN framework with Fusion-based MRF	Difficulty in handling diverse painting features and ensuring accuracy in varied conditions.
[17]	Improve painting image classification by addressing challenges in feature extraction and preservation.	Digital painting images	A hybrid model combining CNN and SVM with weighted k-means clustering	Performance variation based on data quality, diversity, and unseen scenarios.
[18]	Enhance sentiment analysis by integrating multimodal data features for better emotional understanding.	Multimodal data from three datasets	Fuzzy-DNN model with multimodal feature fusion, dual attention mechanism, and fuzzy logic principles.	Difficulty in applying due to cultural and artistic differences.

[19]	Improve bearing fault diagnosis accuracy by addressing limited samples, noise, and load variation.	Bearing vibration signals	TMQACNN	Requires further tuning and validation for diverse operational conditions.
[20]	Improve behavior classification and object detection in smart city surveillance with transfer learning and synthetic datasets.	KITTI	TL-assisted DNN	Limited focus on specific export paintings, lacking broader cultural variations.
[21]	Preserve cultural heritage by restoring Mold-damaged ancient paintings without compromising integrity.	Ancient paintings with Mold damage	Virtual restoration and mold removal technique	Effectiveness impacted by signal quality and generalization to unseen faults.
[22]	Develop a system for evaluating the aesthetic value of Western and Chinese watercolor art for intercultural understanding.	Five renowned watercolors from Chinese & Western historical art.	Correlation analysis and SEM	Accuracy depends on synthetic dataset quality and real-world scenario complexity.
[23]	Enhance AI accuracy in designing traditional Chinese-style architecture with pre-trained model fine-tuning.	Traditional Chinese architectural style elements	Fine-tune AI models using DreamBooth and ControlNet tools	Difficulty in distinguishing original layers from restoration materials.
[24]	Develop automated damage detection for identifying efflorescence and plant growth damage on ancient Fuzhou brick walls for preservation.	High-resolution images of gray brick surfaces with damage annotations	YOLOv8 for automated damage detection	Difficulty in capturing nuances of traditional Chinese architecture through AI models.
[25]	Improve fault diagnosis accuracy in hydraulic systems to reduce maintenance costs and enhance reliability.	UCI hydraulic system dataset	MA-MS1DCNN	Difficulty in handling diverse, complex real-world conditions.
[26]	Analyze cultural and artistic connections between Qing-era Guangzhou trade culture and export painting color traits.	Dataset of 35 export paintings depicting Guangzhou landscapes	HSV color model and k-means clustering algorithm	Requires further validation and tuning for varied operational conditions.

Research gap

Chinese meticulous figure painting progresses considerably in its aesthetics and historical contexts. However, quite limited comparisons of compositional and line characteristics using modern high-tech. This gap provides evidence to require a data-driven methodology for interpreting nuances of line, color palette, and space arrangements in Chinese meticulous figure painting.

METHODOLOGY

This methodology and traditional artistic principles are combined with modern digital technology to probe the finer arguments counselled by representation in a work of art. Conventional techniques, such as proportion, balance, and symmetry, are integrated with advanced digital tools to capture the fine nuances of form and structure. Digital building and rendering software imitate the work, so the interpretation is accurate yet retains a perceptively artistic character. **Figure 2** demonstrates the research outline.

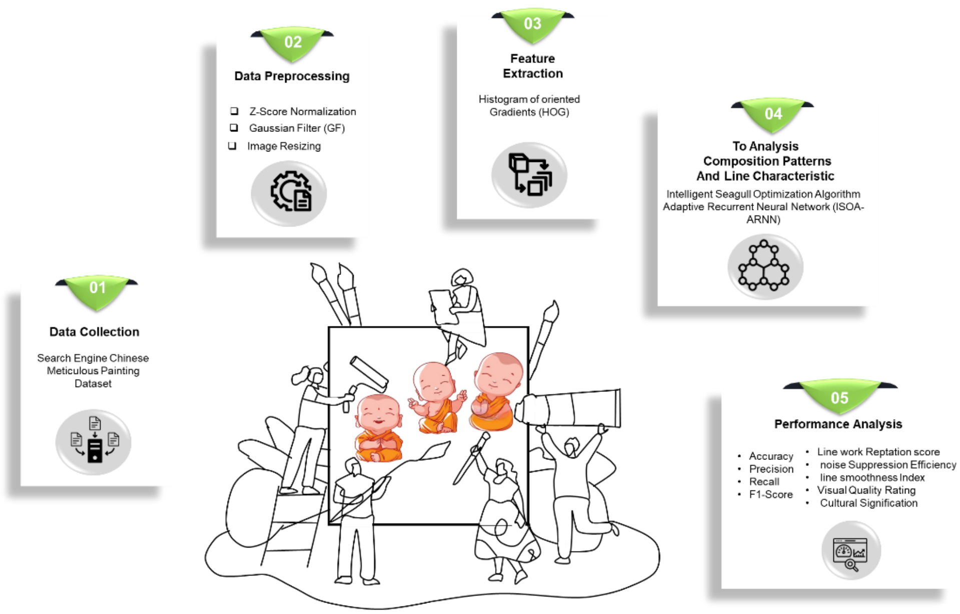


Figure 2: Research outline

Dataset

The research collected the search engine Chinese meticulous painting dataset (https://www.kaggle.com/datasets/myzhang1029/search-engine-chinese-meticulous-painting) from Kaggle. **Figure 3** establishes the example Chinese meticulous painting dataset.

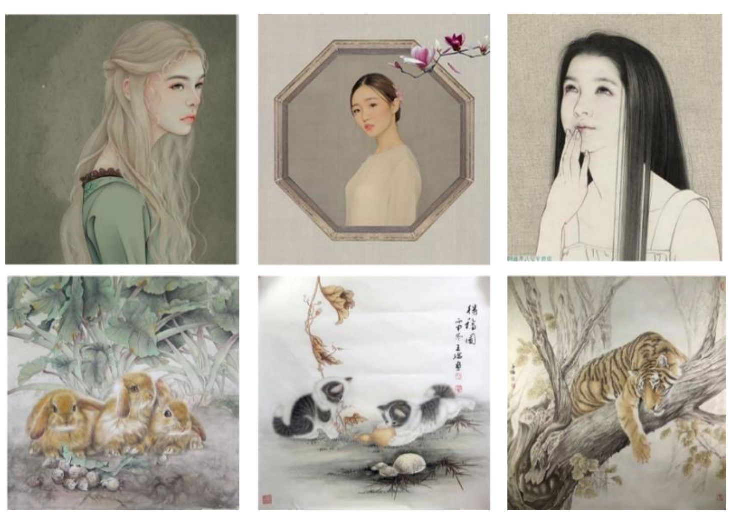


Figure 3: Example images from the dataset

Data preparation

After collecting the painting dataset**,** Z-score normalization ensures a uniform scale for precise analysis and comparison by standardizing values in the Chinese meticulous painting dataset. The GF smooth the Chinese meticulous painting dataset, reducing noise and enhancing image quality for detailed analysis. Image resizing in a Chinese meticulous painting dataset ensures consistent dimensions for analysis, enhancing model accuracy and processing efficiency.

Z-score normalization

The process of z-score normalization also aids in the contextual compositional analysis and the analysis of the line patterns in Chinese artwork that is extremely detailed. It also allows for improving consistency lessening bias and increasing accuracy. The approach enters the data on a zero mean and scales it according to standard deviation. The technique standardizes the painting dataset by converting inputs to a single scale, reducing intensity variations, enhancing model stability, and eliminating distortion, ensuring comprehensive and reliable results. **Equation (1)** provides the transformation of the image quality of the painting data.

$$Z = \frac{(y - \mathrm{mean}(Y))}{\mathrm{std}(Y)} \qquad \textbf{(eq. 1)}$$

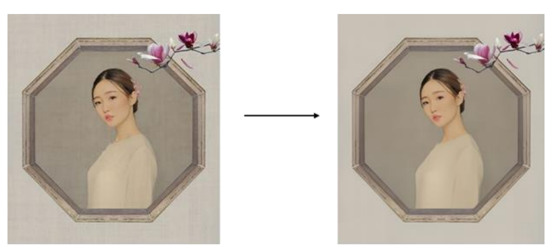
It effectively maintains the quality of invasive vascular painting images by eliminating intensity differences during subsequent painting image analysis stages.

Gaussian filter (GF)

In the analysis of Chinese painting, smoothening the image details, sharpening the line features, and delineating the patterns compositionally utilize the GF as well in understanding the crispness of the brushwork and the texture of the paint. GF is used to reduce noise in painting image data, resulting in better and more accurate quality. Painting images are susceptible to noise during processing, affecting their efficiency in analysis and diagnosis. This system uses GFs for image smoothing and noise removal, employing a custom kernel for convolutional operations and Gaussian distribution values for professional appearance (**Equation 2)**.

$$S(y) = \frac{1}{\sqrt{2\pi\sigma^2}} a^{\frac{(y-\mu)^2}{2\sigma^2}} \qquad \text{(eq. 2)}$$

The Chinese meticulous painting dataset was subjected to feature removal using GF, as shown in **Figure 4.**



(a) (b)

Figure 4: Outcomes of removing features using GF

GFs enhanced the image quality and accuracy by reducing noise, facilitating better image pre-processing, and optimizing subsequent models for efficient analysis and diagnosis.

Image resizing

Chinese meticulous figure painting studies emphasize systematic adjustment of image dimensions to maintain uniformity, structure, and line properties, relating composition processes with stylistic features and artistic expression. Resizing images of the Chinese meticulous painting's dataset becomes pivotal in making the images equipped for ML models or digital analysis. These images as any other traditional forms of art with high and intricate details painted thoughtfully on the canvas require proportionate resizing without losing the quality. Image scaling maintains artistic style and enhances input into DL algorithms, allowing uniform size for quick processing and comparison in classification, recognition, and style transfer tasks. **Figure 5** displays the results of (a) before and (b) after resizing example image data. It illustrates the original file size is 150 KB, while after compression the file size is 112 KB.

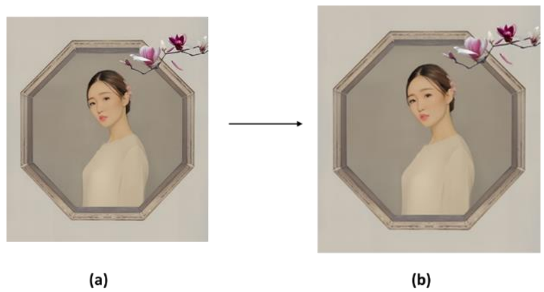


Figure 5: Outcomes of resizing the example painting image data

Feature extraction utilizing histogram of oriented gradients (HOG)

The goal of utilizing HOG in the analysis of Chinese painting is the extraction of compositional and linear features and their arrangement in the piece of art in detail. HOG is a feature extraction technique used to identify patterns and image resizing, extract gradients, segment images, and produce distinct histograms using pixel values. **Equation (3)** calculates the entire gradient magnitude, whereas **Equation (4 &5)** computes the orientations.

$$N = \sqrt{(R_w)^2 + (R_z)^2} \qquad \text{(eq. 3)}$$

$$\tan(\phi) = \frac{R_w}{R_z} \qquad \text{(eq. 4)}$$

$$\phi = \text{btan}\left(\frac{R_w}{R_z}\right) \qquad \text{(eq. 5)}$$

Where R_w is the gradient in the horizontal direction. R_z is the gradient in the vertical direction. The feature extraction procedure employing painting images is shown in **Figure 6**.

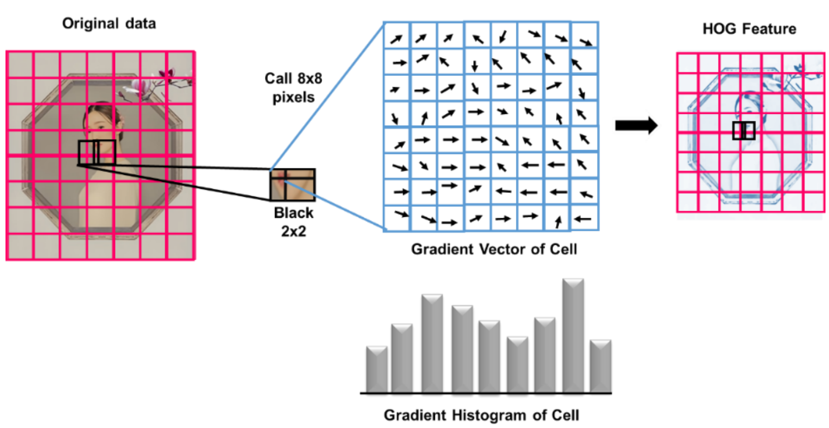


Figure 6: Process of using HOG

HOG offers image shape and texture descriptors, which improve the feature quality and assist with precise cancer categorization in painting images, hence enhancing the entire model prediction performance.

Intelligent Seagull Optimization Algorithm Adaptive recurrent neural network (ISOA-ARNN)

The present model proposes ISOA-ARNN architecture to supplement the analysis and prediction of composition patterns, and line characteristics of works of art. Utilizing the ISOA algorithm, this model helps in tuning the hyper parameters of the ARNN which can be better suited to time-dependent data. The over perceived model enhances the ARNN's understanding of intricate creative work dynamics, making it more accurate and effective in predicting visual components in paintings.

Adaptive Recurrent Neural Network (ARNN)

The ARNN is a sophisticated tool designed to study Chinese meticulous figure painting composition and form characteristics, leveraging its strength in analyzing sequential and contextual information. The NN is dynamic and flexible to the complexities of the stroke's arrangements, the contours' movements, and the composition's variations inherent in this detailed and linear painting style. Due to the impact of temporally ordered connections in the process of creation or its computer visuals, the ARNN perform a deeper analysis or recreate this technique since the machine can distinguish such concepts as a liquid of lines, ratios, distances, and compositions in every art. This ensures the preservation and utilization of traditional methods without discarding knowledge from the stage of computer AI. In **Figure 7**, the architecture of ARNN is shown below.

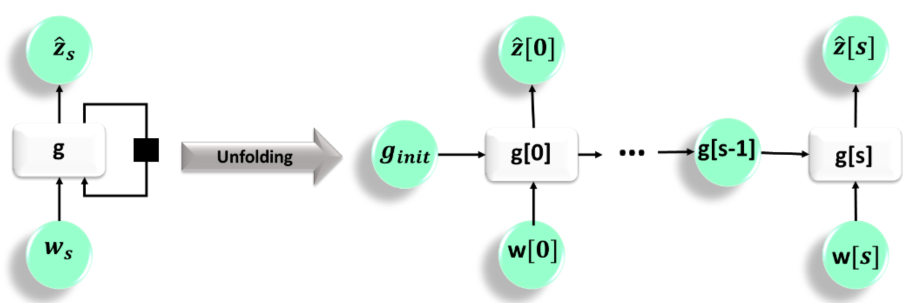


Figure 7: Architecture of ARNN

The continuous learning of ARNN ensures up-to-date and useful responses, promoting improved understanding and painting style. ARNNs perform well on data sequence processing tasks and it employs ARNNs to create a concise depiction of the given input sequence[s]. Function eperforms the planning in **Equation 6**.

$$g[s] = e(g[s-1], w[s];\ \Theta) \quad \textbf{(eq. 6)}$$

The following equation is satisfied by the neural computation when it's expanded and the sequence $w_s = \left[w[0], \dots, w[w_S - 1]\right], w[s];\ JQ^c$is provided in **Equations (7-9).**

$$b[s] = X^S g[s-1] + V^S w[s] \quad \textbf{(eq. 7)}$$

$$g[s] = \phi(b[s]) \quad \textbf{(eq. 8)}$$

$$z[s] = \Psi\left(U^S g[s]\right) \quad \textbf{(eq. 9)}$$

Where $X \in JQ^{mG\times mG}, V \in JQ^{c\times mG}, U \in JQ^{mG\times mP}$ is the influence matrix for hidden-hidden, hidden-output, and input-hidden associations, correspondingly, and $\phi(.)$ is a foundation purpose. S Computation in a single Elman RNN module. An ARNN processes each sequence element individually, preserving its temporal order. The network uses both (a) and (b) to update its internal state $g[s] \in JQ^{mG}$after reading an element from the input sequence$w[s] \in JQ^{c}$ change of the most recent state $g[s-1]$. Time unfolding is a process, and each node in an extended system has the identical consideration as scattered doubles. The network parameters$\Theta = [X, V, U]$ are typically learned through BPTT, a generalized version of standard backpropagation. Through the development process, the ARNN is changed into multiple layers and weight matrices to implement gradient-based optimization. In actual use, TBPTT (τ_a, τ_e) executes BPTT for τ_a timesteps every τ_e processes an input window of length one time step at a time. Setting τ_a to b extremely low integer of consequence in reduced performance. ARNN leverages a thorough understanding of temporal and spatial practices of Chinese fine brushwork painting in an inventive manner while at the same time upholding the traditional style in the use of cutting-edge neural network design.

Intelligent Seagull Optimization Algorithm (ISOA)

ISOA is a metaheuristic optimization technique based on the social life and flying behavior of seagulls, used to study Chinese meticulous figure painting, refine parameters like brushstroke accuracy, symmetry, and composition, and define optimal patterns and composition from the painting database. This makes computational art analysis more effective and advanced, providing more accurate models of traditional styles. Seagulls are intelligent birds that consume fish, amphibians, reptiles, insects, and earthworms. Designers consume both fresh and salt water, as shown in **Figure 8.**The research explores mathematical models of predator migration and attack, focusing on gulls' movement and the use of an additional variable A, to avoid collisions in **Equation (10)**.

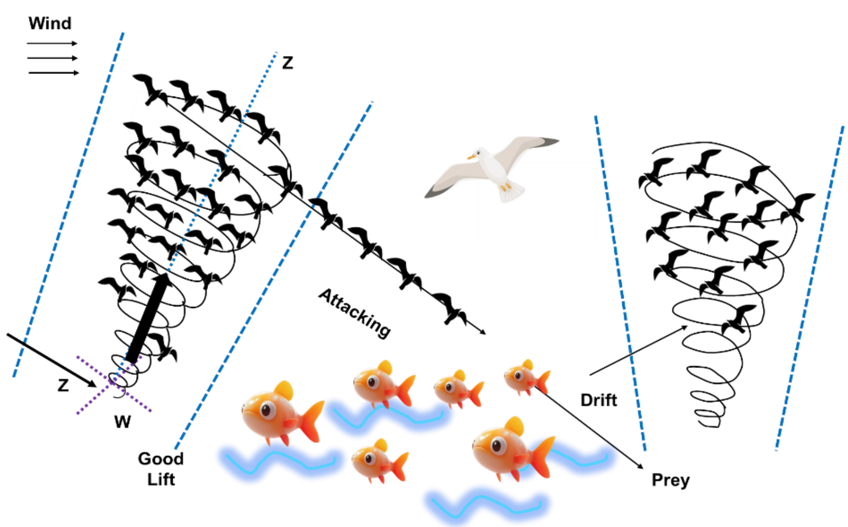


Figure 8: Seagull migration cycles and aggressive behaviors

$$D_t = B \times O_t \qquad \textbf{(eq. 10)}$$

The current iteration represents the search agent's position, a position not colliding with other agents, and their movement in a specific search space in **Equation (11)**.

$$B = e_d - \left(w \times \left(\frac{e_d}{Max_{Iteration}}\right)\right) \qquad \textbf{(eq.11)}$$

Where the frequency of using variable e_d. B is controlled by the introduction of e_d, which is linearly reduced from e_d to 0. The search agents go in the direction of the best neighbour after avoiding neighbour collisions in **Equation(12)**.

$$N_t = A \times (O_{at}(w) - O_t(w)) \qquad \textbf{(eq.12)}$$

Where N_t stands for search agent O_t's positions to search agent O_t, which is the best fit. A's randomized behavior is in charge of appropriately striking a balance between exploration and exploitation. A is computed as followsin **Equation (13)**.

$$A = 2 \times B^2 \times q^c \quad (\textbf{eq.13})$$

where q^c is a random integer that falls between 0 and 1. Finally, the search agent can adjust its ranking based on the top search middleman in Chinese intricate figure painting by **Equation (14)**:

$$C_t = |D_t + N_t| \quad (\textbf{eq.14})$$

Where D_t that best stands for the separation between the search agent and the search agent fits the query. The objective of this development is to capitalize on the search process's past and expertise. The whirling movement occurs in the air when attacking prey. The following **Equations (15-18)** are a description of this behavior in the x, y, and z planes:

$$w' = q \times \cos(l) \quad (\textbf{eq.15})$$

$$z' = q \times \sin(l) \quad (\textbf{eq.16})$$

$$y' = q \times l \quad (\textbf{eq.17})$$

$$q = v \times f^{lu} \quad (\textbf{eq.18})$$

Where l is a random value between 0 and 2π, and q is the radius of each spiral turn. The base of the natural logarithm is a, while the constants v and u determine the spiral form **Equations (15-18)** are used to compute the search agent's new position **Equation (19)**.

$$O_t(w) = (C_t \times w' \times z' \times y') + O_{at}(w) (\textbf{eq.19})$$

Where $O_t$updates the positions of other search agents and store the best answer. Applying the painting data optimal patterns, ISOA enhances Chinese meticulous figure paintings' brushstroke precision, balance, and arrangement. ISOA-ARNN is represented by **Algorithm 1**.

Algorithm 1: Intelligent Seagull Optimization Algorithm Adaptive recurrent neural network (ISOA-ARNN)

ARNN Initialization

Input the sequential artistic data w[s]

Initialize ARNN parameters:

Randomly initialize weight matrices X, V, U

Set activation functions:

$\phi(.)$ for hidden layer activations

$\Psi(.)$ for output layer activations

For each timestep s in sequence w[s]:

Compute the input to the hidden layer:

$$b[s] = X^S g[s-1] + V^S w[s]$$

Compute the hidden state:

$$g[s] = \phi(b[s])$$

Compute the output:

$$z[s] = \Psi\left(U^S g[s]\right)$$

Store the model's state and loss function for optimization.

ISOA Initialization

Initialize the population of search agents:

Set the population size N.

Randomly initialize each search agent's position O_t in the search space.

Define the parameters for the algorithm:

Maximum iterations Max_Iteration.

Linearly decreasing parameter B

Randomized behavior variable A

Spiral movement parameters q, l

Begin optimization loop:

For each iteration w from 1 to Max_Iteration:

Calculate new positions D_t

Avoid collision among search agents.

Move towards the best neighbor using A.

Update positions using spiral flight patterns

Compute spiral movement in x, y, and z dimensions.

Update positions $O_t(w)$ for each search agent.

Evaluate the fitness of each search agent:

Fitness is determined by the ARNN's performance.

Update the best search agent based on fitness.

Combine ISOA with ARNN

Use ISOA to optimize ARNN hyperparameters:

Hyperparameters include learning rate, number of hidden units, weight initialization, etc.

Evaluate the fitness of ARNN for each set of parameters.

Update ARNN with ISOA-optimized hyperparameters:

Modify the ARNN weights and structure based on ISOA optimization results.

Retrain ARNN on the artistic data with the optimized parameters.

Repeat training and optimization until convergence:

Alternate between ARNN training and ISOA parameter refinement.

Output the Optimized Model

Return the ISOA-optimized ARNN:

A trained model that accurately analyses and predicts artistic features.

Use the optimized ARNN to analyze new datasets or evaluate unseen artistic features.

The ISOA improves optimization by imitating the seagulls' dynamic search patterns. This increases the accuracy of assessing the detailed line features of Chinese careful figure painting. For complicated pattern recognition, ARNN provides dynamic flexibility by capturing temporal relationships in the input. Through the synergistic combination of effective optimization and flexible learning, ISOA-ARNN improves the model's capacity to decipher and anticipate subtle line patterns in the artwork, increasing analytical precision and flexibility.

PERFORMANCE ANALYSIS

This study aims to improve the digital representation of Chinese meticulous figure painting concepts by utilizing modern technological tools to bridge the gap between traditional and digital art forms.The performance of the proposed approach is evaluated using a comprehensive set of metrics, including accuracy, precision, recall, F1-score, linework replication, noise suppression, color palette matching, and expert evaluation, with Python serving as the primary tool for analysis.

Experimental Setup

An HP brand system with an Intel Core i912900 processor, an Intel Core i713700 CPU type, 3.50 GHz clock speed, 64 GB RAM, Windows 11 Home operating system, Python version 3.10.0, and a 16 MB L3 cache size is described in **Table 4**, along with the hardware and software components of the computer.

Table 4: Experimental setup

Processor model	Intel(r) core(tm) i912900
RAM	64 GB
Brand	HP
CPU Type	Intel Core i713700
Clock Speed	3.50 GHz
Operating System	Windows 11 Home
Python Version	3.10.0
L3 Cache Size	16 B

Model Performance Metrics

This section includes Accuracy, Precision, Recall, and F1-score to collectively assess the model's ability to truly reproduce the key elements and overall quality of Chinese meticulous figure paintings **Figure 9** and **Table 5** show the outcomes of Indicators for system Performance.

Table 5: NUMERICAL findings of performance assessment metrics

Metrics	Values (%)
Accuracy	96.1
F1-Score	94
Recall	94.3
Precision	93.7

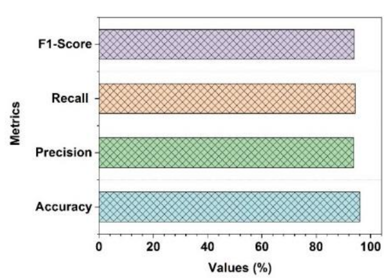


Figure 9: Graphical outcomes of artistic composition prediction metrics

Accuracy

The task involves evaluating the aesthetic and stylistic accuracy of Chinese dimensional figure painting reproductions to ensure they meet artistic standards and maintain their source authenticity. ISOA-ARNN achieves an accuracy of **96.1%** demonstrating high reliability and minimal false positives or negatives.

Precision

It evaluates the model's ability to accurately replicate specific elements, like facial features, clothing, and accessories, within the intricately detailed style of Chinese meticulous figure painting. With a precision of **93.7%** the model correctly identifies positive instances minimizing false positives.

Recall

It reflects the model's proficiency in identifying and reinventing all essential components, from subtle textures to complex motifs, characteristic of Chinese meticulous figure paintings, ensuring comprehensive representation. A recall of **94.3%** shows the model identifies most true positives with minimal false negatives.

F1-score

It combines precision and recall to measure the overall performance, highlighting how effectively the model balances accuracy with the ability to replicate all necessary details and elements of Chinese meticulous figure paintings. The F1-Score of **94.0%** represents a balanced trade-off between precision and recall ensuring reliable performance.

Performance assessment of linework and composition in Chinese art digitalization

This category includes linework replication, noise suppression, line fidelity, colour palette match, composition match, and line smoothness focus on the technical aspects of line replication, visual clarity, colour consistency, and the arrangement of elements in the artwork. **Figure 10** and **Table 6** display the consequences of the composition and structure measures.

Table 6: Numerical findings of Linework and composition metrics

Metrics	Values (%)
Linework Replication Score	92.5
Noise Suppression Efficiency	91.7
Line Fidelity Score	93.2
Colour Palette Match	93.2
Composition Match	91.5
Line Smoothness Index	87

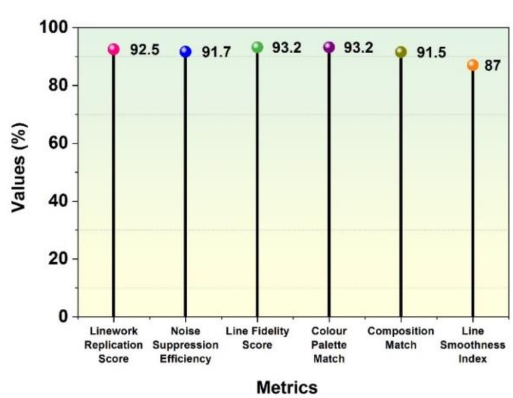


Figure 10: Performance of Line Replication on Digital Chinese Art and Composition Matching

Linework Replication Score

It judges how meticulously the model replicates the fine, flowing brush strokes of Chinese meticulous figure paintings without compromising the essential precision and fluidity deemed necessary for the very high detail levels this art form requires. The replication score for linework stands at **92.5%,** reflecting a high score of accurate replication of structural design with minimal deviation.

Noise suppression efficiency

It assesses the capability of the model for filtering out superfluous visual noise, still retaining the clarity of fine detail that is critical for the aesthetics of Chinese meticulous figure paintings. An effectiveness of **91.7%** for noise suppression indicates more filtered noise but keeps important characteristics.

Line fidelity score

A measure of how well the model captures the complex, consistent lines that define a Chinese meticulous figure painting, which is fundamental for precisely rendering figures, patterns, and textures. The line fidelity scored **93.2%**, demonstrating strong accuracy in maintaining the integrity of lines and structures.

Color palette match

Assesses how well the model reproduces the traditional color schemes used in Chinese meticulous figure paintings, maintaining harmony and authenticity with historical and cultural significance. The color palette match of **93.2%** indicates that the model accurately preserves color consistency and aesthetic harmony.

Composition match

It evaluates the extent to which the model replicates balanced harmonious arrangements of formal elements in the painting-that structured, and deliberate in the manner associated with Chinese meticulous figure painting. A composition match score of **91.5%** shows the model's effectiveness in preserving spatial and visual relationships.

Line smoothness index

It reflects the ability of the model to draw smooth and continuous lines, which are characteristic of Chinese painting and require perfection in brushwork to express grace and precision. The line smoothness index of **87%** indicates good line smoothness with room for improvement in more intricate designs.

Artistic and Cultural Quality Metrics

These metrics include visual quality, cultural significance, aesthetic retention, and cultural embedding: their purpose is to identify the great capability of the model to manage artistic appeal and cultural integrity in Chinese meticulous figure paintings. The results of the Indices of artistic and cultural quality are shown in **Figure 11** and **Table 7**.

Table 7: Digital Reproduction Quality Assessment Table

Metrics	Value (out of 5)
Visual Quality Rating	4.9
Cultural Significance	4.8
Aesthetic Retention Rating	4.7
Cultural Embedding Score	4.6

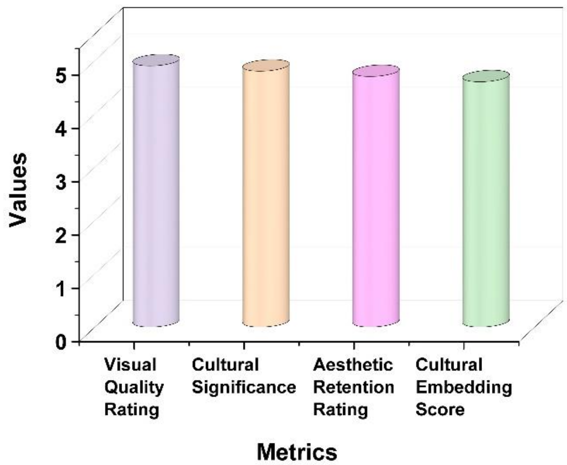


Figure 11: Artistic Integrity and Cultural Embedding Ratings

Visual Quality Rating

Adjudicated according to subjectivity, the attractiveness of the painting when the model applies elegance, balance, and intricate details, typical even to Chinese meticulous figure painting. ISOA-ARNN achieves a visual quality rating of **4.9** out of 5 showcasing exceptional visual appeal with minimal flaws.

Cultural Significance

It measures how well the model integrates cultural elements, ensuring that the replicated figure painting resonates with the cultural context, themes, and symbolism inherent in Chinese art traditions. A cultural significance rating of **4.8** reflects the model's ability to integrate relevant cultural elements into its output.

Aesthetic Retention Rating

It evaluates the model's success in preserving the aesthetic qualities of Chinese meticulous figure painting, emphasizing the visual harmony, grace, and balance central to the art form. With an aesthetic retention rating of **4.7**, the model maintains the original aesthetic integrity of the input.

Cultural Embedding Score

It assesses how deeply the model reflects cultural narratives, history, and symbolism within the painting, ensuring that the artwork embodies the rich cultural heritage of Chinese meticulous figure painting. A cultural embedding score of **4.6** reflects the model’s effective incorporation of cultural themes into the output.

Computational Efficiency Metrics

This section includes Execution Time, GPU Utilization Time, and CPU Utilization Time, which evaluate the model's processing efficiency and hardware utilization during the generation of artwork. The results of computational performance measures are shown in **Figure 12** and **Table 8**.

Table 8: Model Training Time

Metrics	Values (Seconds)
Execution time	2.5
GPU Utilization Time	0.94
CPU Utilization Time	0.45

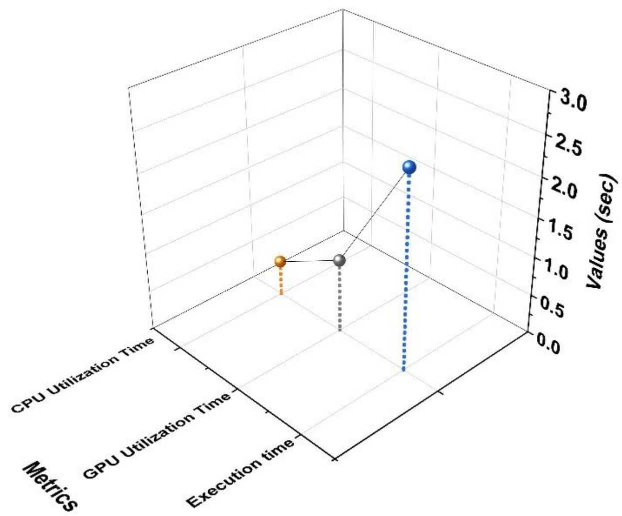


Figure 12: Model Evaluation Time

Execution Time

It measures the time the model takes to process and generate a Chinese meticulous figure painting, balancing speed with quality to ensure an efficient, effective workflow without compromising detail. The model achieves an execution time of **2.5seconds** ensuring fast processing for real-time applications.

GPU Utilization Time

Reflects the amount of time the GPU spends processing the complex data involved in generating Chinese meticulous figure paintings, allowing for efficient handling of intricate details and textures. With a GPU utilization time of **0.94seconds**, the model optimizes hardware performance for faster computations.

CPU Utilization Time

Indicates the time the CPU is engaged in processing the computational tasks necessary to generate a detailed, high-quality Chinese meticulous figure painting, supporting the overall performance of the model. The model uses the CPU efficiently with a utilization time of **0.45sseconds** ensuring smooth processing.

DISCUSSION

The goal of this research is to facilitate the digital representation of traditional artistic principles in combination with modern technology. The operational parameters of the model prove the system's effectiveness in efficiency as well as in producing meticulous Chinese figure paintings. With a notable accuracy of 96.1%, the model demonstrates excellent fidelity in capturing key artistic elements, such as facial features and intricate textures, with a precision of 93.7% and a recall of 94.3%. The f1-score of 94.0% highlights a balanced performance, ensuring both precision and recalls are optimized. Technical aspects like linework replication (92.5%), noise suppression (91.7%), and line fidelity (93.2%) further emphasized the model's ability to maintain artistic integrity and detail. Color palette and composition match scores of 93.2% and 91.5% respectively indicate successful replication of visual and spatial harmony. Aesthetic and cultural quality assessments are equally robust, with the model achieving near-perfect ratings in visual quality (4.9) and cultural significance (4.8), reflecting its effective integration of traditional cultural elements. Furthermore, the model excels in computational efficiency, processing artwork in just 2.5 seconds, with optimized GPU (0.94s) and CPU (0.45s) utilization times, ensuring both high-quality output and real-time application feasibility. These results demonstrated that the model not only replicates technical and aesthetic elements with high fidelity but also preserves the cultural depth and artistic nuances of Chinese meticulous figure paintings, making it a valuable tool for digital art preservation and generation.

CONCLUSION

This study examined the composition and line characteristics of Chinese mechanical figure painting using DL techniques. It reflects aesthetic and cultural values, aiming for heritage conservation and contemporary relevance. The research included performance evaluation metrics such as accuracy (96.1%), precision (93.7%), recall (94.3%), F1-score (94.0%), linework replication score (92.5%), noise suppression efficiency (91.7%), line fidelity score (93.2%), color palette match (93.2%), composition match (91.5%), and line smoothness index (87%) and expert evaluation metrics like visual quality rating (4.9/5), cultural significance (4.8/5), aesthetic retention rating (4.7/5), and cultural embedding score (4.6/5) and execution time metrics including execution time (2.5 seconds), GPU utilization time (0.94 seconds), and CPU utilization time (0.45 seconds).

Drawbacks and future scope: DL can be used to analyze Chinese meticulous figure painting, but it faces challenges like limited datasets, difficulty in capturing intricate styles, and potential loss of cultural context. Future research should focus on creating comprehensive datasets, improving model capabilities, and developing interdisciplinary approaches to preserve and evolve traditional Chinese painting styles.

REFERENCES

1. Zhang Y, Dang R, Li Y, Meng X. A Comparative Study of Early and Late Painting Styles in Zhang Daqian's Lotus Works. IEEE Access. 2024 May 22. https://doi.org/10.1109/ACCESS.2024.3404415

2. Khodami F, Mahoney AS, Coyle JL, Sejdić E. Elevating Patient Care with Deep Learning: High-Resolution Cervical Auscultation Signals for Swallowing Kinematic Analysis in Nasogastric Tube Patients. IEEE Journal of Translational Engineering in Health and Medicine. 2024 Nov 13. https://doi.org/10.1109/JTEHM.2024.3497895

3. Li W, Ma S, Shi W, Lin H, Liu Y, Cui Y, Ao J. Artistic heritage conservation: the relevance and cultural value of Guangzhou clan building paintings to traditional rituals from a kinship perspective through perceptual assessment and data mining. Heritage Science. 2024 Jun 25;12(1):216. https://doi.org/10.1186/s40494-024-01328-9

4. Zhou J, Gai Q, Zhang D, Lam KM, Zhang W, Fu X. IACC: cross-illumination awareness and color correction for underwater images under mixed natural and artificial lighting. IEEE Transactions on Geoscience and Remote Sensing. 2024 Jan 5;62:1-5. https://doi.org/10.1109/TGRS.2023.3346384

5. Yao Y, Wang C, Wang H, Wang K, Ren Y, Meng W. Embedding Secret Message in Chinese Characters via Glyph Perturbation and Style Transfer. IEEE Transactions on Information Forensics and Security. 2024 Mar 19. https://doi.org/10.1109/TIFS.2024.3377903

6. Yu Q, Zhu G. Virtual Simulation Design of Mazu Clothing Based on Digital Technology. Fibers and Polymers. 2024 Jun 18:1-5. https://doi.org/10.1007/s12221-024-00566-9

7. Sun Z, Lei Y, Wu X. Chinese Ancient Paintings Inpainting Based on Edge Guidance and Multi-Scale Residual Blocks. Electronics. 2024 Mar 26;13(7):1212. https://doi.org/10.3390/electronics13071212

8. Yu E, Chevalier F, Singh K, Bousseau A. 3D-Layers: Bringing Layer-Based Color Editing to VR Painting. ACM Transactions on Graphics (TOG). 2024 Jul 19;43(4):1-5. https://doi.org/10.1145/3658183

9. Hu Q, Peng X, Li T, Zhang X, Wang J, Peng J. ConvSRGAN: super-resolution inpainting of traditional Chinese paintings. Heritage Science. 2024 May 31;12(1):176. https://doi.org/10.1186/s40494-024-01279-1

10. Bonfert M, Muender T, McMahan RP, Steinicke F, Bowman D, Malaka R, Döring T. The Interaction Fidelity Model: A Taxonomy to Communicate the Different Aspects of Fidelity in Virtual Reality. International Journal of Human-Computer Interaction. 2024 Oct 2:1-33. https://doi.org/10.1080/10447318.2024.2400377

11. Xu X. A fuzzy control algorithm based on artificial intelligence for the fusion of traditional Chinese painting and AI painting. Scientific Reports. 2024 Aug 1;14(1):17846. https://doi.org/10.1038/s41598-024-68375-x

12. Wang Z, Liu F, Liu Z, Ran C, Zhang M. Intelligent-paint: a Chinese painting process generation method based on vision transformer. Multimedia Systems. 2024 Apr;30(2):112. https://doi.org/10.1007/s00530-024-01316-w

13. Wang L, Zhang L, Zhong Z. Computer Aided Decorative Art Design and Multimedia Dynamic Display Based on Deep Learning Model. Computer-Aided Design. 2024 , 21(S25). https://doi.org/10.14733/cadaps.2024.S25.76-91

14. Zhang Y, Wang M, He J, Li N, Zhou Y, Huang H, Cai D, Yin M. AestheNet: Revolutionizing Aesthetic Perception Diagnosis in Education With Hybrid Deep Nets. IEEE Transactions on Learning Technologies. 2024 May 28. https://doi.org/10.1109/TLT.2024.3405966

15. Wang Z, Liu F, Liu Z, Ran C, Zhang M. Intelligent-paint: a Chinese painting process generation method based on vision transformer. Multimedia Systems. 2024 Apr;30(2):112. https://doi.org/10.1007/s00530-024-01316-w

16. Yu Q, Shi C. An image classification approach for painting using improved convolutional neural algorithm. Soft Computing. 2024 Jan;28(1):847-73. https://doi.org/10.1007/s00500-023-09420-1

17. Hu B, Yang Y. Construction of a painting image classification model based on AI stroke feature extraction. Journal of Intelligent Systems. 2024 May 8;33(1):20240042. https://doi.org/10.1515/jisys-2024-0042

18. Wang X, Lyu J, Kim BG, Parameshachari BD, Li K, Li Q. Exploring multimodal multiscale features for sentiment analysis using fuzzy-deep neural network learning. IEEE Transactions on Fuzzy Systems. 2024 Jun 26. https://doi.org/10.1109/TFUZZ.2024.3419140

19. Tang Y, Zhang C, Wu J, Xie Y, Shen W, Wu J. Deep Learning-based Bearing Fault Diagnosis Using a Trusted Multi-scale Quadratic Attention-embedded Convolutional Neural Network. IEEE Transactions on Instrumentation and Measurement. 2024 Mar 12. https://doi.org/10.1109/TIM.2024.3374311

20. Waheed SR, Suaib NM, Rahim MS, Khan AR, Bahaj SA, Saba T. Synergistic Integration of Transfer Learning and Deep Learning for Enhanced Object Detection in Digital Images. IEEE Access. 2024 Jan 15. https://doi.org/10.1109/ACCESS.2024.3354706

21. Wang S, Cen Y, Qu L, Li G, Chen Y, Zhang L. Virtual Restoration of Ancient Mold-Damaged Painting Based on 3D Convolutional Neural Network for Hyperspectral Image. Remote Sensing. 2024 Aug 7;16(16):2882. https://doi.org/10.3390/rs16162882

22. Wang Y, Jiang Y, Ning X, Gao L. Bridging Cultural Perspectives: Developing a Sustainable Framework for the Comparative Aesthetic Evaluation of Eastern and Western Art. Sustainability. 2024 Jul 3;16(13):5674. https://doi.org/10.3390/su16135674

23. Chen F, Mai M, Huang X, Li Y. Enhancing the Sustainability of AI Technology in Architectural Design: Improving the Matching Accuracy of Chinese-Style Buildings. Sustainability. 2024 Sep 27;16(19):8414. https://doi.org/10.3390/su16198414

24. Zhang L, Chen Y, Zheng L, Yan B, Zhang J, Xie A, Lou S. Investigating the Surface Damage to Fuzhou's Ancient Houses (Gu-Cuo) Using a Non-Destructive Testing Method Constructed via Machine Learning. Coatings. 2024 Nov 18;14(11):1466. https://doi.org/10.3390/coatings14111466

25. Sun J, Ding H, Li N, Sun X, Dong X. Intelligent Fault Diagnosis of Hydraulic System Based on Multiscale One-Dimensional Convolutional Neural Networks with Multiattention Mechanism. Sensors. 2024 Nov 14;24(22):7267. https://doi.org/10.3390/s24227267

26. Ao J, Ye Z, Li W, Ji S. Impressions of Guangzhou city in Qing dynasty export paintings in the context of trade economy: a color analysis of paintings based on k-means clustering algorithm. Heritage Science. 2024 Mar 4;12(1):77. https://doi.org/10.1186/s40494-024-01195-4