Effects Study of CAD Technology on the Dissemination of Artistic Images Using Big Data

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Abstract. The emergence of big data technology has offered fresh insights and strategies for the propagation of artistic visuals. This study focuses on exploring the groundbreaking fusion of art and technology in the distribution of artistic imagery within the digital era. To accomplish this, the research incorporates cutting-edge tools and techniques, namely computer-aided design (CAD) technology, big data analytics, and deep learning algorithms. Specifically, the introduction of deep learning algorithms, such as Convolutional Neural Networks (CNN), has enabled efficient rendering and precise categorization of artistic images, thereby enhancing their visual impact and recognition precision. CAD technology facilitates the meticulous digital representation of artworks, while big data analytics sheds light on audience preferences and behaviours, directing the targeted dissemination of artistic visuals. The findings underscore the pivotal role of digital technology in the dissemination of artistic images. It demonstrates the capacity to meticulously and effectively process and disseminate artistic content, catering to the varied preferences of diverse audiences. Digital technology has brought broader space and richer possibilities to the dissemination of artistic images.

Keywords: CAD; Big Data; Digitization; Artistic Images; Accurate Communication
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1 INTRODUCTION

In the wave of the digital age, the combination of art and technology has become an important driving force to promote artistic innovation. Among them, CAD and big data technology, as two key technologies, are bringing revolutionary changes to the digital communication of artistic images. With the rapid development of digital technology, the dissemination of dynamic 3D art images has become a highly focused research field. Adaptive representation, as an important technical means, is playing an increasingly important role in the dissemination of dynamic 3D art images. Arvantis et al. [1] explored the adaptive representation of dynamic 3D art image propagation in digital technology, as well as its impact and prospects. Adaptive representation is a technique that automatically adjusts and optimizes data based on its characteristics. In dynamic 3D art image propagation, adaptive representation can automatically adjust the resolution, frame rate, compression ratio, and other parameters of the image according to different image content and propagation environments, in order to achieve more efficient and smooth image propagation. This adaptive representation technology can effectively solve problems such as limited network bandwidth and device performance differences, and improve the dissemination quality and user experience of dynamic 3D art images. Adaptive technology can efficiently compress and optimize dynamic 3D art images, further reducing data volume and improving transmission efficiency. This helps to reduce storage space and transmission costs while ensuring image quality and details. With its accuracy, high efficiency, and powerful visualization function, CAD technology is increasingly being used in the art field. Artists use CAD software to create fine art and present their works of art to the audience in a digital way through 3D modelling, virtual reality, and other technical means. With the rapid development of technology, the application of digital tools and technology in the field of art is becoming increasingly widespread. This not only provides artists with new creative methods but also brings new perspectives to the study of art history. Cardinali [2] explored the application of digital tools and technology in painting, as well as the value of digital archives in the history of digital and technological art. Digital tools and technology have brought revolutionary changes to painting creation. The material limitations and creative process in traditional painting have been greatly expanded in the digital environment. Artists can achieve more refined and complex works through digital software and hardware, and digital technology also makes the copying, dissemination, and preservation of painting work more convenient. The rise of digital tools and technological painting has brought new possibilities to artistic creation, while digital archives provide strong support for the study of digital art history and technological art history. In the future, with the continuous advancement of technology, the application of digital tools and technology in painting will become more widespread, and the value of digital archives in art history research will also be further highlighted. This digital presentation not only enriches the expressive force of art but also enables the works of art to be presented to the audience in a more vivid and 3D way, which enhances the appeal of art.

In the Internet era, massive amounts of artistic image data are generated, stored, and transmitted. Copy move tampering is a common image tampering technique aimed at forging or tampering with image content by copying and pasting a portion of the image. To effectively detect such tampering, researchers have proposed various deep learning-based models. Jaiswal and Srivastava [3] will focus on a method of using multi-scale, multi-stage deep learning models to detect copy-move tampering in digital images. Multi-scale deep learning models can capture image features from different scales. In copy-move tamper detection, this model can better understand and detect changes and patterns at different scales in images. By dividing the input image into multiple scales and using deep neural networks to extract features at each scale, the model can comprehensively consider the details and overall structure of the image, thereby improving detection accuracy. Combining multi-scale deep learning models with multi-stage deep learning models can further enhance the performance of the model. At each stage, the model can use multi-scale features to process images, thereby better understanding and detecting changes in the image. Meanwhile, by decomposing tasks into multiple stages, the model can gradually learn and optimize, improving the accuracy and robustness of detection. These data not only record the works of art themselves but also reflect the audience's aesthetic preferences, behaviour patterns, and other information. Through big data analysis, we can dig deep into the value of these data and understand the needs and preferences of the audience so as to recommend and spread artistic images more accurately. This data-driven mode of communication has improved the exposure and influence of works of art, enabling art to reach people more widely. With the rapid development of technology, 3D reality technology (VR) and CAD (computer-aided design) have become indispensable technical means in the field of art today. Combining these two can not only provide artists with richer and more free creative space but also bring immersive artistic experiences to the audience, further expanding the channels for the dissemination of artistic works. Jing and Song [4] discussed the application of the combination of 3D reality technology and CAD in the dissemination of artistic images, as well as the impact and prospects it brings. 3D reality technology is a technology that can simulate virtual environments in the real world. Through special devices, users can experience everything in the virtual world firsthand. CAD is a computer technology used for design, analysis, and optimization, widely used in various industries. Combining 3D reality technology with CAD not only enables real-time 3D modelling and rendering but also improves design accuracy and efficiency through data analysis and optimization. By utilizing 3D reality technology and CAD, artists can tailor unique artworks to the audience's needs and preferences. This personalized art customization method can meet the aesthetic needs of different audiences and expand the market space of artworks.

To realize the efficient dissemination and depth rendering of artistic images, it is not enough to rely solely on CAD and big data technology. As a powerful deep learning algorithm, CNN began to show its unique advantages in the processing and rendering of artistic images. With the rapid development of technology, big data and interactive virtual technology have gradually penetrated various fields, especially in the field of digital image art and design. The combination of these two technologies provides artists and designers with new creative tools, enabling them to explore and express their creativity in unprecedented ways. Li [5] delved into the concepts, advantages, and applications of digital image art and design systems based on big data technology and interactive virtual technology. Through big data technology, we can obtain a large amount of image data from various sources. Artists and designers can use these images as sources of inspiration for their creations, or directly use them as materials for their creations. By analyzing big data, artists and designers can learn various styles, techniques, and trends in image design, thereby enhancing their design abilities. Through interactive virtual technology, artists and designers can enter a three-dimensional environment entirely constructed by their creativity. They can create directly in this environment without worrying about the limitations of the real world. Interactive virtual technology can provide immediate feedback, allowing artists and designers to view the effects of their works at any time during the creative process, thereby making better adjustments and optimizations. By simulating the working principle of the human visual cortex, CNN can automatically learn and extract feature information from images and carry out advanced processing such as classification and recognition. In the rendering of artistic images, CNN can realize complex tasks such as image style transfer, super-resolution reconstruction, and denoising. For example, style transfer technology can separate and reorganize the style and content of artistic works and create new works with unique styles; Super-resolution reconstruction technology can restore low-resolution artistic images into high-resolution images, showing more details and textures; Denoising technology effectively eliminates noise and distortions from images, significantly enhancing their clarity and overall quality. The integration of these advancements has elevated the presentation and reception of artistic visuals, allowing for a more refined exhibition of artistic works.

The convergence of CAD precision, big data insights, and CNN's sophisticated image processing capabilities holds profound theoretical and practical importance for the nuanced examination of artistic image dissemination. This synergy enables efficient distribution, tailored recommendations, and enhanced rendering of artistic content. Our research centers on optimizing artistic image communication through this digital technology trifecta and introduces a CNN-based rendering and optimization algorithm. The research includes the following innovations:

⊖ This article combines the accurate modelling ability of CAD with the depth analysis of big data and applies it to the communication strategy of artistic images. Through CAD technology, works of art can be presented digitally with high precision; big data helps analyze the audience's preferences and behaviour patterns and guides the accurate dissemination of artistic images.

⊜ In this article, CNN is introduced to render artistic images, which realizes the efficient conversion of image styles. By training the CNN model, works of art can be quickly rendered into different styles, and even a variety of styles can be integrated, expanding the possibility of artistic creation and the diversity of works.

Firstly, this article introduces the importance of CAD and big data in art image communication under the background of the digital age, which lays the foundation for the follow-up research. Then, the principle and application of art image rendering and optimization algorithm based on CNN are expounded in detail, which highlights the innovation of this article. Finally, through comprehensive evaluation, it shows the positive influence of digital technology on the communication effect of artistic images and looks forward to the broad application prospect of interdisciplinary research methods.

2 RELATED WORK

In the field of information hiding, multi-image steganography is a technique that embeds multiple secret information into the same image. In order to improve the security and robustness of steganography, an adaptive payload distribution method based on image texture features has been widely studied. Liao et al. [6] explored the application and advantages of this method in multi-image steganography. Multi-image steganography allows for embedding multiple secret information in a single carrier image, thereby increasing the complexity and security of information hiding. To achieve this goal, an effective strategy is needed to determine how much secret information each pixel or subregion should carry. The adaptive payload distribution method is proposed to address this issue. Based on the extracted texture features, classify the image and assign a weight value to each category. These weight values represent the sensitivity of the region to steganography, thereby affecting the allocation of payloads. With the rapid development of technology, machine learning has had a profound impact in many fields. In the field of art and design, machine learning technology is bringing unprecedented opportunities for the creation of artistic works and the dissemination of artistic images. Liow et al. [7] explored how machine learning techniques can bring artworks closer to the design laboratory of art image dissemination, thereby providing artists and designers with more creative possibilities. Machine learning provides a new creative tool for artists and designers. By training machine learning models, artists can generate unique and creative works of art. These works can be paintings, sculptures, music, dances, etc., with a variety of forms and a high degree of personalization and innovation. At the same time, machine learning can also help artists and designers solve some traditional creative problems that are difficult to solve, such as colour matching, composition optimization, etc. Machine learning technology also has extensive applications in the dissemination of artistic images. Through technologies such as image recognition and natural language processing, machine learning can help people better understand artworks and provide more efficient and intelligent channels for their dissemination.

With the rapid development of digital technology, social media has become the main platform for people to share and disseminate information. These images on social media not only reflect social phenomena but also reflect people's lifestyles and culture. Therefore, digital analysis of social media images has become an important research field. Pearce et al. [8] delved into the impact of digital technology on visual cross-platform analysis, particularly on digital analysis methods for social media images. The development of digital technology has provided new methods and tools for visual cross-platform analysis. Through digital technology, we can analyze images more accurately and comprehensively, thereby better understanding their content, significance, and dissemination methods. In addition, digital technology enables us to seamlessly analyze and compare images on different platforms and devices, achieving true visual cross-platform analysis. Through deep learning and computer vision technology, we can recognize and classify social media images. This includes recognizing objects, scenes, faces, etc. in the image, as well as classifying the emotions, themes, etc. of the image. With the rapid development of technology, 3D factory simulation software has been widely used in various fields. Among them, its role in the auxiliary participatory design of artistic image dissemination is becoming increasingly significant. Pelliccia et al. [9] explored the applicability of 3D factory simulation software in participatory design for art image dissemination, as well as the innovation and transformation it brings. Assisted participatory design in the dissemination of artistic images refers to the use of modern technological means, such as digital media, virtual reality, etc., to provide an interactive platform for artists and audiences, enabling them to participate more deeply in the creation and dissemination process of artistic works. This design approach can enhance the audience's immersion and participation, making the artwork more vivid and vivid. 3D factory simulation software can present artworks in a three-dimensional form, allowing viewers to observe the works from multiple angles and obtain a more comprehensive and intuitive visual experience. This visual presentation method helps to enhance the audience's understanding and perception of artistic works.

With the rapid development of digital technology, the application of CAD (computer-aided design) image digital formats in the field of information technology is becoming increasingly widespread. Digital technology provides efficient and accurate storage, transmission, and processing methods for CAD images, greatly promoting the development of information technology. Qasim and Alyousuf [10] delved into the impact of digital technology on CAD image digital formats and its application in information technology. Digital technology enables CAD images to be stored in binary form on computer hard drives, network servers, or the cloud, greatly improving the efficiency of image storage. At the same time, digital technology also enables high-speed transmission of CAD images on the Internet, facilitating remote design, collaborative work and real-time communication. Digital technology provides various processing tools for CAD images, such as scaling, rotating, cropping, filtering, etc., allowing designers to accurately adjust and beautify images. In addition, digital technology can also achieve automated recognition, classification, and retrieval of CAD images, improving the intelligence level of information technology. Low-light image enhancement is an important research direction in the field of image processing, aimed at improving the quality of images captured in low-light environments. With the continuous development of deep learning technology, low-light image enhancement methods based on deep hybrid networks have gradually become a research hotspot. Ren et al. [11] introduce a low-light image enhancement method based on deep hybrid networks and explore its application in image propagation. A deep hybrid network is a method that combines deep neural networks with traditional image processing techniques. It combines the powerful feature learning of deep neural networks with traditional image processing techniques, which can improve the brightness, contrast, and colour saturation of images while maintaining image details. Low-light image enhancement refers to the use of technical means to improve the quality of images captured in low-light environments. Due to the problems of low brightness, poor contrast, and high noise in images captured in low-light environments, corresponding algorithms and techniques need to be used to enhance the images. The low-light image enhancement method based on deep hybrid networks can effectively improve the image quality captured in low-light environments, making it closer to images under normal lighting conditions.

Digital images have become an important component of our daily life and work. At the same time, the emergence of low-cost imaging sensors has made it easier for more people to obtain and disseminate digital images. Riba et al. [12] investigated the impact of using low-cost imaging sensors on digital image propagation. Traditional digital cameras are often expensive, making it difficult for ordinary consumers to afford them. However, with the advancement of technology, low-cost imaging sensors have gradually become popular, enabling ordinary people to have the ability to capture high-quality digital images. This greatly reduces the threshold for obtaining digital images, allowing more people to participate in the creation and dissemination of digital images. The dissemination of digital images still brings many opportunities. Firstly, it provides artists and photographers with a broader creative platform, allowing their works to be appreciated by more people. Secondly, the dissemination of digital images promotes the rapid dissemination of information, which helps to improve social transparency and civic awareness. Finally, digital image dissemination also provides abundant data and resources for scientific research, education, and other fields. With the rapid development of information technology, steganography technology is widely used in military, commercial, and privacy protection fields. However, steganalysis technology has also emerged, aiming to detect and extract secret information hidden in digital media. Singh et al. [13] explored the method of using deep fractal networks for the steganalysis of digital images. The purpose of digital image steganalysis is to detect and extract secret information hidden in digital images. Traditional steganalysis methods are usually based on traditional techniques such as the human visual system and wavelet transform. However, with the development of steganalysis technology, traditional steganalysis methods have gradually lost their effectiveness. Therefore, using deep learning techniques for steganalysis has become a research hotspot. Deep fractal networks have broad application prospects in digital image steganography analysis. Firstly, it can be used to detect the presence of steganographic information in digital images. By training deep fractal networks, they can automatically recognize and classify the types and intensities of steganographic attacks. Secondly, deep fractal networks can also be used to extract secret information hidden in digital images. By learning and analyzing the characteristics and patterns of steganography attacks, deep fractal networks can help extract information hidden in images [14].

With the continuous development of science and technology, digital image technology is increasingly widely used in the field of art education. This technology provides a new teaching method and perspective for art education and greatly enriches the content and form of art education. Digital image technology can provide rich and varied teaching resources. For example, teachers can use digital image technology to display artworks from around the world, artists' creative processes and other content to students in the form of images or videos, so that students can intuitively appreciate and learn a variety of artworks and creative skills across time and space constraints. Digital image technology can improve the interaction and participation of art teaching. Through digital image technology, students can directly participate in the process of art creation, use digital painting tools to create, or modify and recreate existing artworks through digital image processing software, which can not only stimulate students' innovative thinking but also improve their practical operation ability. Digital image technology can improve the efficiency and effect of art teaching. Through digital image technology, teachers can quickly and accurately display and explain the creative skills and concepts of artworks, and students can also quickly master and apply these skills and concepts through digital image technology, so as to improve learning efficiency. At the same time, through digital image technology, teachers can evaluate and guide students' works more intuitively and in detail, and improve the teaching effect. Digital image technology provides a new teaching method and perspective for art education, and injects new vitality into the development of art education. With the continuous development and improvement of digital image technology, its application in art education will be more extensive and in-depth.

However, due to the complexity and diversity of artistic works, achieving high-quality cross-modal artistic image synthesis is a challenging task. To address this issue, Yu et al. [15] proposed an edge-aware generative adversarial network for cross-modal art image synthesis. Edge edge-aware generative adversarial network is a special type of generative adversarial network that introduces edge-aware modules in the generator and discriminator. This module enables the network to better understand and extract edge information from images, thereby improving the details and authenticity of synthesized images. In the generator, the edge perception module effectively describes image edges by combining low-dimensional edge information with high-dimensional pixel information. This enables the generator to generate more realistic images, especially for complex artistic images. In the discriminator, the edge perception module is used to determine whether the edge information of the synthesized image is consistent with the real image. Through this approach, the discriminator can better identify forged images generated, thereby improving the network's discriminative ability.

3 METHODOLOGY

3.1 Overview of Research Framework

While these studies have enriched the digital landscape of artistic images, they also exhibit certain limitations. Some focus narrowly on individual technologies, overlooking their potential for integration and synergy. Others neglect the crucial step of validating their findings in real-world settings. This article aims to address these gaps by integrating the strengths of CAD, big data, and deep learning algorithms, fostering an innovative, holistic approach. Emphasis is placed on rigorous testing in practical scenarios to ensure the research's relevance and impact. Ultimately, this work strives to catalyze a broader and more profound digital transformation in the realm of art. When we study the influence of digital technology supported by CAD and big data on the communication effect of artistic images, we construct a comprehensive methodological framework. This framework seeks to unite the precision modelling capabilities of CAD, the insightful analysis of big data technology, and the cutting-edge image processing powers of CNN. Its objective is to comprehensively investigate the communication impact and refinement tactics of artistic visuals in the digital era.

At the heart of our approach lies the development of a comprehensive multi-dimensional analysis model. This encompasses data acquisition and refinement, feature identification and depiction, model training and refinement, along with impact assessment and feedback mechanisms. By leveraging this model, we aspire to gain a profound understanding of both the inherent patterns and external manifestations of artistic images as they traverse the digital communication landscape. Ultimately, this understanding will inform the provision of theoretical backing and practical directives for the nuanced communication and enhanced rendering of these images.

3.2 Data Collection and Processing

In the data collection stage, firstly, the works of art are modelled with high precision by CAD software, and the works of art are transformed into digital 3D models. These models not only retain the original shape and details of the works of art but also can simulate different lighting and visual angle effects by adjusting parameters and materials, thus generating diverse artistic images.

Big data from the Internet, art databases, social media, and other channels are used to collect art image data. These data include various artistic styles, historical periods, creators' backgrounds, and other information, which provide us with a rich sample base and research resources. In the data processing stage, we use data cleaning, format conversion, normalization, and other technical means to preprocess the collected data to ensure the quality and consistency of the data.

3.3 Feature Detection and Representation

In the phase of identifying and representing features, CNN is employed to draw out pertinent details from artistic visuals autonomously. Through a sequence of convolutional, pooling, and fully connected layers, CNN progressively distills and represents the inputted artistic content. This process enables the extraction of low-level attributes like edges, textures, and colours alongside higher-order concepts such as shapes, structures, and semantics. As depicted in Figure 1, CNNs are feedforward neural networks characterized by sparse connectivity, echoing the biological mechanisms of vision. They are adept at learning rasterized features, including pixels and audio, with remarkable computational efficiency. The hallmark of CNN in image feature extraction is its ability to capture textural details in the initial layers while preserving contextual information in the subsequent layers.

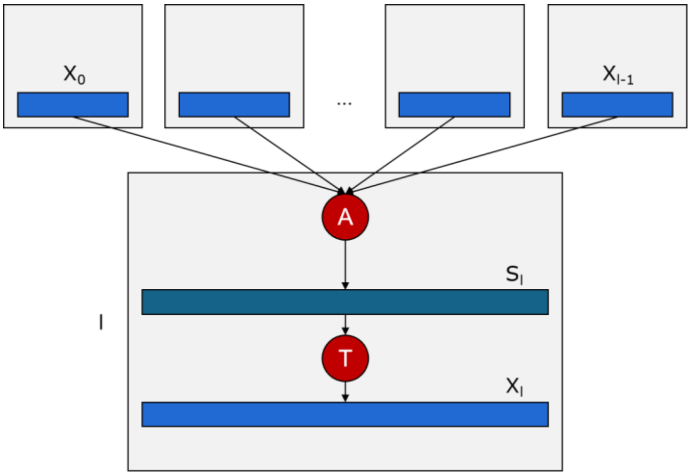

Figure 1: CNN feedforward model.

To facilitate the gradual convergence of the CNN model towards the globally optimal value, it is imperative to initialize the weights intelligently. Within the convolution layer of the CNN, these weights manifest as convolution kernels (or filters). The initialization of these weights occurs randomly, adhering to a prescribed uniform distribution:

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}},\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}\right] \tag{1}$$

In this context, n_{in},n_{out} it represents the count of input and output neurons corresponding to the weight of the convolution kernel.

This layer marks a departure from the conventional fully connected neural network, introducing an innovative approach unique to CNN. Its primary focus is on extracting features from artistic imagery. By leveraging two groundbreaking concepts, local perception and parameter sharing, it effectively accomplishes automatic feature detection. The formula defining its operational specifics is as follows:

$$X^L = f\left(Z^L\right) = f\left(X * K^L + b^L\right) \tag{2}$$

In this context, $*$ it represents the convolution operation, Z^L denotes the input value for the convolution in the L layer, X^L signifies the feature mapping value attained after the application of a nonlinear activation function, and f refers to the activation function itself.

CNN model trains a large number of artistic style images and content image pairs to learn the method of transforming the style of content images into the specified artistic style. In the training stage, the CNN model will automatically extract the features of the content image and artistic style image and fuse these features through an optimization algorithm to generate a new image with the target artistic style. This artistic image rendering method based on CNN can not only realize the transformation of a single artistic style but also create a brand-new artistic style by combining the characteristics of various artistic styles. In addition, because the CNN model has strong generalization ability, it can also transform the style of images that have never been seen before, thus greatly expanding the possibility of artistic creation. In order to better represent the feature information of artistic images, we also adopt technical means such as feature fusion and dimension reduction. By fusing different levels of features, we can get a more comprehensive and rich feature representation; through dimensionality reduction technology, we can remove redundant information from features and improve their compactness and interpretability.

The continuous image function, denoted as $f\left(x,y\right)$ the gradient at a specific point, $\left(x,y\right)$ can be defined as a directional vector.

$$\nabla f\left(x,y\right) = \left[G_x,G_y\right]^T = \left[\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}\right]^T \tag{3}$$

In this context, G_x and G_y represent the gradients in the x and y directions, respectively. The magnitude of the gradient, denoted as $\left|\nabla f\left(x,y\right)\right|$, and its direction angle, $\phi\left(x,y\right)$, are defined as follows:

$$\left|\nabla f\left(x,y\right)\right| = \left(G_x^2+G_y^2\right)^{1/2} \tag{4}$$

$$\phi\left(x,y\right) = \arctan\left(\frac{G_y}{G_x}\right) \tag{5}$$

For digital images, the amplitude $\left|\nabla f\ x,y\right|$ of the gradient, as mentioned in the previous formula, can be substituted with the differential value. This differential value is then utilized as the pixel value for the resulting image.

$$\left|\nabla f\ x,y\right| = \left\{\left[f\ x,y\ - f\ x+1,y\ \right]^2 + f\ x,y\ - \left[f\ x,y+1\ \right]^2\right\}1/2 \tag{6}$$

Given a representation function denoted as Φ, where b equals $R^{H\times W\times D} \rightarrow R^d$, and a predefined target code $\varphi_o \in R^d$, the objective of the art image visualization technique is to identify an image, referred to as $X \in R^{H\times W\times D}$ that satisfies the given criteria.

$$\min_{X\in R^{H\times W\times D}} R_\alpha\ X\ + R_{TV\beta}\ X\ + Cl\ \Phi\ X\ ,\Phi_o \tag{7}$$

The regularization term, referred to $R_\alpha + R_{TV^\beta} : R^{H\times W\times D} \rightarrow R_+$ as encapsulating the prior knowledge inherent to natural images, The relative significance of this natural prior to the target loss is represented by C .

The process of generating an image through maximum activation can be likened to navigating a map using a neural network, seeking the region that activates the desired target neuron. Subsequently, optimization techniques are employed to iteratively refine this region, thereby enhancing the activation level of the target neuron. This iterative process continues until the generated image achieves convergence. The corresponding loss function used to guide this process is as follows:

$$l\ \Phi\ X\ ,\Phi_o\ = -\frac{1}{Z}\left\langle\Phi\ X\ ,\Gamma\ \Phi_o\ \right\rangle \tag{8}$$

In this context, $\Gamma\ \Phi_o$ it refers to the process of selecting and modifying the most actively responding visual object associated with the target code. When $\Gamma\ \Phi_o\ = e_i$ it specifies that only a single neuron's value is maintained while all others are set to 0, the gradient contributing to the generated image predominantly originates from this particular target neuron. The loss function utilized for coding inversion is defined as follows:

$$l\ \Phi\ X\ ,\Phi_o\ = \left|\Phi\ X\ - \Phi_o\right| \tag{9}$$

Φ_o represents the feature map $\Phi\ X_o$, which is derived from the target image via network mapping. To accentuate the specific information within the target image that aligns with a designated area of the visual target code Φ_o, one can introduce a mask M onto the target code. This mask M serves to preserve the regions of interest within the target code Φ_o while suppressing irrelevant areas. Consequently, the loss function takes the following form:

$$l\ \Phi\ X\ ,\Phi_o\ = \frac{\left\|\ \Phi\ X\ - \Phi_o\ \Theta M\right\|}{\Phi_o \Theta M} \tag{10}$$

In most programs, data correlation is difficult to avoid completely. For example, when dealing with arrays or linked lists, it is often necessary to access or modify data items in a specific order, which introduces data correlation. In complex algorithms and data structures, this correlation may be more difficult to identify and deal with. Therefore, in parallel programming, programmers need to carefully analyze the data flow and control flow of the program to determine which parts can be executed in parallel and which parts need to be executed in order. This analysis usually involves modularization or functional division of the program so that irrelevant parts can be assigned to different processing units for parallel processing. The data correlation condition determines whether the program can be parallelized. In general programs, this data correlation is sometimes inevitable, so it is necessary to distinguish which parts of the program are related and which parts are not. In the irrelevant part of the data, parallel operations are performed, and the sequence relationship of programs is maintained in the relevant part of the data. In the design of parallel programs, DCAM design methodology summarizes the general process of parallel algorithms.

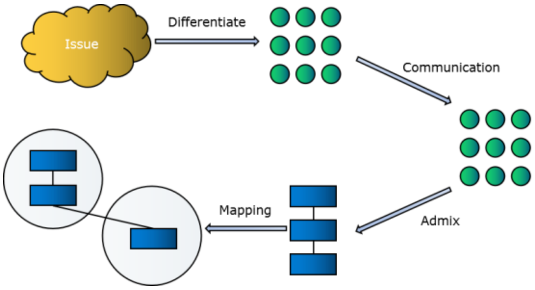

Figure 2: DCAM method.

As shown in Figure 2, DCAM divides problem-solving into four steps: (1) task partitioning, (2) communication, (3) character combination, and (4) processor mapping.

The core idea of layered drawing is to decompose complex images into multiple levels for drawing. Each layer has its specific functions and roles. Artists usually use large strokes to draw at the bottom of the image. These large strokes not only quickly fill the canvas, construct the basic background and main colour gamut of the image, but also provide a solid foundation for subsequent painting. In this layer, the artist focuses on the overall effect and colour combination rather than the depiction of details. As the painting deepened, artists began to use medium-sized strokes on the middle layer for drawing. This layer is mainly used to depict the contour information of the image, namely the shape and position of each object in the image. Through this layer of drawing, the overall structure of the image gradually becomes clear, and the audience can roughly distinguish the various elements in the image. After the bottom and middle layers are drawn, the artist begins to use small strokes on the top layer for drawing. This layer is mainly used to add details and textures to the image, making it look more realistic and vivid. In this layer, artists require extremely high patience and exquisite skills, as any small mistake can damage the overall effect of the work. Figure 3 shows this process.

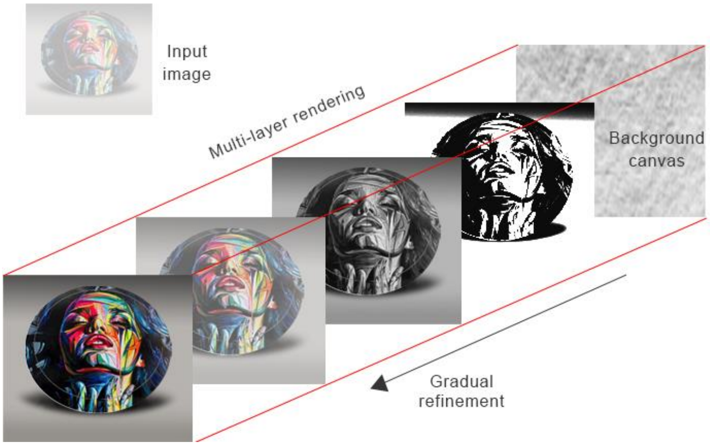

Figure 3: Layered rendering process.

The strategy of using layered drawing is actually a highly organized and logical painting method. Under this strategy, the artist does not start painting directly on a blank canvas but instead chooses a background canvas with a fixed texture or colour as the basis. This choice not only provides a unified visual tone for subsequent paintings but also simplifies the painting process, allowing artists to focus more on the creation of the image itself. This layered drawing strategy is a process of drawing layer by layer from coarse to fine and from large to small. The works drawn through this method often have a rich sense of hierarchy and delicate details.

4 RESULT ANALYSIS AND DISCUSSION

The experiment aims to comprehensively verify the effectiveness and superiority of our proposed algorithm in art image processing. For this purpose, we carefully constructed an art image dataset that includes multiple types and complexities and systematically evaluated the performance of the algorithm in key tasks such as feature detection, rendering simulation, and image classification through experimental methods such as feature detection, rendering effect comparison, classification accuracy evaluation, and runtime comparison. We hope that through this series of experimental designs, we can provide strong support for the algorithm and lay a solid foundation for its promotion and application in practical applications. Figure 4 shows the variation curve of the CNN optimal solution.

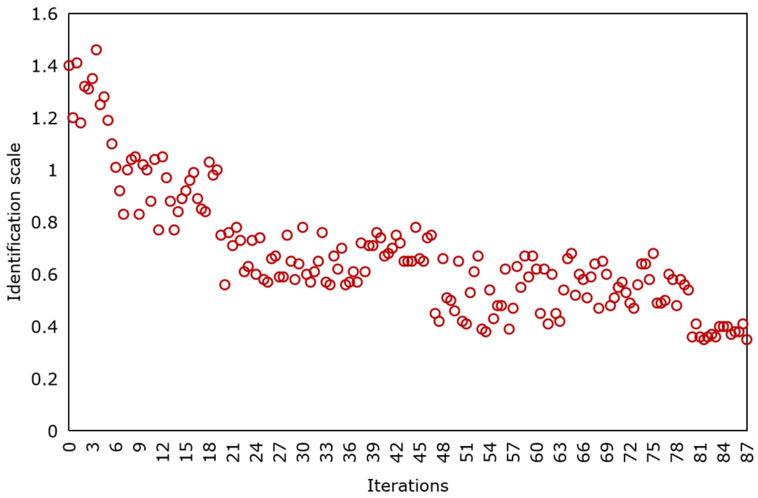

Figure 4: Variation curve of CNN optimal solution.

From Figure 4, it can be seen that the entire art image feature detection process is stable and fast and can quickly approach the optimal solution.

In Figures 5 and 6, a comparison of artistic image rendering effects obtained using different rendering algorithms is shown. These comparative results clearly reveal the advantages and characteristics of our rendering algorithm in artistic image rendering.

When rendering flower images, the algorithm-generated artistic images (top right) show a significant improvement in the texture of the flower surface compared to Rasterization (bottom left) and Ray Trading (bottom right). Our rendering effect is more delicate, with rich layers of light and shadow, giving the flower surface a texture and 3D feeling similar to a real oil painting. This improvement not only enhances the visual impact of the image but also makes the artistic effect of the image closer to people's aesthetic expectations. Rasterization, as a traditional rendering technique, is often limited by pixel-level processing, making it difficult to depict subtle changes in the surface of objects. Although Ray Trading can simulate the physical propagation process of light, it has certain limitations when dealing with complex scenes and real-time rendering.

Figure 5: Comparison of rendering effects.

Figure 6: Comparison of rendering effect of a portrait.

Figure 6 further validates the advantages of our algorithm in character portrait rendering. The character portrait (top right) rendered using our algorithm maintains the basic features of the original image while optimizing details such as skin colour and hair texture, making the entire character image more vivid and realistic.

Figure 7 illustrates the algorithm's classification accuracy across three distinct categories of artistic visuals: concrete, imagery, and abstract images. The findings reveal that the algorithm exhibits robust performance in accurately classifying these three art image types.

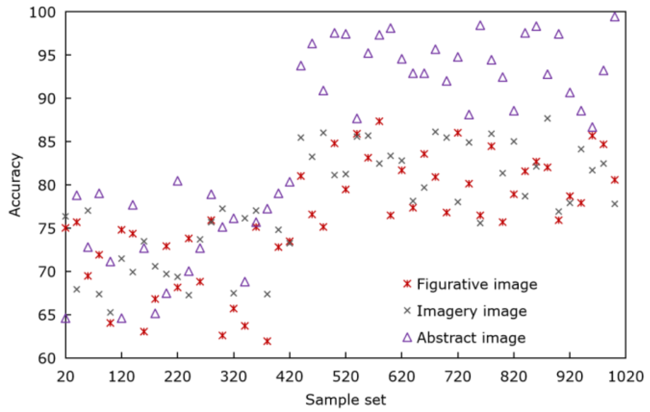

Figure 7: Accuracy of CNN's artistic image classification.

For concrete images, these types of images typically have clear objects and scenes, making them easy for people to understand and recognize. This algorithm automatically extracts feature information from images through deep learning techniques and utilizes these features for accurate classification. From the results, it can be seen that this algorithm has a high classification accuracy on concrete images, indicating that it can effectively capture and recognize object and scene information in images.

For imagery images, these types of images often have a certain symbolic significance and subjectivity, making classification relatively difficult. This algorithm also demonstrates good performance in the classification of image images. This algorithm automatically learns a large amount of art image data during the training process, thereby being able to understand and recognize the implicit information and features in image images.

For abstract images, they often lack clear objects and scenes and are entirely composed of abstract elements such as colour, shape, and lines. Although the classification difficulty of abstract images is the greatest, our algorithm still shows good performance.

Figure 8 shows the comparison between the CNN method and the algorithm proposed in reference [11] in terms of computational runtime.

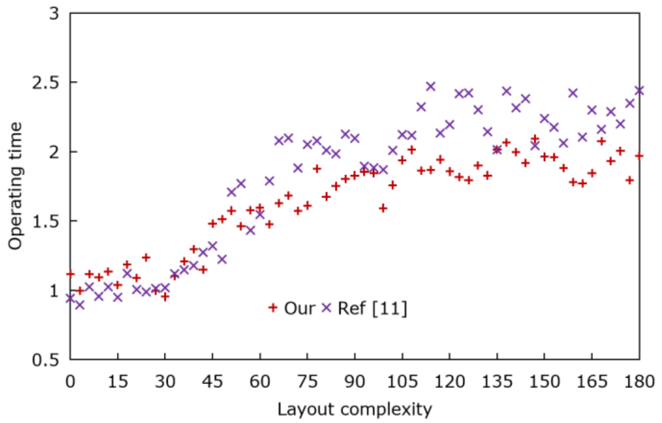

Figure 8: Calculation time comparison of the algorithm.

In the case of low image complexity, the running time of the CNN method and reference [11] method is not significantly different. This is because when processing simple images, both methods can quickly extract the features of the image and process them. However, as the complexity of the image increases, the running time of the method in reference [11] begins to increase significantly, while the running time of the CNN method increases relatively slowly. This advantage is mainly due to the convolutional operation and parallel computing ability of CNN, which enables it to complete computing tasks faster. This result not only verifies the effectiveness of CNN in art image processing but also provides an important reference for subsequent research.

5 CONCLUSION

In the digital era, the fusion of art and technology serves as the main impetus for creative advancements in the arts. Utilizing CAD technology alongside big data analytics, we have delved deeply into the impact of artistic visuals' dissemination within this technological age, yielding numerous profound revelations. CAD software enables artists to draw and carve images with unprecedented precision, achieving more complex and delicate artistic expression. In addition, its multi-format output function ensures that artistic images can spread smoothly on various platforms and media. In the process of dissemination, we have noticed that different types of artistic images exhibit unique characteristics and trends, and the tastes of the audience are becoming increasingly diverse and personalized.

By introducing deep learning algorithms such as CNN, we have successfully achieved efficient and high-quality rendering and accurate classification of art images. These technologies optimize the visual effects and improve recognition rates of artistic images while retaining their original charm, providing solid technical support for the digital processing and dissemination of artistic images.

Research has confirmed that digital technology plays an increasingly crucial role in the dissemination of artistic images. With the help of advanced tools such as CAD technology, big data analysis, and deep learning, we are able to process and promote art images more accurately and efficiently, meeting the increasingly diverse needs of audiences. Looking ahead to the future, with the continuous progress of technology, we have ample reason to expect that digital technology will open up a broader world for the dissemination of artistic images and bring more diverse possibilities.

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