Taillight Shape Creative Design based on Generative Adversarial Networks

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Abstract. With the increased use of light-emitting diode technology, the design freedom of taillight shapes has improved, and the shape design of taillights has become a major design focus and breakthrough point for new energy vehicles. As traditional taillight shape design normally depends on the individual experience of designers who make considerable effort to capture design inspiration by manually searching for design references, taillight shape creative design in the field of computer-aided design is studied to assist designers' creative thinking and design efficiency. In this research, generative adversarial networks are applied to explore the creative generation mechanism of taillight shape designs. First, a dataset of high-quality vehicle taillight shape images is established, which combines safety and aesthetic taillight shape design rules and insights. Then, deep convolutional generative adversarial networks and progressive growing of generative adversarial networks are both introduced to train and construct the taillight shape generative design model, and the commonalities and differences between the two are further compared. Finally, the optimal creative generation design model of the taillight shape is constructed. This research provides a new idea for taillight shape design, and the constructed taillight shape creative generation design model is helpful in realizing efficient, diversified and innovative taillight shape design and provides designers with rapid and sustainable preliminary design proposals and creative inspiration support.

Keywords: Taillight shape; generative adversarial networks; deep convolutional generative adversarial networks; Progressive growing of generative adversarial networks; Creative design; Inspiration
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1 INTRODUCTION

To adapt to the rapidly changing and highly competitive new energy vehicle market, car styling design plays a very essential role in the success of the automotive industry. Taillights, generally regarded as an important component of a car, have become a major design focus for vehicle designers and manufacturers. In the world's motor show each year, taillights are always the focus of attention by consumers and mass media. The eye-pleasing and sophisticated design of taillights are the core competition object of every vehicle company and manufacturer, and help in creating a unique visual signature for the vehicle brand.

The traditional taillight shape design normally depends on the individual experience of designers, and designers normally manually capture design inspiration by observing and learning from design websites, magazines or other design materials. This kind of design process takes considerable time and effort and is inefficient in the design process. How to stimulate designers' design inspiration in an efficient way, increase productivity and expedite reactions of designers during vehicle design and development processes are of great significance and necessity. Several studies have focused on the role of images as the design inspiration. Casakin [1] found that browsing through a large number of different images can help improve the quality of a designer's solution. Malaga [2] pointed out that exposure to image stimuli can prompt designers to generate more creativity in the ice cream flavor design. Goldschimidt et al. [3] found that a design environment with images provided designers with more creative inspiration than a design environment without images. Borgianni et al. [4] pointed out that exposing to pictorial stimuli can increase the rarity and non-obviousness of ideas. Gonçalves et al. [5] demonstrated that images are important for design inspiration by both students and professional designers. Laing et al. [6] found that exposure to the images had minimal measurable effect on the creativity of the design outputs, but the images were still found to have a positive effect on the designers' experience during the ideation phase of the design process. Above findings indicated that images were commonly regarded as an effective assistance to the process of creative design of different objects, and help to stimulate designers' creative inspiration, expand the design space, and have a positive impact on product creative design process [7].

In recent years, product creative design based on artificial intelligence has been increasingly promoted [8]. Generative adversarial networks, as a deep learning method that can achieve good results in unsupervised learning, have shown great potential in the fields of image generation and product creative design. For example, Gan et al. [9] generated social robot design proposals based on a generative adversarial network and contributed to finding social robot creative design solutions for designers. Liu et al. [10] and Schimitt et al. [11] performed chair design generation based on generative adversarial networks and delivered a diversity of generated chair images to inspire chair designers. Liu et al. [12] applied a conditional generative adversarial network to Chinese traditional textile pattern generation and constructed a Chinese traditional textile pattern creative design model. The above research shows that generative adversarial networks have gradually been applied to assist product creative design, which can generate sustainable, unique, novel and inspiring creative design schemes, to deliver a rich design basis for designers to optimize and complete their design cases. Moreover, diverse generated design schemes can further stimulate designers' inspiration for creative and innovative solutions [13-15] and benefit the design process in the ideation phase [6]. For design applied to the automotive industry, the application of generative adversarial networks to vehicle styling design is still at an initial stage, but it shows great research and application potential as well. Specifically, taillight shape design using a generative adversarial network to assist creative is a novel, important and necessary task and has far-reaching significance for the vehicle design and development process.

2 RELATED WORKS

2.1 Creative Generation Design

Creativity and innovation have become major strategies in different disciplines of industries in recent years, and many companies have devoted significant resources to developing novel products. In creative product design, images can provide simple and intuitive clues [2] ; therefore, they are often used by designers to capture and stimulate design inspiration [16]. Creative generation design is an artificial intelligent design process in which a computer automatically creates a large number of design images through an iterative algorithm model to meet user-defined standards and constraints, and designers do not need to participate in direct interaction with products and materials [17, 18]. Creative generation design can help designers capture design inspiration quickly and further enhance their design reaction and productivity during the design process, thereby increasing overall work efficiency [19]. Harvard Business Review has named generative design "the next wave of intelligent design automation" [20] , and creative generation design has become a new design paradigm within the discipline of product design [21-23], providing designers with more creative proposals and ideas and supporting designers in their creative work.

Generative adversarial networks (GANs) are a data-driven generative design research method that was first proposed by Ian Goodfellow in 2014 and has been widely used in unsupervised learning to generate new data and images [24]. As a new generative model, GANs have been widely applied in the field of product creative generation design. For example, Nasrin et al. [25] generated a series of varied henna art images based on generative adversarial networks, verifying the feasibility and potential of GAN methods in the field of creative art design. You et al. [26] developed a visual color analysis system that can automatically color-match an entire advertising image according to the color and other keywords input by the user based on generative adversarial networks and demonstrated the efficiency of this system in quickly supporting brand promotion and marketing activities. Kato et al. [27] proposed a garment design model called DeepWear based on generative adversarial networks. DeepWear can automatically generate diverse garment creative design schemes and can be further delivered to pattern makers for optimizing and craftsmen for sewing.

2.2 Deep Convolutional Generative Adversarial Networks

Deep convolutional generative adversarial networks (DCGANs) are derivative models of GANs [28]. DCGAN introduces a convolutional network into the GAN structure and improves the learning effect of GAN through the powerful feature extraction ability of the convolutional layer. DCGAN has good robustness and performance in data enhancement and image generation and has been widely used in the field of computer vision and creative generation design.

The network architecture of DCGAN generator G is shown in Figure 1(a). The generator maps the 100-dimensional latent space vector (z) to the data space, obeying a uniform distribution in the range [-1, 1], and after a series of deconvolutions, further forms a $64\times64\times3$-pixel RGB image, which has the same size as the training image. Each deconvolution layer is matched with a 2D batch normalization (BN) layer and a ReLU activation layer (except the last layer). The output of the generator is fed back through the tanh function; therefore, the output data range is [-1, 1]. The above structural layers can help keep gradients flowing during training.

The architecture of the discriminator D is basically the reverse of the structure of the generator G, as shown in Figure 1(b). It is a binary classification network based on a convolutional neural network, which takes $64\times64\times3$-pixel image data as input and takes the generated probability value as output, showing the probability of whether the input image is a real image. The discriminator processes the input data through several layers (including convolutional layers, BN layers, and the LeakyReLU activation function) and exports the final probability through the sigmoid activation function. The BN layer and LeakyReLu activation function promote healthy gradient flow, which is crucial to the learning process of both the generator and the discriminator.

DCGANs have been widely applied in product creative design. Wu et al. [8] generated a series of classic oil-paper umbrella creative design schemes based on the DCGAN, which is helpful for designers' creative design practice of oil-paper umbrellas. Zhou et al. [29] conducted the creative design of car front face shape based on DCGAN and further applied aesthetic evaluation on the generated car front face shape design. Oh et al. [30] proposed that generative design of vehicle wheels based on DCGAN can generate high aesthetics, diversity, and robustness of wheel design cases for designers to refer and select. The above studies show that DCGANs have great potential in product creative design and can also be applied to the taillight shape design of vehicles.

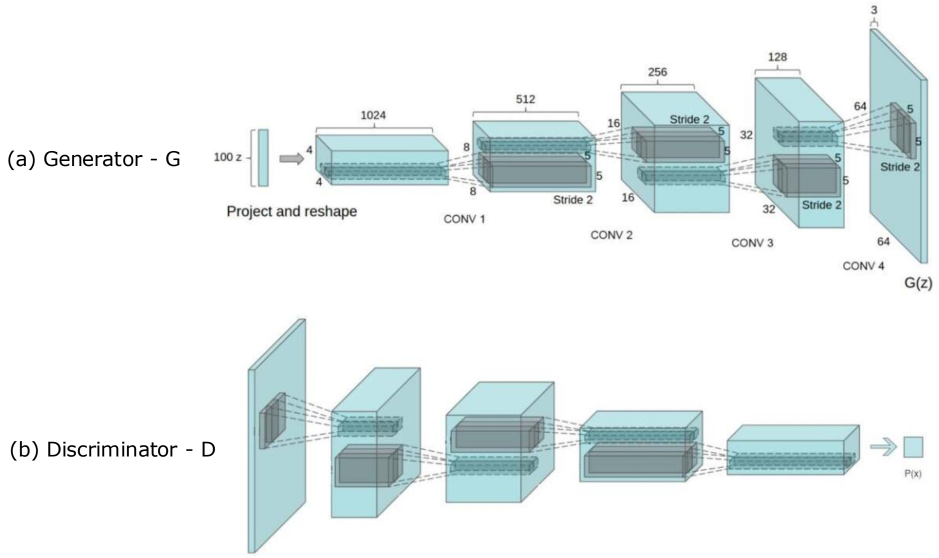


Figure 1: The architecture of DCGAN generator G(a) and discriminator D(b).

2.3 Progressive Growing of GANs

Progressive growing of GANs (PGGAN) is a multistage growth training GAN model proposed by Karras et al. [31]. PGGAN starts training with simple low-resolution images and increases the resolution of the images by gradually adding new layers to the network. As shown in Figure 2, in the early stage of model training, PGGAN first learns and generates low-resolution images, such as 4×4 pixels. Then, the network layers of PGGAN are continuously deepened by adding a layer to the generator and discriminator and learning and generating 8×8-pixel images. By continuously deepening the number of network layers to learn and generate higher-resolution images, a 1024×1024-pixel image is finally generated.

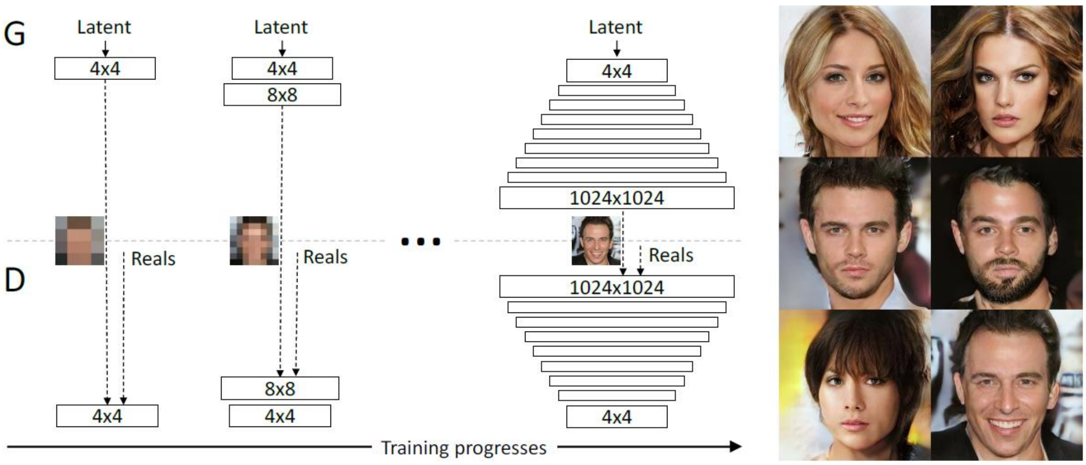


Figure 2: The training process of PGGAN [31].

Different from the DCGAN, the architecture of PGGAN is not strictly fixed and changes continuously as the network deepens during the training process, and the iterative training of PGGAN is performed at lower resolutions; therefore, the training speed of PGGAN is much faster than that of traditional GANs [31]. PGGAN can generate higher resolution images and has been widely applied in the field of image generation among different disciplines. For example, Gautam et al. [32] generated high-quality images capturing river structure and flow details to support hydrological research-based PGGAN. Kokomoto et al. [33] used PGGAN to generate realistic full color intraoral images, providing feasibility for the construction of oral educational materials that are not restricted by patient privacy. Teramoto et al. [34] proposed a PGGAN-based method for automatically generating cytological images and demonstrated the effectiveness of generating images using PGGAN.

In view of the fact that DCGAN and PGGAN may generate diverse, innovative and vivid images, the authors think that applying DCGAN and PGGAN to construct a taillight shape creative design model could also generate diverse, rich and novel taillight shape design schemes that would help designers to stimulate their design inspirations and enhance the design efficiency during the vehicle design and development process.

3 METHODS

In this study, taillight shape creative generation design based on DCGAN and PGGAN is implemented in parallel, and the commonalities and differences between the two are further compared and defined.

3.1 Experiment 1

This experiment aimed to study the creative generation design of taillight shapes based on DCGAN. First, high-quality datasets of taillight shape design were established. Then, the DCGAN performed feature extraction and data training. Finally, the taillight shape creative design model was constructed.

3.1.1 Datasets

To construct the taillight shape creative generation design model, corresponding datasets of taillight shape design should be built. First, the crawler algorithm was applied to crawl all the image data with keywords of vehicle “taillight shape”, “taillight”, “taillight design”, and “taillight shape design” from websites such as Google Pictures, Baidu Picture, Pinterest, etc. Finally, a total of 2490 images regarding taillight shape design were collected, as shown in Figure 3.

Since there were many repeated images in the collected datasets, the hash algorithm was used [35] to deduplicate the images. After removing duplicated taillight images and combining them with manual filtering, low-resolution and irrelevant images were further removed. To ensure that the taillight shape design in the dataset had relatively high design quality, six vehicle designers with more than 5 years of design experience were invited to participate in a focus group for dataset selection. Based on the safety and aesthetic insights of taillight shape design from the study by Luo et al. [36, 37], combined with the design experience of vehicle designers, the dataset was jointly rescreened to remove taillight shape images with relatively low safety and aesthetic features, such as shapes with solid square styles and short-line styles. After the above filtering operation, a total of 1577 taillight shape design images were finally obtained as high-quality datasets.

Since the taillights are located on the rear side of the car, the integration of the taillight shape with its surrounding parts has a certain effect on the car styling design; therefore, it was decided to retain the back of the car body in addition to the shape of the taillights. To highlight the shape features of the taillights and ensure that the shape images of the taillights will not be deformed due to different aspect ratios in the later model training, the shape images of the taillights were manually cropped in a square ratio. The final high-quality datasets of taillight shape design are shown in Figure 4.

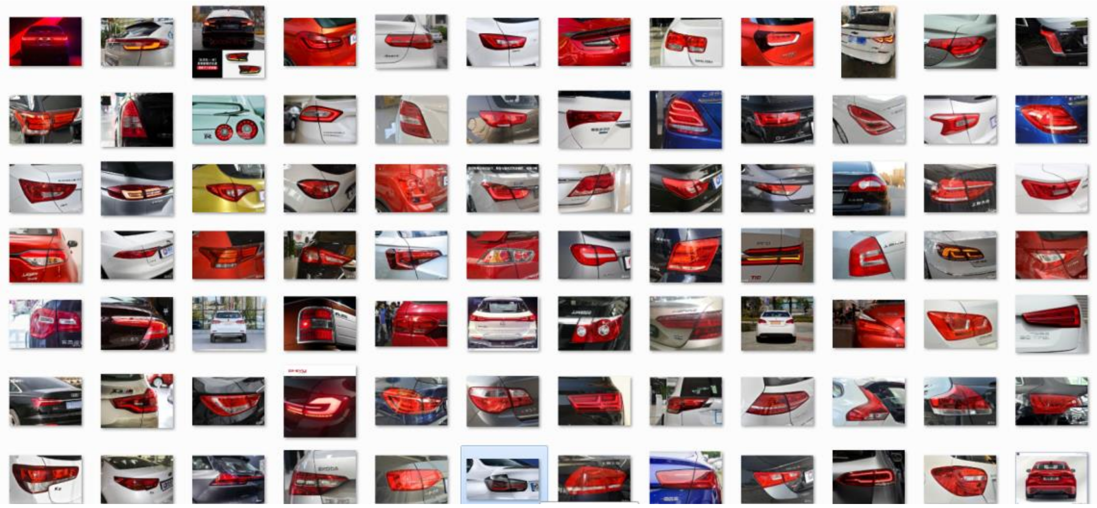


Figure 3: Partial taillight shape design image datasets collected based on crawler algorithm.

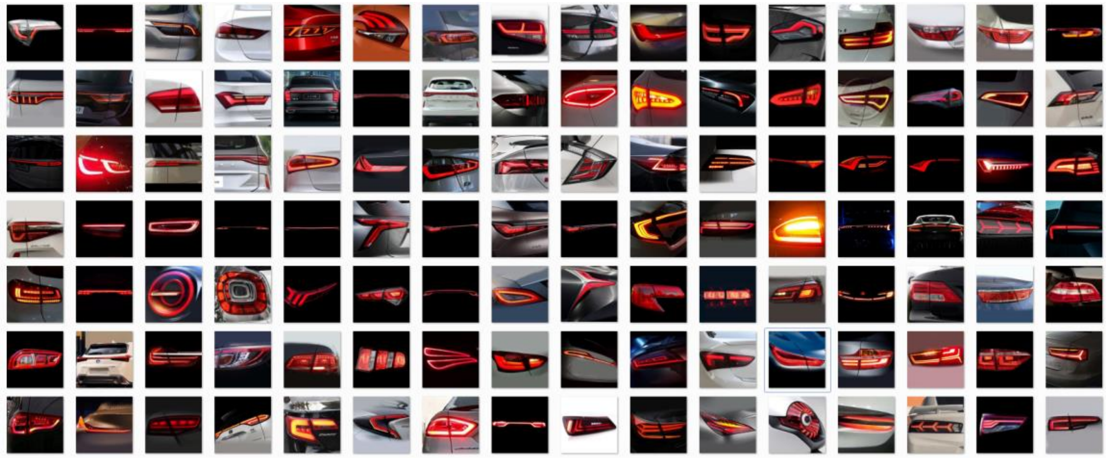


Figure 4: Partial taillight shape design image dataset.

3.1.2 Experimental instrument and environment

The Python language and the PyTorch deep learning framework were used as the experimental instrument and environment. Python is a computer programming language and has become the most popular language in the field of machine learning due to its unique advantages. PyTorch is an open-source Python machine learning library. It is a more optimized deep learning framework based on Torch and has powerful GPU acceleration functions. With the help of PyTorch's deep learning framework, Python can efficiently complete deep learning tasks.

The computer hardware configuration used in this experiment consisted of a 64-bit Windows 10 operating system, 2.8 GHz Intel i7 CPU and NVIDIA RTX 2070 graphics card. The software configuration consisted of Python 3, integrated deep learning framework Anaconda and PyTorch 1.0.

3.1.3 Network training

In this experiment, DCGAN was introduced to learn and train taillight shapes of high design quality and aimed to construct a creative generation design model for vehicle taillight shapes. The overall model contains a generative model and a discriminative model.

The generative model first imports a 100-dimensional noise vector z and further obtains data with dimensions of 4×4×1024 through projection and linear transformation, taken as the input for the next four deconvolution layers. As shown in Figure 5, the deconvolution layer increases the width and length of the data and reduces the depth of the data. Through the deconvolution layers Deconv1, Deconv2, Deconv3 and Deconv4, the dimensions of the output data are 8×8×512, 16×16×256, 32×32×128 and 64×64×3, respectively. The kernel size in the generative model is 4×4, and the stride is 2. Except for the output layer, each deconvolution layer is followed by a BN layer and an activation layer (LeakyReLU activation function). After the last layer of the deconvolution layer is processed by the nonlinear tanh activation function, the model output, that is, the generated taillight shape design images, is defined.

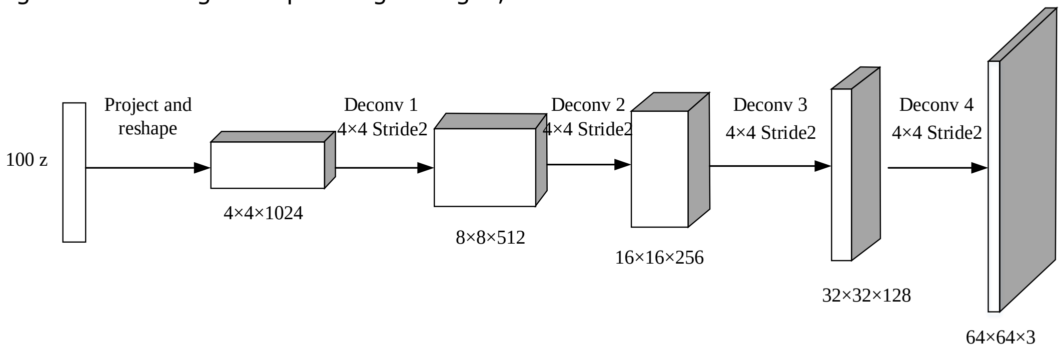


Figure 5: The architecture of generative model.

The input layer of the discriminative model consists of two parts: the real taillight shape image and the generated image output by the generative model. As shown in Figure 6, the image input is followed by four convolution layers, which can reduce the length and width of the data and increase the depth. Through the convolutional layers Convl, Conv2, Conv3 and Conv4, the dimensions of the output data are 32×32×128, 16×16×256, 8×8×512 and 4×4×1024, respectively. The convolution kernel size in the discriminant model is 4×4, and the stride is 2. Except for the output layer, each convolutional layer is followed by a BN layer and an activation layer (LeakyReLU activation function). The last layer of the convolutional layer is processed by the sigmoid activation function to export the model, and then the probability is used to determine whether the output is a real taillight shape image (probability 1) or a fake taillight shape image (probability 0). The above two networks of the DCGAN model constantly train and learn and finally stop when the generator cannot be distinguished by the discriminator. Figure 7 shows the overall architecture of taillight shape generation in this experiment.

During the model training process, noise was added to make the model more stable, and the input noise z obeyed the uniform distribution of [-1,1]. The weight parameters were optimized using the backpropagation algorithm, and the cross-entropy was used as the loss function of the network. After tuning the parameter to obtain a good performance of the generative model, we finally applied the Adam optimizer to update the parameters, setting the batch size to 64, momentum β1 to 0.5, and the initial learning rate to 0.0002.

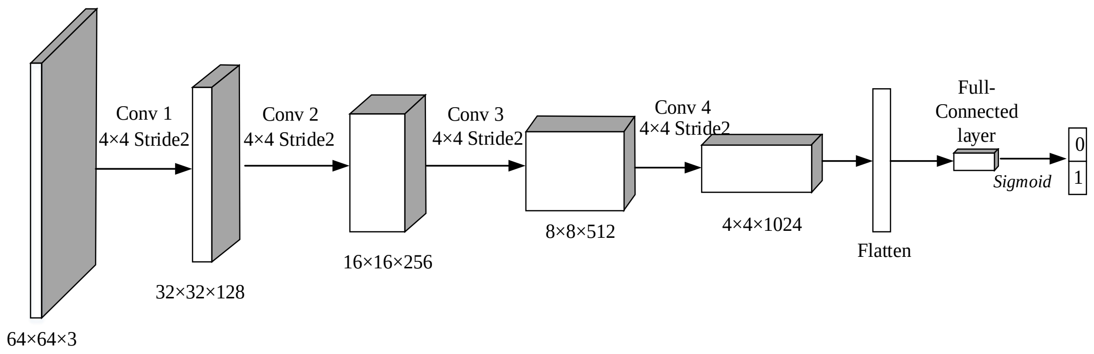


Figure 6: The architecture of discriminative model.

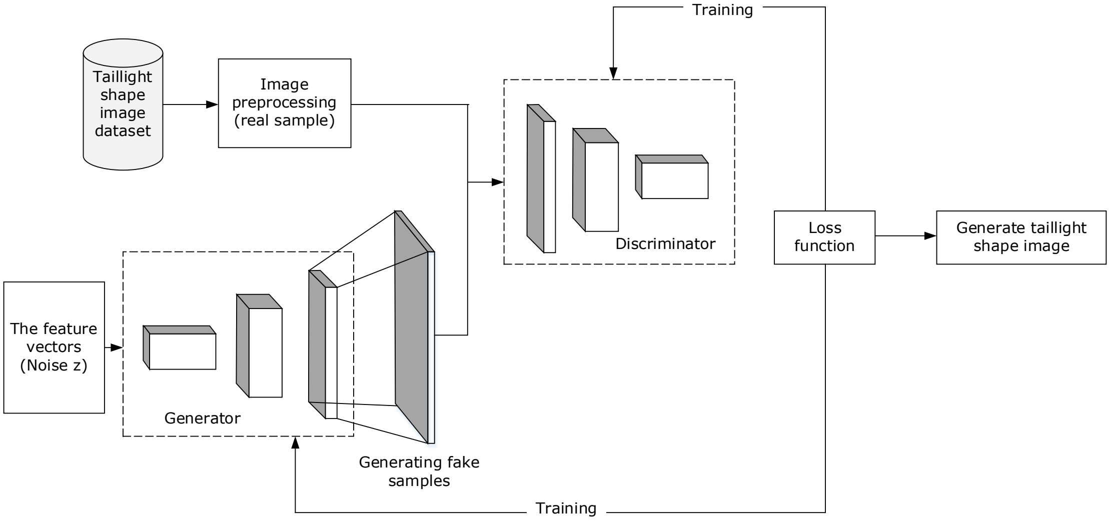


Figure 7: The architecture of taillight shape generation.

The loss function of the generator and discriminator in this experiment was as follows:

$$L_G = \log(1 - D(G(z))) \,, \tag{1}$$

$$L_D = \log(1 - D(x)) + \log(D(G(z))) \,, \tag{2}$$

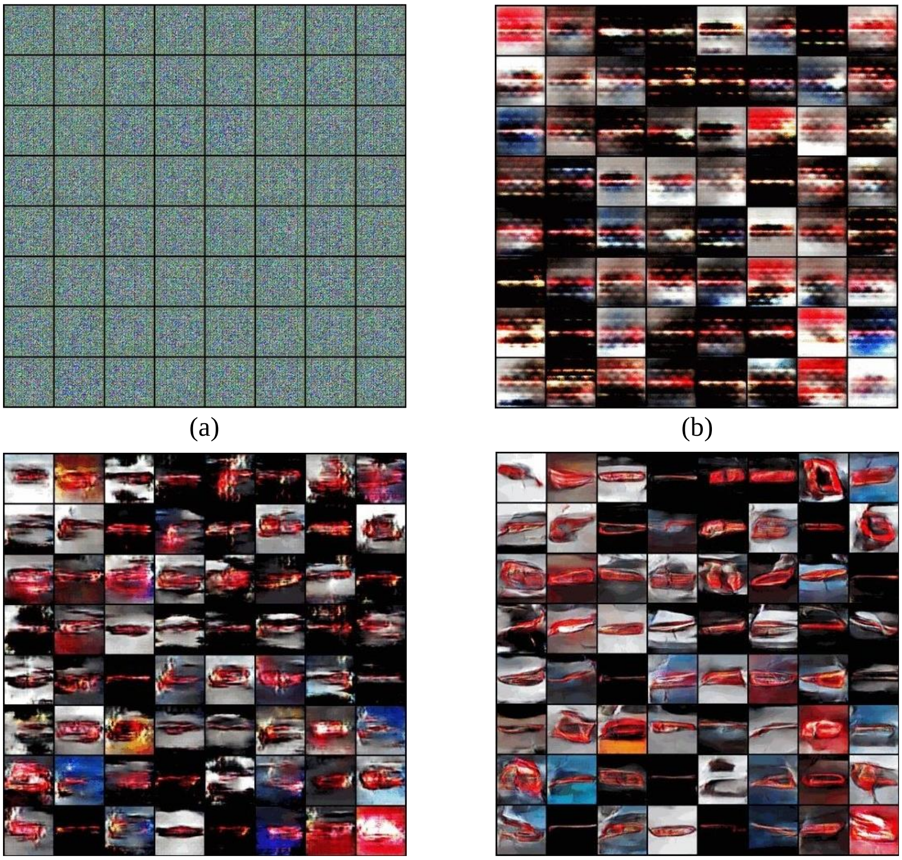
where L_G and L_D represent the generator and discriminator loss functions, respectively z represents the random noise input to the generator, $G(z)$ represents the data generated from the noise z, x represents the real sample data, $D(x)$ represents the probability of belonging to the real sample data rather than the generated sample data, and $D(G(z))$ represents the probability that the data generated by the noise belong to the real sample data.

3.1.4 Results

Different training epochs to find the optimal image generation results were set up. After several tests, when the batch size was 64 and the number of training epochs was approximately 400, the images generated by the experiment were relatively clear and diverse.

Figure 8 shows the image results of the network based on DCGAN under different training epochs, which are 1 epoch, 100 epochs, 200 epochs and 400 epochs. The resolution of the generated images increased with the training epochs. The images with higher resolution showed that the trained model can better obtain shape feature information from the training datasets. Finally, after continuous tuning and training of the parameters, the total training cycle was set to 500 epochs.

The results showed that although the image of the taillight shape generated based on DCGAN becomes clearer with the number of epochs, the final image quality and resolution are not high, and the shape and internal structure of the taillight are still unclear. Therefore, to further improve the image quality generated by the shape of the taillight, the PGGAN model was further applied and explored.



(a) (b) (c) (d)

Figure 8: The generated taillight shape images under different training epochs: (a) 1 epoch (b) 100 epochs (c) 200 epochs (d) 400 epochs.

3.2 Experiment 2

Regarding the high-resolution image generation ability of PGGAN [31] and the fact that the application of PGGAN in the field of product design is rare, this study further applied PGGAN to train taillight shape design images, aiming to explore the feasibility of taillight shape creative design generation mechanisms for higher resolution image quality.

3.2.1 Datasets

The dataset of this experiment was the same as the one described in Section 3.1.1.

3.2.2 Experimental instrument and environment

The experimental instruments and environment configuration were the same as in Section 3.1.2.

3.2.3 Network training

In this experiment, PGGAN was introduced to learn and train high-quality taillight shape design datasets and aimed at constructing a creative generation design model for vehicle taillight shapes. The overall model contains a generator and discriminator. In the generator, the sampling module consists of two convolutional layers (kernel 3×3, stride = 1) and an upsampling layer, and the upsampling method uses nearest neighbor filtering. In the discriminator, the sampling module consists of two deconvolution layers (convolution kernel 3×3, stride = 1) and a downsampling layer, and the downsampling method uses average pooling. The 128-dimensional feature (noise) vector z obeying a uniform distribution [-1, 1] is used as the input data of the generator, and a 4×4-pixel taillight shape feature image is generated. The model is trained from 4×4-pixel taillight shape feature images. After one round of training, new convolutional and upsampling layers are added to the generator to increase the input of the generator and discriminator to an 8×8-pixel taillight shape feature image. By analogy, the size of the taillight feature image was gradually increased until the 128×128-pixel taillight shape feature image required for this experiment was generated. Figure 9 shows the overall architecture of taillight shape generation in this experiment.

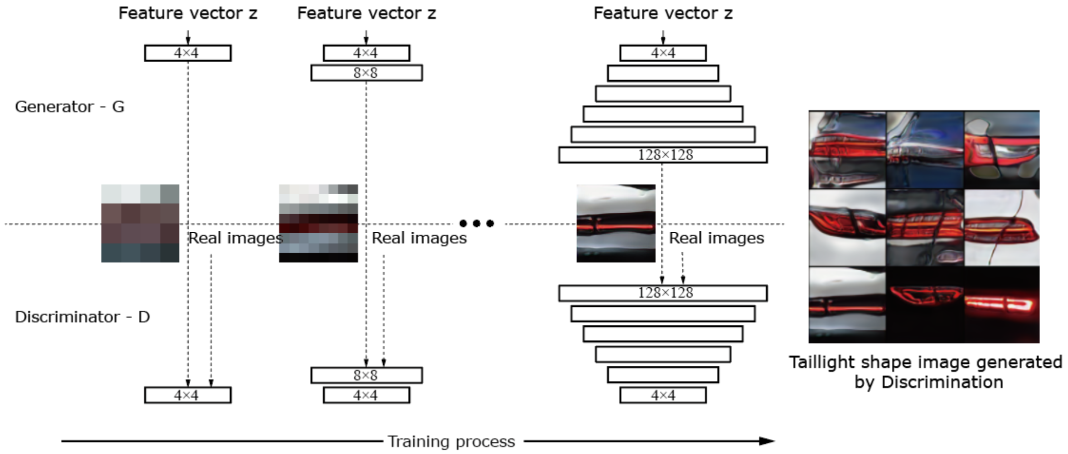


Figure 9: The architecture of the training process of taillight shape based on PGGAN.

This experiment used the Adam optimizer (β1 = 0, β2 = 0.99) to train the generator and discriminator networks, and the initial learning rate was set to 0.001 and the batch size to 4. Due to the progressive architecture, the experiments were set up for 300,000 iterations of training to ensure better convergence results. Throughout the training process, checkpoints were kept every 1000 iterations. After each checkpoint, a script was run to export generated images during a specific training interval, and these images became clearer over time.

The loss function of this experiment adopted the WGAN-GP loss function [38] , which is used to improve the stability of the training process and avoid the disappearance of the gradient. The loss function formula of WGAN-GP is as follows:

$$\min_{G}\max_{D} L_{WGAN-GP}(D,G) = -\underset{x\sim P_r}{E}[D(x)] + \underset{z\sim P_g}{E}[D(G(z))] + \lambda \underset{\hat{x}\sim P_{\hat{x}}}{E}[\left(\left\|\nabla_{\hat{x}} D(\hat{x})\right\|_2 - 1\right)^2] \tag{3}$$

where x is the real sample data, z is the random noise input by the generator, $G(z)$ is the data generated from the noise, $D(x)$ is the probability of x belonging to the real sample data rather than the generated sample data, and $D(G(z))$ is the probability that the discriminator determines that the data generated by the noise z belongs to the real sample data. In the formula, the sum of the first two terms represents the data distribution obeyed and the Wasserstein distance of the data distribution $G(z)$ obeyed, the latter term is the gradient penalty, λ is the weight of the gradient penalty, usually taken as 10, ∇ is the gradient symbol, and $\hat{x}$ is the uniform sampling on the line segment with x and $G(z)$ as endpoints.

3.2.4 Results

During the training process, with the increase in training cycles, the generated samples continuously change from low resolution to high resolution. When the training reaches 240,000 iterations, the outline of the 128×128-pixel image exported by the generation network is relatively clear, and the structure is reasonable. Figure 10 shows the generated images at 8×8, 16×16, 64×64 and 128×128 pixels. The generated taillight shape image shows that the design details of the taillight shape become clearer and richer with the increase in image pixels. In addition, the generated taillight shape image also shows high diversity and a sense of art.

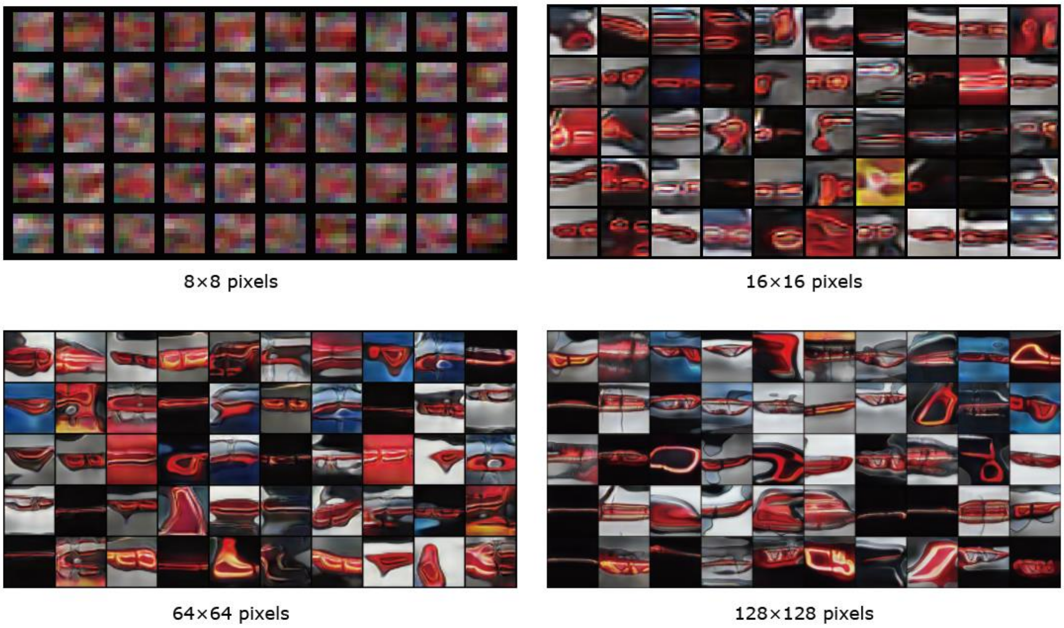
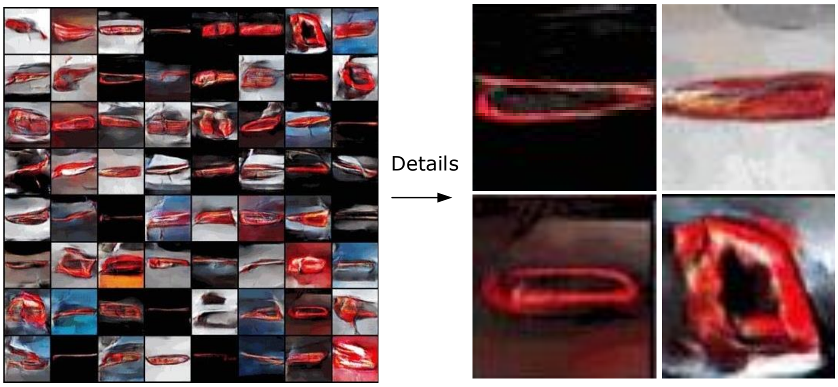


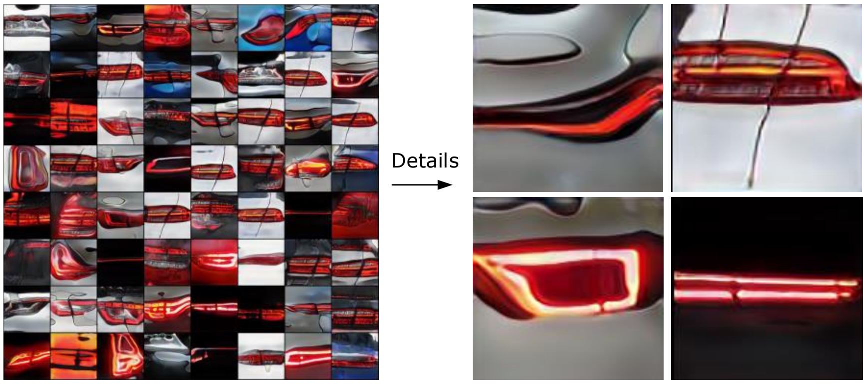
Figure 10: The generated image at 8×8, 16×16, 64×64 and 128×128 pixels.

3.3 Results Comparison and Validation

Figure 11 shows the generated image of the taillight shape obtained from the above two experiments. The 64 taillight shape images generated based on DCGAN have lower resolution and relatively blurry taillight shape boundaries than the taillight shape images generated by PGGAN. As there is no general evaluation method for image generation regarding product creative design, in consideration of the generated taillight shape image aim of assisting the creative design process for designers, the objective quality evaluation of the image and the designer's subjective quality evaluation were combined to evaluate the quality of the generated taillight shape image from both experiments.



(a) Experiment 1: taillight shape design images generated based on DCGAN



(b) Experiment 2: taillight shape design images generated based on PGGAN

Figure 11: (a) Taillight shape image generated based on DCGAN; (b) Taillight shape image generated based on PGGAN.

3.3.1 Objective quality evaluation

Objective quality evaluation measures the data gap between the generated image and the real image [39], The commonly used indicators include structural similarity evaluation (SSIM), peak signal-to-noise ratio (PSNR) and the initial distance of Ferrechet (FID). Because the SSIM index is an image quality evaluation standard that conforms to human intuition and is closer to the subjective perception of the human eye [40], this study selects the SSIM index for image quality evaluation and comparison.

The index of SSIM [41] is used to evaluate the similarity between the generated image and the real image, mainly along three aspects: brightness, contrast and structure of the image. When the quality of the generated image is higher, the corresponding SSIM value is higher. The range of the SSIM value is 0 to 1. When the SSIM value is larger, the similarity of the two images being compared is higher. Therefore, if the SSIM value of the taillight shape image generated by the experiment and the real taillight shape image of the dataset is higher, it means that the image quality generated by the experiment is better.

The formula of the index of SSIM is based on a measure of luminance, contrast and structure between samples x and y, and the formula is as follows:

luminance:

$$l(\mathrm{x,y}) = \frac{2\mu_x\mu_y + C_1}{\mu_x^{\ 2} + \mu_y^{\ 2} + C_1} \tag{4}$$

contrast:

$$c(\mathrm{x,y}) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^{\ 2} + \sigma_y^{\ 2} + C_2} \tag{5}$$

structure:

$$s(\mathrm{x,y}) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{6}$$

Generally, studies take $C_3 = C_2 / 2$, and μ_x and μ_y represent the mean value of x and y respectively, $\sigma_x^{\ 2}$ and $\sigma_y^{\ 2}$ represent the variance of x and y respectively, σ_{xy} represent the covariance of x and y, and $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$ are two constants. To avoid dividing by zero, the default value of the parameter K_1 is 0.01 and the default value of K_2 is 0.03, while the range of pixel values L is generally 255.

So,

$$SSIM(\mathrm{x,y}) = \left[l(\mathrm{x,y})^{\alpha} \cdot c(\mathrm{x,y})^{\beta} \cdot s(\mathrm{x,y})^{\gamma}\right] \tag{7}$$

Setting α, ß, and γ to 1, the SSIM formula can be written as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^{\ 2} + \mu_y^{\ 2} + C_1)(\sigma_x^{\ 2} + \sigma_y^{\ 2} + C_2)} \tag{8}$$

The SSIM numerical calculation is performed on the taillight shape images generated in Experiments 1 and 2 and 1000 real samples drawn from the dataset. Finally, the average SSIM value of Experiment 1 is 0.035 (SD=0.090), and the average value of SSIM of Experiment 2 is 0.137 (SD=0.125). The data showed that the taillight shape image generated by Experiment 2 is better than the taillight shape image generated by Experiment 1. Table 1 shows the comparison results of the first 6 groups of SSIM values of the two experiments. Among them, 5 groups of SSIM values in Experiment 2 are higher than those in Experiment 1.

Experiment	group1	group 2	group 3	group 4	group 5	group 6	average
1	-0.010	0.007	0.022	0.117	-0.009	0.000	0.021
2	0.016	0.032	0.114	0.113	0.091	0.217	0.097

Table 1: Comparison of SSIM values of the first 6 groups of images.

3.3.2 *Subjective quality evaluation*

When facing different scenarios, the judgment of the quality of image generation cannot rely solely on objective evaluation standards. Subjective quality evaluation is an important and necessary evaluation index in an evaluation system that can support comprehensive and effective evaluation. Subjective quality evaluation is generally performed by professionally trained evaluators to score image quality according to their own subjective feelings. The mean opinion score (MOS) is a commonly used subjective evaluation indicator [42]. The MOS index can measure the quality of image generation from a subjective point of view, and the evaluation together with the objective evaluation can ensure the comprehensiveness and effectiveness of the verification results.

The evaluation formula of the average opinion index is as follows:

$$MOS = \frac{1}{n}\sum_{i=1}^{n} R_i \tag{9}$$

where R_i is the personal rating of the i-th evaluator for a given taillight image.

In this experiment, 21 designers (11 males, 10 females, ranging in age from 21 to 33 years old) with up to three years of industrial design experience or design students were invited to make subjective evaluations on 64 generated taillight images. Then, based on Equation (9), the scores and the average value of all subjects were calculated.

Since the purpose of this experiment is to assist the creative design of the shape of the taillight, the questionnaires of subjective evaluation of the experimental setup were as follows:

(1) Question 1: Can the generated taillight image support you in your creative design of taillights?

A 5-point Likert scale was used as the scoring indicator for this question, where 5 meant "very helpful", 4 meant "helpful", 3 meant "average", 2 meant "not very helpful", and 1 meant "not helpful";

(2) Question 2: Which set of taillight images can help you further your creative design of taillight shapes?

The subjects browsed the taillight shape images generated by the two experiments and voted.

After all subjects scored the taillight images subjectively, the data were analyzed by SPSS 25 software, and the score of assistance ability of creative design of Experiment 1 was obtained as 3.429, with a standard deviation of 0.870 and median of 4, while the creative design assistance score of Experiment 2 was 4.333, with a standard deviation of 0.658 and median of 4. Furthermore, a total of 17 out of 21 participants voted for taillight shape images that are more helpful to them regarding the creative design of taillight shapes in Experiment 2. Table 2 shows the evaluation comparison results. The paired sample t-test results show that there is a significant difference in the assistance ability of taillight shape creative design of the two experiments (T(20) = -4.583; p = 0.000), in which Experiment 2 is significantly higher than Experiment 1. This shows that the generated image of taillight shape based on PGGAN is more helpful for designers to carry out the creative design of taillight shapes. Figure 12 shows the details of ratings of all participants.

Experiment	average	SD	median	N	t	df	sig.(double tail)
Exp.1	3.429	0.870	4	21	-4.394	20	0.000
Exp.2	4.333	0.658	4	21			

Table 2: Comparison of the scoring results of the two experiments.

In the two experiments, the average scores of whether to assist the creative design of the taillight shape are greater than the score of 3 (average) and the median score are both 4, indicating that the taillight shape generation images based on both DCGAN and PGGAN are helpful to designers in the creative design of taillight shapes. Furthermore, the PGGAN-based taillight shape creative design model is better in assisting taillight shape creative design than DCGAN.

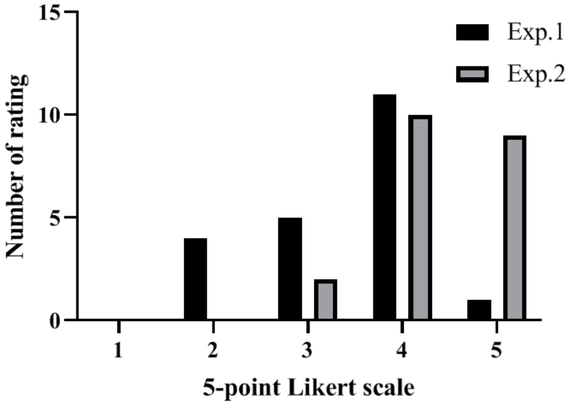


Figure 12: The ratings of all participants.

4 CONCLUSION

In this study, a deep convolutional generative adversarial network (DCGAN) and a progressive growing of generative adversarial network (PGGAN) were used to generate the creative design of taillight shapes, and the optimal creative generation model of taillight shape design was built. A dataset of high-quality vehicle taillight shape images was established, which combines safety and aesthetic taillight shape design rules and insights. The two taillight shape generation models proposed in this study demonstrated that they can both provide creative inspiration for designers; moreover, the taillight shape creative generation model based on PGGAN is superior to the taillight shape creative generation model based on DCGAN. The taillight shape creative generation design model constructed in this study is helpful for realizing efficient, diversified and innovative taillight shape generation and provides designers with rapid and sustainable preliminary design proposals and creative inspiration support.

The advantages of the generative design of taillight shapes of vehicles based on generative adversarial networks are as follows: (1) They provide a method to automatically generate the shape of taillights, which is helpful for realizing the human–machine collaborative innovation design method. Providing designers with a variety of taillight shape preliminary schemes can stimulate designers' creative inspiration and improve the productivity and reactions of designers during the vehicle design and development process, thereby increasing work efficiency. (2) The method proposed in this study could be applied to other parts of vehicle design, such as vehicle interior design, car front design and car body color design or other product design field, and help to assist the product design and development process.

Further study could center on the following: (1) Higher-quality taillight shape image datasets can be upgraded to generate taillight shape images with higher resolution, such as 1024×1024 pixels, and the value of SSIM would be increased; (2) This study is mainly focused on the preliminary exploration and application of the GAN algorithm in industrial design. However, it does not focus on the innovative structure of the algorithm. In the future, the existing taillight shape GAN model can be further improved and innovated to improve the training stability of the model and the quality of image generation. (3) Other GAN-derived structures can be studied and constructed to assist the creative design of taillight shapes. (4) Although this study showed that the generated taillight shape images can assist taillight shape creative design, the deep understanding of the effects of images on creative design assistance by different users group (e.g., student and professional designers) could be further investigated. Moreover, some comparative qualitative studies regarding the taillight shape creative design with or without the assistive tool would be further explored.

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