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Exploration of Human-Machine Collaboration Mode in Brand Pattern Creative Design

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Abstract. As technology advances rapidly, artificial intelligence (AI) and computer technology are revolutionizing our world in unprecedented ways. Notably, in the realm of brand pattern creative design, the incorporation of computer vision (CV) and CAD technology has become pivotal. Deep learning provides an excellent interactive editing channel for user-designed brand perspectives. By interactively editing and processing existing design tools, this article constructs an effective human-machine writing method under brand mode. This article constructs a creative design system for brand pattern design using deep learning and CAD technology. The system utilizes interactive editing of pattern design to enhance the capabilities of deep learning models. After analyzing the innovative construction of interactive patterns, the study integrated interactive editing of pattern brands. The results indicate that this integrated system significantly improves design accuracy and innovation flexibility.

Keywords: Computer Vision; CAD; Brand Pattern; Creative Design; Human Machine Collaboration Mode
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1 INTRODUCTION

In recent years, technological updates and the development of multimedia communication channels have promoted the dynamic and diversified transformation of brand visual image design. The popularization of creative programming and other technologies has led more and more designers to explore innovative methods in the brand design process, and the number of brand visual recognition design practice cases based on generative art is gradually increasing [1]. After reviewing the relevant concepts and current development status, the project analyzes the characteristics of generative art, elaborates on the classification of brands, and discusses the content, current situation, and shortcomings of visual identity design. Generative art, due to its complexity, logicality, and openness, can effectively address the issues of homogenization and poor dissemination in visual recognition design [2]. The current topic explores the value and inspiration of generative art in brand visual identity design, as well as its application strategies in music festival brand visual identity design [3]. Furthermore, from a macro perspective, analyze the advantages and connotations of applying generative art to brand visual identity design. To provide reference for the deconstruction and analysis of existing cases in subsequent design research, and to provide methodological guidance for design practice. Based on case studies, summarize and analyze the four characteristics and demands of visual identity design for music festival brands: functionality, symbolism, culture, and aesthetics. Stylization path, visualization path, participatory path, list specific forms of expression to guide the establishment of the generative visual design system. From a micro perspective, sort out the process of generative art, construct the framework of a generative design system, and plan three application paths based on brand demands and design intentions [4]. Taking TMELAND Electronic Music Carnival as an example, design a visual recognition system, establish a user model through a questionnaire, and analyze the design concept based on the brand's cultural background. Summarize the entry points and advantages of applying birth art to music festival brand visual identity design, and propose strategies, including logical construction level.

Through the training of neural network models, computers are capable of simulating and even surpassing the creative processes of human designers, birthing novel and unprecedented creative elements. This evolution not only enhances design efficiency but also enhances design diversity, aligning brand pattern creative design more closely with the aesthetic sensibilities of the modern populace [5]. Incorporating CAD technology into this field of design not only facilitates rapid and innovative idea generation for designers but also streamlines the process of design conceptualization. Consequently, it not only lessens the workload for designers but also elevates the precision and overall quality of their designs [6]. The brand pattern design system based on computer-aided design not only integrates Kansei engineering theory and methods to capture user perception images but also uses morphological analysis methods to deeply deconstruct and encode patterns. These pieces of information are the core driving force behind the creative design of brand patterns. Afterward, with the help of BP neural network technology, the system established an intelligent mapping relationship between user perception images and pattern design elements. Based on morphological analysis methods, the system deconstructs brand patterns, extracts design elements such as lines, shapes, colours, textures, etc., and encodes them. Using the Kansei engineering theory, the system can comprehensively collect and analyze user perception information about brand patterns, such as emotional resonance, cultural identity, aesthetic preferences, etc [7]. This mapping relationship is not only accurate but also capable of processing a large amount of data, providing strong support for the creative design of brand patterns. Based on design goals, such as specific brand image, market positioning, or user group, the system can calculate and find the corresponding design code combination [8]. The introduction of BP neural network technology enables the system to automatically learn and establish complex mapping relationships between user-perceived images and pattern design elements. Taking clothing Paper Cuttings pattern as an example, the system shows excellent performance in practical application [9]. It not only accurately reflects the perceived image of users in pattern design, but also efficiently provides customized pattern design services for clothing brands. These combinations not only meet the perceived needs of users but are also full of creativity and novelty. This deconstruction and coding approach makes design elements easier to understand and operate by the system. In the digital era of the 21st century, the rapid development of Internet technology and digital technology has brought about qualitative changes in people's lives. The continuous iteration and updating of brand communication media has given birth to a large number of Internet media channels, and its promotion forms and carriers have become more diversified. Faced with this trend, the public has developed a new demand for brand visual images. Enterprises are facing challenges as well as opportunities in this new trend. Propose some forward-looking opinions that can be used for reference for the cultural and historical brand, which has a strong inherent colour and distinctive characteristics. Mainly select two categories of brands: e-commerce brands and cultural and museum brands for case analysis and comparison. Help enterprises in other fields represented by Wenbo products to better adapt to the development requirements of the Internet era and carry out transformation design to a certain extent. The design and promotion of brand visual image in the Internet era has changed in concept, media and form. E-commerce brand mainly relies on the Internet platform for sales, which is the most perfect brand field under the Internet media. It has the advantage of learning from others [10].

The system can quickly generate creative patterns that meet design requirements through the intelligent generation function of DL models. Meanwhile, through the personalized editing function of CAD software, designers can make personalized modifications to the generated patterns based on their own aesthetics and experience, thereby obtaining unique design solutions.

In this article, we delve deeply into the pivotal significance and evolving trends of brand pattern creative design within the contemporary societal framework. Subsequently, we delve further into the expansive application of CV technology and CAD in the realm of brand pattern design. Building on this foundation, we introduce a novel brand pattern creative design system that seamlessly integrates DL technology with CAD. To substantiate the practical efficacy and application prowess of this system, we undertake a comprehensive series of experiments, thoroughly analyzing and discussing the experimental outcomes. In the concluding segment, we consolidate the key research achievements and novel contributions of this study. Additionally, we offer prospective research avenues and recommendations, such as enhancing system algorithms and broadening application scopes, aimed at fostering the enduring progress of brand pattern creative design.

2 RELATED WORK

In recent years, the position of brand semiotics in brand strategy design has become increasingly prominent, especially in the creative design of brand models. It has become a key factor in attracting and maintaining consumer attention. The research results indicate that the application of brand pattern creative design in product packaging has a significant positive impact on consumer brand experience and brand trust. Brand visual image design has become particularly critical in the Internet media. Then, in view of the new development situation, this paper puts forward new methods and strategies for brand visual image design and promotion to adapt to the development of Internet media. Clarify the new demand for visualizing product information, unifying visual elements, and diversifying cognitive channels. First, it describes the concept and function of Internet media and brand visual image systems. Saleh et al. [11] defined the impact of Internet media on brand image and the relationship between them. After the involvement of computer technology, networks, and various electronic devices in brand design and promotion, it is necessary to break the pattern and innovate: grasp the new trends of micro-interaction, hand-drawn dimensions, and minimalist style in brand image design. Create the communication power of the brand image, attract consumers' attention, meet their psychological demands, interact with them, and promote enterprises to better progress and transform to adapt to the booming development of the Internet era. In order to make enterprises stand out, we should change passivity into initiative, study the transformation strategy of corporate brand visual image design and promotion under the Internet media, and combine the two to conform to the new development trend. Then discuss the new forms and trends of brand visual image design and promotion in the era of Internet big data. Make rational use of the new advantages of Internet media in multi-point interaction, instant sharing and interactive experience; Use such new carriers as H5, augmented reality advertising, mobile APP, WeChat official account, etc. as brand promotion to create a new image more suitable for the characteristics of the Internet. It not only enhances the attractiveness of the product but also deepens the emotional connection between consumers and the brand through its unique symbolic significance. In addition, the study also found that the creative design of brand patterns has a positive impact on consumer purchase intention. Therefore, for brand managers, in-depth research and application of brand semiotics principles for the creative design of brand patterns will become an effective way to enhance brand competitiveness and market share.

With the explosive growth of industrial visual information, how to extract valuable elements from it and provide inspiration and a basis for brand pattern creative design has become an urgent problem to be solved. The rise of the Industrial Internet of Things has greatly promoted the intelligent process of industrial manufacturing. By connecting production equipment, mobile terminals, and smart devices to wireless or wired networks, the automation and intelligence of the production process have been achieved. As an important bridge for communication between enterprises and consumers, the creative design of brand patterns is not only related to aesthetics but also involves the transmission of brand value and the resonance of consumer emotions. In this process of intelligence, industrial visual information - such as images, videos, graphics, and text - has become an important carrier of hidden value, especially in the creative design of brand patterns. Shukla et al. [12] proposed a tensor-based visual feature recognition method that can recognize objects with surrounding environments from a multi-attribute perspective. Deconstruct and reassemble various elements in industrial visual information, and extract representative and unique visual features. The current era is characterized by symbolization and branding, as well as brand influence determining market position. With the improvement of the consumption level of Chinese consumers, they are increasingly inclined towards characteristic consumption. While meeting their material needs, they must also meet their psychological needs. To achieve the purpose of identification and uniqueness in communication, the visual system of a brand needs to convey the brand positioning and core brand values of the enterprise through corresponding graphic symbols and unique visual language. In this era where customers are gods, the construction of a brand visual image is of utmost importance in brand communication. Enterprises need to update and upgrade their brand's visual recognition system on time. The era of integrated brand image design has arrived, and the visual identification system of a brand is no longer just a logo. Wang et al. [13] explored the market and economic laws that enterprises need to follow when reshaping their visual image from the perspective of brand strategy. The reshaping of brand visual identity systems not only needs to cater to the personalized needs of consumers but also requires comprehensive consideration of brand strategy. Zhang [14] classified and studied the reasons for the reshaping of brand visual systems through extensive material collection and case analysis. An analysis is conducted on the strengthening of corporate philosophy, enhancement of brand core values, and support for brand innovation in the process of brand image reshaping. Based on the "change" and "unchanging" of some excellent brands in brand image reshaping. Aiming at the difficulties, misconceptions, and risks faced by Chinese enterprises in brand image reshaping, this paper proposes ideas, design strategies, and design methods for reshaping brand visual images based on brand strategy. Propose a formula for brand image asset positioning when enterprises reshape their brand visual system, providing scientific data support for brand visual system reshaping. But gradually improved and upgraded into a comprehensive visual system involving disciplines such as aesthetics, sociology, consumer psychology, and marketing. Based on a review of relevant cases and research status both domestically and internationally, Zhang et al. [15] first defined brand visual identity design. Then, by sorting out the development of the media environment and its characteristics of information dissemination, define the new media environment. By analyzing an event-based case - the visual image system of the Hanover World Expo in Germany - as a starting point, this paper proposes new requirements for brand visual identity design in the new media environment. Compared to the characteristics of information dissemination in traditional printing media, summarize the characteristics of information dissemination in the new media environment. Analyze and compare excellent brand visual identity design cases generated in the new media environment and classify them from the perspectives of their forms of expression, brand promotion, audience needs, and user experience. There are three types of brand visual identity design, mainly based on multi-form logos, dynamic videos, and interactive logos, combined with relevant theories such as communication studies, design psychology, and brand visual identity design. Sort out, summarize, and study the design ideas and methods of brand visual identity design in the new media environment. Finally, it extracts its reference significance and dynamic trend research for the development of brand identity design, hoping to bring new thinking to brand visual identity design.

3 THE APPLICATION OF CV AND CAD IN BRAND PATTERN CREATIVE DESIGN

In addition, pixel-based graphic image processing is also a commonly used technique for style recognition design, such as the most common Glitch art style. There are three difficulties in formulating generation rules for visual paths: ⊖ It is necessary to select the basic technical logic for visual representation based on data features; ⊜ The perceptual potential of the output visual elements should form a corresponding relationship with the data change rules; ⊛ Visual logic needs to form a corresponding relationship with data logic. The visual recognition design created from this is not only the result of visualizing data, but conceptually, it is more like an "information graph", which adds more aesthetic subjective beautification from designers based on the visual representation of data logic. Data technology-driven brands, data analysis brands, and food industry brands are closely affected by weather and climate, or outdoor activities. This path applies to brands in the art field, such as music and dance-related brands.

Extracting pixels of specific colours from an image generates displacement in the same direction, resulting in a faulty artistic effect. It has a distinct sense of modernity, technology, and art, and is often used in the design of the main visual. The design needs to maintain a balance between clear style and the complexity of generating assets to ensure the recognizability of the brand personality reflected by the visual style. By establishing mapping rules from data to visual elements, brand information is encoded, and the audience receives visual results for decoding, perceiving their connotations, and achieving semantic transmission. When stylization becomes the design expression intention of brand visual recognition, the semantic construction of form and the audience's perception of style become the main research content. Under the visualization path, brand-related data is introduced, and a clear mapping relationship between data and design visual variables is established from the perspective of visual motivation. The visual results are subjected to certain aesthetic processing, and the brand story is narrated in a visual aesthetic form. In the framework of the generation system, the input end introduces data that can represent the characteristics of the brand: audio of the music brand, weather of outdoor activities, and so on. Figure 1 shows the application of CAD in brand pattern creative design.

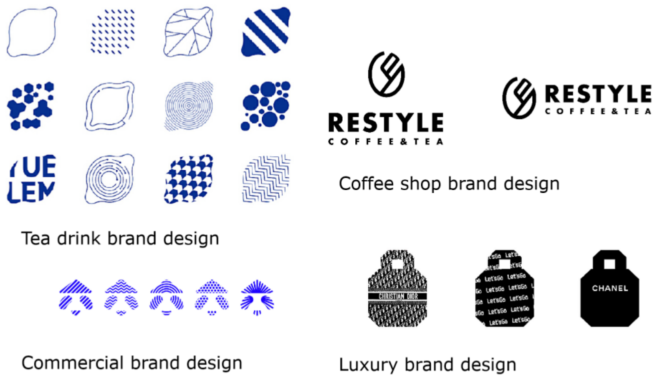

Figure 1: Application of CAD in Brand Pattern Creative Design.

4 BRAND PATTERN CREATIVE DESIGN SYSTEM

4.1 Systems Design

The true significance of using AR technology in brand promotion is to improve the reader's experience, making their reading process easier, more interesting, and more convenient. AR publications can achieve visual diversity, user emotional interaction, and intelligent experience, allowing readers to experience the charm of new technology and share its value. This is a seamless supplement to traditional advertising and a reflection of the transformation of traditional marketing value. The design of the AR brand compensates for the inherent shortcomings of traditional paper media, with advantages such as dynamic, 3D stereoscopic, multimedia video, background music, an independent reading selection, interactive experience, etc., making it "lively". Breakthroughs in science and technology, interaction methods, content, and other aspects are needed to make the world presented to users more vivid and colourful and to seek new breakthroughs in the future development of brands. The immersive experience allows the public to generate aesthetic feelings and experiences during the interaction process. The public is not only viewers of the brand but also directly participates in cultural exchanges with the brand. Big data, Internet thinking, cloud computing and digital interactive devices create an interesting "immersive" interactive experience. The cross-border integration and application of new scientific digital technologies such as augmented reality, virtual reality, 3D technology, holographic imaging, etc., integrates digital information such as sound, graphics, animation, and data, and transforms planar visual information into multi-dimensional spatial perception.

AR technology is currently in the exploratory stage of development. To better apply AR technology to traditional printed materials, the market needs to have a certain awareness of augmented reality, overcome technical problems, and improve the combination of technology and content. In recent years, with the continuous increase in people's material and cultural needs, traditional museums are no longer able to meet people's diverse needs. Firstly, traditional museums have limited space for information transmission and are more constrained by time and space, leading to a gradual decrease in people's attention. The public generates a comprehensive sensory experience through interactive media, including visual, auditory, tactile, and even olfactory senses, enhancing their perception of reality and creating new channels for brand promotion through new technologies. Figure 2 shows the structure of the brand model creative design model based on GAN.

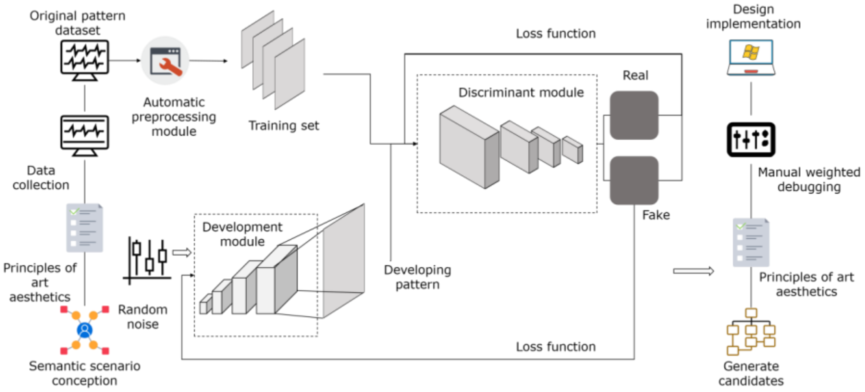

Figure 2: Structure of brand pattern creative design model based on GAN.

4.2 Algorithm Principle

In this process, the two follow function (1) in a minimax game, where the discriminator aims to maximize the value function V to accurately distinguish between true and false data, while the generator G seeks to minimize the same value function V, aiming to generate samples that are difficult to distinguish from real data. Through this continuous optimization process, GAN can ultimately achieve excellent generation results.

$$\min G \max DV \;\; D,G \;\; = Ex \sim Pdata\left[\log D \;\; x \;\;\right] + Ez \sim Pz\left[\log \;1 - D \;\; G \;\; z \;\;\right] \tag{1}$$

Among them, G are the generator and D the discriminator. $Pdata$ Represents the true data distribution and Pz represents the generated data distribution.

In the original GAN model, the discriminator evaluates both the input real image and the fake image generated by a generator G while performing its task. Specifically, the first item in equation

(2) focuses on processing the generated fake images $G(z)$, to accurately identify them as fake by reducing their ratings. The second item focuses on real images, to improve their ratings to ensure they are correctly recognized as true. The training process of the entire model aims to continuously enhance the ability of the generator G, so that the generated images can "deceive" the discriminator, achieving the effect of making the discriminator mistakenly believe that these images are real (G takes $\min$). At the same time, discriminators are continuously evolving to more accurately determine the authenticity of images (D takes $\max$), ensuring that the game between the two can reach an equilibrium state.

$$\min_{G}\max_{D} E\left[\log D(G(z)) + \log(1 - D(x))\right] \tag{2}$$

In the input module, the core of image reconstruction is the encoder, which maps the image to the latent space of the GAN model, enabling the generator to reconstruct the original image. This encoder includes an image encoder, a generative model, and a perceptron. The reconstruction process includes encoding the image, generating the image, and comparing it with the real image through a perceptron. Gradient descent optimization vectors are used to minimize the loss function and ensure that the generated image is similar to the original image.

$$z^* = \min_{z} L_{percept}(G(z), I) + \frac{\lambda_{mse}}{N}\left\|G(z) - I\right\|_2^2 \tag{3}$$

$$L_{percept}(I_1, I_2) = \sum_{j=1}^{4}\frac{\lambda_j}{N_j}\left\|F_j(I_1) - F_j(I_2)\right\|_2^2 \tag{4}$$

Among them, $I_1, I_2 \in R^{n\times n\times 3}$ is the input image, $G(z)$ the pre-trained model N is the number of scalars in the image, z^* the potential code that needs to be optimized, F_j is the feature map output by the convolutional layer, and N_j the number of scalars in the output of the j th layer.

BatchNormalization accelerates the convergence of the model, with the core of standardizing each layer's input to a normal distribution with a mean of 0 and a variance of 1, and introducing scaling and offset parameters to maintain nonlinearity and prevent gradient vanishing. These parameters can be trained, as shown in formula (5).

$$y = \frac{x^{k} - E\left[x^{k}\right]}{\sqrt{Var\left[x^{k}\right]}} * \alpha + \beta \tag{5}$$

Among them, x^{k} is the output value of the k layer unit, $E\left[x^{k}\right]$ and $Var\left[x^{k}\right]$ represent the mathematical expectation and variance of x^{k}, and α, β are the scaling and offset parameters, respectively.

In deep convolutional networks (DCN), to preserve fractal pattern details and meet brand design requirements, we use local affine transformations when generating creative patterns. This transformation ensures that each colour channel pixel value of the creative pattern is derived from a linear combination of local regions of the fractal pattern, thereby avoiding edge colour extension and unevenness. Through this method, we have retained the essence of fractal patterns and achieved customization of creative patterns. The mathematical form is briefly described as follows:

$$L_I^l = \frac{1}{2N_l D_l}\sum_{ij}\left(F_l[O] - F_l[I]\right)_{IJ}^2 \tag{6}$$

Among them, L is the total number of convolutional layers, l the l convolutional layer of DCN, each layer has N_l filters, and each is a vector feature map of size D. $F_l\left[\cdot\right]$ Is the feature matrix.

$$L_S^l = \sum_{c=1}^{C} \frac{1}{2N_{l,I}^2} \sum_{ij} \left(G_{l,I}\left[O\right] - G_{l,I}\left[S\right] \right)_{IJ}^2 \tag{7}$$

Among them, I are the input image, O represents the output image, and S represents the style image.

In the system, the editing and modification module learns z^* vector transformation through converters and generators, thereby changing the attributes of the generated image. Brand pattern design editing is based on vector z^* editing, where data items monitor deviations and smoothing items ensure small adjustments within the potential space to maintain stable image content. The precise definition of editing operations aims to achieve precise adjustments.

$$z^* = \arg\min\left\{ \sum_g \left\| f_g G\left(z\right) - V_g \right\|^2 + \lambda_g \cdot \left\| z - z_\theta \right\|^2 + E_D \right\} \tag{8}$$

$$E_D = \lambda_D \cdot \log\left(1 - D\left(G\left(z\right)\right)\right) \tag{9}$$

Among them, λ is an adjustable feature parameter, and θ is the direction learned in the latent space.

5 RESULT ANALYSIS AND DISCUSSION

To assess the system's performance, we'll embark on experiments. Figure 3 highlights the advantage of the system in terms of brand pattern design accuracy. The refined design of visual recognition systems refers to the deep visual correction and improvement of the designed brand image to ensure the integrity of the VI system and the consistency of dissemination in different media. Transforming these elements into static symbolic norms to prevent deviations in later reuse and maintaining visual standardization and consistency is more conducive to brand communication. This stage of design strictly adheres to the VI system design principles, highlights the characteristics of the Nova brand, and forms a unified brand image. The purpose of forming a guest-host relationship with elements such as logos, standard fonts, and colours is to better apply and disseminate the basic elements of brand image on various media, playing a role in supplementing, enriching, strengthening, and expanding brand image, making the brand more complete, easier to recognize, and remember. Auxiliary graphics are a symbolic graphic system designed according to the needs of different occasions and are one of the basic elements of the VI system. The supplementary plan for auxiliary graphics is based on the brand's easy-to-spread perspective, with colour bands as design elements, which are convenient to use and widely used. The application system, in conjunction with Nova's new brand image, can bring a holistic visual experience and brand belonging to the target audience through standardized and unified visual language. Standardized drafting of basic elements such as identification and auxiliary graphics, data-driven design standards, minimum size limits, minimum spacing limits, and specifications for basic element combinations.

Figure 4 provides a comprehensive analysis. In the era of a large demand for brand visual identity design, a large number of dynamic visual identity design cases have emerged before us. This chapter classifies and defines the types of brand visual identity design. In addition to dynamically representing the brand, it also includes the dynamic trends of the interrelationships between brand applications and the dynamic development of the brand in the new media environment. The dynamism of brand visual identity design mentioned in this article is not solely classified based on the expression form of the brand's core visual image. However, it is classified based on the dimensions of the reasons and effects that arise and develop in the brand environment. From the expression form of the logo, Narrowly defined, dynamic refers to a form of presentation on electronic media that incorporates a temporal dimension in formats such as gif and flash. This is relative to the visual image design that exists on two-dimensional paper media.

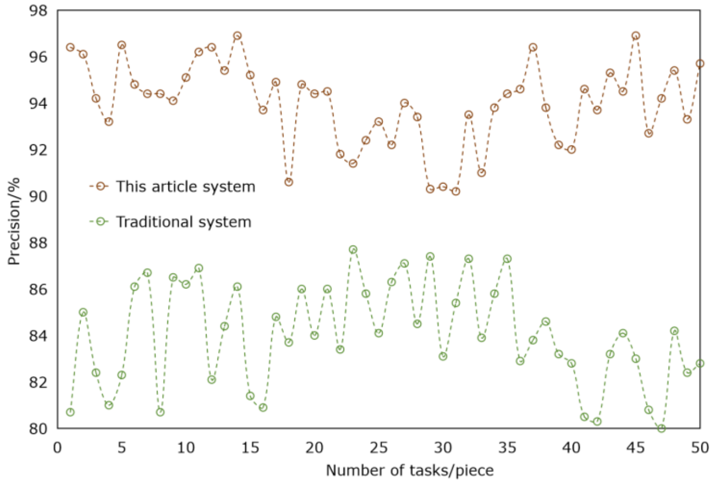

Figure 3: Comparison of design precision.

And analyze the specific performance and presentation effects of the design case, comparing its differences with the brand visual identity design in the traditional media environment in terms of brand visual effects and brand effects. Brand visual recognition design is mainly based on multi-form logos, dynamic video and animation visual recognition design, and the dynamic role of brand recognition design in application expansion. A brand visual identity design that focuses on the interaction between brand systems rather than weakening the logo as the main body.

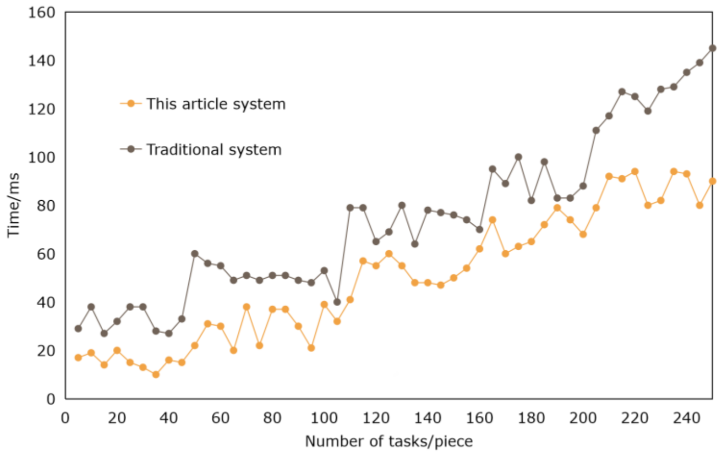

Figure 4: Comparison of task processing time.

In Figure 5, we delve into the comparison between the system designed in this paper and the classic artificial intelligence design system in terms of recall rate. From the illustrated data, it can be seen that the system constructed in this article significantly surpasses traditional artificial intelligence design systems in terms of recall rate. Behind this significant improvement is the deep learning algorithm's deep mining and understanding of massive design data. This intelligent recognition ability enables the system to more accurately match user expectations when generating design results, greatly improving the system's recall rate. Specifically, through detailed research on a large number of brand pattern design cases, our system can automatically extract and identify the commonalities and differences between different brand patterns. This technological breakthrough not only enhances the system's ability to handle brand pattern design tasks but also enables our system to integrate into numerous design results. Presenting designs that meet user needs in a higher proportion, truly achieving a high degree of alignment between design and user needs. Recall rate, as a key criterion for measuring the effectiveness of design systems, directly reflects whether the system can accurately identify and present design results that match user needs. It is precisely this technological innovation that enables our system to more accurately capture the core elements of brand pattern design, thus making the design process more in line with user expectations.

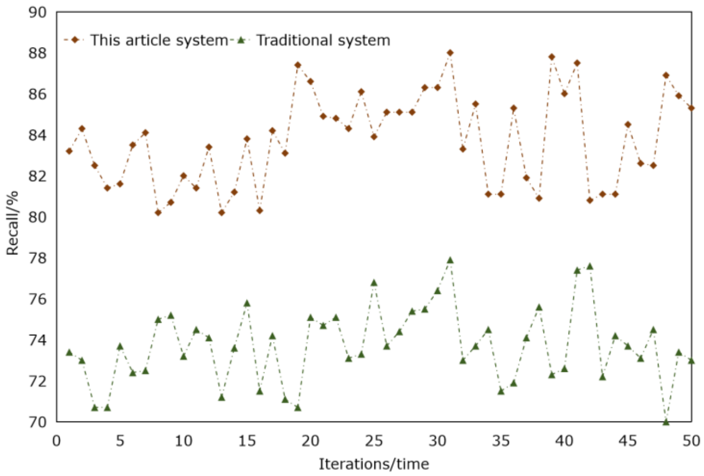

Figure 5: Comparison of recall rates.

In the intuitive comparison in Figure 6, we can clearly see that the system designed in this article has significantly improved user satisfaction compared to traditional artificial intelligence design systems. Not only that, the precise application of computer-aided design (CAD) technology also makes the detailed handling of design results more outstanding, further improving user satisfaction. Through the DL algorithm, our system can accurately capture key elements and current aesthetic trends in brand pattern design, thereby generating design solutions that are more in line with user aesthetic preferences and needs. The core reason for this improvement is the deep learning (DL) algorithm's deep insight and understanding of design data. However, traditional artificial intelligence-based design systems may have some shortcomings in understanding user needs and aesthetic preferences, which leads to a certain gap between the generated design solutions and user expectations. However, the system designed in this article cleverly combines DL technology with CAD technology, not only solving these problems but also providing users with more satisfactory design services.

When we carefully examine the loss function curve of the GAN algorithm in the brand pattern creative design system shown in Figure 7, a notable feature is its astonishing convergence speed. This efficient data processing capability enables the GAN algorithm to quickly reduce loss values through continuous model parameter optimization, thereby providing users with more efficient and accurate design services. On this chart, the loss function curve shows a stable and rapid downward trend, which proves that the GAN algorithm can quickly capture the core features in the data in a short time. This fast convergence speed not only improves user experience, allowing users to see design results faster but also reduces the demand for computing resources, further reducing usage costs.

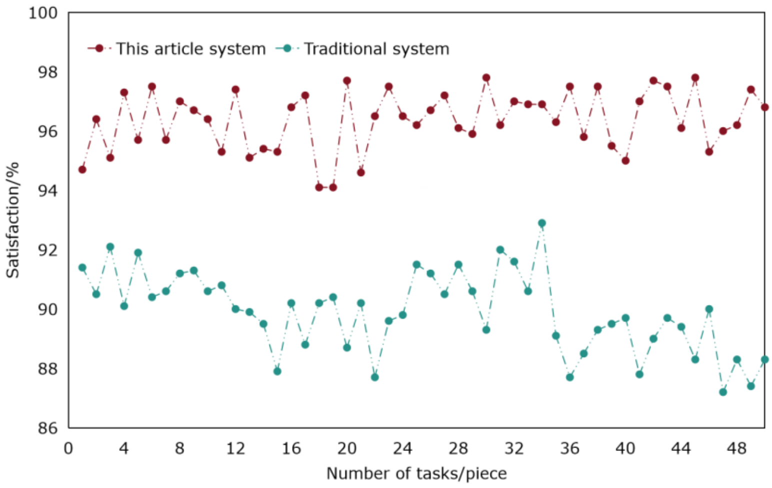

Figure 6: Satisfaction comparison.

The loss function curve, as a key indicator for evaluating the training effectiveness of the GAN algorithm, intuitively reflects how the model gradually approaches the optimal solution during the training process. It can be said that the GAN algorithm loss function curve shown in Figure 7 vividly reflects the efficiency and accuracy of the brand pattern creative design system.

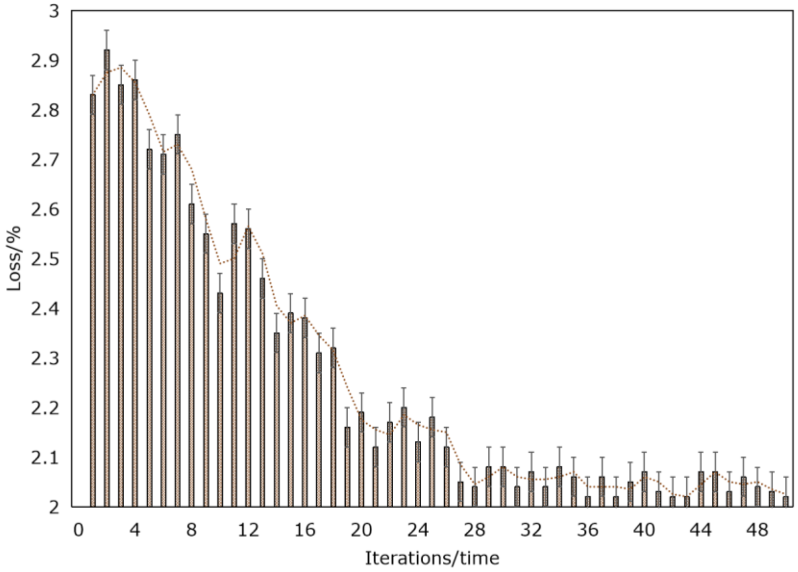

Figure 7: Loss function curve.

Throughput is a key indicator of a system's processing power, reflecting the number of tasks that the system can process at the same time. In Figure 8, the system designed in this article demonstrates higher throughput, which means it can process a large number of design requests more quickly, meeting the needs of users for efficient and fast design services. This advantage is mainly due to the efficiency of the DL algorithm and the precision of CAD technology.

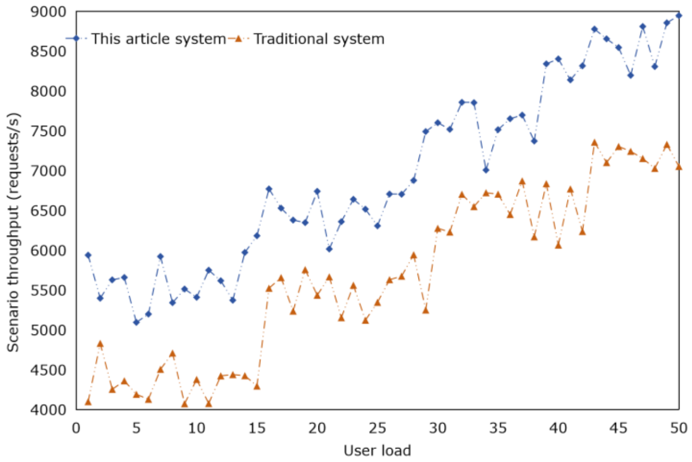

Figure 8: Comparison of scene throughput.

6 CONCLUSIONS

This article proposes a unique innovation that combines deep learning (DL) technology with computer-aided design (CAD) technology to form a new brand pattern creative design system. In this system, the DL model plays a crucial role. It can automatically analyze and extract the core features of patterns through deep learning of a large number of design cases, providing designers with innovative and attractive preliminary design solutions. After a series of experimental verifications, we found that this system can indeed significantly improve the work efficiency of designers. This system not only cleverly combines the creative generation ability of DL models with the interactive editing function of CAD software, but also provides an unprecedented working platform for brand pattern designers. Designers can not only maintain their unique creative flexibility but also quickly respond to their needs through the system, providing a variety of creative patterns for selection. However, just as any innovative technology faces challenges, the system we have designed also faces some shortcomings. The real-time editing function of CAD software allows designers to easily make personalized design adjustments. CAD software, with its powerful interactive editing function, provides designers with tools to adjust and optimize these preliminary design schemes in real time, further improving the accuracy and practicality of the design. The most prominent feature is that the training of DL models requires massive design case data support, and these high-quality design cases are often difficult to obtain easily. This limitation may affect the model's ability to generate design in certain fields or styles. In the future, we will continue to explore how to overcome this challenge further to enhance the performance and practicality of the system. Although the interactive editing function of CAD software is powerful, for some non-professional designers, its operational complexity and learning cost may be higher. In addition, the system still relies heavily on the creative thinking and aesthetic ability of designers, requiring them to have rich design experience and unique creative inspiration.

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