# Deep Neural Network and Human-Computer Interaction Technology in the Field of Art Design

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***Abstract*—Traditional art design is usually based on the designer's intuitive creativity. Limited by individual experience, knowledge and imagination, it is difficult to create more abundant and higher quality works, and the workload is huge, which limits the production efficiency of artworks. Through deep neural networks and human-computer interaction technology, the quality of art design can be improved; the workload and cost of designers can be reduced, and more artistic inspiration and tools can be provided to designers. The main contribution of this paper is to propose the use of a Cycle Generative Adversarial Network (Cycle GAN) to realize the automatic conversion of text to image and provide an immersive art experience through human-computer interaction technology such as virtual reality. In addition, the target audience of this paper is art designers and researchers of human-computer interaction technology, aiming to help them break through the traditional creation mode and lead art design to diversification and avant-garde. The content loss rate of character image conversion in Cycle GAN was reduced by 74.5% compared with that of human image conversion. The average peak signal-to-noise ratio of figure images generated by Cycle GAN was 57.9% higher than that of figure images generated by the artificial method. The character images generated by Cycle GAN reduce content loss and are more realistic. Deep neural networks and human-computer interaction technology can promote the development and progress of art design, break the traditional creative mode and bondage, and lead art to be more diversified and avant-garde.**

***Keywords*—Deep neural network; human-computer interaction; Cycle Generative Adversarial Networks; art design; image generation**

## I. Introduction

Traditional art design often relies on manual production and processing, which requires a longer time and a large amount of labor. This limits the production efficiency and quantity of artworks, making it difficult to meet large-scale market demand. Deep neural networks can automatically generate images, providing artists with ideas and more design options. The sound interaction and motion interaction in the human-computer interaction technology collect the designer's voice input and movement analysis, and deepen the interaction with the art work. Deep neural networks and human-computer interaction technologies provide artists with new ways to create and extend the boundaries of their imagination and creativity. Artists can express their creativity and ideas directly through natural language, without being limited by technology or tools. They can use the language and expression they are familiar with to translate their creative inspiration into images or design works. Although existing research has explored the application of artificial intelligence in art design, most studies have not analyzed in depth the specific advantages of deep learning techniques in improving the quality and design efficiency of artworks, nor have they systematically compared the practicability and effectiveness of traditional methods with emerging technologies.

The deep learning neural network analyzed in this paper is a kind of machine learning technology that mimics human brain neural networks. It can realize automatic learning and processing of massive data by constructing complex networks. This method has been well applied in computer vision and natural language processing. In terms of art design, the use of deep learning neural networks can allow computers to learn different art styles, skills and elements, and then achieve the purpose of artificial intelligence design. In this paper, Cycle GAN is used to automatically generate images. Cycle GAN is a method to understand and process the semantics and grammar of natural language, and corresponding pictures can be automatically generated according to the description of artists. Deep Convolutional Inverse Graphics Networks (DC-IGN) are also used to transform image styles in combination with time or space. Through sound interaction and body interaction in human-computer interaction, artists can interact with their ideas and create the works they want as long as they express them in a natural way. In the existing literature, although some studies have explored the impact of artificial intelligence and digital tools on artistic creation, this paper verifies the actual effectiveness of deep learning in artistic design through empirical research, especially in the innovative application of automatic text-to-image conversion and image style conversion. Further, through detailed technical comparative analysis, this paper demonstrates the remarkable effects of Cycle GAN in reducing content loss and improving realism in art image generation, providing a new creation tool and methodology for art designers.

This paper aims to explore the application of deep neural networks and human-computer interaction technology in the field of art design, especially how to improve the quality and efficiency of art creation through these technologies, while reducing the workload and cost of designers. The goal of the research is to evaluate the performance of Cycle Generative Adversarial Networks (Cycle GANS) in automatic text-to-image conversion, and combine interactive technologies such as virtual reality to enhance the display of art works and the immersive experience of the audience, in order to promote the development of art design in a more diversified and avant-garde direction.

Main contributions:

*1) Deep neural network improves the quality of artistic creation:* This paper proposes to use deep neural network technology, especially Cycle GAN, to realize the automatic conversion of text to image, so as to assist art designers to create more abundant and higher quality art works, and reduce the labor intensity of designers.

*2) Human-computer interaction technology enhances art experience:* This paper discusses how human-computer interaction technology, including virtual reality and multimodal interaction, provides a more immersive and interactive experience for art design, and makes the display and viewing of art works more modern and personalized.

*3) Significant improvement of art design efficiency and economy:* Through practical data and case analysis, this paper shows that the application of deep neural network and human-computer interaction technology in art design can significantly improve design efficiency, reduce costs, and increase the market competitiveness of art works and audience participation.

This paper first sets the research background in the introduction part, and summarizes the research gaps of deep neural network and human-computer interaction technology in art design. Then, the related work section reviews the current status and challenges of the application of artificial intelligence in art design. The main part of this paper is divided into eight core sections: In Section III, the application of deep neural network in image generation and intelligent creation tools is discussed; secondly, Section IV analyzes how human-computer interaction technology promotes art design and display. Finally, the practical effects of these technologies in improving design efficiency, reducing costs, enhancing user experience and economic benefits are evaluated in Section V. In Section VI, the cost-effectiveness of traditional methods and the proposed methods are further compared, and the impact of human-computer interaction design on user satisfaction is deeply analyzed in Section VII. The conclusion in Section VIII summarizes the research results, emphasizes the importance of technological innovation in the field of art design, and puts forward the direction of future research. All citations are listed in the References section, which provides academic support for the research.

## II. Related Work

The field of art design often relies on traditional artificial design. The works designed are affected by many factors, and the design time is relatively long. The emergence of the digital age has provided new means for art design. Changsheng WANG's research showed that AI art creation workflows, such as AI image straight-out method, AI-assisted drawing method and ControlNet precision drawing method, effectively improved the creation efficiency and accuracy, and promoted the innovative expression of digital art [1]. Anantrasirichai explored the application of AI technology in the creative industries, analyzed the use of AI in content creation, information analysis, content enhancement, information extraction, and data compression, and noted that AI's potential as a tool to enhance human creativity was greater than its ability as an independent creator [2]. Through practical workshops for Finnish pre-service craft teachers, Vartiainen explored the potential benefits and challenges of text-image generation AI in art design, such as algorithm-based bias and copyright issues, and analyzed the complex relationship between creative production and generative AI [3]. Wang, Xiaolong designed an intelligent management system of art exhibition based on IoT and AI, which had a short response time and could meet the requirements of practical applications. At the same time, the multi-touch system based on BPNN was developed, and the gesture recognition accuracy was high, providing an efficient solution for the field of interactive art [4]. Cetinic comprehensively reviewed the application of AI in art analysis and creation, including tasks such as art digitization, classification and retrieval, as well as the practice and theory of AI in art creation, and looked forward to the future development of AI in art understanding and creation [5]. Mayo emphasized the importance of pre-service teacher education in integrating AI for artistic creation, proposing the need for structured curricula and technical support to train educators and students while addressing biases and ethical issues in the use of AI to drive innovation in art education [6]. Li Sixian discussed the intelligent development of digital media art through interdisciplinary research methods, analyzed the integration of technology, communication and art, as well as the problems and solutions in the wave of intelligence, and aimed to explore innovative strategies for digital media art [7]. In a critical review of the existing literature, it is found that although the application of artificial intelligence in the field of art and design has been extensively explored, the existing theoretical framework has shortcomings in integrating deep learning with human interaction techniques. For example, while some studies demonstrate AI-based image generation techniques, they often do not consider in depth how these techniques integrate with the creative thinking of designers. In addition, although text-to-image generation methods are theoretically innovative, their application and integration in the actual design process have not been fully explored. At the same time, the existing literature also lacks sufficient depth in exploring how human-computer interaction technology enhances artistic experience.

Deep neural networks and human-computer interaction technology bring new ideas to art design. Nie Zexian discussed the application of artificial intelligence and human-computer interaction technology in art design, through machine learning algorithms and visual interaction technology, and analyzed audience responses to improve the expression of artworks. The design of artistic visual communication systems was proposed, and innovation and development in the art field were promoted [8]. Huang Lihua discussed the application of artificial intelligence technology in visual design, proposed the construction of intelligent design systems to improve design efficiency and quality, and explored the man-machine collaboration model to promote innovation and development in the field of art design through deep neural networks and multi-domain expert systems [9]. Liu Lina studied the methods of context awareness and machine learning to enhance user interaction experience in mobile systems, proposed the design principles of interactive display based on intangible cultural heritage, and discussed the application of augmented reality in folk art appreciation, providing new ideas and practical cases for art design [10]. Guo Qiongqiong studied the application of virtual reality technology in product design, and enhanced user experience through dynamic simulation and haptic feedback. She established product models in combination with computer-aided design, and discussed the implementation mechanism of haptic feedback in virtual environment, providing innovative interactive means and design ideas for art design [11]. Li Xiong proposed an intelligent assisted concept sketch design framework based on deep learning, including GAN and style transfer network for sketch generation and rendering, which verified its ability to quickly generate innovative sketches and style transformations through experiments, and developed an intelligent sketch design generator to reduce the threshold for designers to use AI and improve design efficiency and innovation [12]. ChatGPT's performance as a general-purpose AI model on emotional computing tasks highlighted the broad applicability and robustness of deep learning techniques in diverse fields such as art and design without the need for task-specific training [13]. Although existing research has made progress in applying AI to art and design, they have generally failed to delve into the specific advantages of deep learning techniques in improving the quality of art works and the efficiency of design. In addition, existing approaches have limitations in adapting to diverse design needs and delivering personalized art experiences. Through empirical analysis, this study aims to make up for these deficiencies, verify the innovative application of deep learning technology in art design, and explore how to enhance the display of art works and audience experience through human-computer interaction technology.

## III. Deep Neural Network in Art Design

### A. Image Generation

Deep neural networks can learn and simulate a large amount of image data, to achieve automatic image generation. This provides an entirely new means of creation for art designers, enabling them to better express their creativity and ideas.

At present, the mainstream text-generating image methods need complete text-image data pairs in the training process, which leads to the current methods being mostly trained on some specific data sets, and it is difficult to apply to other scenarios. In recent years, there have been some unsupervised field transitions. Cycle GAN is an image transformation model based on generative adversarial networks that converts text into images without the need for pairs of training data.

Cycle GAN was originally a model for the image domain, but has since been extended to text-image conversion tasks as well. The overall structure of text-image conversion is shown in Fig. 1.

As shown in Fig. 1, text is first encoded by a text encoder into a specific hidden space. By converting text features into vector representations, the encoded text vectors become part of the input generator, which is responsible for converting the text vectors into real images.

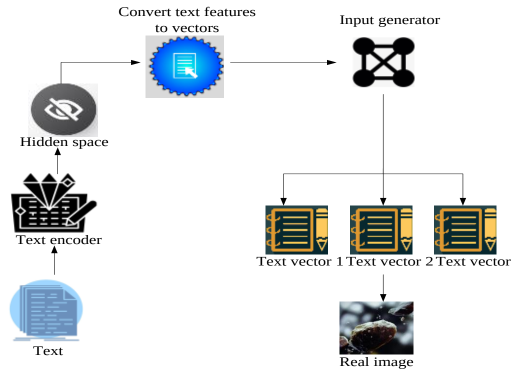



Fig. 1. Overall structure of text-image conversion.

The text is encoded using a pre-trained network to get a semantic embedded representation of the text:

$$w = B_i \cdot L(t) \tag{1}$$

$L(t)$ is the length of text; $B_i$ represents text features at the word level. In order to enhance the diversity of text description, conditional enhancement network is used to make full use of different texts with the same semantics to enhance the semantic information of text vectors. For the obtained text features, it is taken as the input of the network, and the result of data enhancement $F_c(s)$ and noise are taken together as the input $f_0$ of the first stage image generator:

$$f_0 = F_0\left(z, F_c(s)\right) \tag{2}$$

In the text loop, the cross-entropy loss is used to calculate the consistency between the original text $p_t$ and the reconstructed text $s_t$. The cross entropy loss $L_{cycle}$ of the text loop is as follows:

$$L_{cycle} = -\sum_{t=0}^{J-1} \log p_t(s_t) \tag{3}$$

For different attribute information, the encoding method is different. For class information, the variational inference method is used to encode. The encoder inputs a given class of information and a noise vector sampled from a standard Gaussian distribution to make variational inferences about hidden variables. Supposing that the posterior distribution of class information follows a multivariate Gaussian, the formula is:

$$L_{cycle}(G, F) = \mathrm{L}_1 \cdot G(x) \cdot \mathrm{F(y)} \tag{4}$$

$G$ and $F$ are generator network and discriminator network respectively; $x$ and $\mathrm{y}$ represent distribution obedience in two standard Gaussian distributions respectively.

The attribute vector is transformed into the same dimension as the text vector through a learnable linear layer, and then a neural network is used to jointly learn the text information and the attribute information to obtain the fused conditional vector. Through adversarial training, the generator network can continuously improve the authenticity of the generated image, making it more close to the real image distribution of the target domain or the original domain:

$$L_{GAN}\left(D_M, D_N\right) = sim\left(1-D_M\right)\cdot\left(1-D_N\right) \quad (5)$$

$D_M$ and $D_N$ represent the target domain and the original domain respectively, and the cross-entropy loss function is used to constrain the training of generator network and discriminator network.

After the fused code is transformed into the image space through the network, the attention mechanism is used to introduce the text features at the word level to better constrain the image generation. In order to maintain coherence between text and image, cyclic consistency loss is introduced into text-image conversion module. This loss encourages the generator network to retain as much content and style information as possible in the input image:

$$L_{D_i} = \log D_i\left(x_i\right) - \left[\log\left(1-D_i\left(x_i\right)\right)\right] \quad (6)$$

$D_i$ is the weight hyperparameter, which is used to balance the ratio between the individual subloss functions. By optimizing the total loss function, the parameters of generator and discriminator network can be updated by gradient descent to optimize the performance of the network.

In this paper, text with 10, 20, 30, 40 and 50 characters is selected to analyze the success rate of text generation image of artificial method and Cycle GAN, as shown in Fig. 2. In Fig. 2, the horizontal coordinate represents the characters and the vertical coordinate represents the success rate.

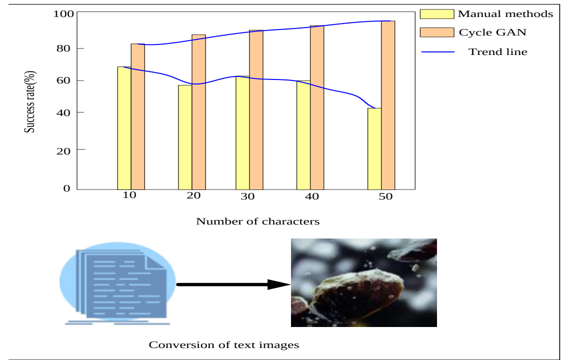



Fig. 2. Success rate of text generation image based on artificial method and Cycle GAN.

As shown in Fig. 2, it can be seen that the success rate of text-image generation in Cycle GAN is always higher than the success rate of text-image generation in artificial methods, which means that the success probability of text-image generation in Cycle GAN is greater.

## B. Intelligent Authoring Tools

The wide application of deep neural network enables it not only to be applied in traditional machine learning tasks, but also as an intelligent creation tool to provide better human-computer interactive creation experience and help in the field of art [14-15].

Generative Adversarial Networks (GAN) are composed of a generator network and a discriminator network, which generate images through adversarial training. Image generation and judgment based on generative adversarial network are shown in Fig. 3.

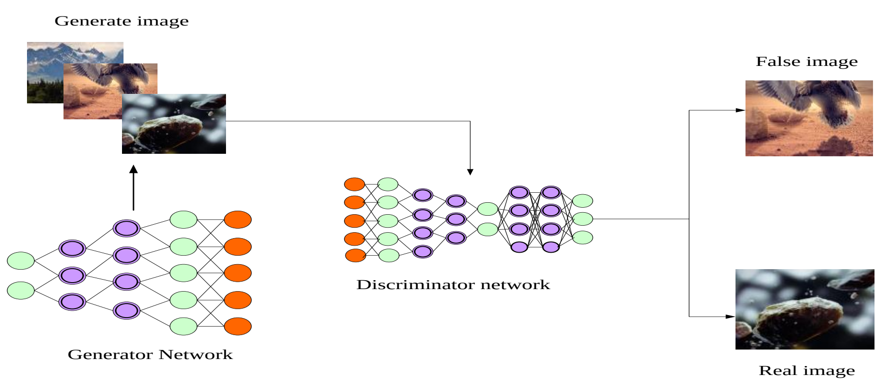



Fig. 3. Image generation and judgment based on generative adversarial network.

As shown in Fig. 3, the generator network is responsible for generating the image, while the discriminator network is responsible for determining whether the generated result is realistic. Through continuous adversarial learning, the generator network gradually improves the quality of generation. The goal of the generator is to produce images that are realistic enough to fool the discriminator so that it cannot tell whether the resulting image is real or not.

The generator's loss function can be implemented by maximizing the probability that the generated image is judged to be true by the discriminator. The specific formula is as follows:

$$\mathrm{L\{G\}} = \xi\left[-\log D(G(z))\right] \quad (7)$$

$\xi$ is random noise sampled from a prior noise distribution. The goal of the discriminator is to judge the difference between the generated image and the real image. The specific formula of its loss function is as follows:

$$\mathrm{L\{F\}} = \log D(h) - \log\left[1-D\left(G\left(z\right)\right)\right] \quad (8)$$

$\mathrm{L\{F\}}$ is the loss function of the discriminator and $D(h)$ is the real image. Through repeated iterations, the generator gradually learns how to generate an image that matches the natural language description, while the discriminator gradually learns how to accurately distinguish between the generated image and the real image. This adversarial training process allows the generator to output images that match the natural language description.

In this process, the antagonistic process of training the generator and discriminator enables the generator to generate an image or design that matches the natural language description. Through iterative training, the generator gradually learns how to generate works of art based on natural language, while the discriminator gradually learns how to accurately distinguish between generated works and real works. This adversarial training process enables the generator to output an image or design that matches the natural language description [16-17].

### C. Improvement of Creation Efficiency

With deep neural networks, artists can turn their ideas into creative works more quickly. Compared with the traditional artificial design or painting process, the use of intelligent creation tools can greatly shorten the creation time and reduce the workload of modification and adjustment [18-19].

As for the current method of text image generation, the quality of the final generated image depends on the quality of the initial generated image, so there are problems in image generation. Deep neural networks can be used to improve the quality of the initial generated image, and different generation tasks can be performed in different generation stages to improve the quality of the generated image. Deep neural network can fully learn the features of different levels of text generated images, so it has good performance.

The time taken by artificial method and intelligent creation of an inset, animation, trademark, person, build, landscape and animal image are counted respectively. The time taken by artificial method and intelligent creation is shown in Table I.

As shown in Table I, when the type of image needs to be created is determined, the creation time of the artificial method is measured in minutes, while the intelligent creation is measured in seconds. In several image types, the longest intelligent creation time is 32.20 seconds, while the shortest artificial creation time is 2.02 minutes.

### D. Image Style Conversion

In the mainstream image style transformation technology, after many repeated operations to achieve the desired effect, some features of the main image are distorted. The most widely recognized is DC-IGN, which takes the full connection of traditional neural networks to replace the convolution operation. It combines time or space, reduces network free parameters, reduces training complexity, and is well used in image style conversion. By using the idea of generative adversarial network and the structure of convolutional inverse graph network, DC-IGN realizes the transformation of image style.

DC-IGN introduces adaptive instance normalization. As long as it inputs a content and a style information by adjusting the input content to match the variance and mean of the input style, it can effectively merge the content of the main and style diagram, and output a new image. It can be calculated using the mean square error as follows:

$$h_t = \mathrm{M_{SE}}\left(\alpha, \beta\right) \tag{9}$$

Among them, the content feature $\alpha$ of the generated image is extracted from the generated image, and the content feature $\beta$ of the target image is extracted from the target image.

The style extraction network uses a similar convolutional neural network to take the style image as input and select the feature output of different layers as the style representation of the image. These features reflect the texture, color, and stylistic features of the image. Style loss is used to measure the difference in style characteristics between the generated image and the target image. It is measured by calculating the $\mathrm{M_{SE}}$ between the generated image and the target image in a specific layer, and the formula is as follows:

$$r_t = \mathrm{M_{SE}}\left(\mathrm{Gram}(\alpha), \mathrm{Gram}(\beta)\right) \tag{10}$$

$\mathrm{Gram}(\alpha)$ and $\mathrm{Gram}(\beta)$ are Gram matrices that generate the stylistic features of the image and the target image at a particular layer, respectively. In order to train a generator in DC-IGN, it needs to define a generator loss function, which consists of content loss and style loss, designed to minimize the goal.

TABLE I. TIMING OF MANUAL METHODS AND INTELLIGENT AUTHORING

| Type | Manual Method (Minutes) | Intelligent Creation (s) |
|---|---|---|
| Inset | 2.44 | 21.84 |
| Animation | 2.02 | 32.20 |
| Trademark | 4.57 | 23.04 |
| Person | 2.05 | 19.39 |
| Build | 2.77 | 24.96 |
| Landscape | 2.61 | 22.51 |
| Animal | 2.38 | 27.83 |

DC-IGN can encode not only the content of the image, but also the style information of the image. The style and content of image can be separated, which also deepens the understanding of image processing. It has a broad application prospect and can be used for image processing, video processing and as an auxiliary tool for style design.

## IV. Human-Computer Interaction Technology in Art Design

### A. Human-Computer Collaboration Design

Human-computer collaborative design refers to the cooperation and interaction between designers and computers to improve design efficiency and quality. By making full use of the computing and processing power of computers, designers can complete design tasks more conveniently and quickly, and obtain better design results [20-21]. In human-computer collaborative design, there are many technologies and tools that can realize the cooperation and interaction between designers and computers, among which sound interaction and somatosensory interaction are some of the common implementation methods [22-23].

*1) Sound interaction*: Sound interaction technology is a simulation system based on human hearing and understanding systems. When the sound sensor converts the sound signal into an electrical signal, the electrical signal can trigger the circuit in the interactive system to work. In art viewing, when the audience's voice is perceived by the interactive system, it can produce corresponding feedback output after being processed by the pre-set system. The sound interaction technology based on sound sensors can also be subdivided into volume-led interaction systems and speech recognition.

In volume-dominated interactions, the system only needs to sense the absolute volume of urine and faeces at a specific location to respond accordingly [24-25]. However, in the speech recognition interaction, the system also needs to distinguish the content of the sound. If the sound emitted in a specific area is meaningless, it can be judged by the system as an invalid sound and cannot give feedback. Only when the sound is carrying information and is successfully recognized by the system can it produce corresponding feedback based on the content of the sound? For example, the "Ascending the River at Qingming Festival" in the Sound Museum is shown in Fig. 4.

As shown in Fig. 4, the art exhibition of "Riverside Scene at Qingming Festival" uses holographic projection and holographic sound technology, and through the independently developed soundscape interaction system, the outdoor exhibition restores the life status of folk people in the Song Dynasty, and people interact with the scroll in sound and painting while walking. Through multi-dimensional immersive experience, people can listen to the sound art that has come to modern society through thousands of years.

By simulating the communication between people, voice interaction enables designers to directly interact with computers in a natural way, such as voice input, which greatly reduces the learning cost and improves the work efficiency of designers [26]. Voice input can realize the voice interaction between the designer and the machine, providing a more convenient and natural way of operation. Through a microphone or other audio device, the designer's voice input is collected, and these voice signals are used as input data for subsequent processing.

*2) Somatosensory interaction technology:* The somatosensory interaction technique is a technique to track, record and dynamically capture human motion trajectory in three-dimensional space by using the mixed method of optical passive and inertial motion measurement. Somatosensory interaction includes gesture interaction and body interaction. Due to the diversity and ambiguity of gesture and body behavior, various combinations can be used to input a variety of information in interaction, as shown in Fig. 5:

As shown in Fig. 5, the somatosensory interaction technology usually relies on infrared sensors, cameras, smart wearable devices and other technologies to achieve the input behaviour in the interaction.

Since people usually use body movements to complete communication with other natural persons in social activities, somatosensory interaction is a simulation of human natural communication behavior, which has the advantage of being easy to use and understand.

Fig. 4. Heard "Ascending the river at qingming festival" art exhibition.

Fig. 5. Somatosensory interactive projection.

*B. Art Display*

Human-computer interaction technology can combine art display with user interaction. For example, digital artworks can be displayed in a virtual exhibition hall, where the audience can experience and interact through technologies such as virtual reality, increasing the interest and interactivity of the works.

*1) Virtual reality:* Virtual reality is an information display technology that uses three-digit graphics generation technology, multi-sensor interaction technology and high-resolution display technology to generate a three-dimensional realistic virtual environment [27]. The environment simulated by virtual reality technology is very similar to that in the real world, which is difficult to distinguish, and people can have a sense of immersion in the experience process. The current virtual reality technology has been able to deliver hearing, vision, smell, touch, taste and other feelings, which is a comprehensive simulation system and has brought a huge revolution to the output of interaction design [28].

The Virtual Reality Painting tool allows users to wear a virtual reality headset and handle and then paint in a virtual environment in the form of an aerial drawing. Users can draw lines, shapes and colors in three-dimensional space with the handle, and create three-dimensional works of art by touching and rotating them. This virtual reality painting tool provides an innovative art creation tool that enables artists to paint in completely new ways, creating artwork with three-dimensional and dynamic effects, as shown in Fig. 6.

As shown in Fig. 6, through the immersive experience and interactive nature of virtual reality, the audience can interact more deeply with the artwork and freely explore and create art.

This virtual reality painting tool can also combine traditional painting with technology, providing more possibilities and innovative potential for artistic creation. Virtual reality technology provides the audience with an immersive experience, allowing them to feel the authenticity and emotion of the artwork. It provides artists with new creative tools and ways of expression to create more free and innovative works of art. Virtual reality can break through the limitations of time and space, bring the audience into different art scenes and art history, and expand the dimension of art creation and viewing.

*2) Augmented reality*: Augmented reality is a technology that integrates virtual information with scenes in the real world [29]. This technology uses multimedia, three-dimensional modeling, intelligent interaction, sensors and other technical means to apply virtual information produced by computers in the real world, which is complementary to the real world, so it is called augmented reality [30-31].

In the art field, augmented reality technology can be used to combine art museum exhibitions with virtual reality. Through the camera of a mobile phone or tablet computer, the audience can interact with these virtual elements by watching, hearing and touching, which entices the understanding and experience of artworks [32-33]. The Museum of augmented reality Art is shown in Fig. 7.

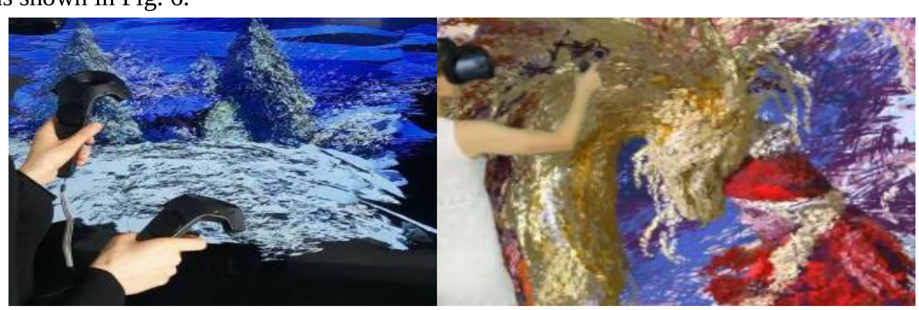


Fig. 6. Virtual reality painting.

Fig. 7. Museum of augmented reality art.

As shown in Fig. 7, the viewer can point the device at the artwork in the museum. Virtual elements related to the artwork would then appear on the screen, such as 3D models, animations, audio, etc.

This augmented reality art museum application expands the form and content of art exhibitions to a certain extent, providing viewers with a richer visual and sensory experience. At the same time, through interaction and participation, the audience can have deeper communication and understanding with the works of art, so as to enhance the sense of participation and the depth of art appreciation [34-35].

Visitors themselves feel and experience art themes through audio-visual touch and even smell, which further broadens the way participants receive information and expands the communication function of art design [36-37]. In contemporary art design, the interactive design running augmented reality technology can better create an immersive display atmosphere and improve the display effect [38-39].

## V. Design Effect of Deep Neural Network and Human-Computer Interaction Technology

### A. Image Generation Effect

The image generated by artificial methods is often a one-of-a-kind work that is not easy to reuse and scale. If multiple similar images need to be generated, the drawing or design work needs to be repeated, which further reduces efficiency and feasibility.

The resulting image fidelity is evaluated using the peak signal-to-noise ratio (PSNR). The sharper image PSNR is between 30 decibel (dB) and 40dB. The higher the PSNR, the more realistic and clear the image. Eight images of people, buildings, landscapes and animals are generated by manual method and Cycle GAN respectively. Compared with the peak signal-to-noise ratio, the average peak signal-to-noise ratio of images generated by different methods is shown in Fig. 8. The horizontal axis represents people, build, landscape and animal; the vertical axis represents the peak signal-to-noise ratio; the unit is dB.

As shown in Fig. 8, the average peak signal-to-noise ratio of person, build, landscape and animal images generated by artificial methods is 23.73dB, 20.58dB, 20.99dB and 21.10dB respectively on the left side of Fig. 8. On the right side of Fig. 8, the average peak signal-to-noise ratio of person, build, landscape and animal images generated by Cycle GAN is 37.48dB, 32.86dB, 33.65dB and 38.04dB respectively.

The average peak signal-to-noise ratio of figure images generated by Cycle GAN is 57.9% higher than that of figure images generated by artificial method ( $\frac{37.48-23.73}{23.73}*100\% = 57.9\%$ ).

Each layer of Cycle GAN can extract the features of each level of the image, and through the effective combination of the features of each level, it has higher complexity and higher quality. In contrast, in the manual method, it is necessary to undergo many processes of processing and debugging in order to obtain a complete image.

### B. Style Conversion Quality

Artificial methods often need to manually select features to express the content and style of the image, while deep neural networks can superimpose multiple neurons layer on layer to form a richer and more abstract image feature expression. Because deep neural networks can process any size and any kind of image, artificial methods often have strict constraints on the size and category of images. Therefore, using a deep neural network for image style conversion can adapt to more applications and have wider applicability.

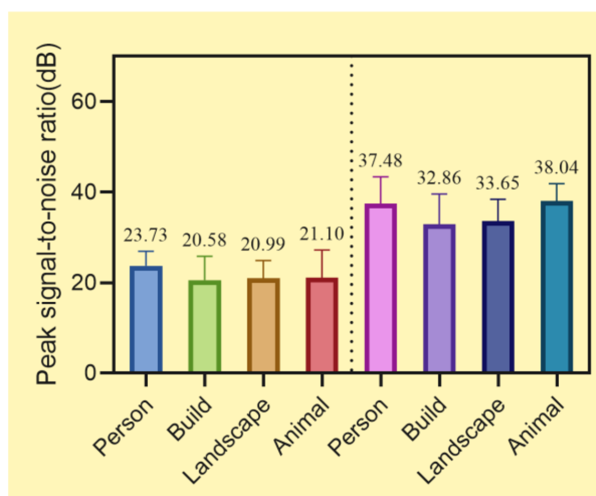



Fig. 8. Average peak signal-to-noise ratio of images generated by different methods.

The content loss rate is used to evaluate the content difference between the converted image and the original image. It can evaluate the style conversion quality of the image. The higher the content loss rate, the worse the style conversion quality. Besides, eight images of people, buildings, landscapes and animals are converted by manual method and Cycle GAN respectively, and their content loss rate is calculated.

The content loss rate of manually converted images is shown in Table II.

As shown in Table II, the average content loss rates of the eight images of person, build, landscapes and animals converted by manual methods are 5.68%, 5.36%, 5.67% and 5.62%, respectively.

The content loss rate of Cycle GAN converted images is shown in Table III.

As shown in Table III, the average content loss rate of each of the eight images of person, build, landscapes and animals converted by Cycle GAN is 1.45%, 1.60%, 1.17% and 1.53%, respectively.

Compared with manual method, the content loss rate of character image conversion in Cycle GAN increases by -74.5%( $\frac{1.45\text{-}5.68}{5.68} = \text{-}74.5\%$ ), that is, the content loss rate of character image conversion is reduced by 74.5%.

Cycle GAN can learn the more complex correlation between image content and style from massive data, and realize rapid transfer of image style through optimization and acceleration technology. Manual methods often take a long time, but Cycle GAN can achieve rapid style change in the case of real-time and interactive.

## C. *Reduce Design Costs*

The cost includes human resource cost, material cost, production cost, equipment cost and site cost. The cost of design work for manual method design and combined method (deep neural network and human-computer interaction technology) is shown in Fig. 9. The horizontal coordinate represents human resources, materials, manufacture, equipment and site; the vertical coordinate represents cost; the unit is yuan.

The left side of Fig. 9 shows the human resource cost, material cost, manufacture cost, equipment cost and site cost of the manual method design work, with the highest cost exceeding 1000 yuan. The right side of Fig. 9 shows the human resource cost, material cost, manufacture cost, equipment cost and site cost of the combined method design work. The maximum cost is less than 1,000 yuan.

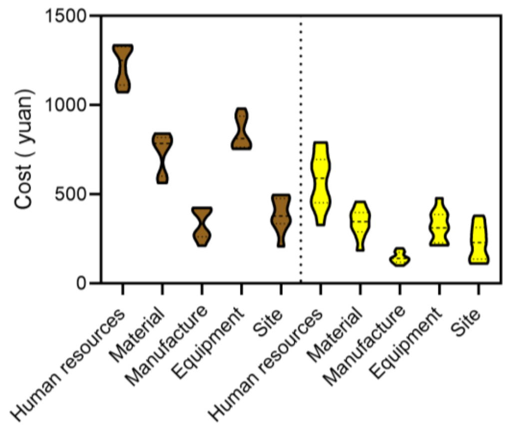



Fig. 9. Cost of manual method design and combined method design work.

TABLE II. CONTENT LOSS RATE (%) OF MANUALLY CONVERTED IMAGES

| Image Sequence Number and Average | Person | Build | Landscape | Animal |
|---|---|---|---|---|
| 1 | 6.88 | 6.18 | 5.25 | 6.19 |
| 2 | 5.34 | 4.00 | 5.36 | 5.84 |
| 3 | 4.50 | 4.52 | 6.37 | 6.93 |
| 4 | 5.79 | 6.32 | 6.78 | 4.81 |
| 5 | 5.47 | 6.49 | 6.00 | 4.65 |
| 6 | 6.89 | 6.80 | 5.48 | 6.04 |
| 7 | 5.89 | 4.25 | 5.26 | 4.38 |
| 8 | 4.70 | 4.30 | 4.89 | 6.14 |
| Average | 5.68 | 5.36 | 5.67 | 5.62 |

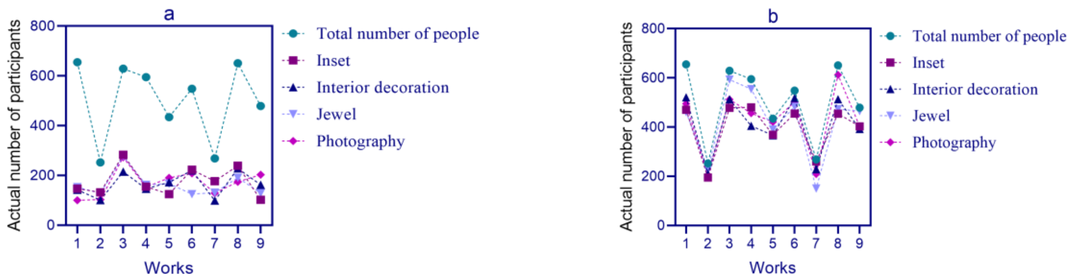
TABLE III. CONTENT LOSS RATE OF CYCLE GAN CONVERTED IMAGES (%)

| Image Sequence Number and Average | Person | Build | Landscape | Animal |
|---|---|---|---|---|
| 1 | 2.48 | 2.41 | 2.01 | 0.62 |
| 2 | 2.37 | 1.08 | 0.98 | 1.81 |
| 3 | 1.16 | 1.32 | 2.32 | 1.26 |
| 4 | 0.76 | 2.05 | 0.62 | 1.06 |
| 5 | 1.13 | 0.91 | 0.67 | 2.19 |
| 6 | 0.53 | 1.97 | 0.51 | 1.20 |
| 7 | 1.89 | 0.72 | 1.62 | 2.03 |
| 8 | 1.26 | 2.36 | 0.61 | 2.03 |
| Average | 1.45 | 1.60 | 1.17 | 1.53 |

Manual methods often take a long time, through the design, production, touching up and other processes, in order to ensure the quality and effect of the work. If the production cycle is too long, it not only causes the rise of production costs, but also misses the changing market demand.

## D. Engagement

The display of artworks based on human-computer interaction can bring real experience to visitors no matter in sensory experience, behavior mode, or use environment [40]. This paper selects nine works of illustration, interior decoration, jewelry and photography designed by manual method and combines method respectively to investigate the audience's participation, as shown in Fig. 10. The horizontal coordinate represents the works, and the vertical coordinate represents the actual number of participants.




(a). Audience participation in the artificial design of the work.

(b) Audience participation in the design of the combined method.

Fig. 10. Audience participation in the design of works by manual methods and combined methods.

Fig. 10(a) shows the participation of the audience in the inset, interior decoration, jewelry, and photography by manual methods. It can be seen that the actual number of participants is much less than the total number, and the highest number of participants is less than 400.

Fig. 10(b) shows the audience participation in inset, interior decoration, jewelry, and photography designed based on the combination method. It can be seen that the difference between the actual number of participants and the total number of participants is not very far, and the highest number of participants exceeds 400.

Human-computer interaction emphasizes "people-oriented", providing the computer with the functions of touch, vision, hearing and other aspects, so that users can interact with people through gestures, expressions, eyes, sounds and other ways. The multi-dimensional input and multi-output of computer have greatly increased the frequency band of communication between human and computer [41-42]. With the electronization of information resources, the diversification of information presentation methods, and the continuous improvement of new application requirements for various industries, art design, as the carrier of human spiritual civilization, cultural tradition and scientific knowledge, is gradually becoming the spiritual food of human beings.

## E. Economic Benefits

The appearance of human-computer interaction technology has brought great convenience and efficiency to art design. This paper uses virtual reality or augmented reality technology, and art designers can quickly preview and adjust the design effect in virtual reality, thus saving a lot of time and cost. Eight works are randomly selected and the economic benefits they brought are calculated. The income generated by manual method design and combined method design is shown in Table IV (the difference in income in Table IV is the income generated by combined method design minus the income generated by manual method design):

TABLE IV. INCOME FROM MANUAL METHOD DESIGN AND COMBINED METHOD DESIGN (TEN THOUSAND YUAN)

| Works | Manual methods | Combining method | Differential income |
|---|---|---|---|
| 1 | 6.01 | 17.48 | 11.47 |
| 2 | 8.16 | 20.72 | 12.56 |
| 3 | 5.25 | 15.04 | 9.79 |
| 4 | 8.33 | 19.02 | 10.69 |
| 5 | 8.78 | 23.51 | 14.73 |
| 6 | 9.40 | 24.83 | 15.43 |
| 7 | 6.45 | 21.81 | 15.36 |
| 8 | 8.88 | 16.17 | 7.29 |

As shown in Table IV, the economic income brought by manual method design is less than 100,000 yuan, while the economic income brought by combined method design is more than 100,000 yuan. It can be seen that the economic income brought by the combined method design is higher.

This paper highlights the advantages of the adopted method through in-depth comparison with previous studies. Through quantitative analysis, this study demonstrates the significant effect of Cycle GAN in reducing the content loss rate in automatic text-to-image conversion, as well as the high fidelity achieved in image style conversion. In addition, compared with traditional design methods, this research method has obvious advantages in improving the quality and creation efficiency of artworks, while reducing the production cost and enhancing the market competitiveness of artworks. These comparisons not only validate the validity of this research method but also demonstrate its potential to drive innovation and progress in the field of art design.

# VI. DISCUSSION

Fig. 9 shows the overall higher cost of designing work using manual methods. In the manual method, designers, engravers, painters, artisans, etc., have to put a lot of energy into completing a work. It not only requires a high technical level, but also requires them to spend a lot of time on each piece of work. In traditional art design, the materials used are generally very expensive, such as canvas, paint, wood, metal and so on. Such materials are prone to loss and waste in the production process, thus increasing the production cost.

Interactive technology is a kind of technology that appears with the computers and artificial intelligence devices in the information age. Therefore, in everyday use, interactive technologies are often designed to have a technological, futuristic look and style. However, in art design, the fundamental goal of interactive technology is to realize the transmission of artistic ideas. Therefore, in the interactive design of art, attention should be paid to the consistency of the interactive equipment with the displayed theme in terms of appearance, audition style, etc., to avoid conflict or incompatibility with the design theme.

Table IV shows that the economic income brought by artificial method design is not as high as that brought by combined method design. The appearance of human-computer interaction technology has brought great convenience and efficiency to art design. By utilizing virtual reality or augmented reality technology, art designers can quickly preview and adjust design effects in virtual reality, thus saving a lot of time and cost.

The works of human-computer interaction design pay more attention to bringing good experience to users, that is, the indicators based on users' emotions, such as satisfaction. It also has a certain subjectivity, emphasizing that users can be immersed in interactive experiences while obtaining information about artworks. Human-computer interaction plays an important role in realizing human value and satisfying human spiritual needs. In the process of art design, users manipulate some interactive elements on the digital media terminal to get corresponding visual, auditory and tactile feedback. If such feedback is consistent with the user's own knowledge, skills or values, it causes a feeling of pleasure in the "emotional center" of the user's brain, thus satisfying the user's deep understanding of the value and connotation of the work.

The research results show that the application of deep neural network and human-computer interaction technology in the field of art design can significantly improve the quality and efficiency of design works. Compared with traditional design methods, these techniques reduce the content loss rate and improve the realism and clarity of images. In addition, they help to reduce design costs and increase the market competitiveness of art works [43-44]. These findings support the importance of technological innovation within the field of art and design and provide designers with new tools and methods to achieve a more efficient and diverse creative process.

## VII. Research Results

The research results of this paper show that the application of deep neural network and human-computer interaction technology in the field of art design has greatly improved the quality and efficiency of design work. In particular, the automatic text-to-image conversion using Cycle GAN technology reduces the content loss rate by 74.5% compared with the traditional manual method, and increases the peak signal-to-noise ratio of image generation by 57.9%. In addition, through interactive technologies such as virtual reality and augmented reality, the display effect of art works and the immersive experience of the audience have been significantly enhanced. These technologies not only optimize the creative process, reduce costs, but also enhance the market competitiveness of art works and audience participation, and bring innovative development opportunities for the art design industry.

## VIII. Conclusion

Through empirical analysis, this study verifies the significant effectiveness of deep neural networks and human-computer interaction technology in improving the quality and efficiency of art design. In particular, Cycle GAN technology reduces content loss in the automatic conversion of text to images and enhances the display of artworks and the immersive experience of the audience through interactive technologies such as virtual reality. Based on these findings, it is recommended that art and design practitioners actively adopt these advanced technologies in order to optimize the creative process, broaden the boundaries of creative expression, and improve the market competitiveness of their works. At the same time, further exploration of the application potential of these technologies in different art and design scenarios is encouraged to promote the continuous innovation and development of the art and design industry.

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