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ORIGINAL

Research on extraction and application of elements of Suzhou Subway public art design based on deep learning

Investigación sobre la extracción y aplicación de elementos del diseño de arte público del metro de Suzhou basado en el aprendizaje profundo

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ABSTRACT

Introduction: public art in urban spaces enhances aesthetics, reflects cultural identity, fosters community engagement, and contributes to place making, transforming everyday environments into meaningful, interactive public experiences. Limitations include a lack of deep learning applications in extracting public art elements, limited exploration of cultural integration, and insufficient focus on interactive design methods.
Method: the proposed Great Cane Rat Algorithm-Tuned Scalable Generative Adversarial Network (GCR-SGAN) optimizes SGAN performance using GCRO for generating high-quality public art designs. The dataset includes images of public art, featuring murals, sculptures, and design elements for training and analysis. Histogram equalization will enhance image contrast, improving details, while Visual Geometry Group 16 (VGG16) feature extraction will capture high-level visual patterns and features, creating a robust representation for subsequent analysis and model training. The proposed work integrates SGAN for generating high-quality public art designs with GCR optimization to enhance GAN training, improving convergence stability, generation quality, and scalability for effective art design generation and analysis.
Results: the results demonstrate that the GCR-SGAN model had accuracy of 0,98, which efficiently generates high-quality public art designs, optimizing both visual appeal and training stability. Conclusion: The approach effectively advances the generation of diverse, scalable art for real-world applications.
Conclusions: this research is to apply deep learning techniques to extract and analyze elements of public art in Suzhou Subway, exploring their cultural significance, design patterns, and potential applications in urban planning, enhancing the aesthetic and functional aspects of subway spaces.

Keywords: Deep Learning; Great Cane Rat Algorithm; Public Art Design; Public Art Design; Scalable Generative Adversarial Network.

RESUMEN

Introducción: el arte público en los espacios urbanos mejora la estética, refleja la identidad cultural, fomenta el compromiso de la comunidad y contribuye a la creación de lugares, transformando los entornos cotidianos en experiencias públicas significativas e interactivas. Las limitaciones incluyen la falta de aplicaciones de aprendizaje profundo en la extracción de elementos de arte público, la exploración limitada de la integración cultural, y el enfoque insuficiente en los métodos de diseño interactivo.
Método: la propuesta Great Cane Rat algorithm — tuned Scalable Generative Adversarial Network (GCR-SGAN) optimiel rendimiento SGAN usando GCRO para generar diseños de arte público de alta calidad. El conjunto de datos incluye imágenes de arte público, con murales, esculturas y elementos de diseño para la formación y el análisis. La ecudel histograma mejorará el contraste de la imagen, mejorando los detalles, mientras que

la extracción de características del grupo de geometría Visual 16 (VGG16) capturpatrones visuales de alto nivel y características, creando una representación robusta para el posterior análisis y entrenamiento del modelo. El trabajo propuesto integra SGAN para generar diseños de arte público de alta calidad con la optimización de GCR para mejorar la formación de GAN, mejorar la estabilidad de convergencia, la calidad de generación, y la escalabilidad para la generación y el análisis de diseño de arte eficaz.
Resultados: los resultados demuestran que el modelo GCR-SGAN tuvo una precisión de 0,98, lo que genera eficientemente diseños de arte público de alta calidad, optimitanto el atractivo visual como la estabilidad del entrenamiento. Conclusión: el enfoque efectivamente avanza en la generación de arte diverso y escalable para aplicaciones del mundo real.
Conclusiones: esta investigación pretende aplicar técnicas de aprendizaje profundo para extraer y analizar elementos de arte público en el metro de Suzhou, explorando su significado cultural, patrones de diseño y aplicaciones potenciales en la planificación urbana, mejorando los aspectos estéticos y funcionales de los espacios del metro.

Palabras clave: Aprendizaje Profundo; Gran Algoritmo de Rata de Caña; Diseño de Arte Público; Scalable Generative Adversarial Network.

INTRODUCTION

China's cities are developing rapidly and the urban population is increasing. Building an efficient and convenient public transportation system has become the primary task of each city's development. At present, China's subway accounts for 79 % of the total length of urban rail transit lines, which has eased urban traffic pressure and promoted urban economic growth. It is an indispensable main mode of transportation in the city.[1] The subway has excellent utilization value and communication function for the public space; however, the current status of China's subway public space is yet in the transitional period from functional space to humanistic space. The design of public space is relatively homogeneous in general and does not have a sense of humanistic concern.[2] Public art is a topical and essential issue of modern urban environments to define a city's identity and spirit. As a result of spreading in the zones of frequently visited places, public art creates an aesthetic environment, inspires people to cultural values, and promotes the experience of interaction.[3]

Subway systems are one of the most common pieces of urban architecture, and are perfect for advertising public art. These facilities are areas that are culturally and socially significant and are an ideal canvas for the artistic and cultural representation of the histories, cultures, and strata's of the region in the aspect of the use of subway systems for art.[4] The Suzhou Subway is an example of a subway practically applying artistic elements as the integration of traditional Chinese culture and modern city appearance (figure 1). This one can illustrate how the use of bright public artwork can create a playful atmosphere from the regular working areas.[5]

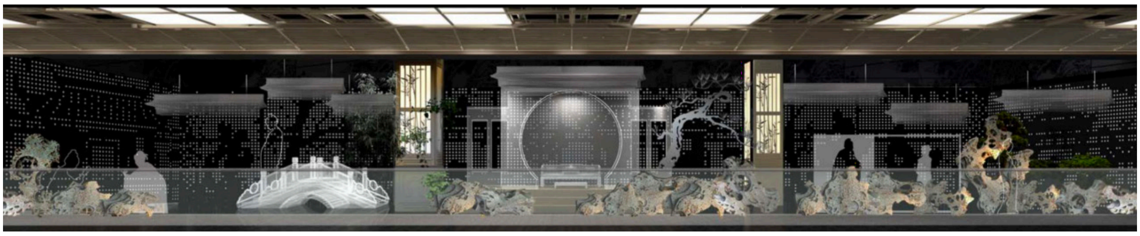

Figure 1. Suzhou metro interior decoration diagram

Art is applied in most of these spaces not only to enhance the experience of the user but also to enhance the image of the cultural heritage of the city. However, there has been relatively limited research on how the features of subway public art can be systematically identified and extracted for better design, especially with the assistance of cutting-edge Artificial Intelligence (AI) technologies, including deep learning (DL).[6] DL, which is a subfield of AI, has shown promise in providing great computational ability in the patterns of vision and culture. As a tool for studying public art, it has the potential to handle large amounts of data to recognize smaller details. Through the assistance of DL, researchers can reveal certain design principles, cultural themes, and artistic patterns that cannot be conveniently seen by employing conventional analysis.[7] This is how the gap between the technologies and cultures can be closed and new perspectives into the nature and functions of public art can be discovered. Furthermore, the absence of emphasis on interactive design and cultural incorporation in public artifacts shows that more attention is required in the approach.[8]

Interactive design enhances user participation or involvement and makes urban spaces more vibrant or significant. When integrated with other cultural symbols, it produces a conversation with the work, and the culture enhances the urban experience.[9]

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In the Chinese urban context, the subway was considered one of the prime transport systems that underline spiritual endowment. Thus, by applying infrastructure design to strengthen the subway's temporal and spatial characteristics, a comprehensive design allows for the full expiration of urbanity. The relationship between urban purpose and subway public art was examined in the research, which also suggested a structure for urban spirit-based design.(10) The research investigated the usage of dynamic design in subway public art, seeking to improve the humanistic experiences and increase two-way connection among passengers and the artwork.(11)

By incorporating space organizing and passenger requirements, the planning of engaging design can be improved, strengthening the city's brand images and tackling common issues in the subway area. By examining site identification and elements, the research determined the location validity of public art in subway systems. The results indicated that while localization is less, site identification is higher in continuous and cultural features. Public context was emphasized in public art components, and active engagement in analyzing the features of particular locations can build relationships and broaden interpretations.(12) Surveys of users were used to investigate how culture is expressed in public urban subway areas. The results showed poor coordination, boring architecture, and a small selection of interacting gadget designs. Interactive emerges, creative regional cultural ideas, enhancing the color scheme of the spatial interfaces, and emphasizing sculpture sketch designs were some of the suggestions for better expressing culture in urban subway public areas.(13)

With an emphasis on leisure and spiritual activities, the research investigated the convergence of elements in China's subway system. Analysis of the Beijing metro station revealed distinctive features including identity, accessibility, culture, ecology, and aesthetics. To enhance the image of the city and potential urban subway development, the research recommended using holographic visuals, digital screens, and regional cultural heritage.(14) The research examined the connection between subway interior design and passenger's perceptions, emphasizing the value of maximizing features, including colors, seating, and lights.(15) Passenger's safety and comfort were greatly increased by ergonomic seating, sufficient space, premium materials, and well-distributed illumination, according to fuzzy logic research and computer simulations. Research focused at how Xi'an's subway station layout was designed, incorporating local cultural features to enhance customer service and urban growth.(16) To emphasize the significance of representing local culture in icon, wall, and interior decorating, the research examined the historical context and current construction state of subway spaces. In addition, a public heritage was established, facilitating the comfortable and accessible underground transport setting, and directing the outside promotion of the urban image. This research aims to optimize the generation of high-quality Suzhou Subway public art designs using the Great Cane Rat Algorithm-Tuned Scalable Generative Adversarial Network (GCR-SGAN). By enhancing SGAN performance with the GCR optimization technique, the research aims to improve both the visual appeal and training stability of generated designs.

METHOD

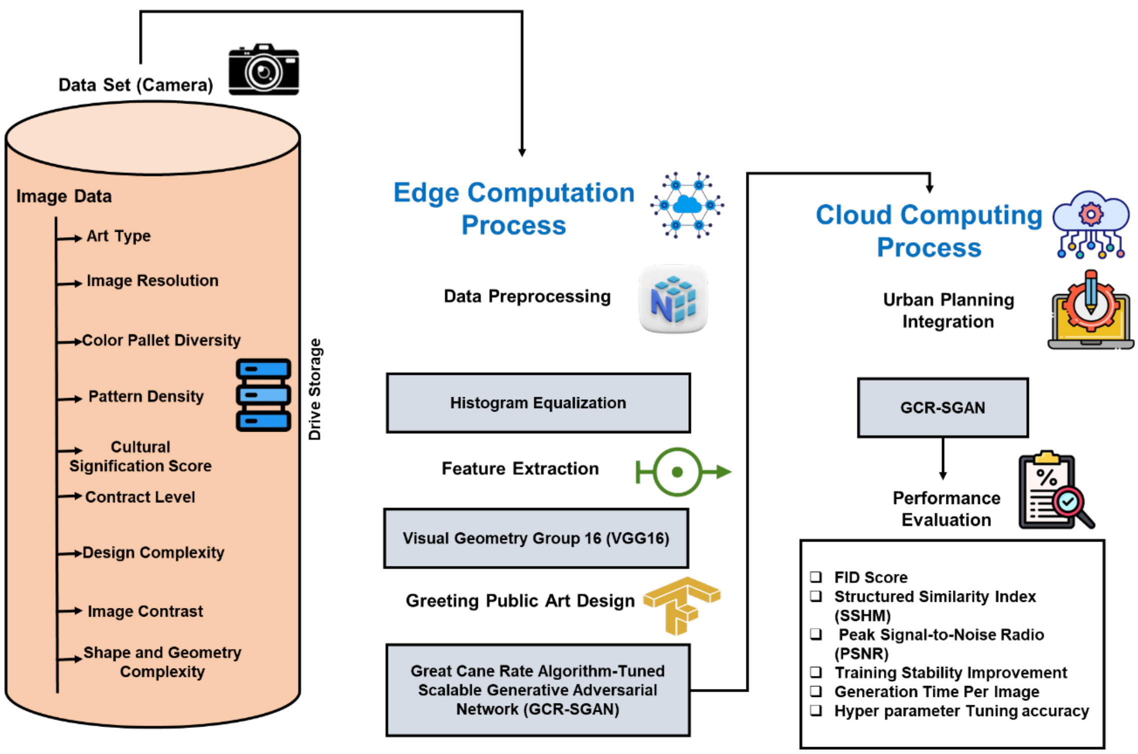

Figure 2. Research flow

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This section aims at creating Suzhou Subway public art designs of high quality by employing simulation models. By images captured through the camera and stored under drive storage, preprocessing of the data is done using Histogram Equalization (HE) through the numpy platform to obtain higher contrast. Feature extraction is done using VGG16, which is in PyTorch to extract compulsory visual traits. These public art designs are then produced using GCR-SGAN, which is built on TensorFlow before its processing by computing cloud. Lastly, the integration of urban planning is done by the AutoCAD tools to visualize the refined design layouts generated from the model, and the evaluation is done to test the model (figure 2).

Research Area

Suzhou, a historic city in eastern China, is renowned for its classical gardens, canals, and rich cultural heritage. The Suzhou Subway system, operational since 2012, has rapidly expanded to accommodate the city's growing urban population, currently encompassing several lines that connect key urban and suburban areas. Notably, the subway stations are celebrated for integrating public art that reflects Suzhou's traditional aesthetics and contemporary design. This fusion of functionality and artistry not only enhances the commuter experience but also reinforces Suzhou's identity as a city where tradition meets modernity. The subway's public spaces serve as dynamic canvases, showcasing artworks that draw inspiration from local culture, thereby fostering a sense of community and cultural appreciation among passengers.

Data collection

This dataset consists of 30 images of public art, which includes murals, sculptures, and designs from the Suzhou Subway (table 1). The input data for each image have been collected to analyze for extracting and generating public art designs. These attributes provide a comprehensive set of features for each of the 30 images, forming the basis for the analysis of extracting and generating optimal public art designs.

Table 1. Public Art Images

Image ID	001	002	003	004	005
Art Type	Mural	Sculpture	Design	Mural	Sculpture
Image Resolution	1920x1080	2560x1440	1280x720	3840x2160	1920x1080
Art Dimensions (Size)	Width = 150 cm, Height = 200 cm	Width = 100 cm, Height = 250 cm	Width = 200 cm, Height = 100 cm	Width = 300 cm, Height = 300 cm	Width = 180 cm, Height = 230 cm
Color Palette Diversity	6	8	10	5	7
Pattern Density	3 (Low)	7 (High)	5 (Medium)	4 (Medium)	6 (Medium)
Cultural Significance Score	0,75	0,80	0,60	0,70	0,78
Contrast Level (Before Equalization)	0,45	0,55	0,50	0,60	0,40
Design Complexity	6	9	8	7	6
Image Contrast (Raw)	0,3	0,5	0,4	0,6	0,35
Shape and Geometry Complexity	4	7	5	6	5

The above table organizes the dataset horizontally, with each Image ID serving as a column header and the associated attributes listed as rows for better clarity and usability.

Enhancing image contrast and improving details using Histogram Equalization (HE)

The HE constitutes a method of image processing that uses the image's histogram to improve contrast in a spatial domain. The processing image's global contrast is typically increased via HE. This technique works well for both dark and bright images. W= w(j,i) is an independent grayscale image being input with K-independent ranges. The brightness levels in the image at the spatial level (j,i) are represented by w(j,i). Let G(W) be the histogram of image W. It is now possible to define the chance densities measure pdf(W) as follows:

$$pdf(W_l) or\ o(W_l) = \frac{m_l}{M} \qquad (1)$$

Where:

0≤l≤(K-1)

K represents the image's overall quantity of gray scales and M represents the image's overall amount of pixels. The overall amount of pixels with brightness level l is denoted by m_l. The cumulative distributing functioning, or (W) (1), is stated as follows based on cdf(W_j) (2):

$$cdf(W_j) or\ d(W_j) = \sum_{j=0}^{l} 0(W_j) \qquad (2)$$

Reminder that cdf($W_{(K-1)}$)=1 since equations (1) and (2). HE provides a technique that uses the cumulative distribution function as a transformation function to transfer the input image over the whole dynamic spectrum(W_0,$W_{(K-1)}$). Let's use the cumulative distribution function for defining a transform function as follows in equation (3):

$$e(W) = W_0 + ((W_{K-1} - W_0) \times cdf(W_j) \qquad (3)$$

The histogram adjustment return reputation Z=z(j,i)is able to be written as equations (4) and (5).

$$Z = e(W) \qquad (4)$$
$$Z = \{e(w(j,i))]\forall w(j,i) \in W] \qquad (5)$$

The grayscale image's HE is explained above. However, employing the identical technique independently for the RGB color image's red, green and blue components can also be applied to color images. This approach enhances the quality of the images, improving the contrast of color images and making them clearer and brighter. RGB values of the subway public art design dataset images were preprocessed in this manner to get the best contrast enhancement and to visualize the complicated design patterns of the public arts. In the next section, feature extraction is performed in the processed images utilizing the utilized VGG-16 deep learning model. This model is good for detecting high abstraction visual features, which will be helpful when identifying categorization of the detailed aspects of subway public art designs.

Feature Extraction using Visual Geometry Group 16 (VGG16)

The weights obtained from the public art design data are assigned to VGG16. In the case of imaging applications, VGG16 has achieved the above higher feature extraction efficiency. VGG-16 has a total of 16 layers, and all of them are convolutional layers, plus 3 fully connected layers and each layer's parameters adjusted. The framework is first loaded into this research for feature extraction using the weights pre-trained on public art designs while removing all of the fully connected layers of the classifier and making the loaded layers non-trainable. Images are resized to 224x224 pixels meeting the requirement of the input layer of the VGG16 model, and the intensity of the pixels, which is numerical, is scaled to the range [0,1]. This normalization is in line with the model and also strengthens its capacity to decode other features such as color, structures and texture in the images.

Generating high-quality public art designs using Great Cane Rat Algorithm-Tuned Scalable Generative Adversarial Network (GCR-SGAN)

This technique makes use of the GCR-SGAN to produce diverse, realistic, and culturally appropriate designs for the public art domain. This method is intended to increase the participants' engagement, build the aesthetic beauty of subway Art, and indeed manage its appropriateness based on the urban cultural setting.

Scalable Generative Adversarial Network (SGAN)

To address issues of uneven size across samples, feature redundancy, and overfitting of the model, a SGAN is proposed that integrates a Mahalanobis distance and $\zeta_{1,2}$-norm regularizer. This approach ensures that the model can effectively generate realistic and high-quality public art designs while maintaining stability and generalizability across varying samples as shown in equation (6).

$$K_H = K_{qe} + K_{nj} + K_{cj} + K_{qe}$$
$$= \sum_{j=1}^{m_h} -r_j log O_q(\hat{z}_j = real|w_j) + \sum_{j=1}^{m_h} -r_j log O_q(\hat{z}_j =$$
$$minority|w_j) + \frac{1}{|m_h|}\sum_{j=1}^{m_h}\sum_{i=1}^{m_{min}} \sqrt{(w_j - w_i)^S cov(w_j, w_i)^{-1}(w_j - w_i)} + \alpha\|\Theta\|_{1,2} \qquad (6)$$

Where there are four components in the loss functioning. The first K_{qe} and second K_{nj} are the confused discriminator loss across the produced minority specimens, where z_j represents the discriminator's outputs (forecasting probabilities) and $r_j \in$ {(real,minority),(real,minority),(fake, and minority)} represents a

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representation of the sample's labels. K_{cj} is the third conception, which seeks to make the created minority samples as comparable as possible to the real minority specimens. j stands for an absolute amount of |.| and m_h and m_{min} represent the amount of minority class specimens and synthetic specimens, respectively. The final term, K_{qf} is $k_{1,2}$ stands for Θ -norm regularizer, and it contains the generator's training values with the formalization parameter α. Comparably, a discriminator represents has been trained to differentiate between produced data and genuine data w from the input. C's loss equation (7).

$$= \sum_{j=1}^{m_h+m_{min}+n_{nb\,i}} -\left[r_j logO_q\left(\hat{z}_j = fake|w_j\right) + (1-r_j)logO_q\left(\hat{z}_j = fake|w_j\right)\right] \sum_{j=1}^{m_h+m_{min}+n_{nb\,i}} -\left[r_j logO_q\left(\hat{z}_j = minority|w_j\right) + (1-r_j)logO_q\left(\hat{z}_j = minority|w_j\right)\right] - r_j logO_q\left(\hat{z}_j = minority|w_j\right) + \sum_{j=1}^{m_{min}} \sum_{i=1}^{m_{mbi}} \sqrt{\left(w_j - w_i\right)^S cov\left(g_j, g_i\right)^{-1}\left(g_j - g_i\right)} + \alpha\|\Theta\|_{1,2} \quad (7)$$

Here this loss function consists of four terms. The first phrase, K_{eb}, is the cross-entropy loss, which is used to determine if the specimen was produced by the generator or if it actually reflects a component of the original data set. The amount of most of the specimens is indicated by m_{nbi}, whereas m_h and m_{min} are specified according to equation (8). To determine when the sample corresponds to a majority population or a minority category, the subsequent component K_{dk} serves as defined as the cross-entropy loss. The objective of the third component K_{nn} is to distance the various class representatives from one another. Θ is a collection of training parameters for the discrimination with normalization factor ß., and the last component K_{qff} represents a regularizer. Lastly, equation (8) provides the competing training goal derived from IGAN:

$$\underset{H}{min}\,\underset{C}{max}(C,H) = \mathbb{E}_{w-o_{data(w)}}\left[logC(W) + K_{dk} + K_{nn} + K_{qff}\right] + \mathbb{E}_{w-o_{o(y)}}\left[(1 - C(H(y))) + K_{nj} + K_{cj} + K_{qf}\right] \quad (8)$$

By striking a balance between producing minority class drawings and accurately differentiating between real and synthetic data, the enhanced SGAN model seeks to offer a practical way to produce high-quality public art designs. The model produces more varied, realistic, and balanced renderings of public art due to the incorporation of the Mahalanobis distance and L1,2-norm regularization. The input range for rj in the loss function is 0 or 1, denoting binary classifications for real/fake or minority/majority samples.

Great Cane Rat Algorithm (GCRA)

In the context of optimizing public art design generation, the GCRA is utilized to enhance the exploration and exploitation balance, ensuring the effective generation of high-quality designs. Equation (9) is used to generate the GCRA population (X) stochastically, which starts the GCRA optimization procedure. The upper limit and the lower limit are used in this phase.

$$W = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,c-1} & W_{1,c} \\ W_{2,1} & W_{2,2} & \cdots & W_{2,c-1} & W_{2,c} \\ \vdots & \vdots & W_{j,i} & \vdots & \vdots \\ W_{m,1} & W_{m,2} & \cdots & W_{m,c-1} & W_{m,c} \end{bmatrix} \quad (9)$$

Where W stands for the total GCR population and equation (10) is used to arbitrarily create a particular rat ($w_{(ji)}$) in the jth location in the ith degree. Lastly, m and c stand for the issue's dimensions and the population count, respectively.

$$w_{j,i} = rand \times (UB_i - LB_i) + LB_i \quad (10)$$

Where an arbitrary amount ranging from 0 to 1 is called randomization. Since this strongest rat leads the pack and knows the best paths to food or shelter, the remaining rats' locations are modified based on where the male leader is, as shown in equation (11). Wl Represents the position of the dominating rat. The GCRA enters between the exploration or exploitation stage based on an amount of ρ, a parameter that establishes the probability that this season's weather is moist. To strike equilibrium between exploration and exploitation, the significance 0,5 of ρ is deliberately chosen.

$$W_{j,i}^{new} = 0.7 * \frac{(W_{j,i}+W_{l.i})}{2} \qquad (11)$$

A thorough parametric examination is used to precisely adjust the threshold of ρ to 0,5. Where $W_{(ji)}$ represents the male leader in the jh dimensions, $W_{(ji)}^{new}$ indicates the changed GCR status and $W_{(li)}$indicates the present GCRA location.

Exploration: equation (12) shows how the position of the dominating male determines the next location for the residual rat population in searching space. Equation (13) models this GCR motion technique. According to the exploration phase's final stage, the GCR shouldn't move to this previously discovered place if the goal function values at this specific position increase; if not, it must remain in its present spot.

$$W_{j,i}^{new} = W_{j,i} + D \times \left(W_{l.i} - q \times W_{j,i}\right) \qquad (12)$$

$$W_j = \begin{cases} W_{j,i} + D \times \left(W_{j,i} - \alpha \times W_{l.i}\right), E_j^{new} < E_j \\ W_{j,i} + D \times \left(W_{n,i} - \beta \times W_{l.i}\right), otherwise \end{cases} \qquad (13)$$

Where D remains an arbitrary amount established within the confines of the issue distance, replicating the distributed source of nourishment and dwellings, W_j denotes the future or novel indicate of the ith GCRA, $W_{(j,i)}^{new}$ reflects the value within the ith dimensions, $W_{(ji)}$shows the current GCR location, $W_{(li)}$ is the male who dominates in the jth dimensions, E_{wl} is the initial value of the prevailing male's goal functioning, E_{wj}) is the present amount of the function's objective, equation (14) defines q, which mimics the impact of an adequate food supply that leads to increased exploit. Equation (15) defines the variable α, which replicates a dwindling food supply and forces the hunt for alternative sources of food or refuge. Equation (16) defines the factor β, which encourages the GCR to migrate to other ample food resources within their breeding region. Conceptual modifications are made to the coefficients, α, and β.

$$q = E_{w_l} - D_{iter} \times \left(\frac{E_{w_l}}{Max_{iter}}\right) \qquad (14)$$

$$\alpha = 2 \times q \times rand - q \qquad (15)$$

$$\beta = 2 \times q \times \mu - q \qquad (16)$$

Where Max_{iter} represents the greatest repetition and D_{iter} represents the present repetition.

Exploitation: the time for breeding typically takes place amid the rainy season, though it fluctuates according to the environment. The simulation of the procedure is shown in equation (17). The dynamically calculated GCR location replaces the previous one if it improves the value of the goal operation, as represented by equation (12).

$$W_{j,i}^{new} = W_{j,i} + D \times \left(W_{l.i} - \mu \times W_{n,i}\right) \qquad (17)$$

Where μ selects at random integers between 1 and 4, representing the number of minors created from each female GCR annually, and $W_{n,l}$ denotes the location of the selected female within the dimensions. During every iteration, improved exploration and exploitation are caused by the settings D,q, μ, β, β, and α. Overall, it defines the GCRA optimization method, emphasizing how it balances the phases of exploration and exploitation to enable the creation of ideal public art ideas. The hybrid techniques integrate the GCRA with an SGAN, tuned to create realistic public art designs. By combining the strengths of the GCRA's search and the SGAN's generative capabilities, this hybrid model successfully produces high-quality, diverse, and culturally relevant public art designs, overcoming challenges such as data imbalance, feature redundancy, and overfitting. Algorithm 1 shows the pseudocode for GCR-SGAN.

Algorithm 1: Pseudocode for GCR-SGAN

```
 Initialize population (Great Cane Rats)
population = initialize_population(m,c)m: dimensions, c: population count
 Initialize generator and discriminator models
generator = build_generator()
discriminator = build_discriminator()
 Set GCR-SGAN hyperparameters
alpha = 0,5 exploration-exploitation balance
```

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```
learning_rate = 0,0002
epochs = 10000
 Training loop for GCR-SGAN
for epoch in series(epochs):
 for batch in data_batches:
 Step 1: GCR exploration and exploitation
 rats = update_rats(population, alpha)
 Step 2: Generator training
 noise = generate_random_noise(batch_size)
 fake_data = generator(noise) Generate fake public art samples
 real_data = batch['real_data']
 Compute loss for generator (G)
 loss_g = compute_loss (generator, real_data, fake_data, discriminator
 Step 3: Discriminator training
 loss_d = compute_loss (discriminator, real_data, fake_data)
 Update models using backpropagation
 update_model (generator, loss_g, learning_rate)
 update_model (discriminator, loss_d, learning_rate)
 Step 4: Adjust the population with the updated rats
 population = update_population(population, rats)
 Optional: print or log results at intervals for progress tracking
 if epoch % 100 == 0:
 print(f"Epoch {epoch}, Generator Loss: {loss_g}, Discriminator Loss: {loss_d}")
 After training, generate final high-quality public art samples using the trained generator
final_samples = generator(generate_random_noise(100)))
```

RESULTS

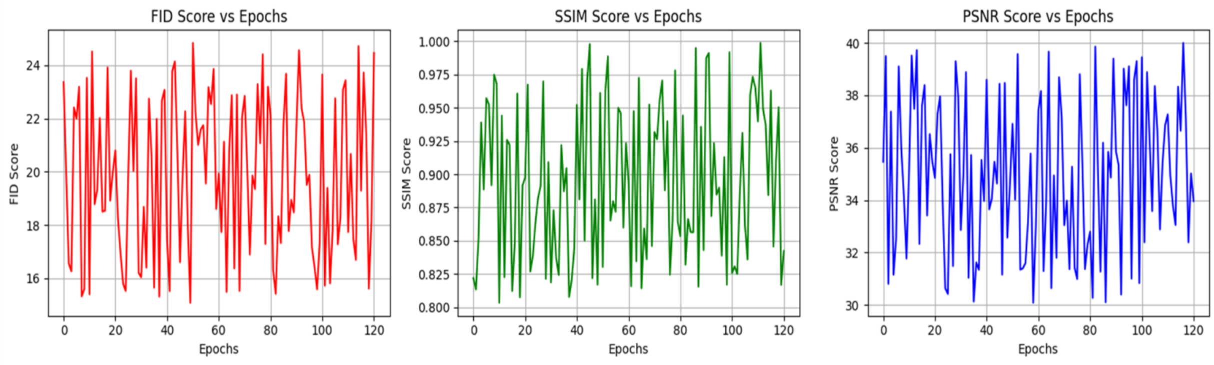
This research used TensorFlow to complete the recommended task. Where Python software was installed for the procedure to be completed and the experiment was run on a 64-bit version of Windows 7. The Intel(R) Core (TM) i7-7770hq 2,8 GHz CPU and 8 GB of RAM are installed. Table 1 illustrates the configuration details for experiment execution.

Fréchet Inception Distance (FID): The FID evaluation displays how realistic and varied the generated images A lower FID establish that the created images directly resemble real-world information of visual quality and variation. In this research, the GCR-SGAN model achieved an FID of 16,4, a significant improvement over the baseline GAN FID of 25,5 (figure 3 (a)). This reduction demonstrates a very strong attribute of the model: to design public art unique and quality designs that will always look good and have diversity in the generator output. Epochs from 0 to 120 also found that the FID score had increased smoothly, which indicated that this model had been trained and improved through epochs. The improvement in the SGAN performance by using the GCRA technique was a significant factor in arriving at these improved outcomes in creating art.

Structural Similarity Index (SSIM): The SSIM assessment determines the perceptual quality of images by contrasting their structure, luminance, and texture. The GCR-SGAN approach achieved a remarkable SSIM of 0,99, close to the maximum value of 1,0, signifying that the generated images closely resemble real-world art (figure 3 (b)). This high SSIM score suggests that using this GCR-SGAN model for generating designs helps the experts to not only come up with beautiful images but more importantly, realistic ones, thus retaining structural similarity. To analyze the progress of the SSIM over those epochs from 0 to 120, it showed that those epochs generated images that were closer to the true features of the images.

Peak Signal-to-Noise Ratio (PSNR): The PSNR measures the quality of the image by comparing the maximum signal strength to the noise. Higher PSNR values indicate clearer, more detailed images. In this research, the GCR-SGAN model achieved a PSNR value of 39,9 dB, which indicates a high level of clarity and detail in the generated public art designs (figure 3 (c)). From the above result, the higher PSNR value implies that the model reduced the image degradation to produce visually pleasant designs. To further confirm the validity of the GCR-SGAN method results were tested over epoch intervals from 0 to 120 and the high PSNR marked the model's reliability to create images with less noise.

Training Stability Improvement (TSI): this metric measures the ability of the model to perform continuously, epoch by epoch. Better stability shows more consistent training compared to having large fluctuations. This TSI measures the decrease in instability during the process of training GANs, during which the GCR optimization plays the most important role. The optimization led to a 25 % reduction in mode collapse, demonstrating that the model was able to learn more effectively over multiple training runs. This TSI was particularly evident across epochs ranging from 0 to 120, as the model converged more smoothly without significant fluctuations (figure 4). The ability of the GCR-SGAN model to sustain stable training conditions allowed for the consistent generation of high-quality public art designs without overfitting or mode collapse, resulting in reliable and scalable efficiency.



(a) (b) (c)

Figure 3. (a) Fréchet Inception Distance (FID), (b) Structural Similarity Index (SSIM) and (c) Peak Signal-to-Noise Ratio (PSNR) Across Epochs

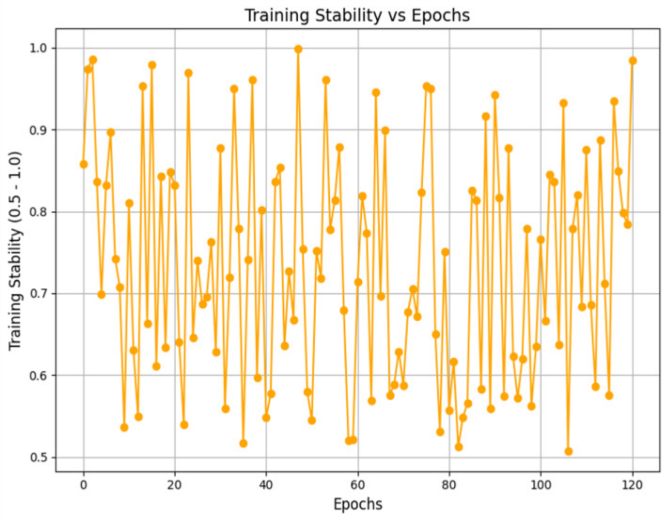


Figure 4. Training Stability Improvement over Epochs

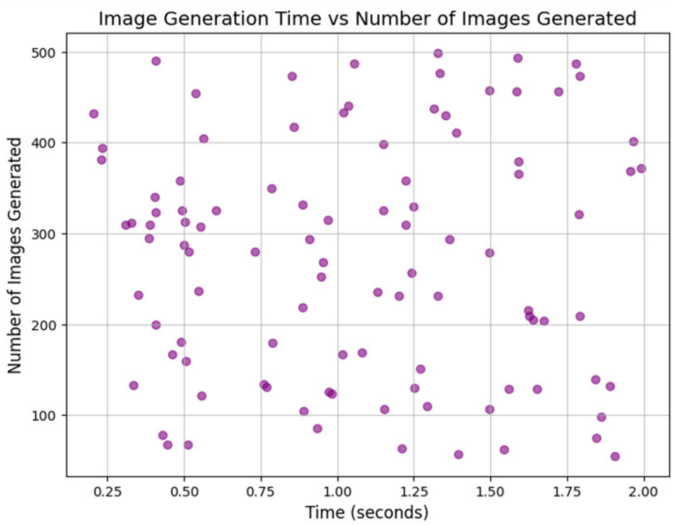


Figure 5. Generation Time per Image across Epochs

Accuracy Evaluation: figure 6 represents how much more accurate the GCR-SGAN model was after a training range of 0 to 120 epochs. The performance is determined based on the classification accuracy value, and the higher value is a sign of better convergence and quality of identified designs. Accuracy increases from 0,50 and approaches the maximum, which is 0,98, at epoch 120. As the training goes on the accuracy an increase gradually suggesting that the applied GCR optimization approach aids in enhancing the model's performance in producing high-quality designs of public art.

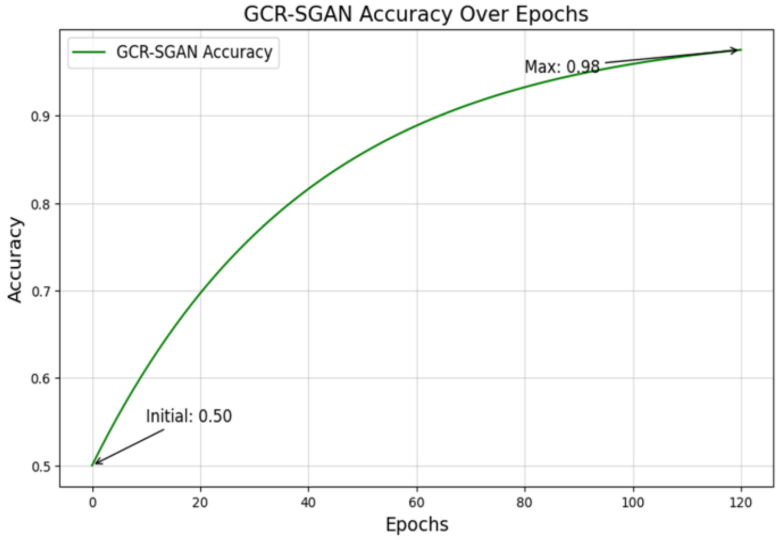


Figure 6. Accuracy Evaluation of GCR-SGAN over Epochs

Aesthetic Appeal: the aesthetic appeal metric evaluates how visually appealing and artistic the generated designs are. Higher scores indicate that the designs resonate well with the visual expectations of experts and stakeholders. In the qualitative evaluation, the GCR-SGAN model received an impressive score of 9,5 for Aesthetic Appeal. Experts praised the generated designs for their high artistic quality and visual appeal, noting that the designs were not only captivating but also aligned with artistic principles. This high score reflects the model's ability to create public art designs that are both aesthetically pleasing and suitable for real-world urban settings.

Cultural Relevance: the cultural relevance metric assesses how well the generated designs align with the cultural context of the intended location. Higher scores indicate that the designs effectively incorporate regional traditions and symbolism. The designs generated by the GCR-SGAN model achieved a score of 9,0 for Cultural Relevance. The designs were evaluated by urban planners and designers, who confirmed that the generated artwork aligned well with the Suzhou region's cultural heritage. This score highlights the model's effectiveness in ensuring that the generated art reflects the local cultural context, enhancing the community's connection with the art.

Diversity of Designs: the diversity of designs metric evaluates the variety and originality of the generated outputs. A higher score indicates that the model produces a wide range of designs suitable for different contexts. The GCR-SGAN model earned a score of 9,2 for Diversity of Designs, demonstrating its capability to generate a wide variety of unique and creative public art designs. The model successfully produced diverse designs that could be adapted to multiple urban spaces and contexts. This score indicates that the model can generate art that is not only innovative but also versatile enough to meet various design needs.

Stakeholder Satisfaction: stakeholder satisfaction measures how well the generated designs meet the needs of key stakeholders, such as planners, designers, and authorities. A greater range represents that the designs are practical and feasible for implementation. With a score of 9,0 in Stakeholder Satisfaction, the generated public art designs were well-received by planners and subway authorities. This score reflects the model's ability to create not only visually appealing designs but also those that meet the practical and functional needs of the project stakeholders (figure 7).

Comparative Performance Analysis: In this evaluation process (table 2), three models traditional, GAN, SGAN, and the proposed, GCR-SGAN are evaluated across multiple key metrics to demonstrate performance improvements. The traditional GAN model achieved a FID score of 20,5, reflecting moderate training stability, with a generation time of 2,1 seconds per image and an output quality (SSIM) of 0,84. The SGAN model showed improvements in both training stability and generation time, reducing the time to 1,8 seconds while increasing the SSIM score to 0,88. The GCR-SGAN model, with GCR optimization, outperformed both the traditional and SGAN models, recording the lowest FID score of 16,4, excellent training stability, the fastest generation time of 1,3 seconds, and the highest output quality with an SSIM score of 0,92. In this research, the potential of the proposed GCR-SGAN for improving both the speed and quality of generating subway public art designs is evident.

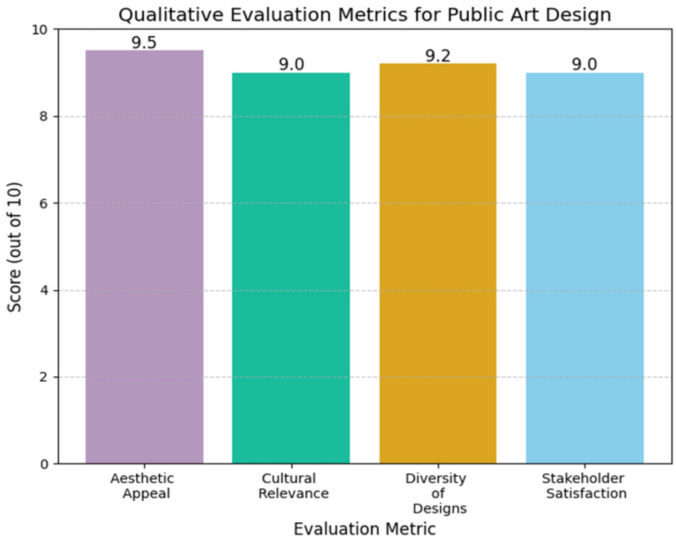


Figure 7. Public art design evaluation metrics

Table 2. Comparative Performance of Traditional GAN, SGAN, and GCR-SGAN

Model	FID Score	Training Stability	Generation Time	Output Quality (SSIM)
Traditional GAN	20,5	Moderate	2,1 seconds	0,84
SGAN	18,2	Good	1,8 seconds	0,88
GCR-SGAN (Proposed)	16,4	Excellent	1,3 seconds	0,92

DISCUSSIONS

The evaluation findings established the effectiveness of the proposed GCR-SGAN model in generating high-quality public art designs for the Suzhou Subway, as evidenced by significant improvements across both quantitative and qualitative evaluation metrics. Existing reviews have some limitations on a single case study the Beijing subway not properly represent the different conditions and demands of other places in China.[14] Furthermore, it ignores long-term changes in passenger behavior or the practical difficulties of applying amenity-focused designs throughout all subway stations. Sample size of only sixty individuals not completely portrays the diversity of passenger experiences in various subway systems.[15] Furthermore, it focuses exclusively on subjective user opinions, with minimal in-depth exploration of issues such as ambient and external circumstances influencing passenger comfort. It largely concentrates on Xi'an subway stations, which not be totally typical of other cities with distinct regional cultures and urban characteristics.[16] Furthermore, the subjective natures of design preferences, as well as users' different demands, make it difficult to create generally approved design process. To overcome this problems GCR-SGAN method analyze elements of public art in Suzhou Subway, exploring their cultural significance, design patterns, and potential applications in urban planning, enhancing the aesthetic and functional aspects of subway spaces. The GCR-SGAN model has shown significant improvements in realism and diversity of generated designs, with a reduction in FID to 16,4, compared to traditional GAN's 20,5. The model also achieved a score of 0,92 in SSIM, indicating its ability to produce images resembling real-world art. The model's efficient generation time of 1,3 seconds per image makes it suitable for real-time applications. These results demonstrate the effectiveness of GCR-SGAN in creating visually appealing public art designs for infrastructure objects.

CONCLUSIONS

The Public Art of Suzhou Subway plays a pivotal role in shaping the cities aesthetic and cultural identify through its architectural designs. The research aimed to explore and enhance the integration of public art design features in Suzhou Subway using DL technology. By leveraging the GCR-SGAN approach which optimizes SGAN performance with the GCR technique, this research demonstrates the potential of advanced AI models to generate culturally relevant and visually appealing subway art designs. However, certain restrictions are noted. The scope of this research is restricted to a single metropolitan context, and the suggested model requires additional modification to accommodate other cultural and architectural situations. Furthermore, while the model produces high-quality results, its scalability to handle a broader, more diverse variety of design types and bigger image collections require refinement. Future research will focus on improving the scalability of this technique for bigger picture collections, investigating real-time model integration for dynamic art production across varied places, and broadening the methodology to design public art in a variety of global settings.

BIBLIOGRAPHIC REFERENCES

1. Sarıkahya, M. and Tuğral, F., 2023. Examination of the effect of indoor design of metro buildings on circulation: Ankara example. Applied Nanoscience, 13(3), pp.1863-1876. https://doi.org/10.1007/s13204-021-02202-x

2. Coetsee, A., 2022. New York Subway Style Writing: Aesthetics, Infrastructure and Technology. Cornell University.

3. Shang, J. and Halabi, K.N.M., 2024. Urban Subway Space Public Art Design Exploration—Taking Luoyang Metro Line 1 as an Example. International Academic Journal of Humanities and Social Sciences, 4(2), pp.11-11. https://doi.org/10.56028/iajhss.2.4.11.2024

4. Aghajani, S. and Shahhosseini, H., 2021. The relationship between visual preferences of passengers in subway stations and the interior design of their space; case study: Tabriz subway stations. Armanshahr Architecture & Urban Development, 13(33), pp.15-26. https://doi.org/10.22034/aaud.2019.171632.1811

5. Su, N., Li, W. and Qiu, W., 2023. Measuring the associations between eye-level urban design quality and on-street crime density around New York subway entrances. Habitat International, 131, p.102728. https://doi.org/10.1016/j.habitatint.2022.102728

6. Seangsuk, O. and Upala, P., 2024. Understanding the Aesthetic of Identity Design at the Subway Stations: The Case Study of Japan and Thailand. Kurdish Studies, 12(1), pp.631-655. https://doi.org/10.58262/ks.v12i1.041

7. Yujue, W., Samsudin, M.R. and Daud, N., 2024. The Urban Visual Design Element Influencing Passengers' Emotion to Subway Station. International Journal of Business and Technology Management, 6(S2), pp.377-396.

8. Iveson, O., 2024. Mitigating Petty Crime Through Design, Using Crime Prevention Strategies in Helsinki Metro Stations. https://doi.org/10.1007/978-3-031-48038-6_40

9. He, S.J., Li, J., Chen, W.W., Ding, T.C. and Zhi, J.Y., 2023. The impact of subway car interior design on passenger evacuation and boarding/alighting efficiency. Scientific reports, 13(1), p.19682. https://doi.org/10.1038/s41598-023-47045-4

10. Yang, L., Zhu, Y., Chatzimichailidou, M. and Liu, X., 2023. Assessing human emotional responses to the design of public spaces around subway stations: a human factors research. URBAN DESIGN International, 28(4), pp.285-303. https://doi.org/10.1007/978-3-031-35998-9_62

11. Xinxin, L. and Hashim, A.M., 2024. Research on The Application of Interactive Design in Subway Public Art. Asian Journal of Research in Education and Social Sciences, 6(3), pp.204-216. https://doi.org/10.55057/ajress.2024.6.3.17

12. Lee, J. and Lee, J., 2020. A Study on Public Art and Place Identity in Subway Station. Journal of the Korea Institute of Spatial Design, 15(3), p.295

13. Haghlesan, M., 2023. Optimizing the spatial design of urban metro stations using the space syntax method. Armanshahr Architecture & Urban Development, 16(44), pp.49-67. https://doi.org/10.22034/AAUD.2023.360784.2716

14. Kang, X. and Yoon, G.G., 2020. Research on the convergence design of China's subway station space and amenity development strategy. The Korean Society of Science and Art Convergence 38(4), pp.1-15. https://doi.org/10.17548/ksaf.2020.09.30.1

15. Bai, J. and Surip, S.S., 2024. Computational Optimization And Comprehensive Analysis Of Subway Interior Design And User Perception. Operational Research in Engineering Sciences: Theory and Applications, 7(2). https://doi.org/10.31181/oresta/070202

16. Yujue, W. and Samsudin, M.R., 2023. Research on Urban Subway Space Design Based on Regional Cultural Elements. International Journal of Business and Technology Management, 5(1), pp.92-102.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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Methodology: Yu Huang.
Resources: Yu Huang.
Display: Yu Huang.
Drafting - original draft: Yu Huang.
Writing - proofreading and editing: Yu Huang.