Visual Analysis of Brand Packaging Design Data Based on CAD and Big Data Technology

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Abstract. In the realm of brand packaging design, designers often employ CAD software to streamline structural design, pattern creation, and colour coordination. This approach not only abbreviates the design process but also trims down costs without compromising on quality. This article introduces a novel image enhancement algorithm grounded in human visual perception. By intelligently fine-tuning image hues, luminance, and contrast levels, the algorithm notably elevates the visual appeal of packaging designs, thereby bolstering the allure of brand packaging. Comparative assessments reveal that our proposed algorithm excels in terms of contrast enhancement, brightness balance, and information entropy. The user rating further confirmed that the packaging graphics designed by this algorithm were highly praised in terms of aesthetics, recognition, innovation, and information transmission. To sum up, the data-driven image enhancement algorithm proposed in this article provides an effective new method for product packaging design. Designers can display the three-dimensional model, colour matching, material selection, and other information about the design scheme intuitively through data visualization tools.

Keywords: CAD; Big Data; Packaging Design; Visualization; Image Enhancement
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1 INTRODUCTION

In the current era of informatization and digitization, brand packaging design is no longer just a display of aesthetics and creativity in the traditional sense but more integrates elements of technology, intelligence, and data analysis. As the "first intimate contact" between products and consumers, the design of brand packaging directly affects the market acceptance of products, the shaping of brand image, and consumer purchasing decisions. With the widespread application of deep learning in the field of brand packaging design, the security and stability of models have become urgent issues to be solved. Especially adversarial perturbations, which add small perturbations to the input data, causing the model to produce erroneous outputs. This poses great risks to brand packaging design. Agarwal et al. [1] aim to explore defense strategies against adversarial disturbances in deep learning models based on the visual transformation of brand packaging design data. Adversarial perturbation is an attack against deep learning models, which adds small perturbations to the input data, causing the model to produce erroneous outputs. This type of attack has great harm in practical applications, so defense strategies for deep learning models are particularly important. A defense strategy based on the visual conversion of brand packaging design data is proposed to address adversarial disturbances. The core idea of this strategy is to transform the raw data into a form more suitable for deep learning models through visual data transformation. This method can resist adversarial disturbances to a certain extent and improve the robustness of the model. In today's market environment, the surface quality of brand packaging has a crucial impact on the market performance and consumer evaluation of products. Any surface defect can damage the brand's image and reduce consumers' willingness to purchase. Therefore, it is crucial to quickly and accurately detect defects on the surface of brand packaging. Cao et al. [2] proposed a two-stage attention-based feature fusion network for detecting surface defects in brand packaging. Firstly, it introduces the importance of detecting surface defects in brand packaging. With consumers' increasing demands for product appearance and quality, the surface quality of brand packaging has become an important factor in consumer purchasing decisions. Therefore, accurate detection of defects on the packaging surface is crucial for improving product quality and consumer satisfaction. Next, a detailed introduction was given to the proposed two-stage attention-based feature fusion network model. The model first uses an attention mechanism to extract features from the input packaging image and capture important information in the image. The attention mechanism allows the model to focus on key areas in the image, ignoring irrelevant information, thereby improving the efficiency and accuracy of feature extraction. Hence, the utilization of contemporary technological tools, particularly Computer-Aided Design (CAD) alongside big data technology, for conducting scientific, precise, and efficient brand packaging design analysis and optimization has garnered significant interest among both industrial and academic circles. CAD technology not only enhances the precision and swiftness of the design process but also facilitates a thorough and profound comprehension of the product's aesthetics, structure, and functionality during the initial design phases via features like 3D modelling, rendering, and simulation, empowering designers with a competitive edge. In brand packaging design, the application of CAD technology is like a fish in water. Designers can use CAD software to carry out various tasks such as packaging structure design, pattern design, colour matching, etc., thereby greatly shortening the design cycle and reducing design costs while ensuring design quality. To truly achieve the intelligence and scientificity of brand packaging design, it is necessary to leverage the power of big data technology. Big data technology can efficiently and accurately process and analyze massive amounts of data, thereby uncovering the hidden values and patterns behind the data. In brand packaging design, big data technology can be applied in various aspects such as market research, consumer behaviour analysis, and design trend prediction.

Product pattern design plays an increasingly important role in brand image and market appeal. To meet this requirement, Chen and Cheng [3] developed a product pattern design system based on the Kansei engineering and BP neural network. It briefly introduces the basic concepts of Kansei engineering and BP neural networks. The Kansei project is an engineering method based on human perceptual cognition aimed at understanding and simulating human perceptual-cognitive processes through the combination of psychology and engineering. BP neural network is a multi-layer feedforward network trained through a backpropagation algorithm with strong pattern recognition and prediction capabilities. Next, it elaborates on the development process of a product pattern design system based on the Kansei engineering and BP neural network. Analyze the needs and emotional cognition of target users through the Kansei project and extract key emotional vocabulary and features. Then, the BP neural network is used to train and learn a large amount of pattern design data, establishing a mapping relationship between pattern features and perceptual vocabulary. Through this process, the system can learn the impact of different pattern features on user perceptual cognition and generate pattern designs that meet user needs based on their perceptual cognition. Chen et al. [4] explored how to design and implement bilingual digital packaging design data visualization based on artificial intelligence (AI) and big data technology. Firstly, the application of artificial intelligence in bilingual digital packaging design is mainly reflected in data analysis and processing. Through AI technology, it can efficiently and accurately analyze a large amount of design data, extract valuable information, and provide valuable references for designers. By utilizing machine learning algorithms, it is possible to analyze the preferences of consumers in different regions and cultural backgrounds towards packaging design, thereby providing designers with more accurate guidance. Secondly, the application of big data technology in bilingual digital packaging design is mainly reflected in data storage, processing, and visualization. By utilizing big data technology, it is easy to store a large amount of design data and extract valuable information through data mining and analysis techniques. Meanwhile, by utilizing data visualization technology, we can present complex data intuitively and understandably, providing designers with a more comprehensive perspective. Data visualization analysis can present complex and abstract data in an intuitive and easy-to-understand way, thereby helping people better understand and utilize data. In brand packaging design, data visualization analysis can be applied to multiple aspects, such as displaying design schemes, evaluating design effects, and grasping design trends. For example, designers can use data visualization tools to visually display the three-dimensional model, colour matching, material selection, and other information about the design scheme, making it convenient for communication and discussion with customers, colleagues, or leaders. Moreover, data visualization analysis can also be used to evaluate market acceptance, consumer satisfaction, and other indicators of design schemes, thereby providing a strong basis for the optimization of design schemes. This article explores the integration of CAD and big data technology in visualizing and scrutinizing brand packaging design data. It underscores the utilization of image enhancement algorithms rooted in human visual traits. These algorithms can finesse the colour, brightness, contrast, and other image aspects, aligning with how the human eye perceives visuals. This, in turn, elevates the image's overall quality and visual impact.

CAD (computer-aided design) and big data technology are playing an increasingly important role in brand packaging design and the food supply chain. The application of intelligent packaging systems further enhances the innovation of brand packaging design and the efficiency of the food supply chain. Chen et al. [5] explored the role of intelligent packaging systems based on CAD and big data technology in brand packaging design and the food supply chain. The application of CAD technology provides more possibilities for brand packaging design. Designers can use CAD software for precise model design and simulation, achieving rapid construction and optimization of complex structures. This not only improves design efficiency but also makes packaging design more refined and personalized, meeting the diverse needs of consumers for product appearance and functionality. At the same time, CAD technology can also conduct simulation tests on packaging performance, such as mechanical performance, barrier performance, etc., to ensure the reliability of packaging in practical use. Secondly, big data technology plays a crucial role in intelligent packaging systems. These data provide an important decision-making basis for brand packaging design, helping enterprises formulate more accurate market strategies. At the same time, in the food supply chain, big data technology can monitor and predict real-time data in production, transportation, sales and other links, improve the transparency and efficiency of the supply chain, and reduce operating costs. The detection of surface defects in industrial products is a crucial step in ensuring product quality, and data visualization is an important means to improve detection efficiency and accuracy. Chen et al. [6] explored how to achieve visual analysis of surface defect data in industrial products based on CAD and big data technology. Firstly, computer-aided design (CAD) technology provides strong support for surface defect detection in industrial products. Through CAD software, designers can create precise 3D models and perform various complex geometric calculations and simulations. This allows designers to predict and solve potential problems during the design phase, reduce production costs, and minimize design changes. In addition, CAD technology can also help designers quickly prototype and accelerate the product development cycle. CAD technology alone is not sufficient to achieve optimal surface defect detection of industrial products. At this point, big data technology can play an important role. By collecting and analyzing a large amount of surface defect data of industrial products, we can understand the patterns and characteristics of various defects, thereby better guiding detection and analysis. These data can provide engineers with valuable insights, helping them understand the relationship between product performance, manufacturing processes, and surface defects.

As a core part of product market strategy, product paper packaging not only plays a role in protecting products but also serves as an important means of conveying brand image and market strategy. Among numerous design elements, visual elements have become an indispensable part of commercial paper packaging design due to their intuitiveness and impact. Ding [7] used the "squirrel" pattern as an example to explore the application of visual elements in product paper packaging design. Firstly, it clarifies the important role of visual elements in product paper packaging design. A successful packaging design can not only attract consumers' attention and stimulate their purchasing desire but also effectively convey information about the product and the value of the brand. Visual elements, as the most intuitive and direct design element for communicating with consumers, their role is self-evident. In specific applications, designers need to select suitable visual elements for design based on the characteristics of the product and the value of the brand. For example, if the product is a nut-based food, choosing squirrels as a visual element can effectively convey a natural and ecological feeling. If the product is a children's product, the cute image of a squirrel can better attract children's attention. In essence, the methodology outlined in this article—leveraging CAD and big data for brand packaging design data visualization—constitutes a substantial advancement in traditional design paradigms. It delves into the potential of modern technologies in reshaping brand packaging design. The anticipated outcome of this approach is a revitalization of brand packaging design, steering it towards greater intelligence and efficiency. Specifically, the innovations within this study are multifaceted and hold significant promise for the industry:

(1) CAD technology is often used for structural modelling and rendering in industrial design, while big data is often used for market analysis and user behaviour research. This article combines these two closely, enabling brand packaging design to have precise structure and visual presentation, as well as receiving real data feedback from the market and users.

(2) This article presents a novel image enhancement algorithm tailored to human visual preferences. Through intelligent manipulation of colour, brightness, and contrast, it markedly elevates the visual appeal of packaging and bolsters brand allure.

(3) Utilizing data visualization techniques in packaging design, this article empowers designers, marketers, and managers with intuitive data comprehension, problem identification, and design optimization. This significantly enhances decision-making proficiency and elevates design standards.

The article commences with an introduction to the research context and objectives, followed by a detailed exposition of the theoretical frameworks and algorithm design. Experimental evaluations underscore the algorithm's performance. Subsequently, user feedback on algorithm-generated packaging graphics is presented, reinforcing its efficacy. Ultimately, the study culminates in a summation of findings and conclusions, highlighting the algorithm's practical value and future potential.

2 RELATED WORK

In the field of archaeology, the reconstruction of pottery fragments is crucial for understanding ancient culture and techniques. However, this process is often challenged by information loss and irregular shapes. Eslami et al. [8] proposed a method based on wavelet transform to semi-automatically reconstruct pottery fragments from 2D images and perform data visualization analysis. Wavelet transform, as a signal processing tool, can extract multi-scale information from images and is particularly suitable for processing irregularly shaped pottery fragments. Firstly, it utilizes wavelet transform to perform multi-scale decomposition on the original 2D image to identify and extract key features. These features include the edges, textures, and shapes of fragments. Next, using semi-automatic reconstruction algorithms based on the extracted feature information, systematically reconstruct the 3D model of pottery fragments. This process considers not only the shape of the fragments themselves but also their position in the overall pottery and their relationship with other fragments. The experimental results show that the semi-automatic reconstruction method based on wavelet transform can effectively reconstruct the three-dimensional model of pottery fragments from 2D images. Compared with traditional reconstruction methods, this method not only improves the accuracy of reconstruction but also greatly reduces manual intervention and reconstruction time. With the development of CAD (computer-aided design) and big data technology, Faishal et al. [9] have optimized these packaging designs, further improving the safety and quality of street food. CAD technology enables designers to create precise 3D models and simulate the performance of various packaging in different environments. This greatly reduces the cost and time of prototype production, making the design process more efficient. Through simulation, it can predict the performance of packaging in real-world use, such as temperature response, barrier performance, and durability in various environments. In this way, designers can predict and solve potential problems during the design phase rather than discovering problems after production. At the same time, the application of big data technology provides deeper insights into packaging design. By collecting and analyzing consumer data, it is possible to understand consumer preferences, needs, and behavioural patterns. These pieces of information can help designers better understand the target market and optimize packaging design to meet consumer expectations.

With the development of industrial automation and intelligence, the application of packaging flat materials in various industries is becoming increasingly widespread. However, surface defects in packaging flat materials can have adverse effects on their performance and application, so it is crucial to detect surface defects in packaging flat materials. Fang et al. [10] explored the research progress of visual surface defect automatic detection of industrial packaging flat materials based on CAD and big data technology. CAD (Computer Aided Design) technology plays an important role in the detection of surface defects in flat packaging materials. Through CAD technology, it is possible to accurately simulate and design the shape, size, and surface quality of packaging materials, thereby predicting and solving possible defect problems before production. In addition, CAD technology can also be used to generate detection algorithms and models, improving the accuracy and efficiency of surface defect detection. By combining CAD and big data technology, automatic detection of visual surface defects in industrial packaging flat materials can be achieved. Firstly, using CAD technology for precise design and simulation, predicting and solving potential problems. Secondly, by using big data technology to collect and analyze a large amount of surface defect data on packaging flat materials, we can understand the patterns and characteristics of various defects. Finally, CAD and big data technology will be combined to achieve rapid iteration and optimization of surface defect data for industrial packaging flat materials, improving detection efficiency and accuracy. Clothing product packaging design plays a crucial role in today's market, as it not only protects products but also conveys brand image and value. With the advancement of technology, the application of intelligent design methods in the packaging field is becoming increasingly widespread. Chen et al. [11] explored the latest developments and future trends in the intelligent design of fibres and textiles for multi-link visualization of human algorithm collaborative clothing product packaging. Through human-computer interaction, designers can utilize the powerful computing power of algorithms while maintaining their unique creativity and aesthetic perspectives. In clothing product packaging design, this method helps to improve the efficiency and accuracy of the design and meet the diverse needs of the market. Visualization technology enables designers to view and modify design effects in real-time during the design process, improving the intuitiveness and adjustability of the design. This design method helps to improve design efficiency, reduce costs, and achieve more refined designs. Fibre and textiles play an important role in the packaging design of clothing products. With the increasing awareness of environmental protection and the demand for sustainable development, new types of fibres and textiles are receiving increasing attention in packaging design. In today's design field, CAD (computer-aided design) and big data technology provide designers with unprecedented opportunities to achieve designs more efficiently and accurately. Hu [12] used tea packaging design as an example to explore how to achieve contemporary visualization of traditional symbols based on CAD and big data technology. Firstly, CAD technology provides designers with a tool to accurately present and modify designs. In tea packaging design, traditional symbols such as cloud patterns, lotus flowers, dragons, and phoenixes have profound cultural connotations. Through CAD, designers can flexibly adjust the shape, size, colour, and layout of these symbols to meet modern aesthetics and market demands. In addition, CAD can also help designers simulate the effects of packaging in different contexts. By simulating the effect of light shining on the packaging, designers can better understand the visual presentation of traditional symbols under different lighting conditions, thereby optimizing the design.

The application of medical plant products in the medical field is becoming increasingly widespread. Packaging design, as an important component of products, plays a crucial role in protecting product quality, enhancing user experience, and enhancing product attractiveness. Lin [13] discussed how to optimize the packaging design mode of medical plant products based on CAD (computer-aided design) and big data technology. Firstly, CAD technology provides powerful design and simulation tools for the packaging design of medical plant products. Through CAD software, designers can create precise 3D models that simulate the appearance, structure, and functionality of products. This allows designers to predict and solve potential problems during the design phase, reduce production costs, and minimize design changes. In addition, CAD technology can also assist designers in rapid prototyping and accelerate the product development cycle. By combining CAD and big data technology, it can achieve the optimal mode of packaging design for medical plant products. Firstly, using CAD technology for precise design and simulation, predicting and solving potential problems. Secondly, through big data technology, collect and analyze relevant data to understand consumer needs and behaviour patterns and guide the optimization of packaging design. With the increasing scale of data, traditional 3D graphics calculation methods are no longer able to meet the real-time requirements of large-scale data processing. To address this issue, Nejur et al. [14] proposed an effective computational visualization analysis method for 3D graphics based on CAD and big data technology. Firstly, CAD technology provides powerful modelling tools for 3D graphics. Through CAD software, it is easy to create and edit 3D models and perform various complex geometric calculations. This provides a foundation for conducting 3D graphic calculations in the big data environment. Through big data processing frameworks such as Hadoop or Spark, it is possible to perform distributed processing on large-scale 3D data. This processing method can significantly improve computational efficiency and reduce computational time. After the calculation is completed, how to effectively visualize the results is also an important issue. Traditional visualization methods often struggle to handle large-scale 3D data. To solve this problem, it adopts volume rendering technology. Volume rendering can generate high-quality images and process large-scale 3D data. Through volume rendering, the calculation results can be presented intuitively, making it convenient for users to analyze and interpret. 3D factory simulation software has been widely used in many industrial fields. In the packaging industry, this simulation technology provides new possibilities for data visualization analysis of workplaces and processes. Pelliccia et al. [15] explore the applicability and advantages of 3D factory simulation software in the packaging industry. Firstly, 3D factory simulation software can create virtual environments that are highly similar to the actual workplace. Through this simulation, enterprises can evaluate and optimize factory layout, equipment configuration, and process design before actual construction. This helps to reduce unnecessary changes and cost waste and improve factory operational efficiency. Secondly, 3D simulation software can achieve data visualization analysis. By combining actual production data with simulation models, enterprises can monitor production status in real-time, analyze process bottlenecks, and optimize resource allocation. This visual analysis helps to improve the accuracy and efficiency of decision-making, further improving the production process.

Quan et al. [16] explored how to achieve brand-intelligent-driven product design based on CAD and big data technology and make effective decisions and analyses through data visualization. Firstly, CAD technology provides strong support for brand-intelligent-driven product design. Through CAD software, designers can create precise 3D models and perform various complex geometric calculations and simulations. This allows designers to predict and solve potential problems during the design phase, reduce production costs, and minimize design changes. In addition, CAD technology can also help designers quickly prototype and accelerate the product development cycle. Data visualization is an effective tool that can help designers better understand and utilize big data.

Through data visualization, designers can present complex data intuitively and understandably, thereby better guiding design decisions. For example, charts, graphics, and interactive interfaces can be used to display sales data, user behaviour data, and market trends, helping designers better understand market demand and brand positioning. With consumers' increasing demand for the quality and appearance of product packaging, the importance of visual defect detection in the packaging industry is becoming increasingly prominent. Accurately and quickly detecting visual defects in packaging design is the key to improving product quality and brand image. Su et al. [17] introduced a complementary attention network model based on deep learning for visual defect detection in packaging design. Firstly, it briefly introduces the background and challenges of visual defect detection in packaging design. With the intensification of market competition, the requirements for packaging design are becoming higher and higher. The existence of visual defects not only affects the aesthetics of products but may also harm brand image. Traditional defect detection methods are usually based on manual inspection or simple image processing techniques, which cannot meet the fast and high accuracy requirements of modern industrial production. Therefore, studying an efficient and accurate visual defect detection method for packaging design is of great practical significance.

Multi-attribute visual feature recognition of brand packaging has broad application prospects in production, quality control, and marketing. Wang et al. [18] proposed a tensor-based multi-attribute visual feature recognition method for brand packaging, aiming to improve the accuracy and efficiency of recognition and provide strong support for industrial intelligence. It briefly introduces the importance of multi-attribute visual feature recognition in brand packaging. It is crucial to quickly and accurately identify multiple attributes of brand packaging on the production line for product classification, quality control, and brand protection. However, in practical applications, there are challenges such as changes in lighting, angle differences, occlusion, and background interference, making accurate recognition difficult. It provides a detailed introduction to the tensor-based multi-attribute visual feature recognition method for brand packaging. This method utilizes tensors as a mathematical tool to extend image information from traditional two-dimensional planes to three-dimensional tensor spaces. By extracting higher-order features, complex structures and patterns in images can be better captured. In addition, an attention mechanism is introduced to weigh the features of different attributes, further improving the accuracy and robustness of recognition. With the rapid development of industrial automation, the detection of defects on the bottom surface of glass bottles has become an important research direction. Zhou et al. [19] proposed a glass bottle bottom surface defect detection framework based on a visual attention model and wavelet transform to improve detection efficiency and accuracy. Firstly, visual attention models are used to capture important regions in images. This model automatically identifies areas related to defects by learning the features in the image, thereby reducing the processing of irrelevant information and improving detection speed. Meanwhile, due to only detecting critical areas, the possibility of false positives is also reduced. Secondly, wavelet transform is used for multi-scale analysis of images. Wavelet transform can decompose images at different scales to extract features at different levels. These features can better describe the shape, size, and position of defects, improving the accuracy of detection. Finally, combining the above two methods, a complete framework for detecting defects on the bottom surface of glass bottles was constructed. This framework first preprocesses the image using a visual attention model to identify key regions.

Although packaging design involves many disciplines, many studies are still limited to a single discipline perspective and fail to make full use of interdisciplinary theories and methods. Some research has failed to keep up with the application of new technologies in packaging design, such as big data and artificial intelligence. In this article, CAD modelling, big data analysis, image enhancement algorithms, and other advanced technologies and methods are used to discuss brand packaging design more comprehensively and deeply. In the data collection stage, this article tries to cover a wider range of consumers so as to improve the universality and applicability of the research results.

3 METHODOLOGY

CAD utilizes computer systems and related software to assist designers in various design activities. Traditional packaging design often relies on manual drawing or two-dimensional graphic design, but this approach is difficult to truly reflect the three-dimensional effect of packaging. CAD technology enables designers to create three-dimensional models in a 1:1 ratio to real packaging on a computer through its three-dimensional modelling function. This not only improves the accuracy of the design but also enables designers to anticipate the final product effect in the early stages of the design. CAD software is usually equipped with powerful rendering tools that can set materials, colours, lighting, and other aspects of 3D models to present realistic visual effects. Through this approach, designers can simulate packaging effects in different environments. Parametric design allows designers to quickly adjust design schemes by modifying parameters, greatly improving design efficiency. Automated design can utilize preset rules and algorithms to generate design solutions automatically, providing designers with more creative space.

Through big data technology, massive market data can be collected, organized, and analyzed to gain insights into market dynamics and competitor situations. By analyzing consumer purchasing history, browsing history, social media interaction, and other data, we can gain a deeper understanding of consumer preferences, needs, and consumption habits. By analyzing historical data, real-time data, and industry development trends, big data technology can predict future design trends and popular elements.

Human visual traits encompass patterns and features observed by the human eye during image perception, including contrast sensitivity and variations in colour interpretation. Leveraging these traits, image enhancement techniques can refine parameters like colour, luminosity, and contrast, aligning them more closely with human viewing preferences and aesthetic sensibilities. In the realm of brand packaging, these human-centred enhancement algorithms can enhance design presentations, evaluate design impact, and more. The resulting visuals are crisp, lively, and captivating, elevating the allure and market edge of brand packaging. In brand packaging design based on big data and CAD, it is necessary to collect various types of data related to brand packaging design. These data include but are not limited to market research data, consumer behaviour data, design element data, etc. Market research data can help us understand the current market demands and trends, consumer behaviour data can reveal consumer preferences, and purchasing decision-making processes, and design element data covers various aspects of packaging design, such as colour, shape, material, etc. After completing data collection and processing, CAD technology will be used for packaging design modelling. Based on the collected design element data, a 3D model of the packaging can be created in CAD software. In this process, it is necessary to fully utilize the powerful functions of CAD software, such as 3D modelling, rendering, simulation, etc., to ensure the accuracy and realism of the model.

The imaging of images by the human eye is the physical foundation of the entire visual system, which determines whether the image we see is clear and whether the colours are bright. In the CAD environment, this process corresponds to the process of designers viewing and evaluating 3D models on the screen. To ensure that the design conforms to the visual habits of the human eye, CAD software typically provides realistic rendering capabilities, simulating the reflection and refraction of light on different materials, thereby generating images similar to those seen by the human eye on computer screens. Designers can adjust the material, colour, and lighting of the model based on the rendering results to achieve the best visual effect. To ensure that the design is easy for consumers to understand and accept, designers need to utilize the interactive features of CAD software, such as real-time preview, dynamic modification, etc., to simulate the visual experience of consumers and optimize the design based on simulation results. The human visual system is a complex visual perception and imaging system, and its contrast sensitivity is related to spatial frequency, as shown in Figure 1.

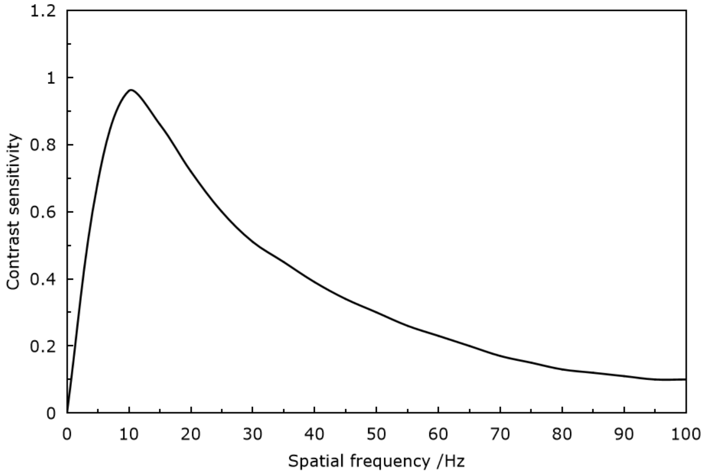
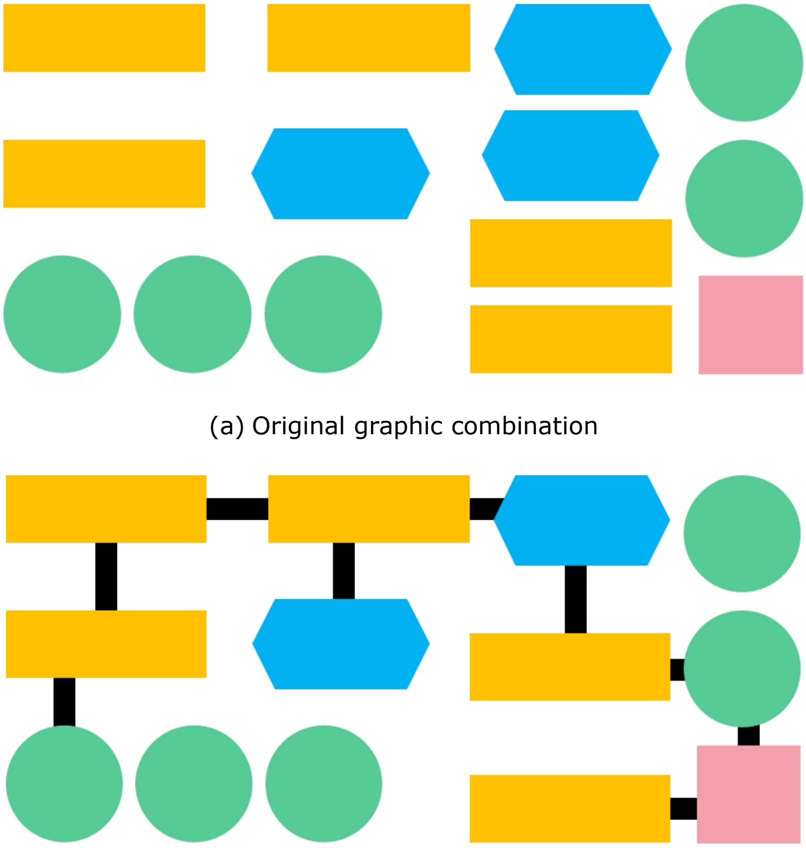


Figure 1: Relationship between human eye contrast sensitivity and spatial frequency.



(a) Original graphic combination

(b) Graphic combination after adding connecting elements

Figure 2: Application example of connection principle.

The principle of connectivity is an important cognitive psychology concept in the field of visual design and information communication. When observers face a series of objects with different attributes, these objects may have different shapes, colours, sizes, or functions. Their visual system instinctively tries to find a pattern or pattern to classify and recognize these objects. In this process, observers often rely on basic principles such as similarity, proximity, continuity, etc., to make initial identification and grouping. Sometimes, these basic principles are not enough to clearly reveal the relationships between objects. At this point, if a highly recognizable element appears that can effectively connect these seemingly different objects, the observer's identification process will become more efficient and accurate. This highly recognizable element can be a distinct visual feature, such as a specific colour, shape, or line, or it can be an implicit concept or semantic connection. Figure 2 shows a specific application case of this connectivity principle.

The principle of connectivity emphasizes the effective connection of multiple objects or elements in design by introducing elements with strong recognizability in order to improve recognizability and information transmission efficiency. In packaging design, this means finding a way to organically integrate various design elements and brand information to form a unified and harmonious visual effect. Although human vision has evolved for a long time, the ability to judge the absolute value of brightness is poor, which can be described by the Weber-Feiner law:

$$C = \frac{\Delta M}{M} \tag{1}$$

Where C is the ratio of contrast sensitivity ΔM to background brightness M; The contrast sensitivity ΔM represents the minimum brightness value that can be distinguished by human eyes.

According to this characteristic, when the image is reconstructed in the process of designing product packaging, it is not needed to maintain the same brightness as the original image, and the reconstruction accuracy can be guaranteed as long as the brightness difference is smaller than the contrast sensitivity so that the visual consistency with the original image can be realized. The light adaptation process occurs when people move from an environment with a small average brightness to an environment with a large average brightness. On the contrary, it is a dark adaptation process. This bright and dark adaptive transformation characteristic can be expressed by the following Gaussian difference function:

$$DG\ i,j\ = G\ i,j,\sigma_2 \tag{2}$$

$$G\ i,j,\sigma_x\ = \frac{1}{2\pi\sigma_x^2} e^{-\ i^2+j^2\ /\ 2\sigma_x^2}, x = 1,2 \tag{3}$$

By subtraction, the remaining frequencies, except for some frequencies in the original image, can be removed so that image enhancement can be realized. When the image information is transmitted to the relevant parts of the brain through the retina and other structures, not all the information will be processed immediately, but the image information in some key areas will be given priority, that is, the attention mechanism of human vision. Through this mechanism, we can effectively use limited brain resources to quickly screen out important information from a large amount of information.

For the continuous image function $f\ x,y$, the gradient at a specific point x,y can be represented as a vectorial quantity:

$$\nabla f\ x,y\ = \left[G_x, G_y\right]^T = \left[\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}\right]^T \tag{4}$$

The gradients of G_x and G_y correspond to the directions x and y, respectively. The amplitude $\left|\nabla f\ x,y\right|$ and the angle indicating the gradient's direction are determined as follows:

$$\left|\nabla f\ x,y\right| = \ G_x^2 + G_y^2\ ^{1/2} \tag{5}$$

$$\phi(x,y) = \arctan\left(\frac{G_y}{G_x}\right) \tag{6}$$

For digital images, the amplitude $\left|\nabla f(x,y)\right|$, as mentioned in the previous formula, can be substituted with the differential value, which then serves as the pixel intensity for the resulting image.

$$\left|\nabla f(x,y)\right| = \left\{\left[f(x,y) - f(x+1,y)\right]^2 + f(x,y) - \left[f(x,y+1)\right]^2\right\}1/2 \tag{7}$$

The above formula is the mathematical expression of difference, which is accomplished by operators in engineering.

The colour enhancement module within the system utilizes a sophisticated inverse colour enhancement algorithm to adjust the overall brightness of the image. Additionally, it employs a histogram-based nonlinear adaptive approach to enhance the image's grey levels; for images containing dark regions, an advanced technique specific to evaluating deep primary hues is employed to ascertain the ideal luminance level. This involves scrutinizing an extensive array of planar visual data. Such images typically display groupings of pixels united by a common colour channel, occasionally punctuated by null points within said channel. The targeted image channel for enhancement can be represented using the following formula:

$$L(l) = \min_{I\in\Omega(\alpha)}\left(\min_{i\in(R,G,B)} L^I(I)\right) = 0 \tag{8}$$

In this context, L^I it represents the dark primary colour, while $\Omega(\alpha)$ it denotes the local area. Once the brightness of the image has been adjusted, the finer details within the overall low-illumination regions become more prominent. Subsequently, to make the image details even more pronounced, it is necessary to enhance the local contrast of image brightness by analyzing the correlation between the grey values of pixels within the designated area. Additionally, to bolster the colour details of the image, the median filtering technique is employed to amplify the image contrast. Following this step, the average brightness is determined:

$$Med_{RGB}(x_k,y_k) = T\cdot Tra_{RGB}(x_k,y_k) \tag{9}$$

In this context, T it denotes the median processing function while $Tra_{RGB}(x_k,y_k)$ it signifies the pixel grey coordinate function. Once the average brightness is computed using the aforementioned formula, the subsequent formula is employed to accomplish the enhancement of the image's colour contrast.

$$\begin{gathered}\mathrm{Re}s_{RGB}(x_k,y_k) = \eta\left(Tra_{RGB}(x_k,y_k) - Med_{RGB}(x_k,y_k)\right) + \\ Tra_{RGB}(x_k,y_k)\end{gathered} \tag{10}$$

In this scenario, η it is designated as the pixel-grey processing coefficient. Within the diagram depicting spatial sampling inconsistencies, interpolation is applied to all integer nodes.

After completing data analysis and visualization, we will optimize and iterate the packaging design based on the results of the analysis. During the optimization process, continuous feedback and adjustments are also needed. If the effect is not satisfactory or there are other issues, adjustments and corrections need to be made on time until satisfactory results are achieved.

4 RESULT ANALYSIS AND DISCUSSION

In the experiment, we deliberately chose 200 sample instances with the highest uncertainty to augment the training set during every iteration. This approach aims to bolster the model's capacity to discern challenging or borderline samples. By including these ambiguous samples in training, the model gains exposure to intricate features and nuanced differences, leading to better generalization. Additionally, in each iteration, we introduced 100, 200, 300, and 400 unlabeled samples exhibiting the strongest confidence in the training mix. This was done to assess how model performance evolves with the influx of varying quantities of high-confidence samples. Figure 3 illustrates a comparative analysis of the experimental outcomes across different learning stages.

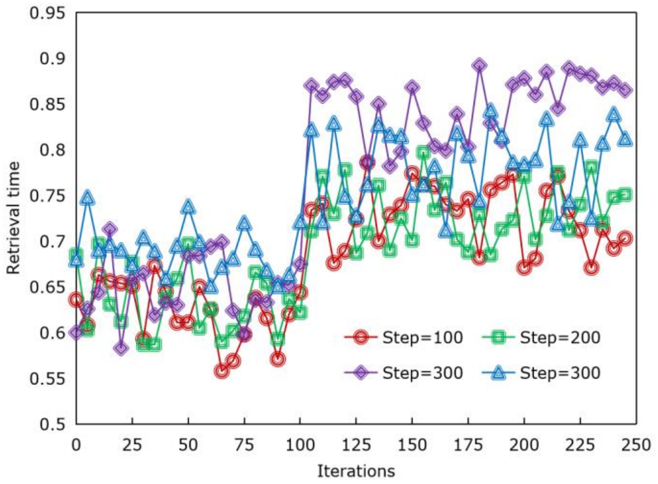


Figure 3: The correlation between the active learning approach and its subsequent performance.

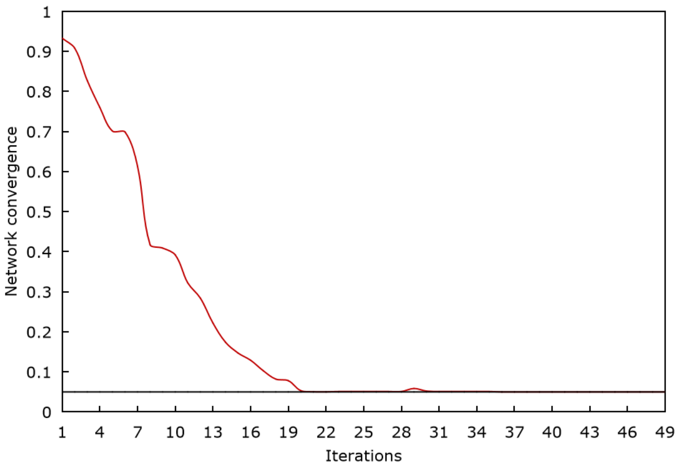


Figure 4: Algorithm convergence trend.

Increasing the high-confidence samples by 100 in each iteration results in a gradual enhancement of the model's performance, whereas incorporating 400 such samples leads to a more notable boost. This suggests that a strategic augmentation of high-confidence samples can positively impact the model's performance. Nevertheless, an excess of these samples might result in the model being overly tailored to them, compromising its ability to generalize to fresh data. Consequently, a judicious selection of the learning step size, tailored to the given circumstances, is crucial for striking a balance between the model's performance and its generalization capabilities.

During the experimental phase, we employed a vast array of product packaging images to train our model aimed at analyzing and optimizing brand packaging designs. These datasets encompassed a diverse range of types, styles, and brands, offering the model a wealth of learning material. Figure 4 illustrates the convergence trend observed in our algorithm.

In the first few iterations, the output error of the algorithm is relatively high. This is because, at this stage, the model is still trying to learn effective features and patterns from a large amount of input data. Due to the random initialization of model parameters, the predictive ability of the model is relatively weak in the initial stage. As the iteration count rises, the algorithm's output error experiences a sharp decline. Following approximately 20 iterations, the error stabilizes at a notably low level, indicating that the model has attained an optimal learning phase. Additional iterations beyond this point are unlikely to yield substantial performance gains.

Figure 5 presents a comparison of processing times for various packaging image enhancement techniques. A clear advantage emerges for the algorithm introduced in this article, demonstrating remarkable efficiency in packaging feature processing. Not only does it significantly reduce processing time, but it also elevates the overall processing efficiency considerably.

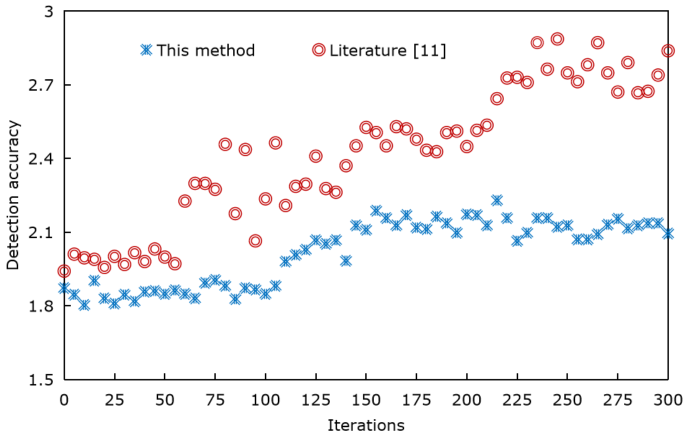


Figure 5: Comparison of packaging image enhancement processing time.

The packaging image enhancement processing based on the method proposed in this article takes less time. This is due to the efficiency of algorithm design and the reasonable allocation of computing resources. By adopting advanced image processing techniques and optimization algorithms, this method achieves fast processing speed while maintaining image quality, which is crucial for real-time requirements in practical applications.

By comparing with the image enhancement method in Literature [11], it was found that our method outperforms other assessment metrics, further demonstrating the potential of this algorithm in practical applications.

Way	Contrast	Brightness relation factor/%	Information entropy/bit
Original	19.89	0.78	6.41
Literature [11]	39.67	0.82	7.63
This method	46.61	0.84	7.99

Table 1: Comparison of image quality assessment.

Analyzing the test results presented in Table 1 reveals that the data-driven image enhancement algorithm introduced in this article outperforms the method described in Literature [11] in terms of contrast, brightness relation factor, and information entropy. The improvement of contrast makes the details of the packaging image clearer, the optimization of the brightness relation factor makes the whole image more natural and harmonious, and the increase of information entropy means that the image contains more information.

Figure 6: Comparison between the original image and the salient image.

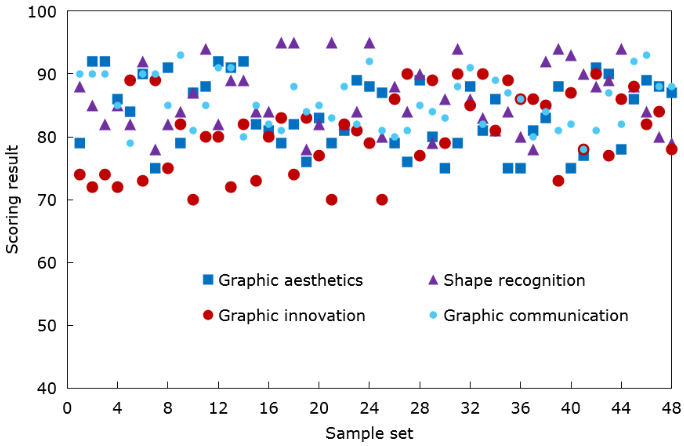


Figure 7: User rating results.

By carefully comparing the original image to the salient image depicted in Figure 6, one can gain a more intuitive understanding of the algorithm's effectiveness presented in this article. The saliency map highlights the important details in the image, which makes the characteristics of ceramic packaging more vivid. The algorithm in this article effectively suppresses the smooth region and further improves the contrast of the image.

Figure 7 shows the scoring results of users' visual effects on product packaging design works in four dimensions: graphic aesthetics, graphic recognition, graphic innovation, and graphic information transmission. These scores reflect users' feelings and cognition of packaging design on the visual level, which has important reference value for designers to understand users' preferences and optimize design schemes.

The packaging graphics designed using the method described in this article have achieved high user ratings in four dimensions: graphic aesthetics, graphic recognition, graphic innovation, and graphic information communication. This result fully demonstrates the effectiveness and superiority of our method, providing strong support for further promotion and application of our method.

5 CONCLUSION

As the first intimate contact between products and consumers, the design of brand packaging directly affects the market acceptance of products, the shaping of brand image, and consumer purchasing decisions. With the support of modern technology, designers can use CAD software to carry out various tasks such as packaging structure design, pattern design, colour matching, etc. This article integrates CAD and big data technologies in visualizing and analyzing brand packaging design. It underscores the use of image enhancement algorithms tailored to human visual attributes. These algorithms adeptly enhance image contrast, brightness balance, and information entropy, resulting in clearer, more natural, and informative visuals. User ratings reveal that our packaging graphics excel in four key areas: aesthetic appeal, recognition, innovation, and information communication. By leveraging extensive product packaging image datasets, the algorithm adeptly extracts valuable features and patterns, applying them to fresh design challenges. This data-driven methodology elevates algorithmic efficiency and precision, paving the way for intelligent and automated advancements in packaging design.

In essence, our proposed data-driven image enhancement algorithm offers tangible benefits to product packaging design. Looking ahead, we anticipate further refinement and broader application of this algorithm, driving progress in packaging design and beyond.

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