Implementation of Color Design Distributed System for Internet of Things and Artificial Intelligence Aided Industrial Design

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Abstract. With the intense pace of work and life, the updating and iteration of industrial design products are also accelerating, and the competition between similar products is becoming increasingly fierce. It isn't easy to take advantage of the user's choice only by the satisfaction of product functions. Scientific and reasonable emotional design of product colors is one of the keys to the success of final product design. Therefore, this research is based on a quantitative experiment of product color emotion using EEG technology. First, the color system and hue relationship are selected as the color variables of the samples based on the product color design elements, and the order and screening are conducted through the beauty principle to build an experimental sample set as the stimulus material for the emotional change of the subjects. Then, EEG technology will collect EEG signals when subjects observe experimental samples, obtain objective physiological data related to subjects' emotional states, and build a color design distributed system oriented to the Internet of Things and artificial intelligence-aided industrial design. The experimental results show that the color recognition accuracy of the color design distributed system is more than 97%, the KMO value of the system is more than 0.5, and the sig value of significance is less than 0.05. The system shows the broad potential of AI-aided industrial design.

Keywords: Artificial intelligence; Industrial design; Color recognition; Emotional design of product color; Random forest

1 Introduction

Centering on the development plan of Made in China 2025, Intelligent Manufacturing Engineering has launched a new application of the integration of new scientific information technology and manufacturing equipment, focusing on key processes to achieve intelligence, machine substitutability, and process standardization and striving to promote the construction of intelligent manufacturing standard system processes has become the major trend of intelligent design development at this stage. The success of intelligent manufacturing depends on several key components and methodologies. Data integration frameworks ensure interoperability across the manufacturing ecosystem, while advanced analytics and AI algorithms extract actionable insights from data. Cybersecurity measures safeguard sensitive data, and standardization efforts promote consistency and regulatory adherence. Real-time data analytics help manufacturers identify bottlenecks and streamline processes to achieve heightened productivity, agility, and competitiveness. By integrating these elements, Industry 4.0 technologies can unlock the full potential of intelligent manufacturing. As a complex human activity, design needs the blessing of intelligent design to a certain extent. AI tools can support designers in various ways: generating ideas, exploring design concepts, enhancing collaboration, automating repetitive tasks, providing personalized recommendations, offering predictive analytics, and supporting iterative improvement. By leveraging AI capabilities, designers can accelerate the design process, augment their creativity and problem-solving skills, and create more innovative solutions across various domains. It is of great social significance to study the color design distributed system of computer-aided industrial design and the intelligent design system further by applying intelligence to replace important manufacturing processes to save the workforce. Integrating color design in distributed systems enhances team communication, comprehension, and decision-making. It also improves the visual appeal and intuitiveness of user interfaces and aids in highlighting critical information or anomalies within complex systems. Adding color design can optimize collaboration, enhance user experience, and improve data visualization, thereby increasing the efficiency of industrial design processes [1]. Color quality detection has been widely used in many research fields, industrial production, and agricultural and sideline product processing. For example, in textile materials, printing materials and coatings, jewelry products, food production and processing, and other industries, certain color standards are required to inspect the quality and classify the grades of products produced and processed to determine whether the products produced meet the national standards. Traditional color quality detection methods include using human eyes for evaluation and a colorimeter for product color quality detection. Color quality detection is a common practice in several industries. Automotive, textiles and apparel, consumer electronics, food and beverage, cosmetics, and personal care are some industries that employ color quality detection to ensure their products' consistency, safety, and visual appeal. Emerging technologies such as computer vision, machine learning, spectrophotometry, digital imaging, hyperspectral imaging, and AI-driven color analysis are revolutionizing color quality detection processes in these industries, improving accuracy, efficiency, and automation [2]. The results of the evaluation method with human eyes will vary according to different people and standards, resulting in strong subjectivity, disunity, and lack of objective and uniform standards. Color difference meters offer more accurate and consistent measurements of color differences compared to subjective assessments by human eyes. They are reliable, efficient, and suitable for high-throughput manufacturing applications like quality control. However, interpreting and understanding the numerical values may require expertise in color science. Subjective assessments by human eyes are better suited for tasks requiring nuanced and qualitative evaluations of color appearance, such as design and aesthetics. The choice between the two depends on the specific needs and context of the color evaluation task. Compared with the method used by human eyes to evaluate the color quality of products, the color difference meter is objective and unified. Color difference meters provide objective and standardized measurements of color attributes, ensuring consistent and reproducible evaluations regardless of lighting conditions or observer bias. Unlike subjective human assessments, color difference meters quantify discrepancies using standardized metrics, ensuring impartial evaluations. By employing automated measurement processes and objective algorithms, color difference meters ensure efficiency and cost-effectiveness compared to manual evaluations. However, when the color difference meter is used to detect the color quality of products, the color difference between the detected products is fragile, so the electric signal output by the color difference meter is correspondingly weak. At the same time, due to the influence of various external interference factors, the results detected by the colorimeter are prone to large errors, it is difficult to detect the color quality of products accurately, it is difficult to distinguish products of different standards or grades, and it is easy to cause confusion between products of similar standards or grade. To ensure accurate and reliable colorimeter-based color quality assessment, standardized sample preparation, regular instrument calibration, appropriate measurement geometry, proper sample presentation and positioning, standardized measurement protocols, and proper data analysis are necessary. These factors help minimize errors and ensure reproducibility in color measurements. The method of using machine vision to detect the color quality is mainly to use color image processing to extract the RGB primary color value of the product image or the product color components such as brightness, saturation, and hue value, and to give the color quality of the product through certain operations [3]. The choice of image processing pipeline and color rendering algorithms in camera firmware plays a crucial role in shaping the final output image characteristics, including color reproduction, contrast, detail, color balance, and artistic style. By carefully selecting and optimizing these algorithms, camera manufacturers can tailor the image rendering process to meet the needs and preferences of photographers, enthusiasts, and professionals. (P. Sathyaprakash et al. 2023) discuss challenges and opportunities in e-healthcare risk prediction systems, including algorithm bias and privacy concerns. Future research may focus on explainable AI models, federated learning approaches, and integration of real-time sensor data to improve patient outcomes. Additionally, the text highlights the importance of emotional design in industrial product design. It proposes a color design distributed system that uses EEG technology and AI to enhance the success of industrial product design. The experimental results show that the proposed system has great potential in AI-aided industrial design. The research on color design algorithms of AI-aided industrial design is mainly applied to computer vision. Computer vision products are a typical application case of simulating the human brain to analyze images. The image sensor of the computer vision system corresponds to the human retina to collect images. Optical sensors with similar functions also exist in image acquisition devices, but different cameras output different images for the same scene. Simulating real-world conditions in the testing environment provides a more accurate assessment of the system's performance and usability. Testing in realistic scenarios helps validate functionality and compatibility across different devices, platforms, and environments while gathering valuable feedback for improvements. Configuring the testing environment to replicate real-world situations leads to developing a more robust and user-friendly system. This is because the image sensor is prone to be affected by various interference factors when collecting images, such as external environmental light sources, object reflection characteristics, and image sensor sensitivity coefficient, which makes the collected image color deviate from the real object color [4]. (Dr. P.M. Kumar et al. 2024) research uses EEG technology to study product color emotion and build a color design distributed system aided by AI for industrial product design. The study shows that emotional design is critical to product success, and the proposed color design system has great potential. The paper also investigates using Artificial Neural Network-Based Expert Systems and crop production systems to predict plant growth and development based on input variables. The suggested model explains 96.9% of the variation in the dependent variable and is considered reliable. The human visual system corresponding to the image sensor has color constancy, and the human eye can automatically adjust according to the changes in the external environment, which can prevent some factors, such as light sources, from interfering with the correct perception of the true color of external objects. The image sensor does not have an automatic adjustment function. Image sensors without automatic adjustment functions struggle to adapt to changes in lighting conditions and maintain accurate color reproduction. Automatic exposure control (AEC) and white balance (AWB) are crucial for optimizing image sensor performance. Without them, image sensors rely solely on fixed settings, limiting their ability to capture accurate and consistent images under different lighting conditions. Advancements in sensor technology and firmware algorithms can enhance the adaptability and performance of image sensors in real-world applications. If the external environment changes, the image collected by the image sensor will have more or less color deviation. Transitioning to automation while minimizing disruption requires careful planning, stakeholder engagement, skill development, phased implementation, job redesign, employee involvement, change management, safety and ergonomics, and continuous monitoring. These strategies can help organizations navigate the transition to automation, minimize disruption, and drive innovation, efficiency, and competitiveness.

The image color deviation of color distributed design can be defined as the deviation between the image acquired by the CCD sensor and the image captured by human eyes in brightness, hue, saturation, etc. Color deviation will interfere with image analysis, affecting the judgment of obtaining things. Therefore, to eliminate the influence of interference factors and realize color constancy of collected images, preprocessing of image brightness and color needs to be added to computer vision. Preprocessing techniques in computer vision adjust image brightness and color for better analysis. Histogram equalization enhances contrast by redistributing pixel intensities, while gamma correction adjusts brightness and color balance. Color normalization techniques like white balancing and color space transformation correct for illumination and color temperature variations. These techniques improve image quality and reliability for computer vision tasks like object detection, classification, and segmentation. Therefore, the color correction of color images in computer vision has vital scientific significance and application value [5].

To sum up, this research is oriented to the Internet of Things and artificial intelligence-aided industrial design. It carries out the construction and implementation of the color design distributed system, providing a new thinking space for industrial design.

2 Related works

Many domestic project teams mainly study image preprocessing algorithms applied in the distributed system of computer vision and color design, including brightness space correction algorithm, color correction algorithm, white balance algorithm, etc. These three key algorithms are used in image processing and computer vision applications: brightness space correction, color correction, and white balance. Brightness space correction algorithms are used to adjust the brightness levels of images to achieve visual consistency or compensate for lighting variations. Techniques include histogram equalization, gamma correction, adaptive histogram equalization, and contrast stretching. Color correction algorithms adjust color balance to ensure accurate reproduction of colors across different devices and lighting conditions. Techniques include color calibration, color constancy, and color grading. White balance algorithms adjust the color temperature of images to ensure that neutral colors appear neutral under different lighting conditions. Techniques include gray-world or white-world assumptions, spectral characteristics of light sources, and manual adjustments based on user input or reference objects in the scene. These algorithms ensure images are visually consistent, accurately represent colors, and are suitable for display and printing [6]. When capturing scene images with cameras, industrial cameras need to reflect the actual color of objects [7]. Therefore, in the specific project application, discussing the related algorithm research in brightness uniformity correction and color preprocessing is necessary. High-quality visual outputs, accuracy, and reliability depend on discussing algorithm research related to brightness uniformity correction and color preprocessing. This is imperative for projects where visual fidelity is paramount, requiring accurate color reproduction or user-centric projects. By discussing adaptive algorithms, we demonstrate their project's robustness and adaptability, augmenting its practical utility and longevity.

Considering various camera imaging factors, there are currently several classical methods for image brightness space correction in the aspect of brightness uniformity correction. Literature [8] uses a two-dimensional elliptical partial differential equation with offset approximation to reconstruct the acquired graphic image to achieve brightness space correction. The two-dimensional elliptic partial differential equation (PDE) with offset approximation is the foundation for various image processing techniques to enhance brightness uniformity across an image. By applying the PDE with offset approximation, researchers can correct for non-uniform illumination and achieve a more consistent brightness distribution. Researchers utilize this PDE to iteratively adjust the brightness values of pixels based on their local neighborhoods, aiming to minimize brightness variations and achieve a more uniform distribution across the entire image. By solving the PDE numerically using iterative methods, researchers can smooth out brightness gradients and enhance overall image uniformity. The two-dimensional elliptic partial differential equation (PDE) with offset approximation is commonly expressed in the following form:

$$\nabla \cdot (c(x, y) \nabla u(x, y)) = f(x, y)$$

In this equation, 'u' represents the image intensity or brightness at every pixel location (x, y), 'c(x, y)' is a coefficient function that captures the spatial variations in brightness, and 'f(x, y)' represents the external sources of illumination or other factors affecting brightness. Essentially, the equation describes how the brightness of each pixel is influenced by its surrounding pixels and external factors. Reference [9] proposed a machine learning luminance space correction algorithm to improve the expected signal estimation accuracy by allocating the weight of the standard deviation through an adaptive weighted average filter. The brightness space correction method of optical fiber all-in-one camera proposed in [10]. The above algorithms directly correct the brightness space of the image gray value. Due to the nonlinearity and heterogeneity of the irradiance response curve, the correction process involves complex nonlinear operations. The computational overhead is significant, and the response characteristics of the human eye to the brightness are ignored. In the calibration process, the grayscale calibration board is relied on to obtain the accurate spatial brightness distribution map, and the wrinkle problem that inevitably occurs in the use of the grayscale board is not considered.

The color correction method based on spectral response needs to calculate the spectral response curve of the current digital camera with good color rendering performance, estimate the spectral response curve of the industrial camera, and find out the transformation relationship between the spectral response of the camera to be corrected and it. Classic algorithms include a correction algorithm based on spectral sensitivity estimation [11] and a color correction algorithm based on independent illumination [12]. The main idea of the color correction method based on the target color is to use the color standard value and measurement value containing a certain number of color samples to establish a correction model to match the mapping relationship between them, which is a simple and practical method. Classic and commonly used color correction algorithms include color correction algorithm based on 3D table lookup [13], polynomial regression analysis method [14], least square method with constraints, pattern search method [15], color correction algorithm based on support regression vector machine [16], etc.

Using the least square method to solve the correction coefficient can not guarantee the accurate reproduction of white, and whether white can be accurately reproduced is an essential indicator of color correction. For this reason, a constraint term needs to be added to the least squares method; that is, the white has zero error after correction. Although the accurate reproduction of white is guaranteed, the error after correcting other colors is further amplified. 2-norm is used to solve the correction coefficient when building the correction model for the polynomial and least-squares methods with constraints. Experiments show that the correction result obtained by 1-norm is slightly better than that obtained by 2-norm. Since the 1-norm is nondifferentiable, for the problem of directly seeking the global optimal solution, the pattern search method can be used to solve the correction model, which can significantly suppress noise amplification and minimize the maximum error. However, the pattern search algorithm may also fall into the local optimal solution; the selected initial solution significantly impacts the calculation results, the brightness level of the images before and after correction is different, and even overexposure [17].

Research on color distribution recognition technology in China began in 1980. Since then, researchers in related fields in China have spent nearly ten years exploring the relevant algorithms for color distribution recognition, summing up feasible implementation schemes, and promoting color distribution from theoretical research to practical application [18]. Since 1990, several color distribution recognition products for the market have appeared in China. At that time, the printed character recognition system independently developed by the research and development team of Tsinghua University was the top performance [19]. In recent years, the main research direction in this field in China has been to optimize the performance of color distribution recognition systems and focus on improving the accuracy and compatibility of system recognition. With the development of the color distribution recognition field, more and more attention has been paid to it in China, and related research in this field has also obtained a more solid economic guarantee. The recognition effect of domestic color distribution products is also improving.

One of the mainstream research methods of intelligent color-aided design is to search in the built model and optimize the search process with a clever algorithm. This method explores the color design law to a certain extent and uses an intelligent algorithm to realize the basic process of color design. However, the quality of the color scheme depends on the degree of the training model [20-21]. Another method is to collect many color-matching design samples and use intelligent algorithms to mine the rules of color design to match cases. For example, in literature [22], case matching of color design is carried out through the probability of simultaneous occurrence of colors in traditional patterns, and the probability between colors is used to generate a scheme that conforms to the image. Organizations should follow a comprehensive strategy to ensure privacy and security when collecting color-related data in IoT and AI-assisted industrial design. This includes minimizing data collection to essential information, using anonymization and pseudonymization techniques for individual privacy, ensuring secure data transmission with encryption protocols, implementing strict access controls and authentication mechanisms, and maintaining clear policies for data lifecycle management. It's also essential to integrate privacy considerations into the design process, obtain explicit user consent, maintain transparency about data practices, conduct regular security audits and risk assessments, and address vulnerabilities to avoid emerging threats. These measures foster trust among stakeholders, comply with regulations, and safeguard color-related data in IoT and AI-assisted industrial design processes. Literature [23] also uses images to find similar cases and uses color rule optimization to match color schemes. Literature [24] used the BP neural network to iterate through the matching between image and style. Document [25] applies a dynamic fuzzy neural network to simulate the color scheme design and selection process and establishes an intelligent color scheme design system. The above two methods have explored the innovative generation of product color design schemes, which has improved the design efficiency to a certain extent. Still, it is challenging to learn the inherent laws of color design directly and generate innovative color schemes, limiting the development of color scheme generation and design to a certain extent. Implementing color design in distributed systems leverages color as a communication tool to enhance visual representation, facilitate collaboration, and improve decision-making processes. By incorporating color-coded diagrams and annotations, the system promotes efficient communication among geographically dispersed team members, enables quick identification of patterns and anomalies, and ensures consistency in visual representation across different devices and platforms. This approach enhances industrial design processes' efficiency, effectiveness, and user experience.

To sum up, given the shortcomings and limitations of some of the above algorithms, this paper proposes a new correction method to improve the accuracy of object surface color reproduction and designs a color design distributed system oriented to the Internet of Things and AI-aided industrial design, making it better adapt to the visual characteristics of the human eye.

3 Mathematical model of color design distributed system

This paper mainly uses this method to classify the target industrial design products' color image words to find the images that meet the product screening conditions. Collect the image words of the target product, and the image words preliminarily screened by experts will be scored against the target samples. Cluster analysis presents unique challenges when integrated with the Color Design Distributed System, as data segmentation into clusters may only sometimes align with human perceptions of color. Additionally, the complexity of clustering algorithms and parameter selection may hinder accessibility and usability within distributed design teams. A nuanced approach is necessary to ensure the outcomes align with the system's objectives and facilitate effective collaboration and decision-making processes. After averaging the scores, cluster analysis will be conducted using SPSS software, and the image words with the highest number of clusters will be selected through classification. Judge the category and calculate the Euclidean distance of the vector distance as shown in Formula (1) and (2):

$$dist_{ed}(x_i, x_j) = \| x_i - x_j \|_2 = \sqrt{\sum_{u=1}^{n} | x_{iu} - x_{ju} |^2} \quad (1)$$

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \| x - \mu_i \|_2^2 \quad (2)$$

Where: $\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$ is the mean vector of the cluster C_i x_i. It is the abscissa and x_j ordinate of the vector coordinate system.

In this paper, the SD semantic analysis method has been used in two places. First, the semantic matching set is established, and further clustering analysis and principal component analysis are carried out to obtain the target image words. An empirical study could benchmark the SD semantic analysis technique against EasyO An empirical study could benchmark the SD semantic analysis technique against EasyOCR and other OCR tools using standard benchmark datasets to evaluate their performance in recognizing text and processing speed. Comparisons reveal that the SD semantic analysis technique achieves higher accuracy in recognizing text, while EasyOCR excels in processing speed. Search academic databases such as IEEE Xplore, Google Scholar, or PubMed for research papers in OCR and document analysis to find the most recent empirical data.CR and other OCR tools use standard benchmark datasets to evaluate their performance in recognizing text and processing speed. Comparisons reveal that the SD semantic analysis technique achieves higher accuracy in recognizing text, while EasyOCR excels in processing speed. Search academic databases such as IEEE Xplore, Google Scholar, or PubMed for research papers in OCR and document analysis to find the most recent empirical data. The other is to establish a screening evaluator, which combines and renders the gradient drop discrete points evenly distributed in the color stereo as a sample questionnaire and then surveys the corresponding target image words to obtain the user's evaluation value of the product under the target image words. Because people often express strongly when scoring colors, it is necessary to average the evaluation values. The generation countermeasure network generator and the screening evaluator built by the BP neural network are two separate individuals. Still, there is a specific relationship between them from the perspective of the scheme set. The generation countermeasure network generator creates countermeasure networks to enhance security while the screening evaluator assesses their effectiveness. By testing and analyzing the performance of the countermeasure networks, weaknesses can be identified and improvements made, leading to more robust and adequate security measures. This collaborative approach ensures security measures are proactive, adaptive, and aligned with the evolving threat landscape. To explain the operation steps from the perspective of scheme set changes, the following definitions can be listed:

Definition 1. For any product P, P^A is used in the product color design process to represent the existing excellent scheme set, as shown in Formula (3):

$$P^A = \{P_i^A\}, i = 1, 2, ..., m \ (3)$$

It indicates that P^A it comprises the color scheme set of I products P.

Definition 2. The scheme is generated according to the color design rules of the existing product color scheme P^A to form a new generation scheme set C^A. There are formulas (4) and (5):

$$C^A = \{C_i^A\}, j = 1, 2, ..., n \ (4)$$

$$P^A \cap C^A \neq \phi \ (5)$$

Definition 3. For any discrete point $B(x_i, y_i, z_i)$ in the color solid, D^B it is used to represent the set of discrete points in the color solid. After scoring, select the first one elements in descending order, and then there is formula (6):

$D^B = \left\{D_k^B\right\}, k = 1, 2, ..., l$ (6)

Definition 4. The intersection of D^B and C^A yields set R^A, with formula (7):

$D^B \cap C^A = R^A$ (7)

According to the definition of the color scheme set and the steps of generating the framework, we can see that the scheme set P^A was collected before the training generator. The sample set D^A was collected before the training screening evaluator; after the training, the intersection set is taken between the new set in the steps of running the generator and the screening evaluator; that is, the newly generated scheme R^A is filtered, and the designer finally selects the color scheme from the set R^A.

Definition 5. D^B includes P^A, so there is formula (8):

$P^A \in D^B$ (8)

In addition, in the process of color design, RGB is converted to HSI, as shown in the following formula (9):

$$H = \begin{cases} cos^{-1}\dfrac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}, B \le G \\ 2\pi - cos^{-1}\dfrac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}, B > G \end{cases}$$

$$S = 1 - \frac{3}{R+G+B} min(R, G, B) \qquad (9)$$

$$I = \frac{R+G+B}{3}$$

Because the number of updated samples generated by the color generator is enormous, and the color design files generated are random. Therefore, in the later demand selection and screening process, instead of directly establishing the mapping relationship between the color design scheme code generated by the generator and the image demand, the combination of discrete points in color three-dimensional space and the image demand is selected to establish the mapping. The sample set range of the color design combination of discrete points in the color three-dimensional space is larger than the excellent sample set of specific products, so there is no direct interactive questionnaire survey on the generated scheme, thus obtaining a screening evaluator of color coding in the color three-dimensional space whose range is more extensive than the coding part of the generated color design scheme, therefore truly realizing the function of screening and designing the color design scheme generated by the generator.

4 Methods

4.1 Architecture and implementation of color design distributed system

As shown in Figure 1, this paper takes the electric vehicle, an industrial product, as an example to collect and extract color samples for the construction of the generator and screening evaluator according to the functions and requirements of the system. Part 1 is a sample set for collecting generator learning rules. According to the pan-ethnic group-based color sample market survey method in Chapter 2, take electric vehicles as an example to collect pan-ethnic group product drawings, define pan-ethnic groups under color attributes, extract primary colors, auxiliary colors, and embellishment colors from available samples, and convert data into color coding as a model for learning rules. The raw data is extracted to transform data into color coding for learning rules. Then, relevant attributes are identified and structured for analysis. Normalization and encoding techniques are applied to ensure compatibility across different data types and scales. The model is trained with normalized and encoded data, predicting or classifying the quality of new color schemes based on their extracted features. Subjective assessments and objective metrics determine the quality of color schemes. This process can enhance the effectiveness and impact of the design process. Part 2 collects and screens the evaluator to form samples into three parts. First, the pan family samples in Figure

1 are randomly selected to select the target image of the evaluator. The second part is the selection of the color layout of the target product. According to the eye movement hot spot result map in the process of extracting the feature color in Figure 1, the target product area is analyzed and distinguished, the perspective proportion is adjusted, and the color layout of the general target product model is obtained according to the preference survey; The third part is to collect the sample set of screening evaluator. Research employs multiple processes to ensure the color-coding model's accuracy and reliability. These include cross-validation, validation on independent datasets, evaluation metrics, expert review and feedback, error analysis, continuous monitoring, and iterative improvement. Researchers can refine and optimize the color-coding model over time by utilizing these methods, ensuring its effectiveness in real-world applications. First, according to the color design principle, the discrete points with uniform gradients are selected to be arranged and combined in the color stereo and then stored as image samples in the general product model as the offspring of color-coding conversion.

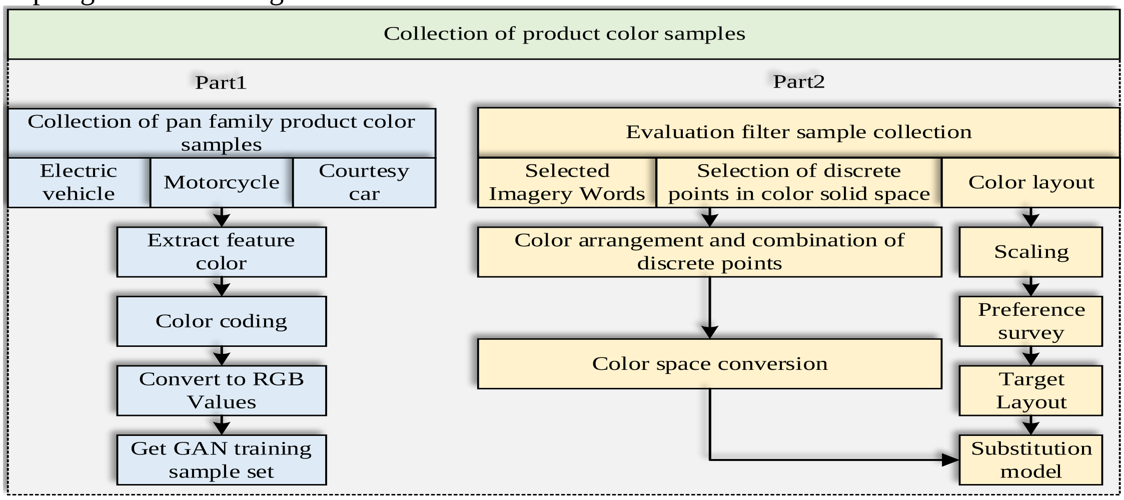

Fig 1. Color sample collection framework of AI-aided industrial design

According to this idea, the color design distributed system can also extract color design schemes that reflect the needs of designers from the generalized homogeneous and heterogeneous groups. A blend of qualitative and quantitative approaches is used to extract color design schemes reflecting designers' needs. To understand color preferences and aesthetic sensibilities, surveys, interviews, and focus groups are employed for homogeneous groups. For heterogeneous groups, cluster analysis and multivariate analysis techniques segment designers into subgroups and unveil underlying patterns in color preferences. Cross-cultural analysis is also done to examine cultural influences on preferences. These methodologies ensure color designs resonate with designers' diverse tastes and needs. Color design schemes are adjusted based on the requirements and objectives of each design group, feedback from members, and iterative design iterations. This involves experimenting with different color combinations, conducting surveys, interviews, or focus groups, and organizing collaborative brainstorming sessions and design workshops to better align with preferences and expectations. The extracted color design schemes are customized and personalized to meet the unique needs of each design group, resulting in more engaging and impactful design outcomes. The process of collecting product samples is divided into two influencing factors: color design type of the same family attribute and color design type of the different family attribute. Taking electric vehicles as an example, in the process of designing such products, in addition to collecting samples of electric vehicles of various brands, as shown in Figure 2, in the brainstorming of electric vehicle products, we can take the color matching of wearable devices such as motorcycles and helmets, step balance bikes, bicycles, skateboards and their protectors, surfboards, bicycles, and other subsequent Lenovo products as members of the pan-ethnic color samples.

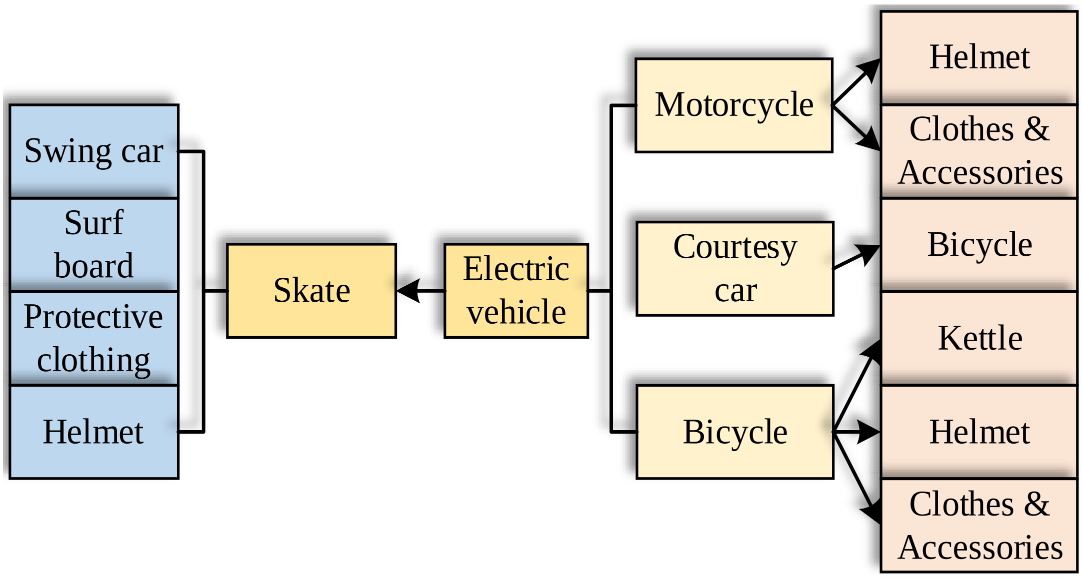

Fig 2. Color Association of Sample Products

Then, according to the basic structure of the system, take brand electric vehicles that have been put into production in the market and have been sold for more than one year as excellent case samples, collect product samples from electric cars with well-known brands such as Emma, Bird, Yadi, Yamaha and their color pan-ethnic groups, and make preliminary selection following the principles of distinguishability, identifiability, and reasonable color quantity; Get part of the collection of color design samples of No. 1-60 electric vehicle pan-ethnic group as shown in Figure 3, and select electric vehicle pan-ethnic group products according to the steps of selecting electric vehicle samples.

Fig 3. Color design sample of electric vehicle pan-ethnic group (sample 1-60)

Then, we extend the case of electric vehicles to industrial products. After the preprocessing of neural network learning, 512 groups of RGB color components of industrial products extracted by applying moment invariants theory are selected for neural network training and education. RGB color components are organized in a structured format for neural network processing. Each group has red, green, and blue values, ranging from 0 to 255. The groups are arranged in a multidimensional array, serving as input variables for the network. The network learns patterns and relationships through training to make accurate predictions and classifications. Figure 4 shows the training and classification structure of the BP neural network. Collecting and analyzing color samples from electric vehicles can be challenging due to various limitations, such as limited sample size, variability in lighting conditions, surface texture, subjectivity in color perception, measurement instrumentation accuracy, and the influence of environmental factors. Addressing these limitations requires careful planning, methodological rigor, and collaboration with experts in color science, automotive design, and data analysis to ensure the accuracy and validity of the collected color data. Each color sample gets three feature values after color feature extraction. After color vector standardization, 512 color samples get 512 * 3 feature quantities with a size of [0, 1], as shown in Table 1.

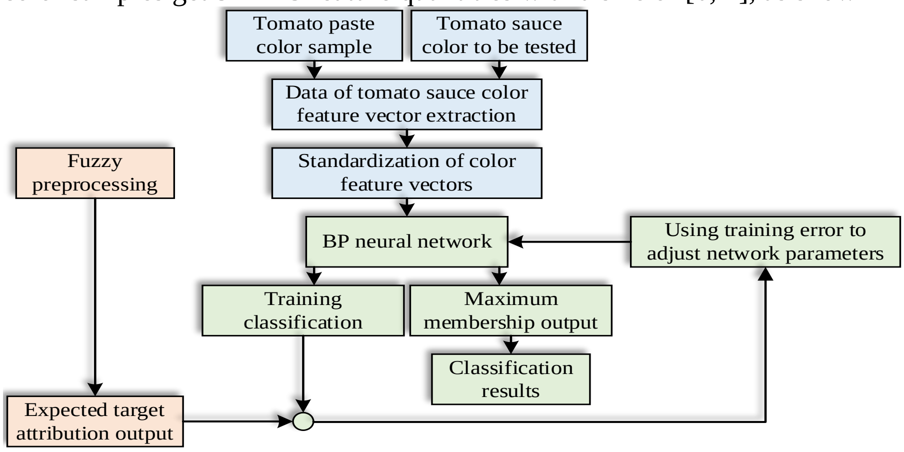

Fig 4. Training flow chart of color design distributed system based on AI-aided industrial design

Table 1
Standardized color feature vector table

Serial No	Characteristic 1	Characteristic 2	Characteristic 3
1	0.6040	0.3223	0.2411
2	0.6070	0.3246	0.2442
3	0.6072	0.3111	0.2409

The structure block diagram of the system is shown in Figure 5.

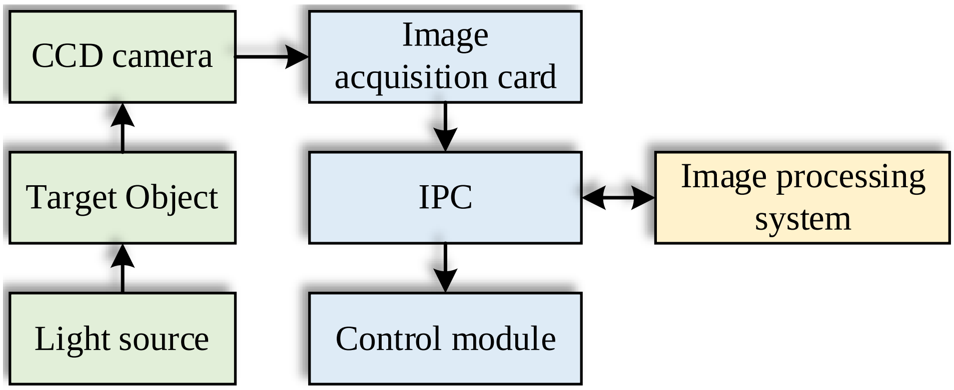

Fig 5. Color Design Distributed System Block Diagram of Industrial Design

As can be seen from the figure, the color design distributed system is composed of peripheral hardware devices and software systems designed through computer software. The hardware design of the system includes the selection and application of external light sources, image sensors, image input devices, etc. The software function of the color design distributed industrial design system is mainly to achieve image histogram equalization, image smoothing and denoising, image segmentation, image feature extraction, and color quality discrimination of industrial products for the real-time collected images of on-site industrial products. The central flow diagram of the system software operation is shown in Figure 6.

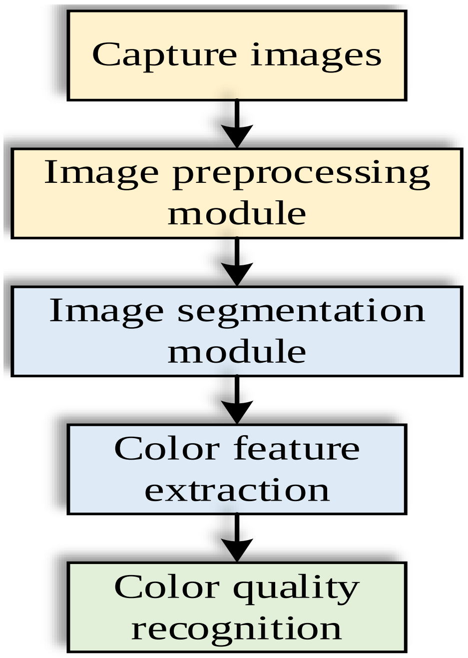

Fig 6. The main flow chart of the color design distributed system software of industrial design

4.2 Color database and coding structure

In this paper, the Munsell color system is used to code colors, and finally, a primary color database of 52 color groups is formed. The results are shown in Figure 7.

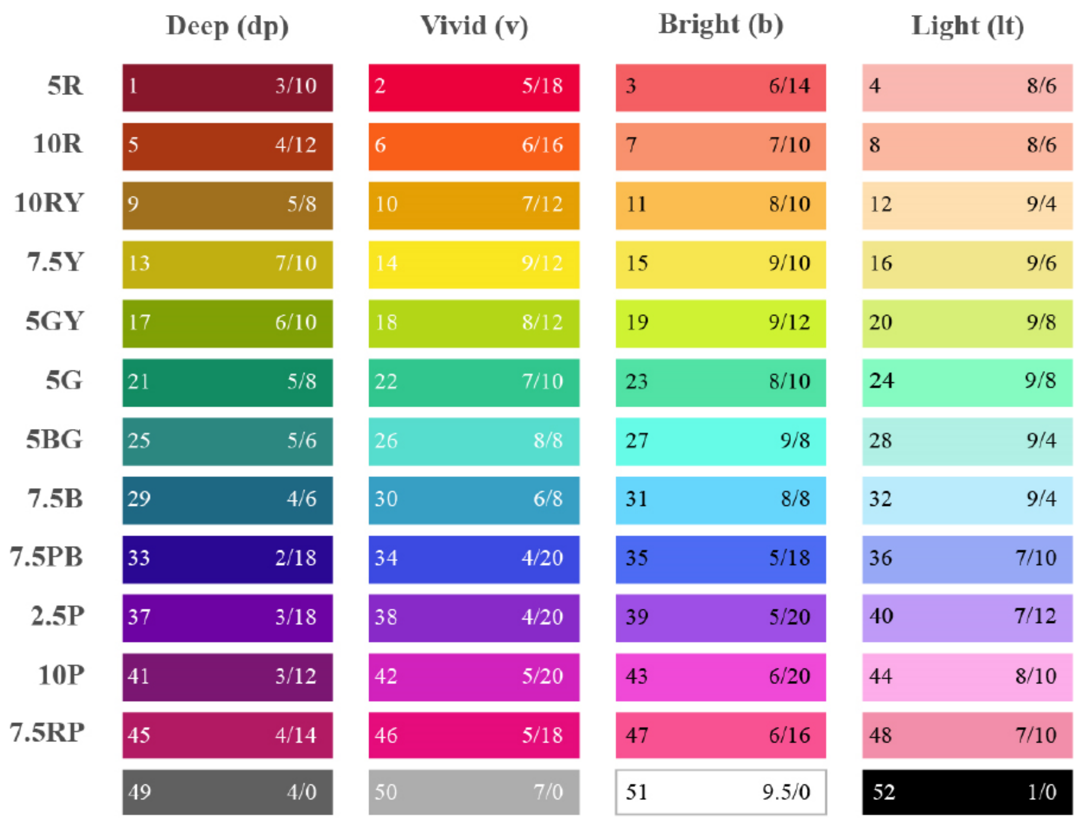

Fig 7. Basic color database

First, the 52 colors in Figure 7 are paired to form 1326 color schemes. It can be seen from the relationship between the colors of Monsbinser that the relationship between colors is vague and ambiguous under the two conditions of the first and second ambiguity, and the color-matching relationship is also vague. The overall ranking is lower because the color relationship is the aesthetic value of the color matching scheme of the first ambiguity and harmony. Based on this, we render 120 experimental samples for model inspection. The results are shown in Figure 8 and Figure 9.

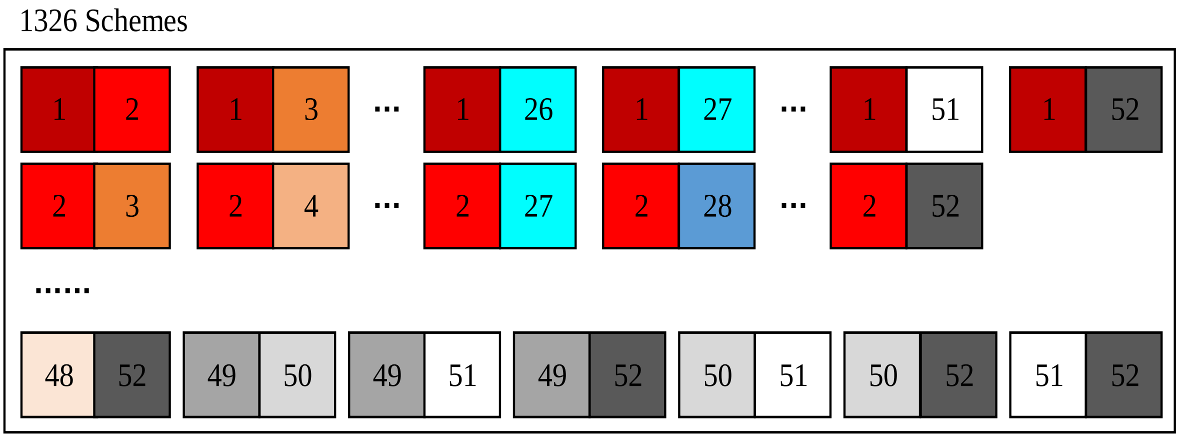

Fig 8. The experimental flow of primary color design distribution

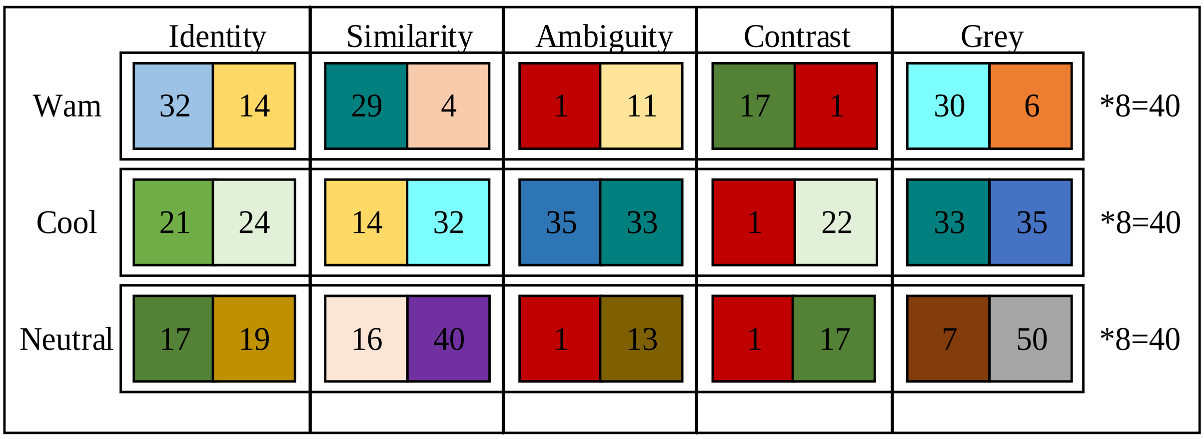

Fig 9. Color division of color design distribution system and final experimental color samples (part)

Image files can be distinguished by their types, such as the number of pixel bits and bit planes, as shown in Table 2. According to the number of pixels, image files are divided into four categories: black-and-white binary, 16-color, 256-color, and 24-bit actual color.

Table 2
Total number of database pixels, number of bit planes, and image file types

Total digits	1	4	8	24

Type	Black white binary			16 color color		Black and white grayscale		256 colors	True color		
Geoplan	1	1	1	1	4	1	1	1	1	1	1
	bw	wb	pal	pal	pal	bw	wb	pal	rgb	rgb	rgb
BMP			*	*				*		*	
TGA						*		*		*	
GIF			*	*				*			
PCX			*					*			*
TIF	*	*		*		*	*	*		*	
JPEG										*	

5 Case study

5.1 System operation and test

System testing is the critical link to realize the function of the color design distributed industrial design system. System testing can detect the problems and deficiencies in the system operation process, help us improve the entire system, and improve the system's overall performance.

The main body of the color design distributed system of industrial design designed in this paper can be divided into the following three parts:

(1) Image preprocessing module

The function of the image preprocessing module is to reduce the interference of various factors that may affect character recognition accuracy in the original image. In addition to basic operations such as image binarization, this module focuses on solving problems such as uneven image illumination distribution caused by environmental factors and image tilt caused by careless image acquisition.

(2) Information area positioning and segmentation module

The information area positioning and segmentation module is the core part of the entire industrial OCR recognition system. Whether the information area can be accurately located and divided into basic recognition units directly affects character recognition accuracy. Considering the difference between industrial information images and general text images, some traditional positioning analysis methods do not apply to industrial information images. The realization of this module adopts a new process and finally realizes the functions that this module should have by combining SSD target detection, color space conversion, edge detection, and other technical means.

(3) Character segmentation and recognition module

Characters in industrial information images are mainly divided into label text characters and digital instrument characters. The character segmentation and recognition module distinguishes these two types of characters and uses different methods to recognize them, maximizing the recognition accuracy of the entire system. Based on the above three modules, the system architecture designed in this paper is shown in Figure 10.

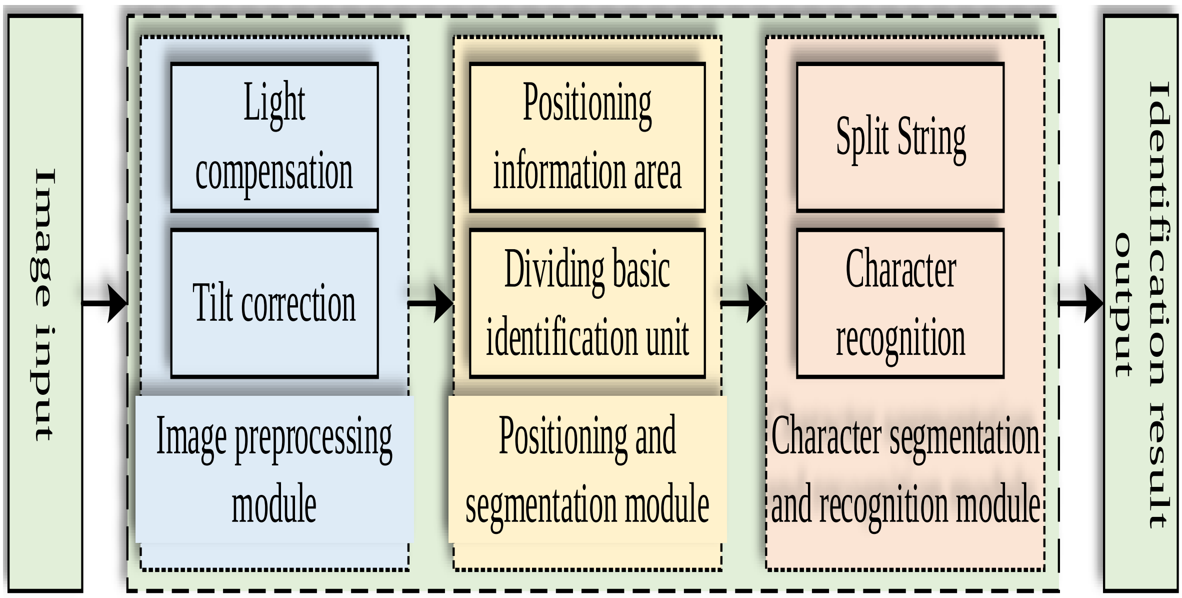

Figure 10 System architecture

The whole system operation process is shown in Figure 11.

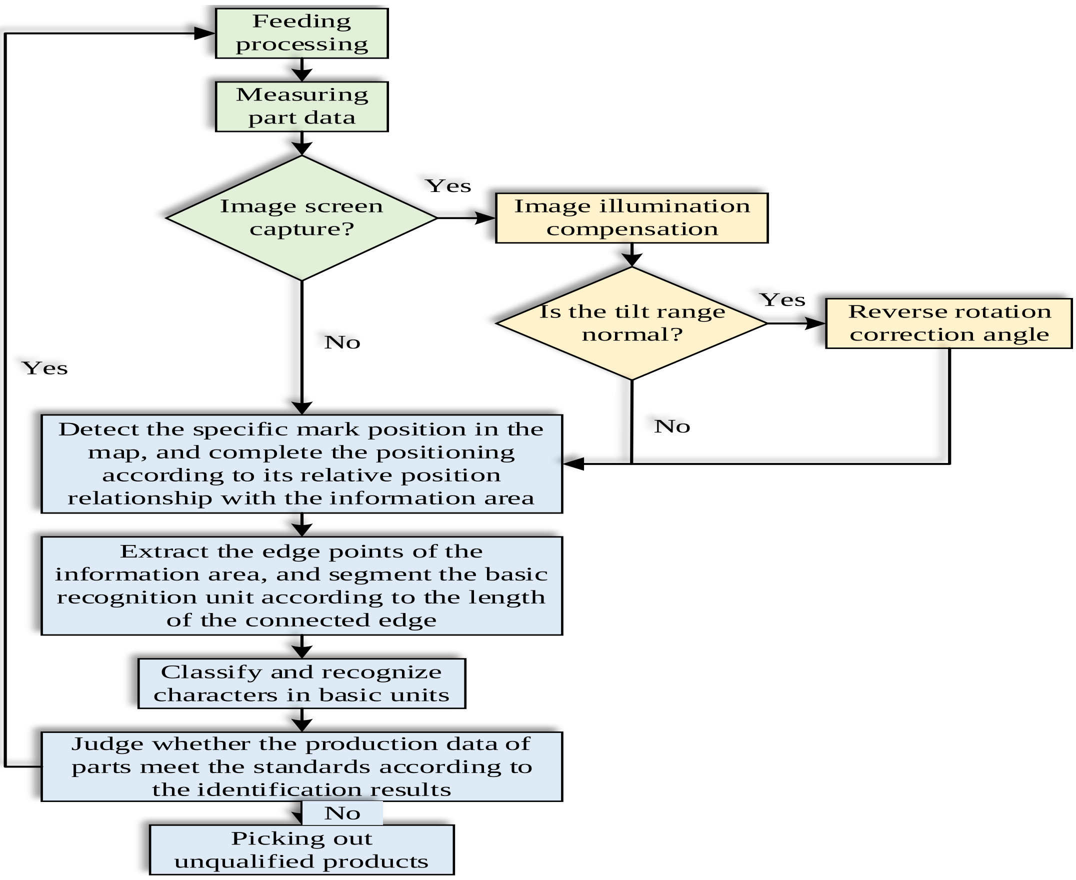

Fig 11. System Operation Process

The system runs under the Windows 10 environment. After receiving the test image input, it recognizes and returns the corresponding recognition results. Table 3 shows the specific system test software and hardware environment.

Table 3
System Test Environment Configuration

Hardware configuration		Software configuration	
Video card	CPU	System platform	Technical tools
AMD Raden R5 230	Intel（R）Core （TM）i7-5500 U	Windows 10	Open CV Tesseract

The specific test

results are shown in Table 4.

Table 4

Statistics of System Test Results

Dataset Source	Character Type	Number of characters	Misiden notification number	Missing number	Accuracy	Average time
Factory screen capture	Label Text	20800	0	0	100%	0.91s
	Digital instrument	2820	0	0	100%	
Camera shooting	Label Text	20800	513	5	97.50%	2.35s
	Digital instrument	2795	9	0	99.75%	

According to the data statistics in Table 4, compared with the color design distributed system without the industrial design, the data set using the system needs additional preprocessing due to uneven light distribution, image tilt, and other conditions, resulting in a relatively long average time to identify a single image; However, as far as the overall recognition accuracy is concerned, under the premise that the image quality is affected, the recognition accuracy of the system for the production color distribution information in this kind of image still reaches more than 97%, basically realizing the automatic and intelligent color design of industrial products.

5.2 Analysis of Empirical Results

In the algorithm core model of the system, nine-digit random noise is input to the input end of the generated countermeasure network to create a color design scheme. Random noise is essential in adversarial machine learning for testing the robustness of the countermeasure network, promoting generalization, defending against adversarial attacks, and augmenting the training dataset. By including random noise in the input data, the network becomes more resilient to input manipulation. It can better handle unexpected inputs, ultimately improving the security and reliability of machine learning systems in adversarial environments. The result of the generated color scheme is shown in Figure 12. Because the generated countermeasure network generates iterations almost infinitely, generally speaking, the more times the model is trained, the better the training effect will be. To improve the system's effectiveness and performance, future iterations should focus on challenges such as acquiring high-quality datasets, enhancing model scalability and efficiency, defending against adversarial attacks, addressing ethical considerations and bias, improving user experience, and ensuring regulatory compliance. Mitigating these challenges can enhance the system's reliability, usability, and compliance, maximizing its impact and value in real-world applications. According to the model experience of handwritten numerals and the performance of the generated color design scheme, 50 times overall training epoch is selected as the number of times of training completion, and 16 * 10 color design scheme solid color image array graphs are set to output, with each color block from top to bottom as the primary color, secondary color, and decorative color respectively. After the epoch cycle reaches 50 times or so and reaches convergence, continue to use the generator to generate 100 groups of data to observe the effect of generating a color design scheme. Training a model until it reaches convergence is insufficient to ensure its reliability and robustness. Generating additional data beyond convergence helps evaluate the model's performance across a broader range of scenarios, assess its generalization ability, and provide insights for further refinement and validation.

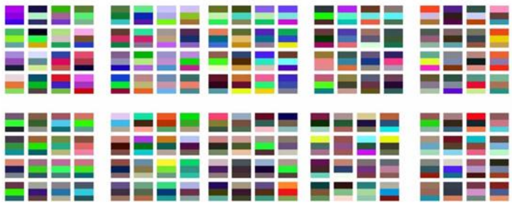

Fig 12. Distributed Color Design Scheme of Industrial Products after 50 Iterations

In actual operation, the generator can generate 16 sets of 9-dimensional color codes with each iteration update. After ten times of overall training, 30 times of overall training, and 100 times of overall training for the generative model, part of the color design scheme generated by the generator is substituted into the effect display diagram of the general model of industrial products rendered in the critical shot. Replacing part of the generated color design scheme into the effect display diagram of the general model of industrial products involves several steps to visualize and evaluate the proposed color scheme within the context of the product's design. These steps include selecting the color design scheme, preparing the effect display diagram, identifying substitution areas, applying color substitution, visualizing and evaluating the impact, refining the color substitutions, and finalizing the updated effect display diagram. By following this process, designers and stakeholders can efficiently assess and refine the proposed color design scheme to ensure alignment with design objectives and brand identity. The color design scheme generated by the generator is becoming more and more distinct on the whole, and its change trend is also gradually stable, reaching the goal of developing a usable color design scheme. The scheme conforms to the concept of "color design" visually and has reference value for assisting with color design.

Then, we randomly selected eight samples from the characteristic color combination of the target product samples learned by the generator for semantic collection. Color samples from electric vehicles can be collected using physical sampling, digital imaging, or spectrophotometry. These methods help generate and evaluate color schemes for vehicle design, enabling designers to select the most impactful schemes, thereby enhancing market competitiveness and consumer satisfaction. The effective questionnaire was 31 samples, and then experts screened 15 image words related to electric vehicles, that is, 15 feature dimensions. The keywords related to image of color design are shown in Table 5.

Table 5

Image keywords of industrial product color design distributed system

Kinesthetic	Personality	Cool	Modern	Texture
Free	New trend	Gorgeous	Urban	Bright
Motion	Fashion	Lively	Science and technology	Fluent

The dimensionality of image words is reduced. In practical operation, SPSS software is used for principal component and K-means clustering analysis. SPSS software is often used in Kansei engineering to conduct quantitative investigation and research on product images. This paper applies the IBM SPSS statistics version 25 software for data analysis. Twelve sample photos were randomly selected from 360 learning samples. Seven industrial design students (1:1 male to female) were given a questionnaire to rate the conformity of image words between 1 and 7. One point was inconsistent with the corresponding image, and seven points were remarkably consistent with the image. Input the image evaluation score into SPSS software for dimension reduction, and get the KMO and Bartlett test in Table 6. The value of KMO in Table 6 is>0.5, and the value of significant sig is<0.05, indicating a correlation between factors, and factor analysis is adequate.

Table 6
Bartlett Test Results of Industrial Product Color Design Distributed System

KMO sampling suitability quantity		0.616
Bartlett sphericity test	Approximate chi-square	80.203
	Freedom	28
	Significance	0.000

The common factor variance table in Table 7 below indicates the degree of extraction of variables expressed by common factors. Since the extracted values are more significant than the minimum common factor variance extraction value, 0.705, corresponding to the urban image, the extracted values of all selected variables exceed 0.7, indicating that common factors can express the selected variables, and no further variable screening is required.

Table 7
Common factor variance of a distributed system for color design of industrial products

Imagery	Initial	Extract
Kinesthetic	1.000	0.928
Free	1.000	0.822
Motion	1.000	0.905
Personality	1.000	0.956
New trend	1.000	0.922
Cool	1.000	0.831
Gorgeous	1.000	0.758
Lively	1.000	0.941
Modern	1.000	0.893
Urban	1.000	0.705
Science and technology	1.000	0.777
Texture	1.000	0.868
Bright	1.000	0.914
Fluent	1.000	0.944

In interpreting the total variance of the semantic experiment shown in Table 7, the number of principal components corresponding to the cumulative value is mainly considered. Principal component analysis

(PCA) is a technique to extract meaningful patterns and relationships from high-dimensional data. The cumulative variance explained by the principal components is crucial in determining the number of principal components required to represent the underlying structure of the data. Selecting an appropriate number of principal components ensures a balance between dimensionality reduction and information retention, leading to reliable and interpretable results in semantic experiments. Generally, the total variance in the principal component analysis is more than 80%. It can be seen from the cumulative value of the initial characteristic value and the sum of squares of the extracted load in the table that when the principal component is taken to the third-ranking principal component factor, the cumulative value of the initial characteristic value and the sum of squares of the extracted load has reached 76.463%, nearly 80%. In contrast, when the principal component is taken to the fourth-ranking principal component factor, the cumulative value of the initial characteristic value and the sum of squares of the extracted load has reached 85.888%, more than 80%, so three or four principal components are temporarily selected. As shown in Table 8 and Table 9.

Table 8

Total explanation of variance

Component	Initial characteristic value			Extract the sum of squares of the load		
	Total	Percent Variance	Cumulative%	Total	Percent Variance	Cumulative%
1	5.977	39.833	39.833	5.977	39.833	39.830
2	3.226	21.517	61.353	3.226	21.517	61.353
3	2.265	15.111	76.466	2.265	15.111	76.466
4	1.411	9.423	85.888	1.411	9.423	85.888
5	0.777	5.196	91.081	0	0	0
6	0.581	3.864	94.942	0	0	0
7	0.323	2.143	97.083	0	0	0
8	0.195	1.325	98.404	0	0	0
9	0.135	0.875	99.288	0	0	0
10	0.064	0.444	99.727	0	0	0
11	0.044	0.277	100.000	0	0	0
12	4.052E-16	2.710E-15	100.000	0	0	0

Table 9

Composition Matrix

Imagery	1	2	3	4
Kinesthetic	0.913	0.214	-0.227	-0.028
Free	0.655	0.291	-0.555	-0.007
Motion	0.758	-0.103	-0.369	-0.427
Personality	0.866	-0.325	-0.246	0.177
New trend	0.833	0.008	0.333	0.344

Cool	0.599	0.414	0.182	-0.522
Gorgeous	0.476	0.026	0.674	-0.281
Lively	0.811	-0.477	0.126	0.176
Modern	0.227	0.813	-0.424	-0.053
Urban	0.266	0.784	0.133	0.064
Science and technology	-0.038	0.755	-0.095	0.022
Texture	-0.555	0.614	0.404	-0.142
Bright	0.909	-0.144	0.124	-0.232
Stable	0.117	0.475	0.813	0.212
Fashion	0.425	0.342	-0.236	0.757
Kinesthetic	0.913	0.214	-0.227	-0.033

According to the result, the standard factor value obtained by principal component analysis is 3. In this step, the cluster number of cluster analysis in SPSS software is set to 3, and the color image score is classified as a vector value. Randomly select 12 sample photos from the characteristic color set of learning samples for scoring; 1 point is the wildly inconsistent image, and 7 points is the remarkably consistent image. Cluster analysis is a technique that groups similar data points or objects into clusters based on their similarities. It can be applied to image classification to identify groups of image terms or features that exhibit similar characteristics or visual properties. The next step is to interpret the cluster results by examining the characteristics and composition of each cluster. Finally, the cluster analysis results can be applied to classify image terms based on their cluster membership or similarity to cluster centroids. This helps researchers organize and categorize image terms, facilitating tasks such as image retrieval, annotation, and content-based image retrieval. After averaging the evaluation values, they are input into SPSS software for clustering. The settings are divided into three categories, and the cluster center results are shown in Table 10.

Table 10

Cluster Center Results of Industrial Product Color Design Distributed System

Clustering category	1	2	3
Sample 1	6.00	3.11	2.31
Sample 2	7.00	5.77	6.15
Sample 3	1.00	4.15	1.81
Sample 4	2.00	4.36	2.65
Sample 5	3.00	4.15	5.50
Sample 6	1.00	5.77	2.00
Sample 7	3.00	2.61	3.15
Sample 8	3.00	4.15	3.33
Sample 9	6.00	4.86	3.15
Sample 10	3.00	4.00	3.33
Sample 11	3.00	3.86	5.85

Sample 12	4.00	3.50	2.65

According to the experimental planning and the establishment of the BP neural network, the initial backpropagation results show that the ordinate shown in Figure 13 is the training error, and the abscissa is the coordinate map between the epoch times when all data have been run. When the training reaches the tenth time, the loss value of the neural network has become stable. The loss in the figure decreases to convergence. Building a regression model is feasible since the error loss value when the output is a vector is much lower than that under the softmax classification mode. The regression model analyzes historical data on color combinations, user preferences, and design trends to identify correlations and relationships between color attributes and their impact on design outcomes. By leveraging machine learning algorithms, it predicts the popularity, appeal, and suitability of different color combinations. It informs decision-making processes, enhances the efficiency and effectiveness of the color design distributed system, and plays a critical role in empowering designers to create compelling color designs that resonate with users and stakeholders.

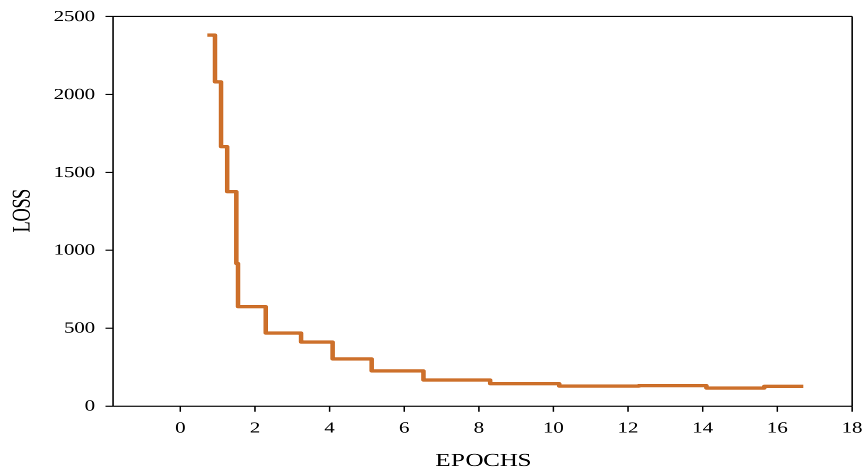

Fig 13. Regression of training error value

The industrial product color design distributed system can investigate and evaluate the conformity of the selected image words under the model set brought in by the color three-dimensional discrete point combination. The obtained data is used as the input of the neural network model. Then, the mapping relationship model between the image and the solid color discrete point combination is obtained by comparing the results with high accuracy and low error rates. A curated dataset is preprocessed and analyzed with feature extraction techniques, such as color histograms, texture descriptors, or spatial patterns, to obtain an accurate mapping relationship model between images and color combinations. The machine learning model is then trained using supervised algorithms like CNNs or deep learning architectures, optimizing its parameters to minimize prediction errors. Cross-validation techniques and error analysis help identify and address potential errors or biases, resulting in a mapping relationship model that predicts color combinations from images with high precision and low error rates. After debugging, a stable and convergent screening evaluator model is obtained. When the color combinations generated by the generator are input, they can be sorted according to the image, and the color schemes with high image degrees can be selected to achieve the purpose of AI-aided industrial design.

6 Conclusion

Under the trend of relying on enterprises to closely follow the intelligent production process, AI-aided industrial design has become the general direction of developing the complex work of color-distributed design. On the other hand, designers have some limitations and need computers to assist in design. Implementing intelligent design in specific work forms is also part of the research content of computer-aided industrial design. This research constructs a color-design distributed system oriented to the Internet of Things and AI-aided industrial design and conducts system operation debugging and empirical testing on this system. The experimental results show that the color recognition accuracy of the color design distributed system is more than 97%, the KMO value of the system is more than 0.5, and the sig value of significance is less than 0.05. The system shows the broad potential of AI-aided industrial design.

Acknowledgments
The authors would like to thank those techniques who contributed to this research sincerely.

Consent for publication
All authors reviewed the results, approved the final version of the manuscript, and agreed to publish it.

Data Availability
The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest
The authors declared that they have no conflicts of interest regarding this work.

Funding Statement
There is no specific funding to support this research.

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