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Deep Learning-Based Machine Color Emotion Generation

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ABSTRACT

This paper investigates generating machine color emotion through deep learning. The grayscale image colorization model's training process resembles human memory color. Sixty images were recolored and quality evaluated to explore machine generated color impressions. Six experimental samples were recolored under D65, A, CWF, and TL84 light sources. Changes in lightness, chroma, and hue angle compared the original and colorized images, exploring light source effects on machine color perception. Analyzing differences in coloring results within the CIEL* a* b* color space for pixels with equal grayscale verified machine color emotion generation. Results show the machine learns to form color impressions from samples. Different light source color temperatures impact color prediction accuracy. The machine accurately colors images based on semantic context, demonstrating spontaneous color emotion generation through deep learning. This research positively contributes to the development of intelligent devices with color emotion.

KEYWORDS

Artificial Intelligence, Color Emotion, Color Perception, Deep Learning, Light Source

INTRODUCTION

Emotional intelligence is an advanced stage in the development of artificial intelligence (AI); it is at the forefront of contemporary information development, and a new product that incorporates emotion into the field of information science. The extended cognitive theory argues that with the development of computer and AI technologies, human cognitive activities must rely on intelligent devices to be completed. The cognitive subject not only is an individual natural person but also includes these electronic devices, which are cooperative or symbiotic (van Holland, 2013). It provides ideas that can be applied to developing AI and emotional machines. Developing emotional robots is a trend and requirement for changing weak AI to strong AI and super AI (Fjelland, 2020). The creation process

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has eight steps: discovering the problem, acquiring knowledge, gathering relevant information, conceiving ideas, generating ideas, combining ideas, selecting the best idea, and externalizing the concept. Today's machines are not equipped with the ability to discover problems and formulate them, nor can the data selection and collection rules be set by the devices themselves. However, in data processing, data has an advantage that humans cannot match. In this case, the model of human-machine collaboration is still the optimal solution. Suppose the ability of emotion recognition and expression is given to machines. In that case, this advancement will not only push AI to a higher platform but also assist in human emotion understanding and expression. It will also facilitate the overall development of human beings (Korsmeyer, 1999).

Although previous researchers have described the creation of many robots and architectures for autonomous agents that can mimic human emotion, most of this research has focused on social domains, such as medical services (Esteva et al., 2017), teaching services (Ling, 2022; Yang, 2022), and family services (Breazeal, 2003; Lee-Johnson & Carnegie, 2010), mainly possessing speech recognition communication technologies (Lafaye et al., 2014).

In contrast, robots with color emotion have been less developed. There are few applications in the field of color perception and art creation. However, vision is the most potent way humans perceive objective things in communication with the outside world (Li et al., 2022). More than 87% of people obtain information visually, with 70% to 80% of this information obtained from color (Wu & Fang, 2022; Xu et al., 2022), so the emotion conveyed by color is essential (He & Lv, 2022). Color emotion refers to the light information of different frequencies of color acting on the human visual organs, through the optic nerve to the brain, and then associated with memories and experiences, thus forming a series of color psychological responses.

A colorimeter obtains the current machine perception of color by measuring the spectral properties of the material surface to obtain color data, which for color perception, remains only at the level of physical properties and color measurement. This measurement is formed by three links: light source, object, and sensor. However, color is a subjective response of the human visual system to electromagnetic radiation in the visible spectrum with wavelengths between 380 nm and 780 nm. Four factors are required to form human color perception: the light source, the object, the eye, and the brain. Human color perception involves physics, physiology, and psychology (Zeger et al., 2021); therefore, compared with humans, machines lack psychological perception of color, and their perception of color does not resonate with humans. This limitation hinders better human-machine communication and collaboration.

Nowadays, many artists have gradually moved away from traditional paper-based creations and embraced artistry using mobile smart devices. If machines possess color emotion, they can synchronize their color perception with the creators and stimulate their inspiration by autonomously learning and performing image coloring. By combining color emotion with mobile smart devices, users can engage in creative activities more conveniently on their mobile devices while enjoying intelligent creative assistance and personalized artistic experiences. Thus, determining how to make machines acquire color emotion is one of the urgent challenges to be solved.

Deep learning, one of the most rapidly developing branches of AI, can fill this gap because the field of visual perception in AI has some relevance to the processing of visual information in primate brains. To maximize the simulation of human color perception, we investigated the generation of machine color emotions and propose a "machine vision system," which consists of four elements: light source, object, sensor, and "emotional intelligence system." We used grayscale image coloring models for experiments. First, we trained the coloring model with a large number of samples for simulating AI to form color impressions. Second, we explored the importance of color appearance factors in perceiving color by changing the light source. Finally, we analyzed the color prediction process of the system to understand the process of machine-generated color emotion. This process is similar to the process of human memory and association of colors, so deep learning is the way to generate color emotion and gain color intelligence.

The main contributions of this paper are summarized as follows:

First, we underscored the importance of machines possessing color emotions for the development of AI and the promotion of human-machine collaboration. Machines can acquire color emotions through deep learning. Compared with objects with social attributes, machines are more likely to form fixed color impressions on objects with natural attributes or specific color patterns.

We then discussed how machines measure color. When machines perceive color, differences in the color temperature of different light sources can affect the accuracy of color prediction. Light source A enhances the chromaticity of the machine's color prediction images. We suggest that AI should not only perceive the colors of objects themselves but also consider the color appearance phenomena specific to humans to more accurately simulate human color perception to a greater extent.

In the remainder of this paper, we discuss the experimental setups for evaluating the quality of coloring results, explain how we conducted the light source variation experiment, analyze and discuss the results, and present our conclusion.

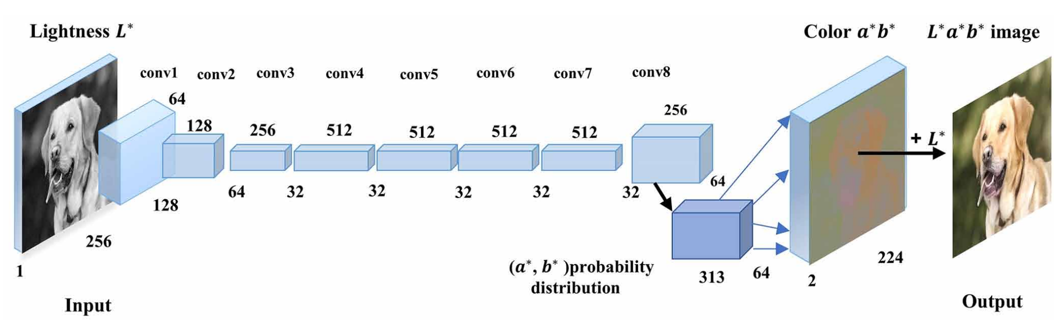
METHODS

Image Quality Assessment of the Colorization Results

To conduct our experiments for this paper, we used the automatic colorization model proposed by Zhang et al. (2016). This model contains eight layers of convolutional blocks, as shown in Figure 1. Given the lightness channel L of the input image in the CIE color space, a convolutional neural network (CNN) predicts the probability distribution of the corresponding a and b color channels (Zhang et al., 2022). The final result is transformed into an RGB image (Zhang et al., 2016). The automatic coloring model was trained in a CNN and the results were determined using a training set of over 1 million color photos on ImageNet, a large visualization database for visual object recognition software research.

The objective assessment metrics used in this study were peak signal-to-noise ratio (PSNR) proposed by Wang et al. (2004), structural similarity index (SSIM) presented by Wang et al. (2003), and root mean square error (RMSE) shared by Deshpande et al. (2015) and Larsson et al. (2016). PSNR and SSIM are two measurement tools widely used for image quality assessment (Lin et al., 2020). PSNR is used to measure the difference between the generated color image and the ground truth image and evaluate the recovery algorithm's performance. MSE is the mean square error between the ground truth image and the color image. Therefore, the smaller the MSE value and the larger the PSNR value, the lower the distortion and the higher the image quality will be. SSIM is a relatively new measurement tool designed to evaluate the structural similarity between the original and generated images based on luminance, contrast, and structure (Peng et al., 2020). The structural similarity index

Figure 1. The architecture of a colorization neural network
Source: Zhang et al. (2016)



ranges from -1 to 1, and the value of SSIM is equal to 1 when two images are identical. However, the agreement between these objective assessment metrics and the subjective perception of the human observer has not been well demonstrated (Teng et al., 2021). Therefore, subjective assessments need to be referred to when assessing the scientific validity of image coloring (Cao et al., 2017; Iizuka et al., 2016; Zhao et al., 2020).

The formation of human color perception is based on the brain's memory and association with previous color experiences. Our experiment aims to verify that the machine can simulate the formation of human color perception using deep learning.

In the test dataset of the color vision simulation experiment, we selected six types of images to test multiple types of coloring effects: animals, people, objects, vehicles, scenery, and animations. There were 10 images of each type, and we selected all 60 images from copyright-free websites (https://www.pexels.com, https://pixabay.com). We recolored these images using the colorization model that Zhang et al. (2016) proposed. We performed an objective quality assessment of the resulting images generated by recoloring, supplemented by a subjective quality assessment.

Light Source Change Experiment

We conducted this experiment to investigate the influence of varying external light sources on the coloring results. Color is a joint product of the visual environment, lighting, and the human brain. The existence of color appearance phenomena determines the importance of observation conditions on human color perception. Once two identical colors are placed under different observation conditions, the human color perception will change even though the tri-stimulus values remain the same (Safdar et al., 2021). These conditions will also lead to the phenomenon of metamerism (Foster et al., 2006).

The light source is a significant factor affecting visual perception, and the color temperature can affect human psychological and physiological sensations, resulting in different observational perceptions (Huang et al., 2018). Therefore, in this experiment, we took the variation of the light source as an entry point to investigate the influence of the light source on the coloring system. Based on this experiment, we explored the importance of observation conditions on machine color perception. We conducted the experiment in the standard illumination box (X-rite [Macbeth] Judge II) with dimensions of 690 mm x 570 mm x 570 mm. As shown in Figure 2, the standard illumination box is painted to be N7 in the Munsell color system. The light source is located at the top of the box, and there is no other light source in the laboratory, thus avoiding the influence of ambient light.

The light sources used in the experiment are D65, TL84, CWF, and A. The D65 light source represents the average natural daylight with a relevant color temperature of approximately 6,500 K (Lam & Xin, 2002). The A light source represents tungsten incandescent lamps with a distribution

Figure 2. Photographs of the viewing booths

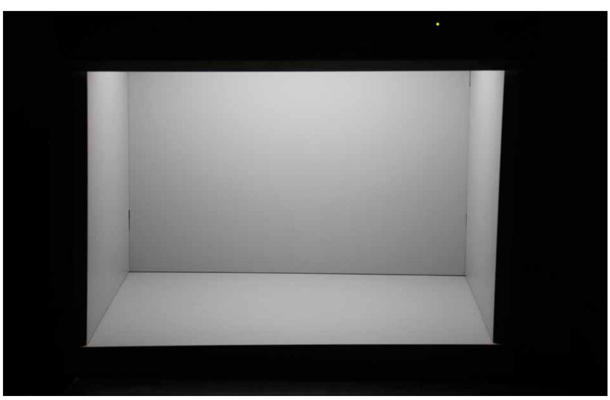
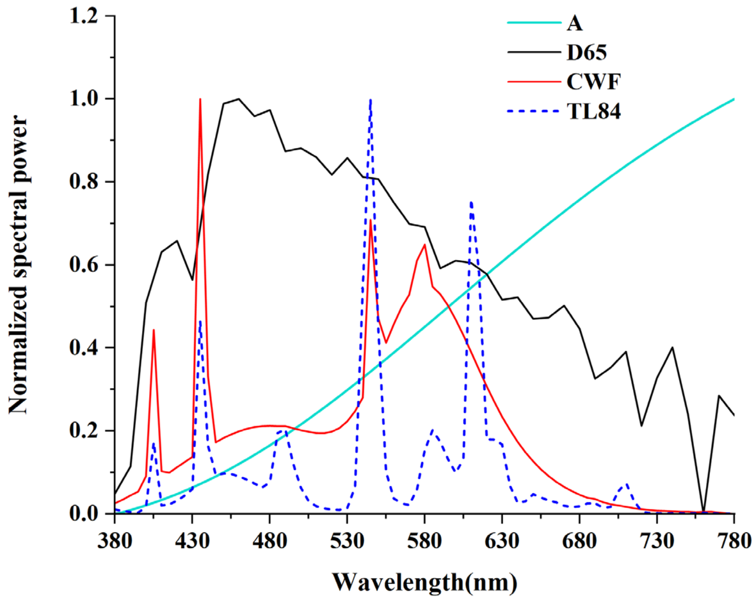


Figure 3. Relative spectral power distributions of all illuminants



temperature of 2,856 K; these lamps are mainly used for home room lighting. The CWF light source represents cool white fluorescent lamps with a relevant color temperature of 4,150 K; these lamps are mainly used for shopping mall lighting in the United States. The TL84 light source represents narrow-band fluorescent lamps with a distribution of 4,000 K; these lamps are mainly used for lighting in office premises in Europe and Japan (Tang et al., 2019). The normalized relative spectral power distributions of these four light sources are shown in Figure 3.

To conduct our experiment, we placed six experimental samples in a lightbox and captured photographs under four different light sources. We then processed the photos into grayscale and recolored them using the coloring system. Finally, we compared the images captured under different light sources with the corresponding re-colored results.

RESULTS AND DISCUSSION

Machines Form Color Perception

In the experiments for colorization picture quality evaluation, all experimental images and coloring results can be viewed in Figure 11 in the appendix. From the subjective observations, we selected 12 sets of images from the 60 experimental results, as shown in Figure 4. To facilitate the description of each image in the following text, they are numbered as 1–12 (Teng et al., 2021).

In the objective quality assessment of the images, we divided the 60 recolored resulting images into six groups by image type, and the data of the three indicators in Table 1 were taken from the group average. The statistical results from Table 1 show that for the PSNR metrics, the images in the people and vehicle categories have higher scores (their scores are 23.660 and 22.192, respectively). For the SSIM index, the values of all six groups are close to 1, indicating that the structural similarity of both the resultant and original images is high. The people and animal categories performed the best (their scores were 0.936 and 0.931, respectively). The RMSE metric shows that the people, vehicle, and animation images are of high quality (their scores are 0.141, 0.166, and 0.166, respectively). The lowest objective quality of all three indicators is in the category of scenery. In Figure 4, the color

Figure 4. Examples of the colorization results

Table 1. Image quality evaluation metrics for the experimental photo

Metric	Animal	Scenery	Object	Vehicle	People	Animation
PSNR	21.081	20.575	21.504	**22.192**	**23.660**	21.173
SSIM	**0.931**	0.896	0.900	0.926	**0.936**	0.898
RMSE	0.177	0.191	0.180	**0.166**	**0.141**	**0.166**

Note: Bold font indicates the type of image with high objective quality evaluation.

reproduction of the clothes-like colors for images 9, 10, 11, and the hot air balloon picture for image 3 is not accurate enough from subjective observation.

As seen in Figure 4, for images 1, 6, 9, 10, and 11, the human skin tones and animal fur coloring are satisfactory and highly realistic with good fidelity. The vehicle's shape is recognizable, and the coloring model can often accurately distinguish the vehicle and color it. Therefore, all three types of pictures have high overall evaluation scores. Interestingly, the animation images were also well colorized in the test. The sky and grass in image 2 are even more saturated than in the original image.

The colors of the scenery are inherently diverse, changing over time and with the seasons. From the subjective evaluation, the natural scenery and buildings in images 4 and 5 can be rendered realistically, with no incongruous colors appearing.

However, these three indicators measure only the degree of similarity between the resulting image and the original image. Because the resulting images of the scenery group images do not recover the original image's color, the overall score of the scene group images is low. Generally, the images that perform well in the coloring model are things with natural properties or specific color laws. These findings show that the machine has formed a fixed color impression, and similarly, for these types of images, humans can also easily form a deep color memory. In contrast, poor performers include clothing and decorative items. These findings indicate that the machine does not form a complete color impression of these items, which have social attributes and tend to be characterized by color diversity. Likewise, humans have difficulty creating a fixed color memory for such things during their growth.

This experiment demonstrates that learning from a large volume of samples is similar to accumulating color memory and experience in the human brain. As the volume of samples increases, the impression of color becomes complete, just as a child learns from the outside world as it grows. The machine can color grayscale images successfully, which means it has formed a correct color perception of such things. However, the great gap between machines and humans is the size of the training datasets required. Humans can usually learn concepts quickly from a single training sample, whereas current deep learning approaches require enormous datasets (Cox & Dean, 2014).

The Effect of Illuminants on the Machine Color Emotion

In the light source variation experiment, the photographs of the six experimental samples and the corresponding recolored results are shown in Figure 5. For ease of description, we numbered these images in Figure 5 as 1–6. Because the two table tennis rackets in image 6 are two colored objects in the original image, we refer to the red table tennis racket as 6A and the black table tennis racket as 6B.

To quantify the effect of light source changes on the original and resulting images, we used the color model of CIE $L^*C^*h^*$ to analyze the changes in the original and resulting images' lightness, chroma, and hue angle. We measured the $L^*a^*b^*$ color values of all the images with the help of Photoshop. In the analysis, the L^*, a^*, and b^* values were converted into CIE $L^*C^*h^*$. L^* indicates the lightness, and C* represents the chroma, the vividness of the color. Finally, the h^* refers to the hue angle of a color in the $a^* - b^*$ plane (Yan et al., 2021).

As shown in Figure 6, after the light source is changed, the changing trend of the lightness of the original image and the resulting images' lightness are the same. For images 4, 5, and 6B, changing the light source has some effect on the lightness, whereas for the other images, changing the light source has little effect on the lightness. Compared with other light sources, images 4 and 5 appear brighter under the A light source, and the black table tennis racket in image 6B shows lower brightness.

Figure 7A shows that the chroma of our experimental sample images taken under the A light source is higher. The chroma of the experimental sample images (Figure 7A) taken under CWF and TL84 light sources is close. In the resulting picture (Figure 7B), images 1, 3, and 4 have higher chromas under the A light source, contrasting with the effect under other light sources.

As seen in Figure 8A, except for images 5 and 6B in the original image, the light source change has minimal effect on the hue angle of the other original images. Note that the h^* is meaningful only for describing colored objects. The h^* loses its meaning when the object is colorless (black, white, and gray). However, a real colorless object will always deviate a little from the standard colorless object, so the measured value of h^* will vary significantly for objects that tend to be neutral. Therefore, it is normal for there to be a large deviation in the hue angle of a black table tennis racket under different light sources. Figure 8B shows that the change of light source has a more significant influence on the h^* of the coloring result image, and overall, the h^* under the D65 light source is larger than that under the A light source.

Figure 5. Original and recolored images of experimental samples taken under four light sources

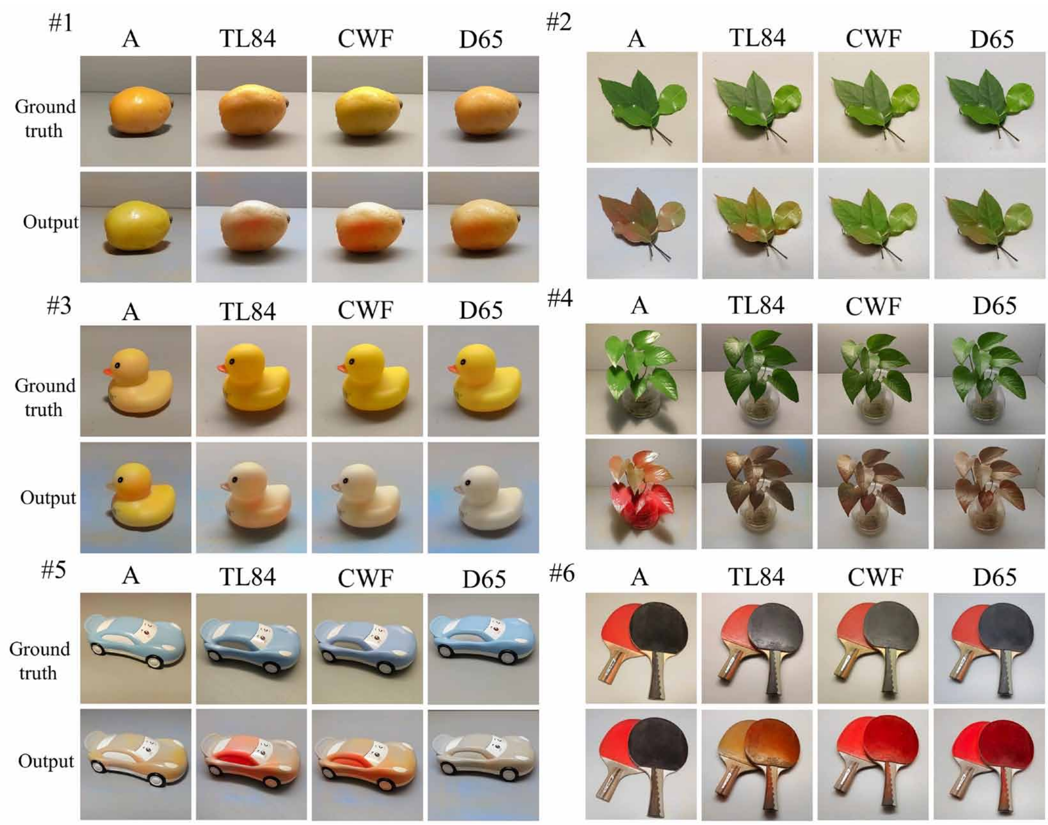
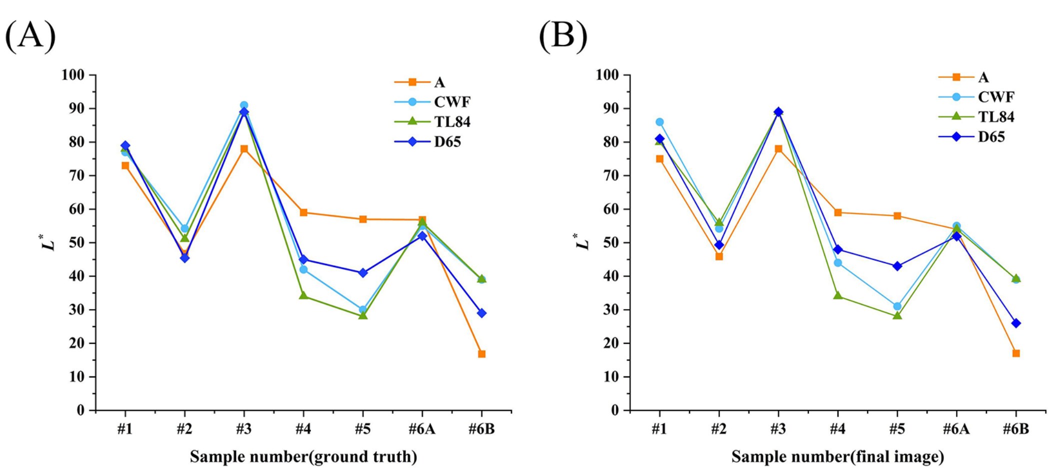
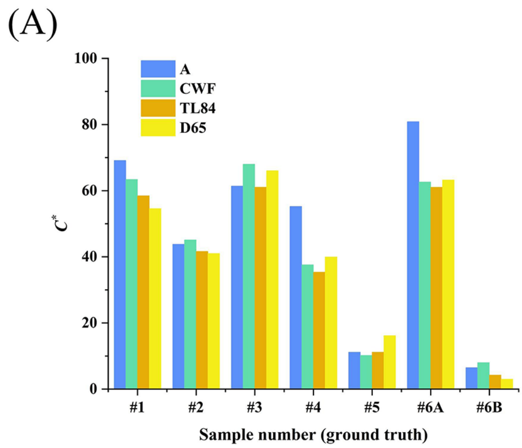


Figure 6. The lightness (L^*) of the original and final images under different illuminants



As shown in Figure 3, compared with the other three light sources, the light from light source A has the highest radiated power at 630-720 nm wavelength. The color temperature is low, and the

Figure 7. The chroma (C^*) of the original and final images under different illuminants



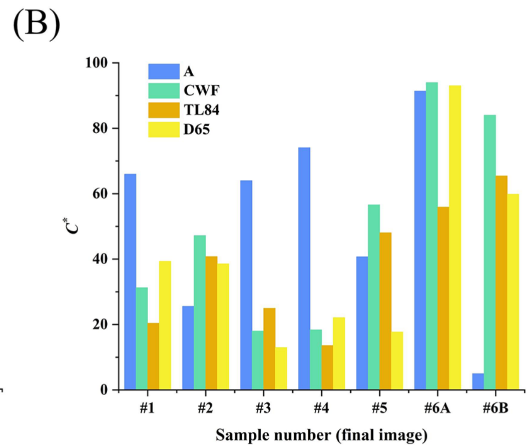
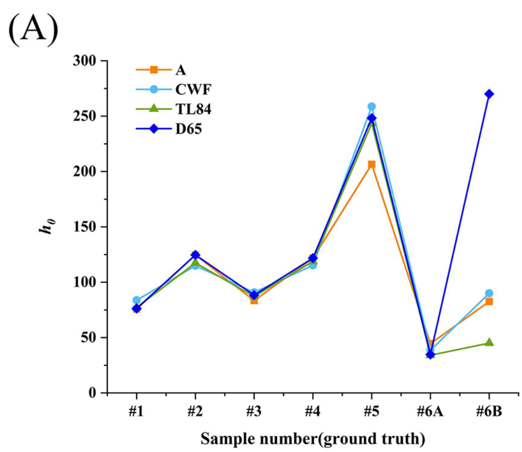
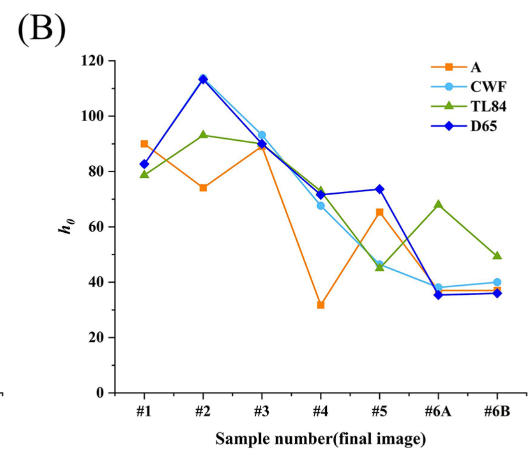


Figure 8. The hue (h^*) of the original and final images under different illuminants





visual perception is warm. The A light source can well distinguish the object from the environment and highlight the essential features of the object; note that the coloring result is satisfactory, the picture is saturated with color, and the chroma value is high. The D65 light source is close to daylight and has a cool visual perception, which best objectively reflects the item's color (Kim & Suk, 2020). However, the coloring results of the D65 light source pictures are generally not vivid enough. Both the CWF light source and the TL84 light source are fluorescent light sources with similar color temperatures, and there are significant differences in the spectra. However, the final coloring result graph is also similar, indicating that the color temperature size affects the machine's perception of color.

Figure 5 also clearly indicates that changing the light source can lead to significant color differences in the resulting image. It can even affect whether the coloring model can restore the original image's color. In Figure 5, image 6 shows that only the images under the A light source are recolored into black table tennis rackets. In contrast, the images under other light sources are colored red. For this group of experimental samples, each object has its most suitable light source when coloring.

Therefore, the effect of observation conditions needs to be considered when perceiving color by AI to avoid the problem of inconsistent color perception between machines and humans.

Machines Generate Color Emotion

We chose two images from a copyright-free photography website (www.pexels.com) and processed them into grayscale images. Two points with the same luminance value were taken separately—M and N in the first image and P and Q in the second image. In the CIE $L^*a^*b^*$ color space, $L_M^* = L_N^*$ = 54, $L_P^* = L_Q^*$ = 28. The a^* and b^* channel values of these four points are all 0. These two photos were recolored, and the $L^*a^*b^*$ color values of the corresponding positions of these four points were captured in the resulting image using a Python 3.8 program. To indicate the color change, we adopted the color difference ΔE to quantify the calculation: the Euclidean distance between two coordinates depicted by L^*, a^*, and b^*.

$$\Delta E = \sqrt{\left(L_1^* - L_2^*\right)^2 + \left(a_1^* - a_2^*\right)^2 + \left(b_1^* - b_2^*\right)^2} \tag{1}$$

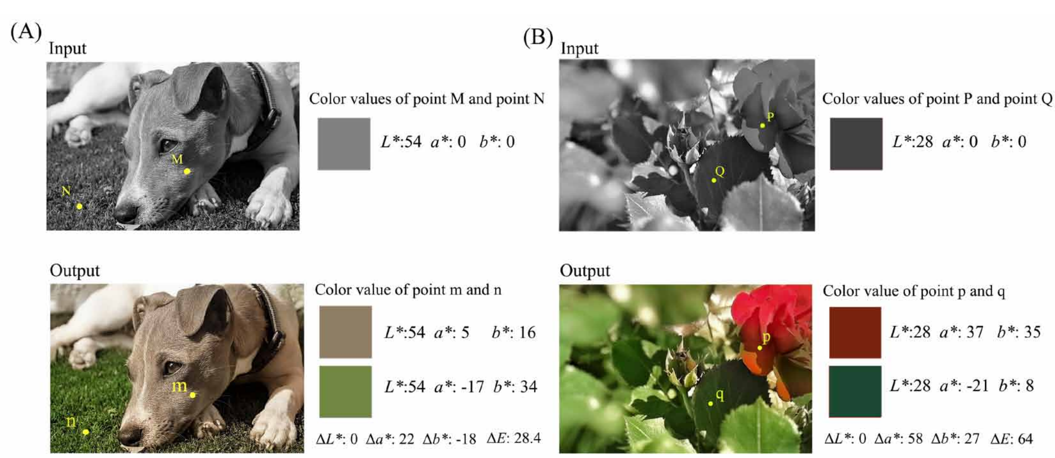
$$\Delta L^* = L_1^* - L_2^* \tag{2}$$

$$\Delta a^* = a_1^* - a_2^* \tag{3}$$

$$\Delta b^* = b_1^* - b_2^* \tag{4}$$

Figure 9 shows the color information of the four points m, n, p, and q. To facilitate the description in the following text, we represented the lab color values in coordinate form. Then point M (N) of Figure 9A is converted from (54, 0, 0) to point m (54, 5, 16) and n (54, -17, 34), respectively. Point P (Q) (28, 0, 0) of Figure 9B is converted into point p (28, 37, 35) and point q (28, -21, 8), respectively. From the color difference formula, we can calculate that for M and N points, ΔE = 28.4, ΔL^* = 0, Δa^* = 22, Δb^* = -18. For P and Q points, ΔE = 64, ΔL^* = 0, Δa^* = 58, Δb^* = 27. Because the coloring model retains the luminance channel in the original image during the coloring process, the lightness does not change, and the color difference is mainly reflected in the chromaticity difference; that is, Δa^* and Δb^*.

Figure 9. Comparison of the grayscale image with the recolored image and the $L^*a^*b^*$ color values of M, N, P, and Q: A) the Color difference between m and n points; B) the color difference between p and q points



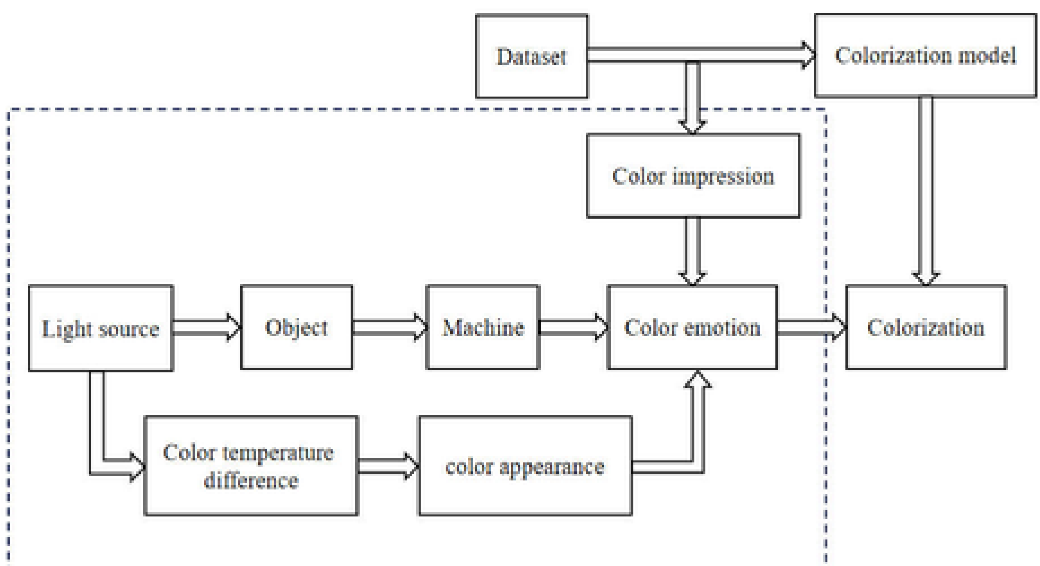
The system learns from a large number of samples and identifies point m as the dog's skin color and point n as the color of the grass. Point p is identified as the color of the flower, and point q is identified as the color of the green leaf. The input images of the colorization model are all grayscale images. In terms of color, only the gray level differs; that is, the difference in lightness value. M and N points have the same grayscale value, and the system can perform differential coloring while processing the same input information. The system's comprehensive analysis of the semantic environment, such as shape, texture, and location of the objects in the diagram—as well as the system's ability to associate this data with the previously formed color impressions—enabled us to finally distinguish between animal fur and lawn. Color impressions are formed by the coloring system's learning and training on numerous samples.

The difference between the chromaticity values of points m and n after recoloring reflects the result of the system's thinking about the color choice of these two points and the generation of color emotion. The experimental results show that the machine has a primary color impression of the object after learning numerous samples and has the ability to recognize color. The coloring system can give different color feelings to different semantic environments in the pictures. Figure 10 displays the proposed workflow for machine color emotion, with the content inside the dashed box representing the generation aspect of machine color emotion proposed in this article. Because the system has gone through a learning and training process just as humans do, it differs from other rule-based algorithms for coloring objects. In the creation of art, it has a human-like "intelligence" and is free from the "orderliness" of the rule-based algorithm. The works are more dynamic and artistic than those produced by the rule-based algorithm.

CONCLUSION

We discussed the generation of AI color emotion from three important aspects: the formation of machine color perception, variation of light sources, and the emergence of color emotion. The machine forms color impressions by training the sample set, and it is easy to form color impressions

Figure 10. The proposal workflow of machine color emotion



for objects with natural properties or specific color laws. On the contrary, forming a fixed color memory for objects with social properties is challenging. When the machine perceives the color, the light source change will affect the correctness of the predicted color. The color temperature affects the chroma and hue angle of the coloring result image. Compared with the three light sources, D65, CWF, and TL84, the A light source can highlight the image subject more when coloring, and the image has higher chroma. When predicting color, the colorization model can possess different color perceptions based on image features, such as texture, shape, and spatial relationships. This process reflects the machine's perception and thinking.

Several limitations still exist in this paper. First, when exploring the effect of the change of light source on the coloring system, we could choose only items with smaller sizes owing to the volume limitation of the standard lighting box; this limitation led to a lack of a variety of experimental samples. Despite the relatively limited samples, in this study we preliminarily explored the effect of the color appearance phenomena on the perception of color by AI. Machine vision systems are trained to produce color appearance phenomena so that machines can resemble human color perception, which is the future direction of in-depth research on machine color intelligence. Furthermore, although deep learning is accurate in image recognition, it requires various images for input training; this training process can be time-consuming and requires high computer computing performance. Researchers can make more optimizations in the methods of deep learning. In the future, it will be possible to develop mobile applications that provide users with intelligent art creation tools. These tools will have the ability to learn and adapt to users' preferences, styles, and emotions, enabling the generation of personalized art pieces. The devices will also be capable of interacting with users, incorporating their feedback and input to generate and refine artistic works.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the authors upon reasonable request.

CONFLICT OF INTEREST

We declare there are no competing interests.

FUNDING STATEMENT

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APPENDIX

Figure 11. All experimental photographs used for the color perception formation experiment were divided into six groups

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