ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

CandyCycleGAN: Candy Color Coloring Algorithm Based on Chromaticity Verification

Shisong Zhu[1], Mei Xu[1,*], Bibo Lu[1], Huan Xu[1]

[1]*School of Computer Science and Technology, Henan Polytechnic University, Jiaozuo City, Henan Province, 454003, China*
[*]*Corresponding author: xm@home.hpu.edu.cn*

Abstract: *Candy color is a new way of existence in the field of photography, and its characteristics of high brightness, low saturation, and low contrast bring a different color experience to the world. However, no relevant algorithm dedicated to candy color processing has been found yet, for this reason, the CandyCycleGAN network based on color verification is proposed to realize candy color recoloring. Based on the CycleGAN network, we implement multi-scale fusion to enhance the detailed features of the output image and improve the quality of the output image; we design the Chromaticity verification process to constrain the range of the generated chromaticity values to ensure that the final effect meets the expectation; we use the Smooth* L_1 *Loss as the loss function of the Chromaticity verification to measure the gap between the generated image and the expected image, and at the same time, compare the coloring quality of the image with that of the image using different loss functions; we add a gradient penalty to the coloring quality; we add a gradient penalty to the coloring quality. The gradient penalty is added to construct a new data distribution between the generated image and the expected image, and the gradient penalty is applied to each input data, which changes the gradient limitation method of the discriminator network and improves the stability of the network during the training process; the output of two different sizes of discriminant matrices allows the generator to generate images with higher resolution and better details. In comparison experiments with five algorithms such as CycleGAN, AdaAttN, etc., the CandyCycleGAN network reduces the computation by 37.95%, improves the PSNR by 49.83%, improves the SSIM by 54.77%, and improves the COLORFUL by 29.09% compared to the basic CycleGAN network model, and compared to the suboptimal AdaAttN model, the computation rises by 0.93%, but PSNR improves by 7.36%, SSIM improves by 7.14%, and COLORFUL improves by 17.30%. Comparative experimental results show that the proposed CandyCycleGAN network can achieve the optimal effect of high brightness, low saturation, and low contrast of candy color compared to the existing algorithms, which further validates the effectiveness of the algorithm.*

Keywords: *CandyCycleGAN; Candy color; color verification; multiscale fusion; CycleGAN*

1. Introduction

Ben Thomas was the winner of the Street/Urban category of the Hasselblad Masters, one of the most prestigious photography competitions in the world, and was awarded the title of "Hasselblad Master" for his "Candy Colors" series in 2018. The realization of the candy color effect requires professionals to input color images, through Lightroom, Photoshop and other software for more complex editing can be achieved. The processed image has the characteristics of low saturation, low contrast, and high brightness, and the unique color tone brings users a pleasant and relaxing feeling, creates a positive emotional atmosphere, and renders a fantastic and colorful tone, which brings a new color experience to the world, and also brings a new creative direction in the field of photography, and is therefore widely popular on social media.

Candy color tone is not only the expression of art but also the expression of visual culture. Photographers create unique candy color tones through color processing and adjustment to express creative intent and emotional attachment, highlight the theme of the artwork, and increase the artistry and appeal of the artwork. By adding candy color tones, the artist adds a sense of fun and vitality to the work, enhances the viewability and memorability of the work, and at the same time increases the visual appeal and artistic sense. Professional color sense and more complex post-processing operations make laymen shy away, so we need to use image recoloring technology to achieve candy color recoloring.

Image recoloring technique is an important method for style transformation rendering, which changes the expressive and visual effect of an image by automatically adjusting the color, brightness, and contrast of the input image, etc., and researchers devise many ways to recolor the image. Cao et al. (2019)[1] searched for matching pixel points on the target image based on the classification results of the image based on the texture features of the reference image and then used locally adaptive weight-mean filtering for color diffusion. Traditional image recoloring techniques usually require a large number of computations and iterations, which not only requires a lot of time and effort but also has some limitations in image detail processing and content image understanding. Unlike traditional methods, deep learning techniques can capture contextual information in images through models such as convolutional neural networks, which can better understand the semantics and structure of an image, and thus more accurately perform coloring. For example, CycleGAN (Zhu et al., 2017)[8] network can gradually learn the mapping relationship between two domains by alternately training the generator and discriminator. The network only needs to provide some sample data for training to achieve the image conversion. Zhang et al. (2017)[2] predicted user behavior by learning the semantic similarity of images, thus reducing the workload in a user-controllable manner. Sangkloy et al. (2017)[3] input sketches with color lines to a generative adversarial network, perform feature extraction and up-sampling operations on the images using encoder and decoder network structures, and used the L_1 distance loss function[19] to maintain the consistency of the colorized image with the color markers. Zhou et al. (2022)[4] addressed the problems of texture clutter and poor quality of the generated images when dealing with the unsupervised style migration task in the image transformation class of generative adversarial networks, and designed a cyclically corrected multiscale evaluated generative adversarial network based on the chromaticity cyclic loss to strengthen the effect of the migration from the source domain to the target domain. Wang et al. (2023)[5] optimized the generator network structure by improving the chromaticity cyclic generative adversarial network by adding Ghost convolution and inverse residual improvement module, and at the same time, enhanced the feature extraction ability of the network, which effectively enhances the content details of the generated image and the color effect of the stylized texture. Ding et al. (2023)[6] adaptively learn style features for different style images by layer-consistent dynamic convolution method and fuse content features and style features on the input images to realize the conversion of multiple image domains. Qin et al. (2023)[7] calculate a model Multi-Content GAN (MCGAN) that can convert multiple art styles at one time, using the CycleGAN network as the main body, combined with CGAN[20], to solve the problem of homogenization of multiple styles through the introduction of the channel, spatial attention mechanism, and style discretization loss function.

According to the literature review, no relevant algorithm dedicated to candy color processing has been found yet. In order to realize the candy color recoloring effect, in this paper, we design a CandyCycleGAN candy color recoloring based on chromaticity verification network, which enhances the detailed features of the output image through multi-scale fusion, increases the chromaticity verification process to better constrain the range of the chroma values, and adds chromaticity verification loss to make the generated target domain image as close as possible to the real image of the target domain, and uses Smooth L_1 Loss to learn the corresponding chroma information well while retaining the structural features of the image itself. CandyCycleGAN network achieves the transformation from basic color to candy color and is committed to breaking through the lack of algorithms related to candy color processing in the field of image recoloring.

2. Network Model

Directly using the CycleGAN network for candy color recoloring have three problems: firstly, the image recoloring results are not ideal to meet the candy color coloring requirements; secondly, the training process is unstable, and the resultant image lacks important feature details and produces a blurring effect; finally, it will learn something other than the original input image's own features.

Therefore, in order to solve the above problems, the CandyCycleGAN network is designed. The structure of the CandyCycleGAN network consists of two generators *E* and *F* and one discriminator, in which the generator *E* converts the source domain image to the target domain image, and the generator *F* converts the target domain image to the source domain image, and the structure of the two generators is identical.

The flowchart of the CandyCycleGAN candy color recoloring network based on chromaticity verification in this paper is shown in Figure 1 below and described in detail as follows: firstly, the input RGB image transformed into a color space, which separated into the L luminance channel and the a and b chromaticity channels[17]; secondly, the CandyCycleGAN coloring network designed, in which the luminance boosting module carries out the luminance boosting for the L luminance channel, and the

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

chromaticity image reconstruction module performs feature extraction and recoloring for the a and b chromaticity channels. After retrieve chromaticity value in the recoloring process, the chromaticity verification is carried out, and the verification results are input into the discriminator if the recoloring is close to the expected results, then it is reconstructed with the feature extraction part to compose a new ab chromaticity image, otherwise, the above steps are repeated; finally, the processed L luminance image and ab chromaticity image merge by channel merging, and then converted to the RGB color space, to get the final candy-color style images.

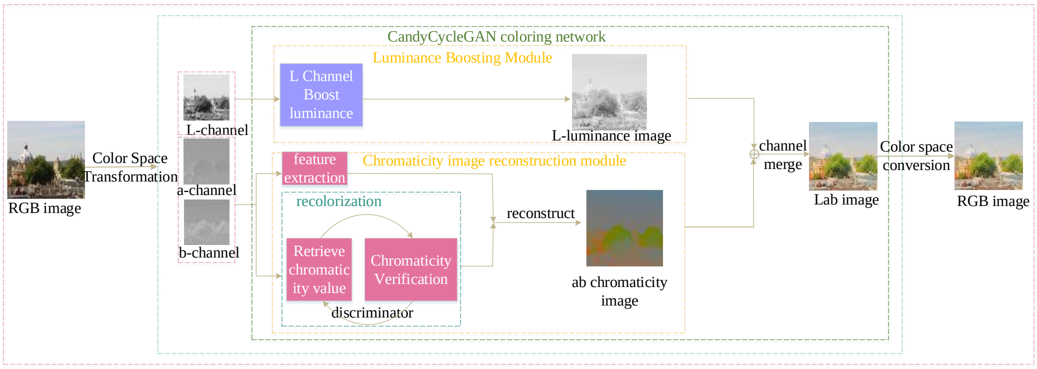


Figure 1: Flowchart of CandyCycleGAN Candy Color Recolor Network Model for Candy Verification

2.1 CandyCycleGAN generator structure

The structure of the CandyCycleGAN generator shown in Figure. 2, which is divided into two modules, chromaticity learning module, and luminance boosting, where the chromaticity learning module is used for the learning of chromaticity information and preserves the detailed information of the original image to a certain extent by fusing multi-scale features. The luminance boosting module learns the luminance information through three convolution and three anti-convolution operations. The chromaticity learning module realizes the 5×5 convolutional input through two 3×3 convolutional layers and the 7×7 convolutional input through three 3×3 convolutional layers. By using the 3×3 convolutional input instead of the convolutional input with a larger convolutional kernel, the depth of the network increased, the amount of computation reduced, and the training speed of the network improved under the condition of ensuring that the receptive field is the same; at the same time, the features of the three different scales fused, to obtain more detailed information and to retain the original image information. In turn, more detailed information is obtained, which is conducive to reducing the loss of feature information between the layers and improving the output recoloring effect of the generator.

Among them, the Conv and Squeeze-and-Excitation Networks (CSE) module realizes the multi-scale fusion of images, so that the obtained image contains more detailed information, which is conducive to enhanced feature representation. Adding Squeeze-and-Excitation layer (SElayer)[9] can learn the correlation between the channels, reduce the value of the loss function, let the CandyCycleGAN model pay attention to the important feature information, learn the chromaticity information in the process of ab chromaticity channel coloring, and at the same time, restrict the coloring area and the range of chromaticity values; the input image is fused with the feature map obtained from the CSE module through a 1×1 convolution operation to enhance the image detail information while retaining part of the input feature information. The ReflectionPad-Conv-and-ReflectionPad-Conv and ConvTranspose (RC_2CT) module reduces the size of the input image by using boundary padding, convolution operation and inverse convolution operation to restore the size of the input image dimensional size and reduce the output and input deviation. To minimize the loss of image detail information, the input image information is directly applied to the subsequent network layer, which outputs the input image after feature fusion with the feature map obtained from the RC_2CT module.

luminance boosting re-adjusts the input image luminance, based on the input luminance, the luminance is boosted to enhance the luminance of the image, making the final coloring result look clearer and sharper, and making the ultimate coloring result more transparent.

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

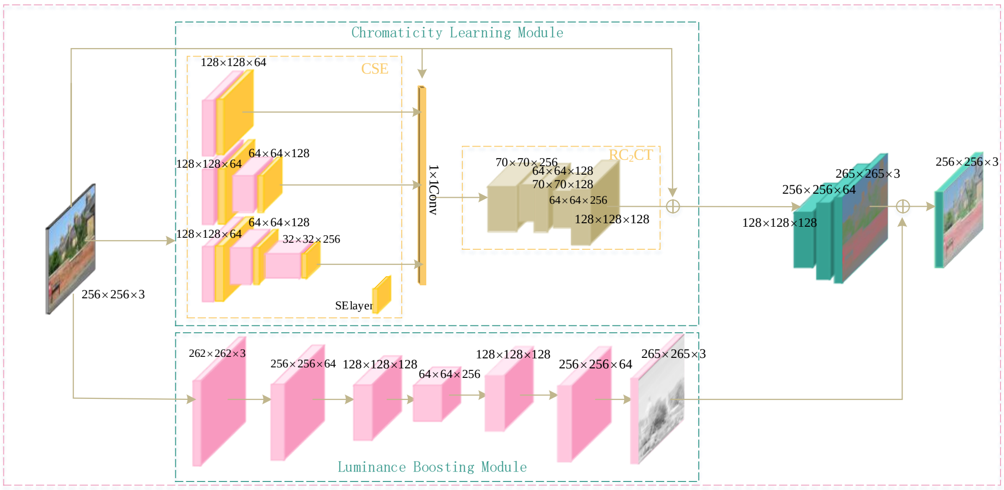


Figure 2: The generator structure of CandyCycleGAN

2.2 CandyCycleGAN discriminator structure

The CandyCycleGAN network discriminator uses the PatchGAN (Luo et al. 2021)[10] structure, where the PatchGAN output is an $N \times N$ matrix with two choices of true or false for each pixel in the matrix. The advantage of PatchGAN over traditional GAN discriminators is the ability to allow the generator to produce images with higher resolution, and better detailed images.

The structure of the CandyCycleGAN discriminator is shown in Fig. 3, which consists of five layers of 3×3 convolution, and in the last layer of the convolution output channel, the number of *256* channels change to *1* to form the matrix feature map, and each element in the matrix represents the discriminative result of the corresponding region. The CandyCycleGAN discriminator network outputs the full-size and *1/2* discriminative matrices with different sizes, which improves the training stability and convergence speed of the CandyCycleGAN network. The full-size discriminator captures the detailed information of the overall image by discriminating the overall image. The *1/2*-size discriminator focuses on capturing local details and generates a more realistic and detailed image. Combining two different-sized discriminator networks makes the GAN network more stable during the training process, thus achieving faster convergence speed and improving the quality of the generated images.

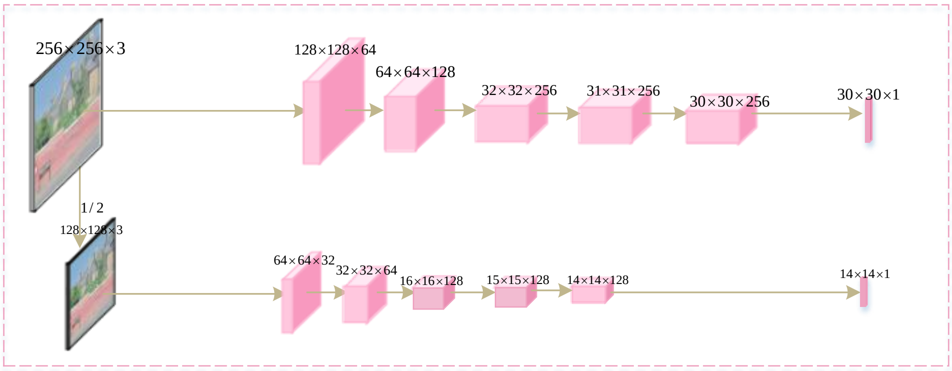


Figure 3: The discriminator structure of CandyCycleGAN

2.3 Chromaticity verification

Chromaticity verification is shown in Fig. 4, in which generator E converts a source domain image to a target domain image and generator F converts a target domain image to a source domain image, both of which are structurally identical. Chromaticity verification can be described in detail as follows: the original input chromaticity image is generated by generator F to generate image 1; image 3 obtained by the chromaticity cycle is re-inputted into the generator F to generate image 4; finally, image 4 and image 1 are inputted into the generator F at the same time to obtain the final output image. The chromaticity cycle is the original input image through generator E to generate image 2, after generator F generates

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

image 3, image 3 re-entered into generator E to repeat the above steps until the generated chromaticity image and the candy color chromaticity value range is the same.

The chromaticity verification process strengthens the game process between the discriminator and the generator to ensure that the converted image chromaticity values are in the candy color chromaticity value range. Using the chromaticity image obtained from the chromaticity cycle as an input for chromaticity validation is a very important step in designing the CandyCycleGAN network, and this process improves the accuracy and quality of the image conversion. In addition, this approach increases the data diversity and helps the CandyCycleGAN network to learn the structural features of the input chromaticity image, constrains the structural similarity between the generated image and the input image, and further improves the quality of the generated image.

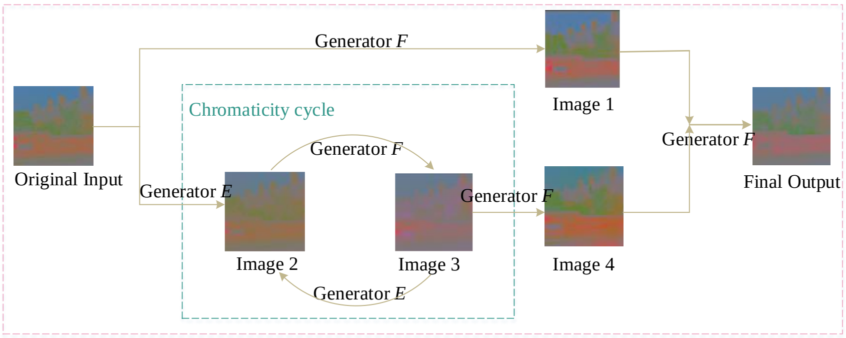


Figure 4: Chromaticity verification

3. Loss function

The CandyCycleGAN network loss function includes the adversarial loss and the Candy loss. The overall expression is shown in:

$$L(E,F,D_X,D_Y) = \lambda_1 L_{GAN} + \lambda_2 L_{Candy} \tag{1}$$

Adversarial loss as shown in:

$$\begin{aligned} L_{GAN} &= L_{GAN}(E,D_Y,x,y) + L_{GAN}(F,D_X,x,y) \\ &= E_{x\sim P_{data}}[\ln(D(x))] + E_{x\sim P_{data}}[\ln(1-D(G(x)))] + E_{y\sim P_{data}}[\ln(1-D(x))] + E_{y\sim P_{data}}[\ln D(G(y))] \end{aligned} \tag{2}$$

where x denotes the source domain, y denotes the target domain, and P_{data} denotes the datasets distribution, where D denotes the discriminator, G denotes the generator, λ_1 and λ_2 are parameters.

Candy loss includes chromatic cyclic loss and chromatic verification loss. It is shown in:

$$L_{Candy} = L_{Candycyc} + L_{Candyver} \tag{3}$$

3.1 Chromatic cyclic loss

Chromatic cyclic loss uses L_1 Loss as a loss function, L_1 Loss is used to preserve the low-frequency information of the image and the detailed features of the generated image, the Chromatic cyclic loss is shown in:

$$L_{Candycyc} = E_{x\sim P_{data}}[\|F(E(x)) - x\|_1] + E_{y\sim P_{data}}[\|E(F(y)) - y\|_1] \tag{4}$$

where x denotes the source domain, y denotes the target domain, and P_{data} denotes the datasets distribution, E denotes the generator E, and F denotes the generator F.

3.2 Chromatic verification loss

L_1 Loss in the late stage of CandyCycleGAN network training, the gap between the real value and the predicted value is small, the gradient stays the same, and the model training is unstable. Smooth L_1

Loss is an improvement of L_1 Loss, in which the gradient still changes when the difference between the real value and the predicted value is small, and it is more reflective of the detailed information compared to L_1 Loss.

The specificity of the chromaticity verification process, using L_1 Loss is not enough to get as close as possible between the generated target domain image and the real image of the target domain. Therefore, Smooth L_1 Loss is chosen as the chromaticity verification loss. Smooth L_1 Loss can learn the corresponding chromaticity information well while retaining the structural features of the image itself well. Smooth L_1 Loss is shown in:

$$S = \begin{cases} \frac{1}{2}[\boldsymbol{Y(i,j)} - \boldsymbol{X(i,j)}]^2 & |\boldsymbol{Y(i,j)} - \boldsymbol{X(i,j)}| < 1 \\ |\boldsymbol{Y(i,j)} - \boldsymbol{X(i,j)}| - \frac{1}{2} & |\boldsymbol{Y(i,j)} - \boldsymbol{X(i,j)}| \geq 1 \end{cases} \tag{5}$$

where ***Y(i,j)*** denotes the target value and ***X(i,j)*** denotes the original value of each pixel point.

The optimization goal of the CandyCycleGAN network generator is to minimize the difference between the true and generated distributions. When the discriminator network reaches optimality, there is no overlap or little overlap between the two distributions, resulting in a gradient of *0*. Therefore, the network model cannot continue to update its parameters. Arjovsky et al. (2020)[12] designed WGAN to use the Wasserstein distance (referred to as W-distance) to measure the real image and the generated image, which can smoothly reflect the distance of the distributions even if the two distributions have no overlap case, it can also reflect the distribution distance smoothly. To satisfy the Lipschitz continuity, weight pruning is used to limit the discriminator network parameters to a certain range, which is empirically set to [-0.01,0.01], and most of the parameters fall at the ends of this range in the actual network training, which can easily lead to the gradient vanishing and gradient explosion. Gulrajani et al. (2017)[13], to solve the problem, change the method of limiting the gradient of the discriminator network by constructing a new data distribution between the generated image and the real image distribution using linear interpolation to apply gradient penalty (GP) to each input data to improve the convergence speed and stability of the network model performance. Therefore, the $L_{Candyver}$ loss function of the CandyCycleGAN network after adding the gradient penalty is shown in:

$$L_{\text{Candyver}} = S + \lambda_3 \left(\underset{\hat{x} \sim \boldsymbol{P}_{\hat{x}}}{E} [(\|\nabla_{\hat{x}} \boldsymbol{D}(\hat{x})\|_2 - 1)^2] + \underset{\hat{y} \sim \boldsymbol{P}_{\hat{y}}}{E} [(\|\nabla_{\hat{y}} \boldsymbol{D}(\hat{y})\|_2 - 1)^2] \right) \tag{6}$$

where $\hat{\boldsymbol{x}}$ is the source domain through generator *F* to generate images, $\boldsymbol{P}_{\hat{x}}$ is the set of images generated by the source domain through generator *F*, $\hat{\boldsymbol{y}}$ is the target domain through generator *E* to generate images, $\boldsymbol{P}_{\hat{y}}$ is the set of images generated by the target domain through generator *E*, and *D* denotes the discriminator, where λ_3 is parameter.

Fig. 5 shows a graph of the change in the value of the Chromatic verification loss function during training using L_1 Loss, Smooth L_1 Loss, Smooth L_1 Loss with the addition of a gradient penalty(GP).

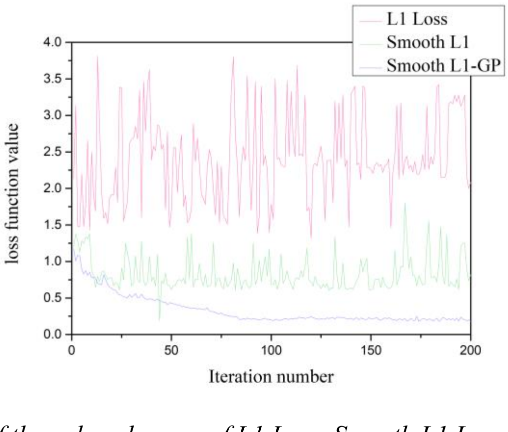


Figure 5: Comparison of the value changes of L1 Loss, Smooth L1 Loss, and Smooth L1 Loss loss functions.

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

As can be seen from the figure, in the process of chromaticity verification, compared with the use of L1 Loss, the use of Smooth L_1 Loss in the training process of the loss function value changes are smaller and relatively stable, the overall decline in the loss function value is more obvious, and ultimately, the loss function convergence speed and stability greatly improved. However, in the late stage of model training Smooth L_1 Loss began to see obvious fluctuations, in the Smooth L_1 Loss function based on the addition of gradient penalties, it can significantly found that the convergence of the loss function compared to the L_1 Loss and Smooth L_1 Loss function to achieve better results, and the final loss function convergence faster and relatively stable.

4. Experimental Results and Analysis

4.1 Datasets

The source domain images in the CandyCycleGAN network are taken from the publicly available Oxford Architecture datasets, which contains 5062 images, and the target domain images are collected through the Internet and self-made by individuals, with a total of 4896 images in the datasets. The datasets are all 256×256 RGB color images.

4.2 Experimental settings

In the experimental environment based on the Linux operating system and Pytorch deep learning framework, the batch is set to 10, and the optimization algorithm uses ADAM, the learning rate is set to 0.00002, and the λ_1, λ_2 in loss function is set to 10, and the λ_3 setting is set to *1/2*. All the experiments are done on one computer system.

4.3 Experimental Results

4.3.1 Evaluation Indicators

User Study[11] is used for tasks that cannot be measured by quantitative metrics, and giving subjective evaluations through questionnaires is a better alternative. Zhu et al. (2017)[8] conducted a voting experiment at AMT (Amazon) with two choices of true and false coloring: a series of colored image pairs were presented to 40 participants, each pair with its own designed algorithm as well as a composition of results from other coloring algorithms. Participants were asked to choose which coloring they thought was false, and the final results of the experiment showed that participants judged false images based on the presence of artifacts and saturated colors in the generated results. Users' subjective evaluation not only correctly evaluated the advantages and disadvantages of each coloring algorithm, but also provided a direction for the optimization of subsequent algorithms.

To objectively evaluate the quality of coloring images between different models, peak signal to noise ratio (PSNR), structural similarity index (SSIM), and the amount of computation (Floating Point Operations, FLOPs) are also used. PSNR evaluates how close the reconstructed image is to the real image, and SSIM evaluates the structural similarity of images to compensate for the fact that PSNR cannot fully reflect the image quality and the consistency of the visual effect of the human eye. FLOPs are used to measure the training time used by the model in the process of training, the consumption of resources, and the efficiency of the reasoning, in which the bigger the PSNR is the better, and the bigger the SSIM is the better[14], and the smaller the FLOPs the better.

To evaluate the color richness of the experimental results more objectively, the color richness index is introduced[15], and the calculation formula of color richness is shown in:

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

$$\begin{aligned} \hat{M} &= \sigma_{rgyb} + 0.3 \times \mu_{rgyb} \\ \sigma_{rgyb} &:= \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} \\ \mu_{rgyb} &:= \sqrt{\mu_{rg}^2 + \mu_{yb}^2} \\ \mathrm{rg} &= R - G \\ yb &= \frac{1}{2}(R+G) - B \end{aligned} \tag{7}$$

where σ and μ denote the standardized variance and mean of the dot product operation along the matrix, respectively, and the larger the final result the better.

4.3.2 Comparative Experiment

To verify the effectiveness of the CandyCycleGAN network, five algorithms, CycleGAN[8], AdaAttN (2021)[16], Li(2021)[18], Zhou(2022)[4], and Wang(2023)[5], are selected as the comparative experiments, to ensure the consistency of the environments of all the comparative experiments, and the results of the comparative experiments are shown in Table 1.

Table 1: Comparison test evaluation index results

algorithms	PSNR	SSIM	COLORFUL	FLOPs
CycleGAN	18.8667	0.5901	42.9864	1296.4801
AdaAttN(2021)	26.3309	0.8524	47.3058	**797.1180**
Li(2021)	21.5930	0.7428	29.8753	942.5705
Zhou(2022)	20.0176	0.7936	36.0587	1048.6276
Wang (2023)	18.7532	0.7092	35.1046	1118.9138
CandyCycleGAN	**28.2679**	**0.9133**	**55.4909**	804.5264

Note: Bold indicates optimal value

Table 2: Comparison table of effects between this article and five algorithms

algorithms / real image	CandyCycleGAN	CycleGAN	AdaAttN (2021)	Li(2021)	Zhou(2022)	Wang (2023)

Table 1 records the mean values of various metrics on the validation set, CandyCycleGAN achieves

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

the best results in all three metrics in the five comparison experiments set up, CandyCycleGAN reduces the computation amount of the CycleGAN model by 37.95%, compared to CycleGAN, PSNR improves by 49.83%, SSIM improves by 54.77%, COLORFUL improves by 29.089%. The comparison experiments results show that the CandyCycleGAN network not only reduces the model computation to improve the model performance but also enhances the details of the generated image to improve the quality of the generated image. Compared with the sub-optimal AdaAttN algorithm, CandyCycleGAN model computation rises by 0.92%, but PSNR improves by 7.36%, SSIM improves by 7.14%, and COLORFUL improves by 17.30%.

In order to see the final coloring effect of the CandyCycleGAN network more intuitively, Table 2 shows the comparison image of the effect of this paper with five algorithms.

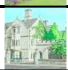
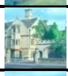
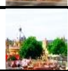
While quantitative evaluation metrics can certainly reflect the performance of different models very objectively, they also have certain drawbacks.

The coloring effect of deep learning based image coloring models cannot be expected. When coloring the same image, the final result may not be completely consistent with the original image. The uniqueness of the coloring content of the CandyCycleGAN network determines the one-sidedness of the objective evaluation criteria. If the overall coloring result of the image presents a high brightness, low contrast, low saturation state, and the color matching is in line with the visual aesthetics, the picture structure is complete, and the detail information is rich, it is considered that the coloring ability of this model should be recognized. Therefore, to increase the image evaluation index based on user evaluation, the five algorithms and the coloring images generated by the CandyCycleGAN network, randomly select a certain number of coloring images, without informing the user of the specific algorithms for each image, so that the user can select the image with better coloring effect according to their subjective intention.

The evaluation method based on the user's subjective intention had a total of *48* participants, of which the number of participants aged *18-35* years old was *24*, the number of participants aged *35-55* years old was *12*, and the number of participants aged *55-65* was *12*, controlling for the ratio of the number of men and women to be *1:1*. Each participant was presented with an image of the results generated by the five comparison algorithms with the CandyCycleGAN network, and was given five seconds to select the participant who the result that was considered to have the best coloring effect, in Table 3 which shows the results of the image quality evaluation based on the user study, and the values *R* on the right side of the image indicates the percentage of participants who thought that the model produced the best colorization compared to the total number of participants.

It can be seen that the CandyCycleGAN network coloring effect is more accepted by the users, and the image color brightness and color saturation are also preferred by the users.

Table 3: Comparison of User Evaluation on Different Models for Coloring Experiments

Original-images	CandyCycle-GAN	R %	Cycle-GAN	R %	AdaAttN (2021)	R %	Li (2021)	R %	Zhou (2022)	R %	Wang (2023)	R %
		**43.5**		3.3		9.1		5.1		15.4		23.6
		**39.5**		4.4		5.9		6.5		10.3		33.4
		**50.7**		0.0		4.7		2.0		18.9		23.7
		**51.3**		2.8		10.8		7.8		11.5		15.8
		**60.9**		1.7		4.9		2.3		11.8		18.4

Note: Bold indicates optimal value

4.3.3 Ablation experiments

To verify the effectiveness of designing the CandyCycleGAN network, ablation experiments are set up and the results of the experiments are shown below in Table 4 Ablation Experiment Results:

As can be seen from the results of the evaluation metrics presentation, compared with the original CycleGAN by adding CSE and RC_2CT modules respectively, all the indexes are slightly improved. Simultaneously adding CSE and RC_2CT modules also improves the evaluation indexes by a small margin compared to adding them individually, and reduces the computation amount of the CycleGAN network by 18.59% compared to the original CycleGAN network. After joining the chromaticity verification, SSIM is improved by 23.47%, COLORFUL is improved by 26.50%, and after adding Candy loss based on chromaticity verification, all the indexes are improved by a small margin. The last group of ablation experiments is the CandyCycleGAN network, and all the indexes are compared to the CycleGAN network, in which the SSIM is improved by 61.98%, PSNR by 79.76%, COLORFUL by 42.56%, and FLOPs by 31.47%, which can be verified from the experimental data that the algorithm of this paper can be recognized for its coloring ability.

Table 4: Ablation Experimental Results

Network Models	SSIM	PSNR	COLORFUL	FLOPs
CycleGAN	0.5589	16.5682	39.9372	1189.4673
CycleGAN+ CSE	0.5896	19.7601	42.0481	962.7292
CycleGAN+ RC_2CT	0.5798	19.7729	40.7235	962.6710
CycleGAN+ CSE + RC_2CT	0.6527	20.1728	45.1273	968.2934
CycleGAN+ Chromaticity Verification	0.6901	22.0853	50.5207	975.6288
CycleGAN+ Chromaticity Verification + Candy's loss	0.7768	24.4572	52.4701	975.6288
CycleGAN+ discriminator +CSE+ RC_2CT + Chromaticity Verification + Candy's loss	**0.9053**	**29.7826**	**56.9351**	**815.1044**

Note: Bold indicates optimal value

Figure 6 shows a comparison of the loss function of CandyCycleGAN and CycleGAN, it can be seen from the figure, that the convergence speed and convergence effect of the loss function value of the basic CycleGAN network is relatively poor, in terms of the fluctuation of the value of the loss function is large, and the final result of the output is full of artifacts, coloring the region of the error, and other uncertainty factors. Compared with the basic CycleGAN network, the convergence speed of the loss function and the final loss function value of the CandyCycleGAN network have been greatly improved, and the loss function result of the CandyCycleGAN network is relatively stable, and the volatility has been greatly improved. In context, the CandyCycleGAN network performs optimally in all indicators, and the CandyCycleGAN network is effective.

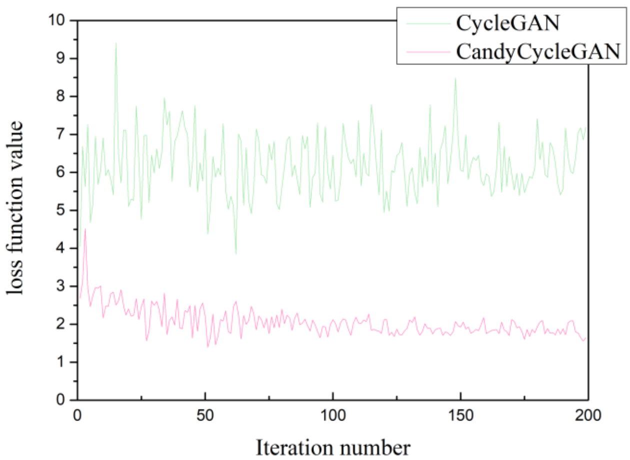


Figure 6: Comparison of CandyCycleGAN and CycleGAN loss functions.

4.3.4 Results Show

From the final results, it can be seen that the algorithm in this paper performs recoloring on top of the RGB image, and the candy-toned image obtained carries bright, vivid, and colorful colors, and has better expressive power in the presentation of both images' colors and image detail features. After recoloring, the image better expresses the meaning of the image, enhances the characteristics of the image, improves the human eye's cognition, and conveys visual enjoyment. So that the human eye can capture the meaning and information of the image itself faster and better, and then give full play to the value of the image. A graphical representation of the results of CandyCycleGAN is shown in Figure 7.

Figure 7: Candy-colored coloring effect

5. Conclusion

CandyCycleGAN network greatly accomplishes the task of candy color recoloring color images, enhancing the detailed features of the output image through multi-scale fusion, reducing the loss of image information during the convolution process, and improving the coloring effect of the network. Adding Selayer increases the computational effort a little, but ensures that the coloring results are within the specified range and prevents color overflow. Use Smooth L_1 Loss as the loss function for chromaticity verification and add a gradient penalty to ensure the coloring edge information. The chromaticity verification process is designed to limit the value range of chromaticity channels to ensure that the color of the colorized image is rich in color and bright in chromaticity. The CandyCycleGAN network structure adopts CycleGAN as the base network, so that the generated colorized image is richer in color compared to other GAN structures, and the CandyCycleGAN network achieves the best performance in terms of improving the quality of the image and keeping the structural information of the image. The CandyCycleGAN network achieves optimal performance in improving image quality and maintaining image structural information, but the experiments of the CandyCycleGAN network are conducted on a small sample datasets with limited categories of coloring images, and a richer image datasets will be used in the subsequent research to further improve the training efficiency of the training model. Whether CandyCycleGAN network or other comparative algorithms in this paper, there are phenomena such as inaccurate coloring of some images or artifacts appearing in some images, and objective evaluation indexes can only give an overall evaluation result, and there is still a lot of room for improvement in the coloring effect of deep learning, and if you want to further improve the network coloring effect, you can train on a larger datasets or choose a more suitable loss function and optimize the network structure to improve the network coloring effect while improving the network training speed.

References

[1] Liqin Cao, Yongxing Shang, and Tingting Liu. Novelimage colorization of a local adaptive weighted average filter [J]. Journal of Image and Graphics, 2019, 24(08): 1249-1257. [DOI: 10.11834/jig.180608]
[2] Zhang R, Zhu J Y and Isola P. Real-time user-guided image colorization with learned deep priors[J]. ACM Transactions on Graphics, 2017, 36(4): Article No.119. [DOI: 10.1145/3072959.3073703]
[3] Sangkloy P, Lu J W, Fang C. Scribbler: controlling deep image synthesis with sketch and color[C] //Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Los Alamitos: IEEE

ISSN 2616-5775 Vol. 6, Issue 13: 196-207, DOI: 10.25236/AJCIS.2023.061327

Computer Society Press, 2017, 6836-6845 [DOI: 10.1109/CVPR.2017.723]
[4] Yuechuan Zhou, Jianxun Zhang, and Wenxin Dong. 2022. Unsupervised Landscape Painting Style Transfer Network with Network with Multiscale Semantic Information[J/OL]. Computer Engineering and Applications: 1-15[2023-07-05].
[5] Shengxiong Wang, Ruian Liu, and Da Yan. 2023, Image Style Transfer Algorithm Based on Improved Generative Adversarial Network[J/O L]. Electronic Science and Technology, 1-9[2023-07-05].
[6] Wenhua Ding, Junwei Du, and Lei Hou. Fashion Content and Style Transfer based on Generative Adversarial Network[J/OL]. Computer Engineering and Applications.: 2023, 1-11.
[7] Wenhui Tan, and Yilai Zhang. Design and Implementation of Multi Collection Style Transfer Algorithm[J] Journal of Fujian Computer. 2023, 39(04):42-48
[8] J. Y. Zhu, T. Park, P. Isola and A. A. Efros. Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks. IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 2242-2251, [DOI: 10.1109/ICCV.2017.244].
[9] Y. Peng and Y. Zhou. Specific Emitter Identification via Squeeze-and-Excitation Neural Network in Frequency Domain. 2021 40th Chinese Control Conference (CCC), Shanghai, China, pp. 8310-8314. [DOI: 10.23919/CCC52363.2021.9549470].
[10] Dunlang Luo, Min Jiang, Linjun Yuan, et al. Research on Image Coloring Based on Conditional Generative Adversarial Network.[J]. Computer Engineering and Applications. 2021, 57(13):193-198.
[11] P. Isola, J. -Y. Zhu, T. Zhou and A. A. Efros. Image-to-Image Translation with Conditional Adversarial Networks. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 5967-5976. [DOI: 10.1109/CVPR.2017.632].
[12] Arjovsky M, Chintala S, and Bottou L. Wasserstein GAN[OL]. [2020-08-20]. https://arxiv.org/pdf/1701.07875.pdf
[13] Gulrajani I, Ahmed F, and Arjovsky M. Improved training of Wasserstein GANs[C] //Proceedings of the 31st International Conference on Neural Information Processing Systems. New York: ACM Press, 2017: 5769-5779.
[14] Zhou Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli. Image quality assessment: from error visibility to structural similarity. in IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600-612, April 2004. [DOI: 10.1109/TIP.2003.819861].
[15] David Hasler and Sabine E. Suesstrunk. Measuring colorfulness in natural images[J]. Volume 5007, Issue. 2003. PP 87-95. [DOI: 10.1117/12.477378].
[16] Songhua Liu, Tianwei Lin, and Dongliang He, et al. AdaAttN: Revisit Attention Mechanism in Arbitrary Neural Style Transfer. IEEE/CVF International Conference on Computer Vision (ICCV), Montreal, QC, Canada, 2021, pp. 6629-6638, doi: 10.1109/ICCV48922.2021.00658.
[17] Nguyen R, Kim S J , and Brown M S. Illuminant Aware Gamut-Based Color Transfer[J]. Computer Graphics Forum, 2015, 33(7):319-328.
[18] Hongan Li, Qiaoxue Zheng, and Jing Zhang, et al. Pix2Pix-Based Grayscale Image Coloring Method [J] Journal of Computer-Aided Design & Computer Graphics. 2021, 33(06):929-938.
[19] Zhang R, Zhu Junyan, Isola P etal. Real-time user-guided image colorization with learned deep priors [J]. ACM Transactions on Graphics, 2017, 36(4): 1-11. https://doi.org/10.1145/3072959.3073703
[20] Vitoria P, Raad L, Ballester C. ChromaGAN: Adversarial Picture Colorization with Semantic Class Distribution[C]// Work-shop on Applications of Computer Vision. IEEE, 2020. pp. 2434-2443. [DOI: 10.1109/WACV45572.2020.9093389].