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FCIGAN: A Three-dimensional Ink Rendering Brushwork Based on Generative Adversarial Network

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Abstract. *Three-dimensional ink rendering is a NPR (Non-Photorealistic rendering) art style, widely used in a range of fields, including gaming and animation.Although, CycleGAN is a standard image transformation model, however, it prefers Western painting methods, resulting in less-than-ideal ink rendering effects. As a result, this investigation focuses on the characteristics of ink painting by merging attention processes with three-dimensional depth information. It emphasizes differences in ink color depth to depict the relationship between distance and three-dimensional perception of things in the picture. It also makes use of methods like line thickness and curves to show the contours and textures of things. Additionally, to make the picture as close to the real traditional Chinese ink painting as possible, we use the thickness and bending of lines to show the outline and texture of objects, and highlight the key points or depict some details in the picture by leaving blank. This method is named FCIGAN (Freehand Chinese Ink Generative Adversarial Network). We have also gathered and created a matching dataset called FCI Images to aid in the experiment's smooth progression. In conclusion, the experimental results show that, the FCIGAN approach suggested in this research has much better performance when compared to conventional techniques and may be used more effectively in the 3D rendering field.*

Keywords: Ink and wash rendering, Deep learning, Attention mechanism

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1. **Introduction.** The globalization of traditional Chinese culture will unavoidably necessitate new avenues for distribution due to the rising popularity of metaverse-related technology nowadays. A historic Chinese art form with distinctive terminology and methods is ink painting [1]. It exhibits a distinct unique notion, atmosphere, and artistic conception using merely water and ink. As a result of this, ink painting has received extensive attention and appreciation in the international arena. As a form of NPR creative style in computer rendering technology [2, 3, 4, 5], three-dimensional ink rendering has significant aesthetic value and significance. By continuously improving and promoting three-dimensional ink rendering technology, Chinese traditional culture can be inherited and developed. Many excellent models for picture style transfer have emerged with the introduction of GAN (Generative Adversarial Network) [6], with Pix2Pix [7] and CycleGAN [8] serving as prominent examples. However, in the area of visual style transfer, it is quite challenging to obtain a matched dataset. Due to its unsupervised nature, CycleGAN can successfully address this difficulty, but it is unable to translate pictures from the source domain into the target image with aesthetic value, perhaps leading to the loss of crucial information. CycleGAN's picture modification is based on pixel-level manipulation and lacks a thorough knowledge of semantics. As the consequence, the resulting target domain picture and the source domain image will lack semantic consistency. Therefore, CycleGAN supports Western painting techniques that emphasize texture, and the effect on ink rendering will be unsatisfactory [9], [10]. This paper will make use of Deep learning technology, attention mechanisms, and three-dimensional depth information increase the constraints of ink painting expressive means and enable deep integration of computer technology and ink painting techniques. This study will open up new development avenues for Chinese ink painting in the computer internet ecosystem, and it will have a significant impact on the inheritance and development of scientific and technical traditional Chinese art and culture. This project will do ink rendering research on the three-dimensional scene of Sanfang Qixiang, a picturesque site in Fujian Province, China.

2. **Method.** Figure 1 depicts the FCIGAN structure presented in this research. The model trains on non-paired datasets and gives two mappings: $G : X \to Y$ and $F : Y \to X$. The input 3D picture domain is X, the target ink image domain is Y, and the associated discriminators are D_Y and D_X.

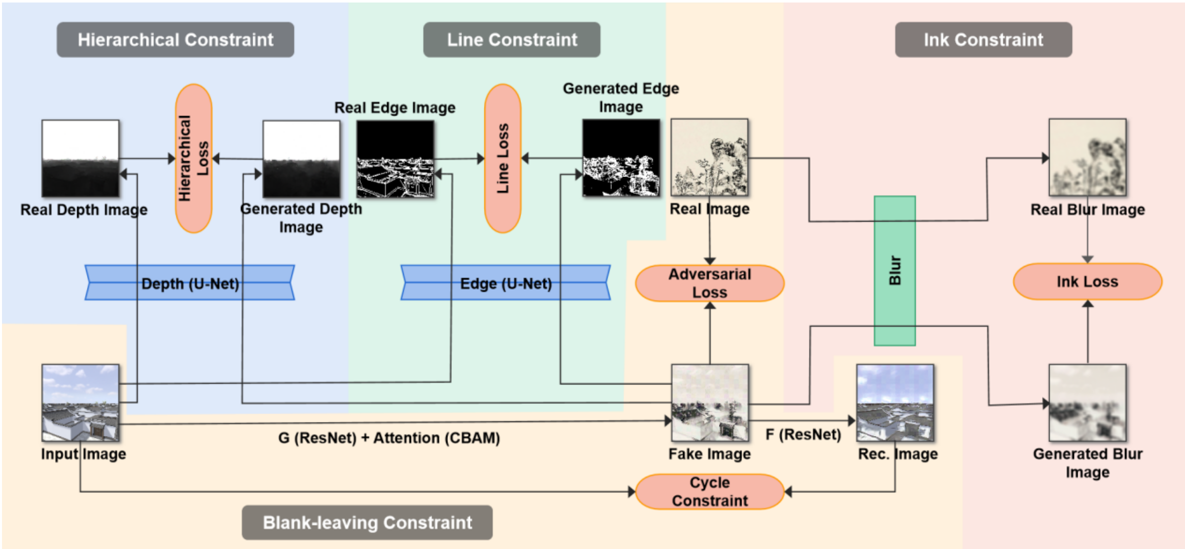

FIGURE 1. FCIGAN

ResNet [11] overcomes the problem of gradient vanishing in deep convolutional neural networks via skip-connect in this model, enabling deeper network topologies to be built for greater in-depth feature extraction. Therefore, this paper uses it as the network model for the generator G and F.At the same time, PatchGAN [8] has the property of partitioning pictures into numerous tiny blocks for discrimination, which enhances training stability and detail preservation. As a result of this, it is employed as the network model in this study for all discriminators. In the process of ink rendering, FCIGAN extracts the diffusion feature and the overall tone through fuzzy processing, and carries out ink color constraint; edge detection is used to achieve line constraints; attention mechanisms, cycle consistency, and adversarial loss are combined to constrain the blank-leaving in the image; and finally, the model achieves final constraints on the hierarchical sense of the picture based on three-dimensional depth information. In the next section, this essay will offer a thorough introduction from four perspectives: ink color, lines, vacant space, and hierarchical sense.

2.1. **Ink colour.** Ink color is an essential element in ink painting, as it directly influences the artwork's temperament and artistic conception through variations in intensity, depth, and gradation. In the ink constraint, more attention will be paid to the overall situation of the picture. In this study, the image is blurred using a Gaussian blur technique to minimize the amount of detailed information in the image and suppress the high-frequency noise, which helps the network concentrate on the overall tonal condition and pay more attention to global aspects. The loss $L_{ink}(G, D_{blur})$ of the ink color constraint is illustrated in the following equation:

$$\mathcal{L}_{ink}(G, D_{blur}) = \mathbb{E}_{y \sim p_{data}(y)}[log(D_{blur}(Blur(y)))] + \mathbb{E}_{x \sim p_{data}(x)}[log(1 - D_{blur}(Blur(G(x))))] \tag{1}$$

The function in the above formula Blur the picture, and the D_{blur} kernel, which is the discriminator for the Gaussian blurred image, completes this stage.

2.2. **Lines.** Lines are primarily represented through thickness, softness, hardness, and fluency in ink paintings as one of the fundamental ways to depict the shape and structure of objects. Light and delicate lines can represent the smooth texture of mountains and rocks in landscape paintings, but powerful and stiff lines can show the vitality and force of birds and animals in flower and bird paintings. Lines may also impact the rhythm and rhythm of the picture, giving it vitality. The text uses a pre-trained U-Net [12] as the extractor for the edge detection picture: Edge, to extract the line outlines, and the GraphCut [13] algorithm's edge detection image as training data. The key justification for using U-Net in this instance is that it is a deep learning model that is frequently used in picture segmentation and can provide segmentation results by mixing low-level characteristics with high-level features, increasing the accuracy of edge information. At the same time, despite being quite small in comparison to other deep neural network models, it performs very well. The GraphCut algorithm, on the other hand, is a image segmentation method based on graph-theoretic that creats a weighted directed graph to represent pixels in an image as nodes in a graph, using the similarity between pixels as the weights of the connected edges between nodes, and then uses a least-cut algorithm to segment the image into different regions. The GraphCut method has an advantage over other picture segmentation algorithms in that it can handle complicated situations and maintains more detailed information, considerably improving training data quality. However, because of its inefficiency, it is not employed directly as a module in the neural network algorithm there. The last line constraint's loss $L_{edge}(G)$ is given in the following equation:

$$\mathcal{L}_{edge}(G) = \mathbb{E}_{x\sim p_{data}(x)}[||Edge(G(x)) - Edge(x)||_1]. \tag{2}$$

2.3. **Blank-leaving.** Blank-leaving is a deliberate attempt to leave blank space in an ink painting to generate a balanced and harmonious appearance, and it is frequently used to accentuate the subject matter of a picture or the mood of a picture. blank-leaving is also viewed as an aesthetic notion in Chinese cultural heritage, emphasizing the value of 'nothing' over 'something' and communicating a profound philosophical and cultural connotation. Dropout is therefore employed not only to remove a part of the neurons for some randomization but also to selectively focus on certain portions of the picture via the attention mechanism, thereby leaving certain blank spaces to better produce images with ink painting qualities. As a result, CBAM (Convolutional Block Attention Module) [14] is chosen as the attention module in this research. The Sigmoid function in the traditional CBAM is replaced with the Tanh function since the FCIGAN model processes the data normalized to [-1,1]. CBAM is a neural network module that integrates channel attention and spatial attention and may focus on essential channels as well as positional properties. This can assist the network pay more attention to the vacant region, allowing it to generate pictures with ink painting qualities. At the same time, CBAM's channel attention method allows it to efficiently modify the ink color and overall tone of the image. To allow the produced picture to preserve as much information from the source domain as feasible, a cyclic consistency loss $\mathcal{L}_{cycle}(G, F)$ is applied to restrict suitably λ_c working as weight coefficient so that $F(G(x)) \approx X$ and $G(F(y)) \approx Y$. Thus, there are two concurrent generative adversarial losses, $\mathcal{L}_{GAN}(G, D_Y, X, Y)$ and $\mathcal{L}_{GAN}(G, D_X, Y, X)$. The following equation depicts the final white-out loss $\mathcal{L}_{blank}(G, F, D_Y, D_X)$:

$$\mathcal{L}_{cycle}(G, F) = \mathbb{E}_{x\sim p_{data}(x)}[||F(G(x)) - x||_1] + \mathbb{E}_{y\sim p_{data}(y)}[||G(F(y)) - y||_1] \tag{3}$$

TABLE 1. Computer-related configurations used in the experiment

OS	Ubuntu 20.04.4 LTS (64 bit)
CPU	Intel® Xeon(R) Silver 4210 CPU @ 2.20GHz × 40
GPU	NVIDIA GeForce RTX 3080 Ti (12GB) × 4
RAM	128 GB

$$\mathcal{L}_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y\sim p_{data}(y)}[log(D_Y(y))] + \mathbb{E}_{x\sim p_{data}(x)}[log(1 - D_Y(G(x)))] \tag{4}$$

$$\mathcal{L}_{GAN}(F, D_X, Y, X) = \mathbb{E}_{x\sim p_{data}(x)}[log(D_X(x))] + \mathbb{E}_{y\sim p_{data}(y)}[log(1 - D_X(F(y)))] \tag{5}$$

$$\mathcal{L}_{blank}(G, F, D_Y, D_X) = \lambda_c \mathcal{L}_{cycle}(G, F) + \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(G, D_X, Y, X) \tag{6}$$

2.4. **Layering.** Ink, line, and blank-leaving often make up the layering of ink painting surfaces. The different ink tones may depict the objects' distance and three-dimensionality; the lines can depict the items' contour and texture through thickness and curve; and the blank-leaving can be utilized to draw attention to important features or emphasize certain spots in the image. All of them contribute to the image's depiction of hierarchy. The inking constraint, the line constraint, and the blank-leaving restriction interact with one other and with the hierarchy constraint, which has an overall impact. U-Net excels in medical picture segmentation problems because it has a typical convolutional neural network structure, yet in many field, depth estimate tasks have shown to be extremely effective. In this instance ,the pre-trained U-Net is also utilized as the depth image extractor: Depth, whose structure is the same as that of Edge in Chapter 2.2, is used to extract the picture's layer information, and the depth image created by the 3D program is used as its training data. The original picture is given to this depth image generator during the ink generator training phase together with the created ink image and the loss $L_{depth}(G)$ of the hierarchical sense constraint as illustrated in the following equation:

$$\mathcal{L}_{depth}(G) = \mathbb{E}_{x\sim p_{data}(x)}[||Depth(G(x)) - Depth(y)||_1] \tag{7}$$

2.5. **Global loss.** The final global loss $\mathcal{L}(G, F, D_Y, D_X, D_{blur})$ of the FCIGAN is represented in the following equation based on the hierarchy constraint, ink color constraint, line constraint, blank-leaving constraint, and constraint on blank-leaving that were previously described.

$$\mathcal{L}(G, F, D_Y, D_X, D_{blur}) = \alpha\mathcal{L}_{ink}(G, D_{blur}) + \beta\mathcal{L}_{edge}(G) + \gamma\mathcal{L}_{blank}(G, F, D_Y, D_X) + \delta\mathcal{L}_{depth}(G) \tag{8}$$

Among them$\mathcal{L}_ink(G, D_{blur}), \mathcal{L}_{edge}(G), \mathcal{L}_{blank}(G, F, D_Y, D_X), \mathcal{L}_{depth}(G),$ are the loss of ink constraint, line constraint, white space constraint and hierarchical constraint respectively α, β, γ, δ, are the weight coefficients of the loss of ink constraint, line constraint, white space constraint and hierarchical constraint in the overall loss respectively.

3. **Results and Discussions.**

3.1. **Experimental configuration.** he configuration of the computer used for this experimental training is shown in Table 1:

The programming environment is Python 3.8 and the deep learning framework is PyTorch (1.13.0 + cu116). With a training Epoch count of 40 and a batch size of 1, the Adam optimizer is employed with a 0. 0002 learning rate for the generator and discriminator. The number of training epoch is 35. The training Epoch count for the pre-trained feature extractors is 100. All of the discriminators in this research are 62×62 PatchGANs in order to better capture the detailed information in the images.

3.2. **Dataset description.** For this research, four different 512px×512px size datasets were gathered: a 3D image dataset, a 3D image depth dataset, a 3D image edge detection dataset, and an ink and wash dataset. Figure 2 displays an example of each type in the larger dataset, which is known as FCI Images. Each type has 1000 training sets and 200 test sets.

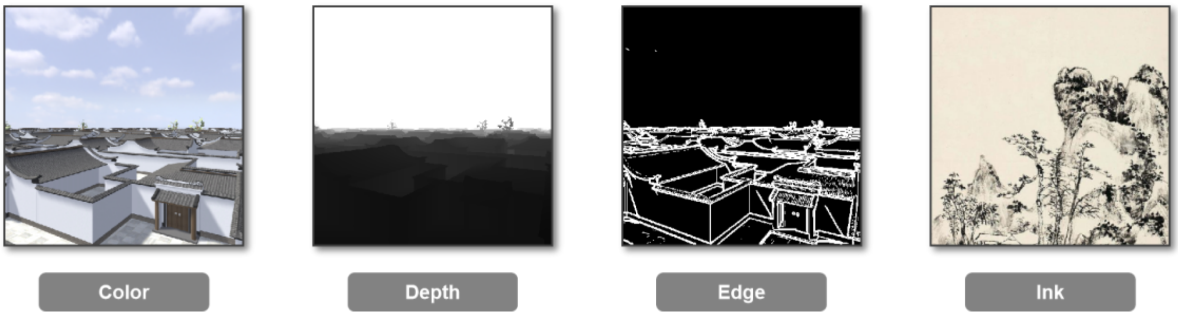

FIGURE 2. FCI Images

The Unity Engine used the Unity Shader to gather the depth data from a random screen capture of the Sanfangqixiang 3D scene in order to create the 3D graphics dataset and the 3D image depth dataset. The GraphCut method is used to identify the edges of the 3D image dataset that was first captured to create the edge detection dataset. As a result, there is a one-to-one link between the 3D image dataset, the 3D image depth dataset, and the 3D image edge detection dataset. The public dataset's ChipPhi [15] is scaled and randomly cropped to produce the ink dataset.

3.3. **Results analysis.** To evaluate the discrepancies between the various models and actual ink and wash pictures, we compare the FCIGAN developed in this article with CycleGAN, the most representative method for image style transfer.While the image hierarchy is made up of ink color, line, and blank-leaving, the evaluation of ink painting is not as mathematical as a problem that can be expressed in precise numbers; instead, it is influenced by subjective factors like expression, connotation, and culture and has a highly subjective component [16]. In order to minimize subjective impacts, this research focuses on evaluating the effects of ink color, line, and blank-leaving from the perspective of ink techniques. Figure 3 presents its overall comparison.

Objective aspect. This paper evaluates the ink color, lines and blank performance effect of ink painting techniques. Through detailed observation and analysis of the application of techniques, the variation of ink color, the fluency of lines and the degree of application of white space, etc.

3.3.1. *Color comparison of ink.* This part examines if the ink colors in the output picture exhibit the natural diffusion effect that a true ink painting should have, as well as whether they match the color distribution of the input image.

FIGURE 3. Overall comparison

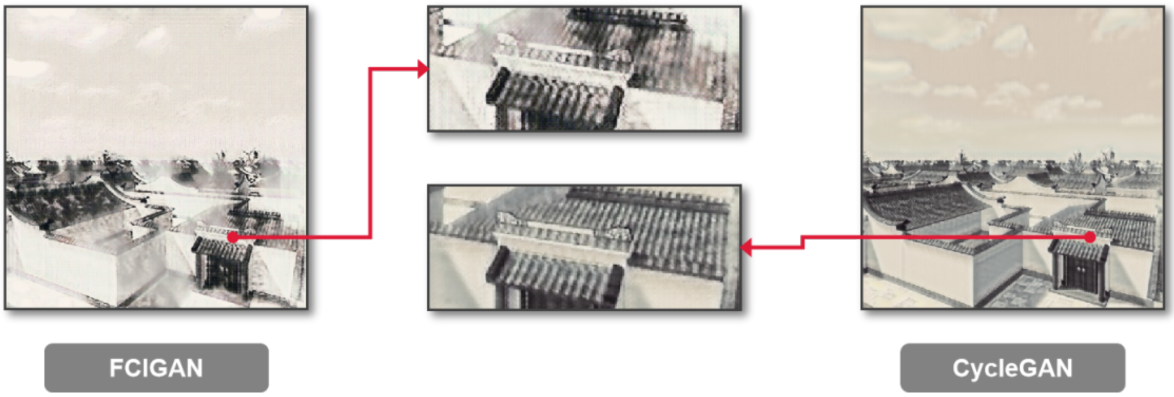

FIGURE 4. Ink colour comparison

As shown in Figure 4, the ink diffusion effect of FCIGAN is more natural, whereas CycleGAN's performance is more akin to merely modifying the picture by tone modulation. As a result, the ink color is dispersed uniformly throughout the screen and lacks the physical qualities of genuine ink.

3.3.2. *Line contrast.* This part mainly considers whether the generated image has flexible variability in its lines, while being able to use line techniques reasonably according to the semantics to show the size, distance, outline, details and other aspects of the object's characteristics.

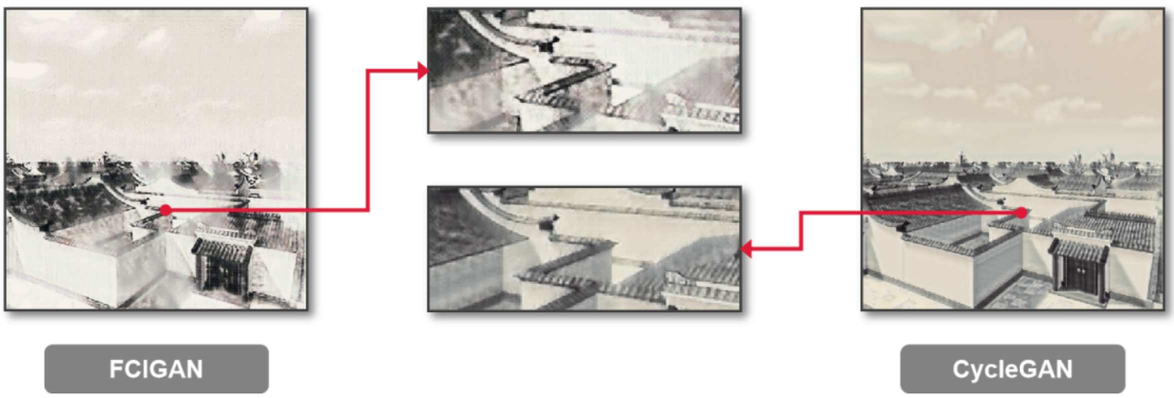

FIGURE 5. Line comparison

Figure 5 shows how FCIGAN employs lines more effectively, representing the size and distance of the item through rich changes in thickness, defining the main object with the appropriate lines, and drawing the details that require attention. On the contrary, CycleGAN's performance is fairly consistent in terms of line variations throughout the image.

3.3.3. *Contrast in blank-leaving.* In general, this component should be influenced by subjective variables, although it still has some degree of evaluability when considering its effect as opposed to the picture's content.

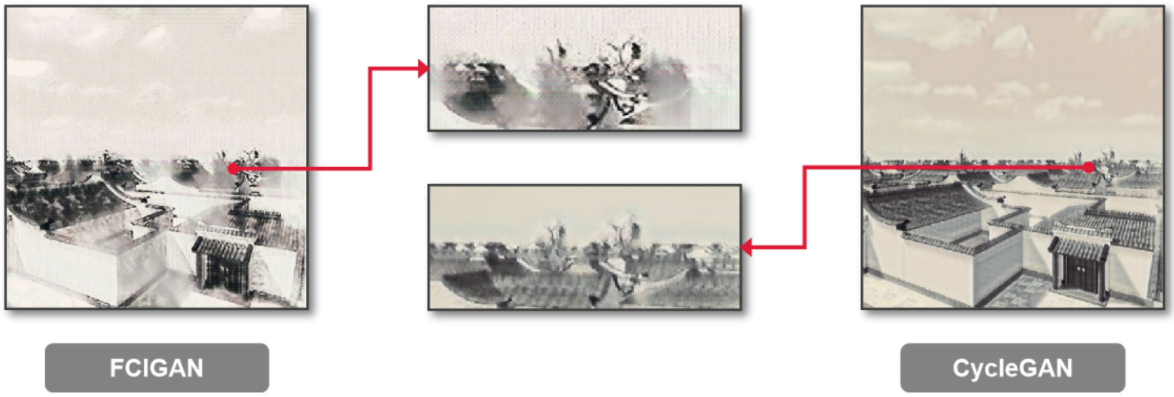

FIGURE 6. Contrast in blank-leaving

Figure 6 FCIGAN has a more obvious primary and secondary emphasis on how each aspect of the image is portrayed than CycleGAN, and its use of blank-leaving has a stronger impact on how non-essential objects are portrayed. CycleGAN, on the other hand, uses a more uniform blank-leaving that lacks variation and is less obvious. In conclusion, FCIGAN and CycleGAN, which are examples of the image style, produce ink paintings with ink color, line, and blank-leaving, and FCIGAN is able to produce pictures that are more similar to traditional Chinese ink paintings.

3.3.4. *Subjective aspect.* In this paper, a survey consisting of 200 online questionnaires was designed to obtain the participants' subjective evaluation of the ink painting style images generated by FCIGAN and CycleGAN. We pay attention to the participants' judgment on the authenticity of the real image and the generated image, as well as the feedback on the overall effect of the picture, artistic feeling, expressiveness, painting skills and other aspects, so as to understand their subjective impression on the images generated by different models. The survey results are shown in Figure 7:

Through objective and subjective comprehensive analysis, we found that FCIGAN's images are more in line with the performance of traditional Chinese ink painting than CycleGAN , which is very representative in the field of image style migration, in terms of ink color, line and blank effect. In the use of ink, FCIGAN can better present the characteristics of ink painting, making the picture more rich in the atmosphere of traditional Chinese art. In addition, the lines generated by FCIGAN are more fluent and natural, which can better show the charm of ink painting. For the use of white space, FCIGAN can also more accurately grasp the artistic conception of white space in ink painting, making the picture more ethereal and artistic conception. To sum up, FCIGAN shows better consistency and artistic effect in the generation of ink painting style.

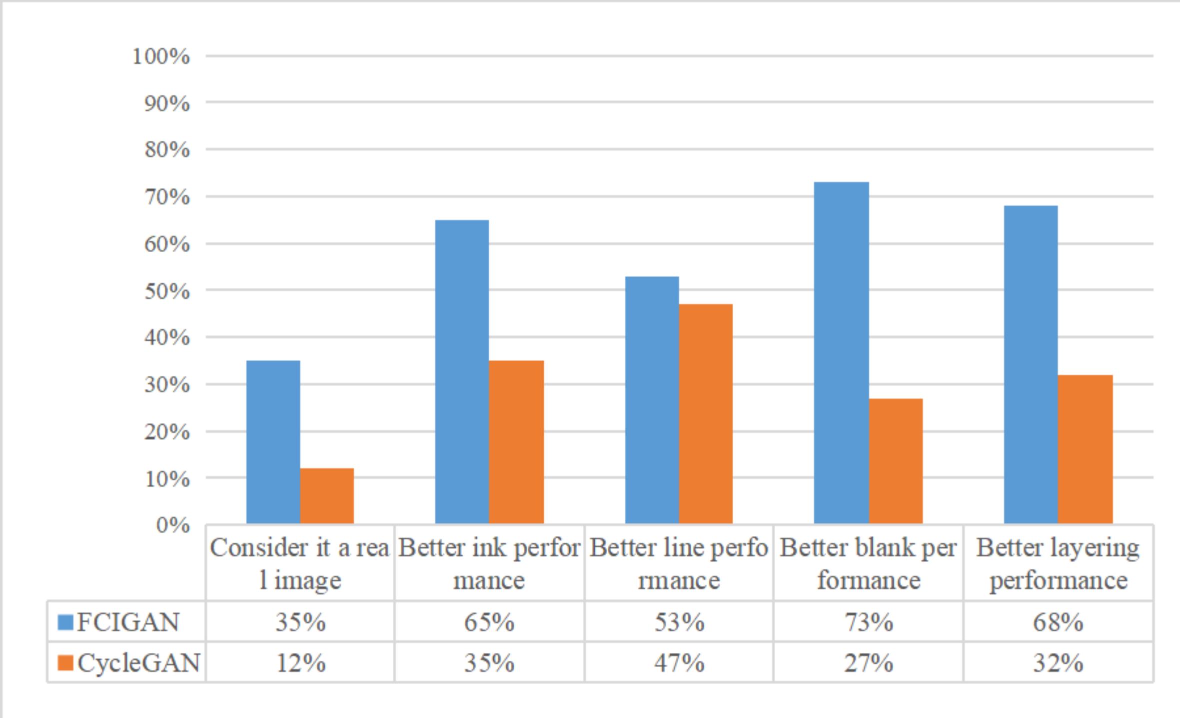

FIGURE 7. Survey results of 200 online questionnaires

4. **Conclusion.** We examine the use of deep learning technology in ink rendering in this paper and propose a novel ink rendering model, FCIGAN, which achieves various constraints on the image during ink rendering with the aid of attention mechanism and 3D depth information, while using various constraints, such as ink color constraints, line constraints, blank-leaving constraints, and hierarchy constraints. At the same time, in order to carry out the experiment smoothly, we also collected and made a set of data sets with four types of information, and named them FCI images. The final experimental results demonstrate that the proposed FCIGAN can effectively transform an image from the 3D image domain to the ink image domain while preserving key details and semantic information, as compared to more conventional image-style migration models like CycleGAN. The generated ink paintings also exhibit high artistic value and visual effects. Using the picturesque area of Fujian Province, China - Sanfang Qi Xiang 3D scene as an example, this study explores the use of this technology in the actual scene in depth by rendering it in ink and wash style, demonstrating its broad application possibilities and research worth. The research is also very important for the continuation and growth of Chinese ink and washes painting.

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