Computer Aided Decorative Art Design and Multimedia Dynamic Display Based on Deep Learning Model

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Abstract. This article aims to explore the integration of computer-aided design in decorative art with multimedia dynamic display technology, leveraging a deep learning model. Initially, it delves into the prevailing challenges in decorative art design and the evolving trends in multimedia display, highlighting the transformative potential of Deep Learning (DL) in elevating design creativity and multimedia engagement. By synthesizing insights from DL, computer graphics, and multimedia design, we have developed a computer-aided system for decorative art design featuring a deep-learning model. This model is adept at learning and generating aesthetically pleasing decorative patterns. Through rigorous training on a vast array of traditional decorative art patterns, it generates innovative and original design concepts. Furthermore, this study utilizes computer graphics processing techniques to facilitate the dynamic presentation of these designs on multimedia platforms, elevating the visual experience for users. Experimental findings reveal that the generated patterns not only retain the aesthetic essence of traditional art but also seamlessly blend modern design elements, resulting in a distinctive and captivating visual impact. Additionally, the implementation of multimedia dynamic display technology significantly boosts the interactivity and appeal of the design works.

Keywords: Deep Learning Model; Deep Learning; Computer-Aided Design; Decorative Arts; Multimedia
DOI: https://doi.org/10.14733/cadaps.2024.S25.76-91

1 INTRODUCTION

Decorative art design serves as a form of artistic expression primarily focused on aesthetic enhancement and ornamental value. In contemporary architectural design, the design of indoor landscape architecture is increasingly valued. It can not only improve the quality of space and enhance the comfort of the indoor environment but also meet people's yearning for nature and ecology. However, traditional indoor landscape architectural design methods often face problems such as low design efficiency and limited creativity. To address these issues, Ackerman et al.[1] analyzed the visual elastic interior landscape architectural design based on deep generative models. Visualization technology provides an intuitive and vivid display method for indoor landscape architecture design. Through visualization technology, designers can present design solutions to users in the form of 3D graphics or virtual reality, allowing users to more intuitively experience and understand the design effect. This intuitiveness not only helps users better participate in the design process but also improves communication efficiency and satisfaction in design. By skillfully blending elements such as spatial arrangement, shape, colour palette, and material selection, it creates visually arresting works rich in unique aesthetics. Mobile augmented reality (AR) technology is gradually penetrating the field of education, bringing a new teaching mode and learning experience to interior design teaching. Chang et al. [2] explored the effectiveness of using AR technology to teach interior design students floor plans and analyzed the learning effectiveness based on the ARCS learning motivation theory model. AR technology allows students to intuitively experience the presentation effect of design solutions by overlaying virtual information onto a real environment. In interior design teaching, the application of AR technology can help students better understand the design intent of floor plans and improve their spatial perception ability. Students can use AR devices to simulate furniture layout, adjust colours and materials, and other design elements in a real environment so as to more intuitively experience the design effect and deepen their understanding of design principles and methods. Characterized by its emphasis on formal beauty, meticulous attention to detail, overall harmony, cultural depth, and symbolic meaning, decorative art design finds widespread application in various domains such as architecture, interior design, furniture, and artisan crafts, thus becoming an integral aspect of human life. In the field of sculpture art, spatial expression techniques are the key means for artists to convey emotions and showcase creativity. With the rapid development of computer technology, computer-aided deep generative modelling has gradually become a new favourite in the expression of sculpture art space. Guo and Wang [3] explored the application of computer-deep generative models in the spatial expression techniques of sculpture art. By training a large amount of data, these models can learn the patterns and features of sculpture modelling and generate novel and unique design designs. In sculpture art, spatial expression techniques are the key to showcasing the layering and three-dimensional sense of a work. Computer deep learning models can quickly generate spatial style designs based on the needs of artists, providing them with more creative inspiration and possibilities.

CAD (Computer Aided Design) software provides a new perspective and solution for interior decoration landscape design with its powerful 3D modelling and rendering capabilities. Deep learning can achieve precise analysis and processing of image and video data by training neural networks. In the multimedia dynamic display of decorative artworks, deep learning models can optimize visual presentation effects, enhance the viewing and attractiveness of the works. Through deep learning image processing techniques, we can achieve more delicate and realistic image rendering, enhancing the visual impact of our works. Jiang and Zhang [4] will explore the application and advantages of CAD 3D visualization technology in interior decoration landscape design. CAD 3D visualization technology can visually display design effects. Traditional interior decoration landscape design often relies on two-dimensional drawings and the imagination of designers, making it difficult to accurately express design intentions. CAD software can create three-dimensional models, allowing designers to observe design effects from all angles and angles and more accurately grasp spatial layout, colour matching, and material selection. CAD 3D visualization technology helps to improve the accuracy and efficiency of design. Through precise modelling and measurement, designers can accurately adjust design schemes in CAD software, avoiding problems such as size discrepancies and scale imbalances in actual construction. At the same time, CAD software also supports parametric design, which can quickly generate multiple design schemes by adjusting parameters, greatly improving design efficiency. The combination of Building Information Modeling (BIM) and Spatial Augmented Reality (SAR) technology has brought revolutionary changes to the field of decorative art design. In the field of decorative art design, BIM-based SAR technology has brought many advantages to design collaboration. Firstly, it breaks the spatial limitations of traditional design patterns. Jin et al. [5] simulated and displayed design solutions in real space through SAR equipment, allowing team members to more intuitively understand and feel the design effect. This helps to reduce communication barriers and improve collaboration efficiency. Secondly, BIM-based SAR technology provides designers with the ability to provide real-time feedback and modification. During the collaboration process, team members can make real-time adjustments and modifications to the design scheme in the SAR environment and immediately see the modified effect. This instant feedback mechanism makes the design process more flexible and efficient, helping to quickly respond to customer needs and market changes.

Color is a crucial element in decorative art design. Deep learning models can achieve precise control and optimization of colors by learning and analyzing a large amount of color data. In multimedia dynamic displays, deep learning models can adjust color matching and transition effects according to design requirements, making decorative artworks more harmonious, unified, and layered in color. At the same time, the model can automatically adjust the brightness and saturation of colors based on changes in ambient lighting, ensuring that the work can present the best results in different scenes. The application of deep generative models in various fields is becoming increasingly widespread. In the field of interior decoration art design in office buildings, the decision support model based on deep generative models is becoming an important tool for designers and decision-makers, providing new ideas and methods for interior decoration art design and decision-making. Juan et al. [6] analyzed the application of deep generative models in the interior decoration art design of office buildings. Deep generative models can learn the combination and variation patterns of various design elements, styles, colours, etc., and generate new design solutions that meet design requirements. The decoration decision support model based on the deep learning model constructs a multi-level neural network, takes design elements, user needs, spatial layout and other factors as inputs, trains and optimizes the model, and outputs the optimal design scheme that meets specific goals and constraints. This model can not only consider the influence of a single factor but also comprehensively consider the interaction between multiple factors, providing designers with comprehensive decision support. In the digital age, scene art design is no longer limited to static and one-way presentation methods but increasingly integrates human-computer interaction and multimedia information systems to create more vivid and interesting interactive experiences. This interactive perspective-based scene art design not only enriches artistic expression forms but also provides audiences with a more in-depth and immersive artistic experience. Human-computer interaction is an indispensable part of scene art design. Through advanced interactive technology, Liang [7] participates in the creation and display process of artistic works and interacts with them in real time. This interaction not only enhances the audience's sense of participation and experience but also brings more possibilities and changes to the artwork itself. Multimedia information systems provide powerful technical support for scene art design. This comprehensive way of expression not only makes artistic works more vivid and interesting but also provides the audience with a more comprehensive artistic experience. Meanwhile, multimedia information systems can also make real-time adjustments and optimizations based on audience behaviour and feedback, making artwork more in line with audience expectations and needs. In the modern era, as lifestyles evolve and living standards improve, decorative art design increasingly pervades our daily surroundings, enhancing spaces ranging from domestic interiors to public arenas and contributing to the creation of everything from handcrafted objects to branded identities. Additionally, the advancing technological landscape and the proliferation of new media have presented opportunities for decorative art design to intersect with multimedia technologies, unveiling more vibrant and dynamic expressive possibilities. Such integration promises a more engaging artistic encounter for spectators while expanding the creative palette for designers. Notably, computer-assisted decorative art design leveraging deep learning model represents a significant research avenue in this transformative trend. Our research endeavours to delve into the potential offered by deep learning model in advancing decorative art design. Specifically, we aim to explore how multimedia dynamic display technologies can effectively showcase the allure of decorative arts to a wider audience. By doing so, we anticipate not only catalyzing innovations in this artistic realm but also bolstering the technological proficiency and market prowess of allied industries.

The uniqueness of this study is found in its integration of deep learning models with decorative art design, introducing a fresh approach to computer-aided design. This approach not only enhances design efficiency and quality but also offers designers a more diverse and adaptable range of creative tools. Additionally, the study contributes novel concepts and techniques for implementing multimedia dynamic display technology in the realm of decorative art design.

The primary objective of this study is to investigate the utilization and impact of deep learning models in the realm of decorative art design. Specifically, we aim to delve into the practical application of GANs and VAEs for the automated creation and original conception of decorative artistic components. Furthermore, we endeavour to explore the integration of these generated elements with multimedia dynamic display techniques, aiming to craft more engaging and interactive decorative artworks.

Section 1 elaborates on the application background of computer-aided design software in decorative art design. It points out the potential of deep learning models in promoting decorative art design. Section 2 analyzed the research results of computer-aided decorative art design by relevant scholars. Section 3 conducted an analysis of deep generative models and their applications in art and design. Section 4 analyzed the application of multimedia dynamic display technology in art design, and conducted an interactive experience of decorative art based on augmented reality. Section 5 conducted simulation experiments and result analysis. The experimental results show that the model can produce decorative patterns with excellent artistic quality, demonstrating excellent color coordination, elegant line fluidity, and good composition structure.

2 RELATED WORK

In the current field of interior decoration landscape design, designers are gradually abandoning traditional linear thinking and exploring more complex and innovative nonlinear design methods. The simulation of multidimensional interior decoration landscape design parameters based on nonlinear theory is a forward-looking design approach that can help designers understand the complexity of indoor spaces more deeply and create more unique and harmonious design works. Nonlinear theory emphasizes the complexity and uncertainty of systems, believing that changes in things are often not simple linear relationships but rather exhibit a variable and interrelated state. In interior decoration landscape design, this nonlinear thinking can help designers break through traditional limitations and achieve more flexible and innovative designs [8].

Grid-based image feature-matching technology mainly divides the image into several grid units and extracts feature points within each unit to achieve accurate image matching. The application of this technology in ancient architectural decorative art design can effectively capture the local details and overall structure of decorative patterns, providing designers with richer design materials and inspiration. Nie et al. [9] organized and classified complex decorative patterns in an orderly manner through grid partitioning, facilitating designers to quickly retrieve and reference them. Multi-density feature matching technology uses different feature extraction densities based on different regions or elements of the image. In the decorative art design of ancient architecture, due to the complexity and diversity of decorative patterns, single-density feature matching is often difficult to meet the needs. Multi-density feature matching technology can adaptively adjust the density of feature extraction based on different decorative elements and style characteristics, thereby more accurately capturing the details and features of the image. Interior decoration art design based on deep generative models emphasizes data integration and analysis. Deep generative models can process a large amount of decoration design data, including information on styles, materials, colours, layouts, and other aspects. Interior decoration art design based on deep generative models emphasizes generative design thinking. Traditional design thinking is often limited to the personal experience and imagination of designers, while deep generative models can generate new design concepts and solutions through learning algorithms. Triatmaja [10] use deep generative models to expand and extend creativity, generating diverse design options. This generative design thinking not only helps to break traditional design frameworks but also stimulates the creativity of designers and drives innovation and development in design. Under the wave of digitization and intelligence, interior decoration art design is gradually shifting from traditional manual drawing and physical model-making to a digital and automated design mode. The combination of intelligent colour point clouds based on CAD symmetry and low-cost digital twin technology provides a new solution for interior decoration art design. CAD technology, as a representative of computer-aided design, has long been widely applied in the fields of architecture and interior design. Its powerful modelling and editing capabilities enable Wu et al. [11] to accurately draw and modify design proposals. Symmetry, as a commonly used aesthetic principle in interior design, can be easily achieved through CAD technology, making the design more unified and coordinated.

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In the wave of the digital age, the application of computer graphics and image-assisted design in the field of art and design teaching is becoming increasingly widespread. The application of these technologies not only enriches teaching methods but also improves the design efficiency and creative quality of students. Zhang and Rui [15] conducted an in-depth analysis of the application of computer graphics and image-assisted design in art and design teaching, exploring their advantages, challenges, and future development trends. Image-assisted design also plays an indispensable role in art and design teaching. Image-assisted design mainly utilizes image processing technology to optimize and improve design works. By adjusting parameters such as colour, contrast, and sharpness, students can easily improve the visual effect of images. By using image synthesis technology, students can fuse multiple image elements to create novel and unique works. With the rapid development of information technology, the application of computer-aided design (CAD) in the field of decorative art design is becoming increasingly widespread. Especially with the support of collaborative design systems, Zhang and Deng [16] have achieved more efficient design creativity, and the use of colour effects has been greatly improved. The CAD-assisted collaborative design system provides strong technical support for decorative art design. Through this system, designers can share design resources and collaborate to complete design tasks, greatly improving design efficiency. At the same time, the built-in colour management tool in the system enables designers to accurately select and adjust colours, providing richer colour expression methods for decorative art design. In decorative art design, colour is a very important visual element. It can not only create a specific atmosphere but also convey the designer's emotions and intentions.

3 DEEP LEARNING MODEL AND ITS APPLICATION IN ART DESIGN

The deep learning model is an important branch in the DL field, which uses the structure and algorithm of NN to learn and simulate the distribution law of data, thus generating new data similar to real data. Compared with the traditional learning model, the deep learning model has stronger representation ability and higher generation quality and can handle more complex and diverse data types. In the realm of art design, the utilization of deep learning models manifests primarily in two ways. Firstly, they can produce novel works that emulate the distinct styles and traits of artistic creations. Secondly, these models can facilitate automated and intelligent art design by abstracting artistic components and adhering to design principles.

(1) GAN

GAN, a representative deep learning model, comprises two neural networks: a generator and a discriminator. The generator strives to produce fresh data that closely resembles genuine data, while the discriminator aims to discern whether the inputted data originates from an authentic dataset or is a creation of the generator. Throughout the training phase, both the generator and discriminator engage in a constant quest to enhance their performances via mutual competition. Ultimately, this adversarial process enables the generator to produce highly realistic data that challenges the discriminator's discernment capabilities.

In essence, the adversarial nature of GAN underlies the training of both the generator and discriminator. The generator's objective is to create samples of utmost authenticity, whereas the discriminator aims to accurately differentiate between genuine samples and those crafted by the generator. These two networks are trained by resisting the loss function and constantly optimizing their respective capabilities. The common countermeasure loss function is based on cross-entropy loss. For the discriminator D and generator G, the countermeasure loss can be expressed as:

$$\min_G \max_D L_{adv} = E\left[\log D\left(\hat{y}^b\right)\right] + E\left[\log\left(1 - D\left(G\left(V\left(E\left(p^a\right), a, b\right), c\right)\right)\right)\right] \tag{1}$$

Among them, E it stands for the encoder, V visual angle converter, p^a is the original input image from a a visual angle, c stands for single thermal coding and $\hat{y}^b$ is the real image. During the training procedure, the optimization of both the discriminator and the generator occurs in an alternating fashion. Initially, while the generator remains static, the loss function of the discriminator is refined to enhance its capacity to differentiate between authentic and generated samples. Subsequently, with the discriminator's parameters set, the loss function of the generator is adjusted to improve its ability to produce increasingly lifelike samples, aiming to deceive the discriminator. This alternating process persists until a stable equilibrium is achieved. Figure 1 depicts the architecture of the discriminator network.

If I^i it represents the source image and $\hat{I}^i$ denotes the sample image produced by the generator, the discriminator assigns a probability to determine the authenticity of the image. The formula for its loss function L_D^R is expressed through cross-entropy, as outlined below:

$$L_D^R\left(I\right) = -t \cdot \log\left[D_R\left(I\right)\right] + \left(t-1\right) \cdot \log\left[1 - D_R\left(I\right)\right] \tag{2}$$

$$s \cdot t \cdot \quad t = \begin{cases} 1 & if\ I \in \ I^i \\ 0 & if\ I \in \ \hat{I}^i \end{cases} \tag{3}$$

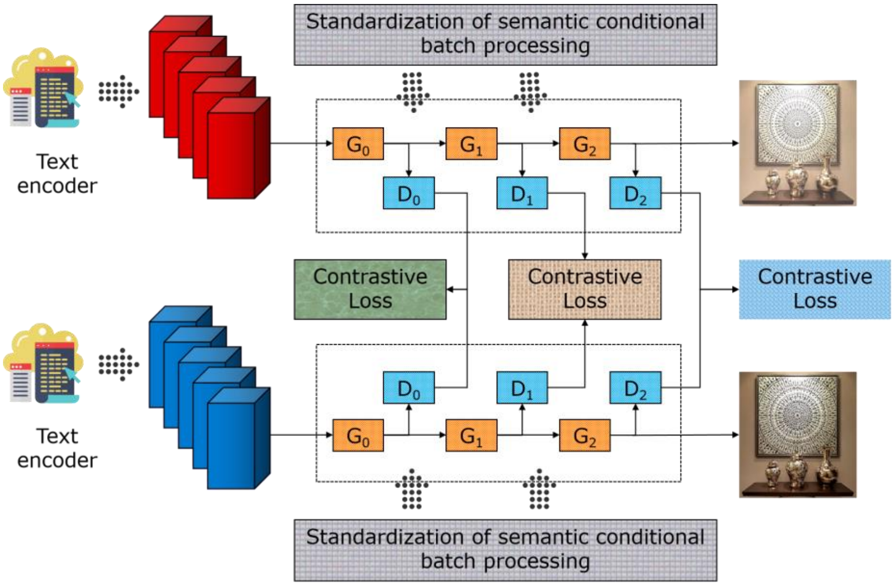

Figure 1: Discriminator network.

The Sigmoid function, a frequently utilized logical function, can transform any real number into a value falling between 0 and 1. It is often employed as the activation function for the output layer in binary classification tasks, converting the model's output into probability values. Within the discriminator of a GAN, the Sigmoid function serves to translate the discriminator's output into a probability, indicating whether the sample belongs to the authentic class. The mathematical expression for the Sigmoid function is as follows:

$$sigmoid\ \ z\ = \frac{1}{1+e^{-z}} \tag{4}$$

Then, the discriminator network structure is as follows:

$$D_{\varphi}\ \ s\ = sigmoid\ \ \varphi_l^T F_{\varphi_f}\ \ s\ \ = sigmoid\ \ \varphi_l^T f \tag{5}$$

Where $D\ \cdot$ stands for discriminator network, φ stands for parameters in discriminator network, and $F\ \cdot$ stands for feature detection network. The output of the feature detection network is defined as f, and this process can be expressed as:

$$f = F_{\varphi_f}\ \ s \tag{6}$$

Among them, the high-order features f of the text have dual functions: they can be input to the output layer of the discriminator as intermediate results in the process of discriminator processing to enhance its discriminating ability. At the same time, these features can also be transmitted to the generator network, which can be used as a guiding signal under the reinforcement learning framework to guide the generator to generate texts that are more in line with the real data distribution.

In the field of art design, GAN can be used for style transfer, image restoration, super-resolution reconstruction and other tasks. By training the GAN model, designers can quickly generate new works with specific styles and artistic characteristics, which greatly improves design efficiency and quality.

(2) VAE

VAE is another important deep learning model, which uses an encoder-decoder structure to realize data generation and reconstruction. Different from GAN, VAE does not generate new data directly through NN but first learns a potential space, then samples it in this potential space to get the representation of new data, and finally restores this representation to new data through a decoder. This method enables VAE to better control the diversity and interpretability of generated data.

The encoder of VAE receives the input data and maps it to a potential space. This potential space usually has a lower dimension, which captures the key features of the input data. The output of the encoder is not a specific point in the potential space but a parameter of the probability distribution of the point. Assuming that the input data is x, the role of the encoder is to map it to a potential space and output a parameter pair of mean μ and variance σ^2, indicating the distribution of potential variable z:

$$p_\theta\left(z \middle| x\right) = N\left(\mu\left(x\right), \sigma^2\left(x\right)\right) \tag{7}$$

In which θ represents a parameter of the encoder. Once the latent variable z undergoes decoding, it is re-mapped to the data space, resulting in the reconstructed data denoted as $\hat{x}$.

$$\hat{x} = \backslash\text{decode}\left(\text{z}\right) \tag{8}$$

Where $\backslash\text{decode}$ is a function of the decoder, and its parameter is θ', indicating the parameters of the decoder. The decoder receives the points sampled from the potential space and attempts to reconstruct them back to the space of the original input data.

Set a threshold T and use it to divide the image data into pixel groups larger than T and pixel groups smaller than T, and give them different values to extract feature points:

$$I_B\left(u,v\right) = \begin{cases} 255 & I_P\left(u,v\right) > T \\ 0 & I_P\left(u,v\right) < T \end{cases} \tag{9}$$

In this context, $I\left(u,v\right)$ it stands for the pixel value corresponding to a specific point within the image. Figure 2 depicts the architecture of the VAE.

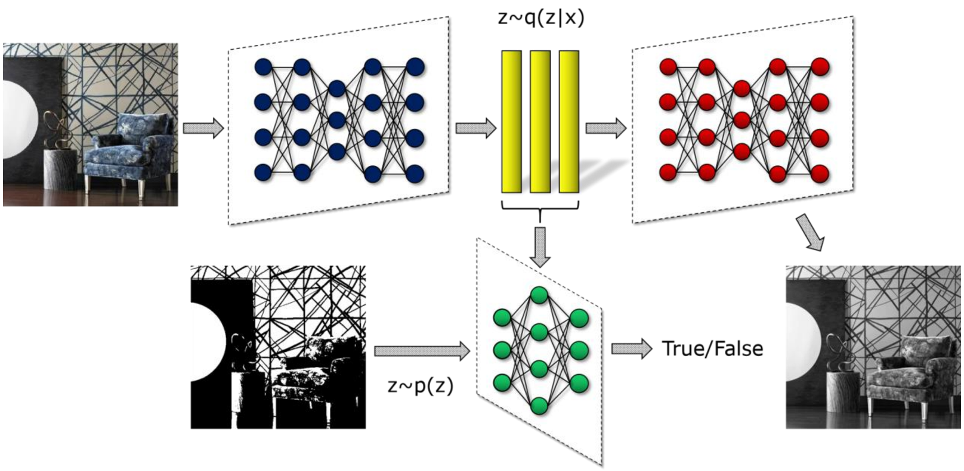

Figure 2: VAE structure.

The loss function of the VAE comprises two distinct components: reconstruction loss and KL divergence. The reconstruction loss quantifies the disparity between the original input and the output of the decoder, whereas the KL divergence gauges the variation between the probability distribution of the latent representation and a predefined prior distribution. By striking a balance between these two elements, the VAE ensures both diversity and fidelity to the original data when generating novel instances. Let x and y denote a frame from the test sample and a general template, respectively; these are utilized to facilitate the computation of similarity, denoted as $s\ x,y$.

$$h_p^{'}\ x,y = \begin{cases} 1 & if\ x_p \in y_p \\ 0 & otherwise \end{cases} \tag{10}$$

During the computation, if x,y it fails to align, $s\ x,y$ it will not be set to zero but will instead receive a negative value, denoted as $h\ x,y$ -5 serving as a penalty. This approach accentuates the disparities between distinct images.

In the field of art design, the application of VAE is mainly reflected in the abstraction and expression of artistic elements and design principles. By training the VAE model, designers can transform complex artistic elements and design principles into computable potential representations, thus realizing automatic and intelligent artistic design.

System architecture design is the key link to building a computer-aided decorative art design system. At this stage, it is needed to design a reasonable system architecture and module division to ensure the scalability, maintainability and reusability of the system. This article divides the system into several functional modules, including a user management module, project management module, design tool module, deep learning model module and so on. Each module is responsible for realizing specific functions and services and interacting and cooperating with other modules through interfaces. In addition, this article also designs a reasonable data storage and management scheme to ensure that the system can efficiently store and manage a large number of decorative art elements and design data. The extension structure of the system is shown in Figure 3.

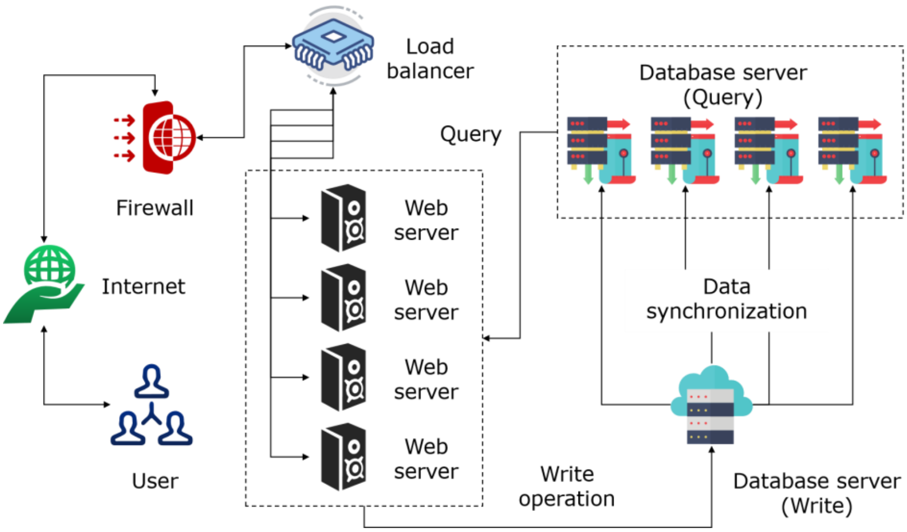

Figure 3: System topology diagram.

The decorative art element database constitutes a pivotal segment of the computer-aided decorative art design framework. It is tasked with the storage and administration of diverse elements and patterns of decorative art, thereby equipping designers with an abundance of resources and creative impetus. This article contemplates various aspects like the provenance, categorization, archiving, and retrieval of this data while fashioning the database. By way of illustration, the compilation of data encompasses existent works of decorative art, historical and cultural legacies, and natural panoramas, among others, which are then sorted and stockpiled according to their individual traits, including style, theme, and medium. Additionally, the integration of an efficient algorithm and an intuitive interface for data retrieval enables users to effortlessly procure the requisite decorative art components and designs.

One of the cardinal techniques underpinning the computer-aided decorative art design system is the algorithm centred around a profound generative model. The current phase necessitates the employment of such a model to assimilate and emulate the idiosyncrasies and aesthetics of decorative art design, forging novel compositions in a similar vein. Specifically, we can discern the underlying patterns and distribution principles of decorative art components by educating the generative model. Its generative capabilities can then be harnessed to conjure up fresh decorative art motifs and patterns. Simultaneously, a customizable decorative design algorithm, tailored to users' preferences and requirements, can also be devised leveraging this profound generative model, ultimately culminating in the automated crafting of personalized decoration plans that align with the designated criteria. The implementation of these algorithmic advancements promises to endow designers with a more robust and flexible design toolkit, thereby fostering innovation and expansion within the decorative art design landscape.

4 MULTIMEDIA DYNAMIC DISPLAY TECHNOLOGY

4.1 The Application of Multimedia Technology in Art Design

The utilization of multimedia technology in art design has gained significant traction, affording designers an expanded and varied palette of expressive tools. Through the amalgamation of textual, visual, audio, and video components, designers can craft artworks that are both captivating and immersive. In the realm of decorative art design, multimedia technology finds application in two principal ways: firstly, it facilitates the presentation and exhibition of decorative artworks, thereby enriching the sensory experiences of viewers. Secondly, its integration into the creative workflow of decorative artworks fosters flexibility and creativity. Illustratively, designers might leverage multimedia technology to fashion dynamic decor motifs or merge audio-visual elements with decor components to produce more engaging and interactive pieces.

Dynamic exhibition technology, on the other hand, involves the utilization of computer technology and multimedia means to transform static artworks into dynamic displays. This is achieved primarily through the application of computer graphics, animation, and human-computer interaction techniques, which facilitate the digital manipulation and control of artworks to generate dynamic visuals and interactive features. In the context of decorative art design, the incorporation of dynamic exhibition technology significantly boosts the allure and expressiveness of pieces. For instance, it can be employed to create animated decorative paintings, sculptures, and installations, offering viewers a more vivid and engaging visual experience. Techniques used to realize dynamic displays are diverse and include, but are not limited to, animation, video editing, and programmatic controls.

4.2 Dynamic Display of Decorative Arts Based on Virtual Reality

VR technology, which enables the creation and exploration of computer-generated worlds, has become a transformative tool in art design. Using VR headsets and accompanying interactive devices, users can immerse themselves in virtual environments and intuitively engage with digital objects. In the realm of decorative art design, the incorporation of VR-based dynamic display technology offers viewers an unparalleled sense of immersion and realism. Designers leveraging VR can construct immersive virtual environments, showcasing decorative artworks in three dimensions. By introducing dynamic elements and interactive capabilities, they empower audiences to freely explore and engage with the works in novel ways. This type of presentation not only fosters a heightened sense of participation and immersion for viewers but also opens up new creative horizons for designers, allowing for greater flexibility and expressivity in their work.

4.3 Visual Color Presentation of Multimedia Dynamic Display Technology

In the dynamic display of decorative arts based on virtual reality, the quality of visual presentation directly affects the audience's experience. Through learning a large amount of decorative art data, deep learning models can grasp the visual characteristics of different art styles, thereby generating dynamic display effects that are more in line with artistic laws. Meanwhile, deep learning models can continuously optimize visual effects based on audience feedback and interactive data, enhancing audience immersion and satisfaction. Color is one of the indispensable elements in decorative art. The application of color is particularly important in dynamic displays based on virtual reality. Deep learning models can analyze the color distribution and matching patterns of decorative artworks, and accurately restore these color effects in dynamic display. At the same time, the model can also adjust and optimize colors in real-time based on factors such as lighting and materials in the virtual environment, making decorative artworks present more realistic and vivid color effects in the virtual space.

5 SIMULATION EXPERIMENT AND RESULT ANALYSIS

Before the simulation experiment, this section first set up a suitable experimental environment and prepared the necessary data sets. The experimental environment includes the required hardware configuration, such as a high-performance computer, professional graphics processing card, and software configuration, such as DL framework and programming language. These configurations ensure the stability and efficiency of the experiment. Choosing the right dataset is crucial for the experiment's outcome. In this segment, we've carefully curated data about decorative art design, including elements like decorative motifs, textures, colour schemes, and more, sourced from both public repositories and our own collections. This diverse and representative dataset encompasses various decorative themes and styles. During the experimental design phase, we've tailored a detailed plan aligned with our research goals and practical requirements. We've selected a suitable deep learning model and algorithm for our purposes. Additionally, we've devised multiple sets of comparative experiments to validate the model's efficacy and advantages.

Figure 4: User rating results.

To ensure an unbiased assessment of the experimental outcomes, we've established a comprehensive set of evaluation metrics. These metrics encompass generation quality, diversity, innovation, and other relevant aspects to provide a holistic view of the model's performance. Our evaluation approach combines both subjective and objective assessments for a more comprehensive and precise analysis. Subjective evaluation involves human observation and analysis, focusing on the visual appeal and artistic merit of the generated works. The outcomes of this subjective evaluation are presented in Figure 4 and Table 1.

User number	*Visual effect evaluation*	*Artistic evaluation*	*Comprehensive assessment*
U001	Rich and harmonious colours, clear details, and strong attraction.	Unique creativity, distinctive style, and strong artistic appeal.	Excellent works, both visual and artistic.
U002	The visual effect is good, but the colour matching of some parts is a little abrupt.	There is some creativity and artistry, but the style is not uniform enough.	Overall performance is good; there is room for improvement.
U003	The picture is vivid and lifelike, with strong layering and great visual impact.	Creative, unique artistic style, impressive.	Both visual and artistic are excellent, which is worth recommending.
U004	The visual effect is average, lacking bright spots and attraction.	Artistic performance is mediocre, lacking innovation and uniqueness.	The overall performance is average, and creativity and visual design need to be improved.
U005	The colour matching is just right, and the visual effect is excellent and fascinating.	Extremely artistic, unique, infectious, unforgettable.	Excellent works, both visual and artistic, have reached a high level.

Table 1: User subjective evaluation details.

Table 1 aims to show users' specific evaluation of the visual effect and artistry of the generated works so as to fully understand the acceptance and improvement direction of the works among different users. Through the experimental results, it is found that the model performs well in terms of generation quality, diversity and innovation. The subjective evaluation results further verify the performance of the model, and all the scores are high.

The objective evaluation is to use quantitative indicators, such as PSNR (Peak Signal to Noise Ratio), SSIM (Structural similarity index), and MAE (Mean absolute error), to evaluate the generated works quantitatively. PSNR is shown in Figure 5.

The higher the PSNR value, the better the image quality and the less the distortion. From Figure 5, we can see the changes in PSNR value under different experimental conditions. It reaches the PSNR value of 30dB, which is a relatively high-quality level, indicating that the generated works and the original images maintain good consistency at the pixel level. SSIM is shown in Figure 6.

The higher the SSIM value approaches 1, the greater the resemblance between the two images. Referring to Figure 6, the model's SSIM value stands at approximately 0.9, indicating a strong structural similarity between the generated output and the original image, with near-perfect retention of the original's key visual elements. Meanwhile, Figure 7 displays the MAE results.

The nearer the SSIM value approaches 1, the stronger the resemblance between the two images. In the realm of image generation, MAE serves as a metric to gauge the average pixel-level disparity between the generated and actual images.

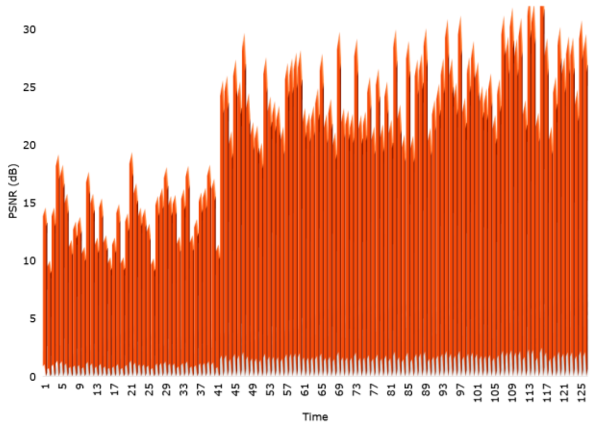

Figure 5: PSNR.

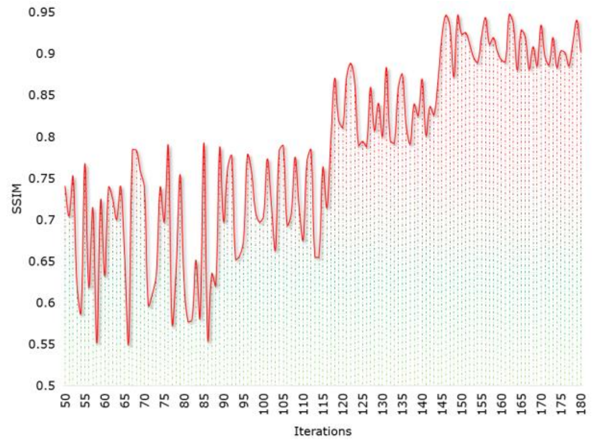

Figure 6: SSIM.

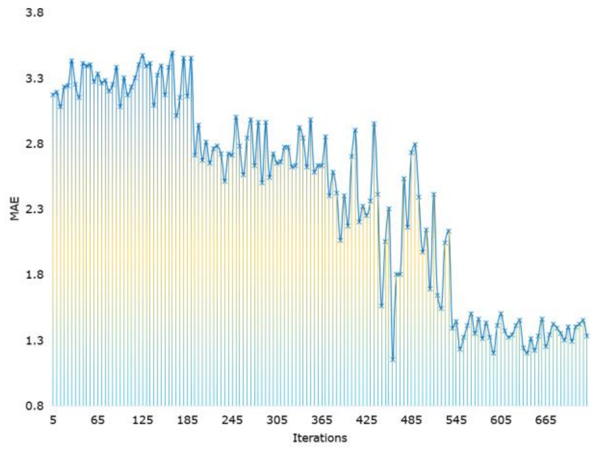

Figure 7: MAE.

A lower MAE score signifies a higher resemblance between the generated output and the real image. As evident in Figure 7, the model proposed in this study has attained a notably low MAE value, indicating that the generated images are remarkably similar to the real ones at the pixel level, making them challenging to discern.

In addition, this article also shows the diversity and innovation of the works generated by the model through the visualization results, as shown in Figure 8.

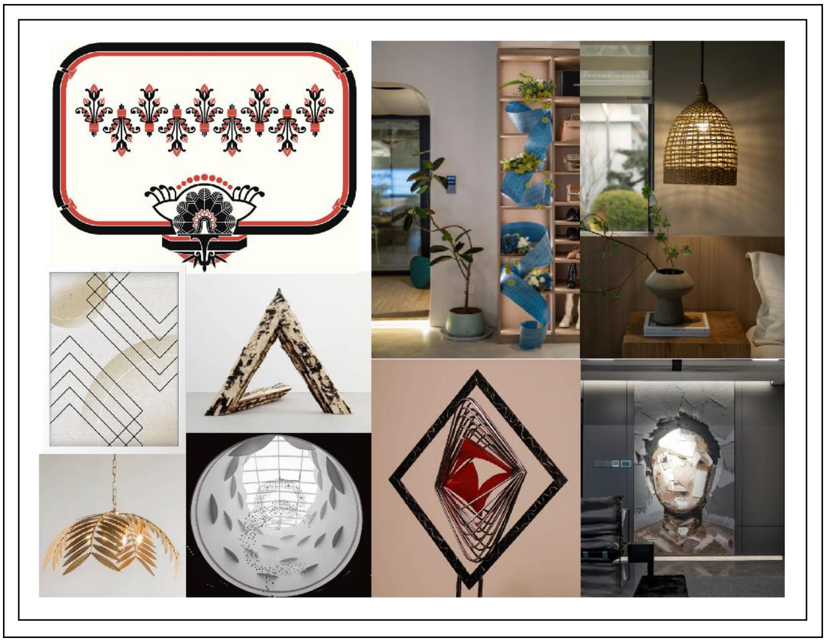

Figure 8: The model generates the visual result of the work.

The experimental outcomes reveal that the model is capable of producing decorative patterns of exceptional artistic quality, exhibiting superior colour coordination, elegant line fluidity, and well-structured compositions. Furthermore, this model exhibits versatility by generating a diverse array of patterns spanning traditional to modern aesthetics, as well as simple to intricate designs. This diversity underscores the model's adaptability and range. Additionally, the model excels at amalgamating diverse artistic influences and original concepts, resulting in distinctive and imaginative patterns. These designs strike a harmonious balance between preserving the elegance of classical art and incorporating contemporary design elements, presenting a fresh and original visual experience. In conclusion, the computer-assisted decorative art design approach rooted in the advanced deep learning model introduced in this study proves effective, offering innovative perspectives and techniques to the realm of decorative art design.

6 CONCLUSIONS

This article presents an in-depth examination of deep learning model, specifically highlighting GANs and VAEs and elucidating their utilization and merits in the realm of decorative art design. Furthermore, a computerized system for aiding in decorative art design has been devised, and its efficacy and practicality have undergone rigorous simulation-based testing.

The key findings of our research are as follows:

Firstly, we introduce a novel approach to decorative art design that leverages deep learning models, thereby revitalizing and injecting creativity into traditional design practices.

Secondly, our computer-aided system for decorative art design facilitates the automated creation and innovative design of artistic elements, significantly enhancing both the efficiency and quality of the design process.

Thirdly, the validity of our proposed methodology and system has been confirmed through simulation experiments, offering valuable insights for future research and practical applications in related domains.

Nonetheless, our study is not without limitations. Currently, our focus is narrowed to the generation of a specific type of decorative art element. Future research endeavours could broaden this scope to encompass a wider array of decorative art designs and styles. As deep learning and artificial intelligence technologies continue to evolve, the utilization of deep learning models in art design is poised for significant growth and opportunity. We anticipate the emergence of even more intelligent, personalized, and innovative art design techniques and tools that are rooted in deep learning models. Additionally, as virtual reality, augmented reality, and other cutting-edge technologies become more prevalent, there is potential to explore the integration of deep learning models with these technologies to create even more immersive and diverse artistic design experiences.

7 ACKNOWLEDGEMENT

This work was supported by 2023 Shaanxi Provincial Department of Education Key Scientific Research Program (23JZ018).

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