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AI Generative Technology-Driven Comic IP Image Character Design of Agricultural and Side Products in Jilin Province Helps Rural Revitalization Research

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ABSTRACT

In this study, generative adversarial network is used as the basic architecture, and the multi-head attention mechanism is introduced to enhance the model's ability to perceive and process image features. The image generation process is optimized by bilinear interpolation to further enhance the detail expression of character design. The generation efficiency of the model and the quality of the IP image are improved by the improved network structure. A personalized recommendation model with implicit feedback and explicit feedback is also used to achieve targeted placement of IP image characters for agricultural and sideline products cartoons. The study combines the local characteristics of Jilin Province, taking Jilin rice as an example, and designs two rice brand IP images with regional characteristics, “Rice Xiaoji and Rice Xiaoling”, which have a good migration effect. When the recommended list length is Top=10 and 20, the recommendation effect of internal diversity of Jilin rice brand reaches 83.47% and 89.09% respectively, and the recommendation effect of overall diversity reaches 88.43% and 95.31% respectively. It can be seen that the method of this paper can improve the market competitiveness of agricultural and sideline product brands in Jilin Province, which provides a technical path and practical reference for rural revitalization in Jilin Province.

Keywords: Generative Adversarial Network, Multiple Attention Mechanism, Bilinear Interpolation Method, RecGAN, Agricultural and sideline products IP image design

1. Introduction

China's quality of agriculture strategic planning pointed out that the core task of the current agricultural brand building is to create an internationally recognized iconic brand, which not only involves the enhancement of brand awareness, but also relates to the deep-level promotion of China's agricultural brand culture [1]. Exploring the cartoon IP image design of agricultural and sideline

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products in Jilin Province in the context of the times is a positive exploration to build a brand of agricultural products with regional characteristics in response to the call of the state and in combination with the geographic location and the advantages of the agricultural industry in Jilin Province [2-4]. In addition, with the advancement of globalization and the rapid development of modern science and technology, local characteristics of agricultural products gradually become an important part of regional economic development, and the sustainable development of rural revitalization can not be separated from the design of agricultural products IP image [5-8]. It not only helps to inherit and promote the cultural heritage of Jilin Province, but is also an important way to enhance the competitiveness of local agricultural brands [9-10].

In the context of the new era, the evolution of consumer demand has led to the fact that the visual presentation of traditional agricultural brands is no longer sufficient to cope with the market's pursuit of emotional and aesthetic diversity [11-12]. Successful IP image design can help strengthen the visual tension of the brand, construct an emotional bond with users, and then enhance the market recognition of the product [13-14]. The rise of AI generation technology has revolutionized this field. The traditional method of comic IP image character design requires designers to manually draw a large number of sketches and constantly experiment to find the best character proportion, details and color matching [15-17].The application of AI generation technology simplifies the process, and through deep learning algorithms, relying on the designer's cue words to generate compliant character sketches, which can be quickly adjusted to get the ideal state of the character modeling [18-20]. Not only that, AI generation technology in assisting designers to create at the same time, but also retains the designer's creative space, designers can let their own creativity through personalized editing functions to freely display [21-23]. With the help of AI generation technology to achieve brand design and strategy implementation, local characteristics of agricultural products can realize the whole chain upgrade from production to sales, and ultimately achieve the goal of industrial prosperity, farmers' income and rural revitalization.

In the IP image design process, AIGC (Artificial Intelligence Generated Content) technology is often used to generate tasks such as character design, and some scholars have analyzed its application in various fields. In the field of game creation, Li, J. et al. examined the potential application of AIGC technology in the field of game character design, by establishing a game character image generation model based on product neural network and generative adversarial network model, it can provide game character design quickly and with high quality, which significantly improves the game experience and competitiveness [24]. Mi, X. et al. investigated the AI in the field of game character design assisted design path, utilizing AIGC technology to generate game character images with cultural connotations and aesthetic characteristics, providing reference for game character creation [25].

In the field of film and television creation, Yan, H. et al. emphasize that the integration of AI technology and humanities technology plays an important role in the field of art production, and the application of AIGC technology in the film character design industry reflects the pursuit of technological innovation and also maintains the consideration of traditional art [26]. Li, X. uses generative AI technology to train the style of operatic stage costumes and design elements into a stylized LoRa model and use it to design theatrical film costumes, which can produce a relatively stable style and meet the actual needs of the costume lineup, and improve the efficiency of the film and television character design [27].

In the field of animation design, Tang, M. et al. introduced the application of AI technology in animation character design, which not only improves the efficiency, creativity, and interactivity in the character design process, but also deepens the perception and experience between animation designers and audiences, which has high practical value [28]. Park, H. evaluated the advantages of generative AI tools for character design, which simplify the character creation process through keyword extraction, information synthesis and visual creation and refinement to simplify the character creation process to accurately generate diverse character designs [29]. It is not difficult to see that AIGC technology shows great potential and advantages in IP image design in various fields, however, few scholars have studied the application of this technology in the field of agricultural product branding. Designing appropriate IP image characters for agricultural products with the help of AIGC technology not only helps to strengthen the brand value, but also injects the regional culture and spiritual qualities, and conveys the vision and values of agricultural product brands, which is of great significance.

In this study, based on Generative Adversarial Network (GAN), a multi-head attention mechanism is introduced to enhance the model's ability to capture image features. The bilinear interpolation method is used to optimize the details of image generation to make the character design more attractive. Meanwhile, the network structure is improved to effectively enhance the generation efficiency and the quality of the IP image of agricultural products. The generation effect is evaluated after quantitative analysis, including the quality of the image and the similarity of the image structure. Ablation experiments are designed to verify the effectiveness of the improvement of the multi-head self-attention technique and bilinear interpolation technique. Taking the characteristic rice of Jilin Province as the research object, we created 2 rice brand IP images with local characteristics, and analyzed the recommendation effect of agricultural and sideline products brand IP promotion and products in Jilin Province by RecGAN personalized recommendation algorithm, and helped Jilin Province to carry out rural revitalization through the agricultural products cartoon IP image character design.

2. BicycleGAN-based mathematical model of IP image of agricultural and sideline products

2.1. Generating Adversarial Networks

2.1.1. Fundamentals of generating adversarial networks. Generative Adversarial Network [30-31] consists of two neural network models: generator G and discriminator D, the process of GAN learning is the zero-sum game process of generator G and discriminator D. The overall structure of GAN is shown in Figure 1.

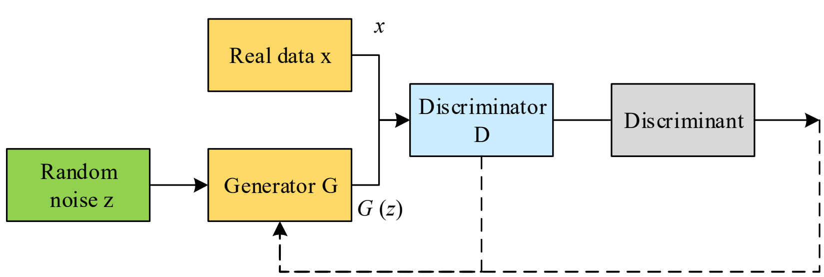


Fig. 1. Generate the basic structure of the confrontation network

The process of running a generative adversarial network can be summarized in the following three steps:

1) Input a random noise z to generator G, generator G generates a fake sample through this noise, denoted as $G(z)$. The main goal of generator G is to not allow the discriminator D to discriminate that the generated fake sample $G(z)$ is a fake sample.

2) The sample x from the real data and the fake sample $G(z)$ produced by the generator before are input to the discriminator D, and a probability value $D(x)$ is output, if the output $D(x)$ is 1, it means that the discriminator D decides that the input sample is a real sample, if the output $D(x)$ is 0, it means that the discriminator D decides that the input sample is a fake sample produced by the generator G.

3) After many alternating optimization training of generator G and discriminator D, the fake sample $G(z)$ generated by generator G becomes more and more like the real sample x, i.e., generator G and discriminator D have reached a dynamic equilibrium, which is also called Nash equilibrium.

2.1.2. Training process for generating adversarial networks. The training needs to start from discriminator D, and each training process can be summarized into two parts:

1) The function of discriminator D is to distinguish which of the received samples belong to the real samples in the dataset (positive class) and which are the fake samples generated by generator G (negative class), which are mathematically expressed as $D(x)=1$ and $D(G(z))=0$, respectively.During the training process of deep learning, the objective function of the objective function of this binary classification problem is generally structured using cross-entropy, i.e., it is of the form $\log(x)$. Thus the objective is transformed into maximizing $\log(D(x))$ and minimizing $\log(D(G(z)))$ i.e. maximizing $\log(1-D(G(z)))$. Thus the maximization objective function of discriminator D in the training process is:

$$\max_D (D,G) = E_{x\sim P_{data(x)}}[\log D(x)] + E_{z\sim P_z(z)}[\log(1-D(G(z)))] \tag{1}$$

where, $E_{x\sim P_{data(x)}}$ - real samples from real dataset; $E_{z\sim P_z(z)}$ - fake samples generated from generator G. $D(G(z))$ Discriminator D scores the fake samples $G(z)$ generated by generator G based on input noise z.

2) The function of generator G is to make the discriminator D not be able to distinguish whether the received sample is a real sample or a fake sample generated by itself, so the objective of generator G training is to maximize $D(G(z))$, according to the principle of cross-entropy is to maximize $\log(D(G(z)))$, that is, $\log(1-D(G(z)))$ is required to be minimized. In the training of generator G, the parameters of discriminator D are fixed, so the objective function does not need to have $D(x)$ related terms. The minimization objective function of generator G during training is:

$$\max_D (D,G) = E_{z\sim P_z(z)}[\log(1-D(G(z)))] \tag{2}$$

where, $E_{Z\sim P_z(z)}$ - Fake samples generated from generator G.

The total objective function of the generative adversarial network can be obtained by combining the respective objective functions of the discriminator D and generator G with each other:

$$\begin{aligned}\min_G \max_D V(D,G) = {} & E_{x\sim P_{data(x)}}[\log D(x)] \\ & + E_{z\sim P_z(z)}[\log(1-D(G(z)))]\end{aligned} \tag{3}$$

During the adversarial learning process of generator G and discriminator D, the data distributions of various types of samples at different stages are shown in Fig. 2, where (a) ~ (d) represent the very beginning stage, the optimized training of discriminator D, the optimized generator G and the final training result, respectively. The data distribution of the real sample is represented by the red dashed line, the data distribution of the generated fake sample is represented by the green dashed line, and the discrimination distribution made by the discriminator D is represented by the blue line. Several slanted lines with arrows indicate the process by which the data distribution of the fake samples generated by the random noise z is constantly approaching the data distribution of the real samples x.

(1) Is the very beginning stage, when both the discriminator D and the generator are untrained and have limited classification ability. The data distribution of the fake samples generated after receiving the input of random noise is far from the data distribution of the real samples.

(2) Fix the generator G and carry out the optimization training of the discriminator D, so that the discriminator D can more accurately identify the real samples and the fake samples, and optimize the discriminant distribution of the discriminator D.

(3) According to the optimization results of discriminator D to optimize the generator G, generator G to generate the data distribution of the fake samples closer to the real sample data distribution at the same time as the discriminator D to make the discriminatory distribution also gradually converge. $D(x)$ changes throughout the process as:

$$D^*(x) = \frac{p_{data(x)}}{p_{data(x)} + p_{g(x)}} \tag{4}$$

where $P_{data(x)}$ - refers to the real sample distribution, $P_{g(x)}$ - refers to the fake sample distribution, and $D^*(x)$ - the temporary state of $D(x)$.

(4) If the number of training times is large enough, the data distribution of the real sample and the data distribution of the fake samples are basically completely overlap, that is, $P_{g(x)}$ is more and more close to $P_{data(x)}$, $D^*(x)$ will slowly converge to 0.5, at this time, the discriminator can no longer distinguish the received samples from the real samples or from the fake samples generated by the generator 8.

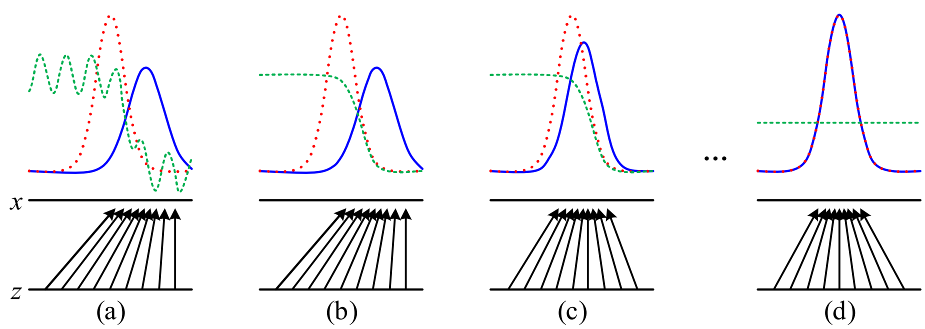


Fig. 2. GAN training hours are distributed

2.1.3. Disadvantages of generating adversarial networks. Disadvantages of generating adversarial networks:

1) Prone to model collapse problem: If the discriminator D is trained too strong, the gradient of generator G becomes very small or very large, generator G can only generate a limited number of samples after training, and most of these samples are very similar and lack diversity.

2) Non-convergence problem: For example, if there is a lot of noise that causes the image to be too blurry, then the model may not converge; Generative Adversarial Networks have a lot of parameters that need to be adjusted, such as the learning rate, the batch size, the optimizer, and so on.

3) The training time is long and the model is not easy to control: in the original generative adversarial network, generator G receives a random noise as input when generating new samples, so it is difficult to accurately control the final generated results.

4) Requires a large amount of computational resources during training: the computer configuration requirements are high, and larger models require the use of GPU or cloud computing resources.

2.2. BicycleGAN image style migration model

2.2.1. Multi-pronged self-attention mechanisms. Self-attention mechanism [32] is a mechanism that can model global dependencies within sequences, and it can play a crucial role in the design of IP image characters for agro-cartoons in this paper. Its formula is as follows:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{5}$$

The structure of self-attention is shown in Fig. 3. The multi-head self-attention mechanism consists of multiple self-attention modules, which are essentially the integration of multiple self-attention computations. Each self-attention computation is called a “head”, and different heads are independent of each other. The multi-head mechanism can learn different subspace representations of queries, keys, and values in parallel.

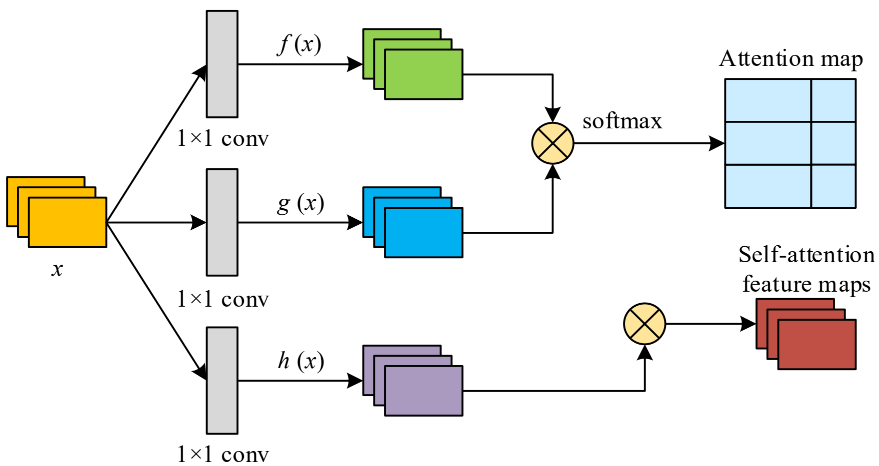


Fig. 3. Self-attention structure

The specific computational procedure of the multi-head self-attention layer is:

1) Obtain Q, K and V vectors: assume the input sequence is $X = [x_1, \ldots, x_L] \in \mathbb{R}^{L \times D}$, where L is the length of the sequence and D is the dimension of the input vector. The input sequence X is first linearly transformed, and for each x_i, its corresponding query vector $q_i \in \mathbb{R}^D$, key vector $k_i \in \mathbb{R}^D$ and value vector $v_i \in \mathbb{R}^D$ are obtained. The linear transformation process for the whole input sequence X can be expressed as follows:

$$Q = XW^Q \in \mathbb{R}^{L \times D} \tag{6}$$

$$K = XW^K \in \mathbb{R}^{L \times D} \tag{7}$$

$$V = XW^V \in \mathbb{R}^{L \times D} \tag{8}$$

where $W^Q \in \mathbb{R}^{D \times D}$, $W^K \in \mathbb{R}^{D \times D}$, $W^V \in \mathbb{R}^{D \times D}$ are learnable linear mapping matrices. Next, the vector subset $\{Q_i \in \mathbb{R}^{L \times Dh}, K_i \in \mathbb{R}^{L \times Dh}, V_i \in \mathbb{R}^{L \times Dh} \mid i = 1, 2, \ldots, H\}$ used for each head can be obtained by splitting it into H equal parts according to the number of heads along the direction of the last dimension of the mapped Q, K, V vectors, which is the dimension D of the vectors, which $D_h = \frac{D_w}{H}$ denotes the dimension of the vectors of each head for D.

2) Self-attention calculation: calculate the self-attention of each head separately, take the j th head $head_j$ as an example, the formula is:

$$head_i = Attention\left(Q_j, K_j, V_j\right) \in \mathbb{R}^{L \times Dh} \tag{9}$$

3) Multihead result fusion: multiple self-attention results are fused to obtain the final output vector Z:

$$Z = MultiHeadAttention\left(head_1 \oplus head_2 \oplus \ldots \oplus head_H\right)W \tag{10}$$

where $\oplus$ denotes a splice along the last dimension of the vector, the dimension of the spliced vector may not be equal to the dimension of the original vector D, so the matrix W^0 is multiplied here to map the vector to the original input dimension. I.e:

$$MultiHead(Q,K,V) = Concat\left(head_i,\ldots,head_h\right)W^0 \tag{11}$$

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{12}$$

To further enhance the model's ability to generate IP images of crop brands, a multi-head self-attention mechanism is used, i.e., the input features are mapped to multiple subspaces, self-attention computation is performed individually in each subspace, and finally the outputs of all heads are spliced together. This allows learning the contextual dependencies of different semantic representations of the input, such as the color of the crop brand, the texture of the IP character image, the shape of the IP character setting, etc. Due to the complexity of the CycleGAN task, the multi-head design introduces an additional model representation capability, which allows the attention module to better adapt to the semantic differences between the source and target domains, enhances the ability to model the differences in the distribution of the source and target domains, and facilitates the learning of the style migration of the IP image of the Jilin Province agricultural products brand.

2.2.2. Bilinear Interpolation. Inverse convolution in the up-sampling will lead to artifacts in the resultant image of agricultural by-products, for this problem, the sampling method of bilinear interpolation (BI) [33] is used instead of the inverse convolution, which can provide smoother sampling and avoid the artifacts problem of the inverse convolution. The principle is as follows: let the image to be up-sampled be I, whose size is $H \times W$. Scale it to obtain image I', whose size is $rH \times rW$ (r is the scaling factor). For each pixel (x, y) in I', its corresponding coordinate $\left(x', y'\right)$ in the original image I is first calculated:

$$x' = \frac{x}{r} \tag{13}$$

$$y' = \frac{y}{r} \tag{14}$$

The pixel values are then calculated by the bilinear interpolation formula:

$$\begin{aligned} I'(x,y) &= (1-\lambda x)(1-\lambda y)I\left(x'', y''\right) \\ &+ \lambda x(1-\lambda y)I\left(x'', y'+1\right) + (1-\lambda x)\lambda y I\left(x'+1, y''\right) \\ &+ \lambda x \lambda y I\left(x''+1, y''+1\right) \end{aligned} \tag{15}$$

where $\lambda x = x' - x''$, $\lambda y = y' - y''$, x'' are the coordinates obtained by rounding down x', and y'' is the coordinate obtained by rounding down y'.

2.2.3. Improving the network structure of the model:

1) Improved generator network structure. The improved IP image generator structure of agricultural and sideline product brand is based on the basic structure of the original encoder-converter-decoder, firstly, the feature image of the agricultural and sideline product brand is input as 256×256 pixels, 3 channels, the encoder adopts the form of Conv+IN+ReLU, and the 64-channel agricultural and sideline product feature image is obtained by the convolution operation in the first layer with the step length of 1, the size of convolution kernel of 7×7, and activation function of ReLU, the second layer convolution value is set to 2, the step size is 2, the convolution kernel is 3×3, and the number of

channels is 128, the third layer convolution layer value is still 2, the step size and the convolution kernel are 2 and 3×3, respectively, and the number of channels is 256. At this time, the output agro-products brand IP feature map size is $64 \times 64 \times 256$, and then by applying a 1×1 convolutional layer, the number of output channels is kept at 256 in order to downsize the channel number in the agro-products feature map. number of channels in the agricultural and sideline products feature map. A Flatten operation is used to reshape the agri-product feature map into a 4096×256 two-dimensional matrix, and then the multi-head self-attention is computed on this two-dimensional matrix. The number of heads is set to 8 and the dimension of each head is $256/8 = 32$. Finally, the outputs of all heads are spliced to obtain a representation that is still 4096×256. Later, a fully connected layer with 256 output channels is applied to adjust the feature dimensions. By integrating the information from different locations through parallel attention heads, the global information is captured to obtain greater sensory and contextual information, and more detailed features are extracted for agricultural products.

2) Discriminator network architecture. The discriminator adopts the PatchGAN architecture, and its basic idea is to segment the agricultural and sideline products input image into multiple patches, and judge the authenticity of each patch, and finally aggregate all the patch judgment results to arrive at the authenticity of the overall agricultural and sideline products image. Specifically, the PatchGAN discriminator in CycleGAN evenly slices the agricultural products image into 70×70 chunks, totaling 196 patches. The discriminator contains 4 convolutional layers, the first layer has 64 channels, convolution kernel size 4×4, and step size 2; the second layer has 128 channels, convolution kernel size 4×4, and step size 2; the third layer has 256 channels, kernel size 4×4, and step size 2; and the fourth layer has 1 channel, convolution kernel size 4×4, and step size 1. The last layer outputs the binary discrimination result for each patch. All layers use LeakyReLU activation function with a slope of 0.2, which can avoid the problem of gradient vanishing. Finally, by averaging the predicted values of all patches, the continuous authenticity prediction of the whole agricultural product image is obtained, and the loss is computed with the real labels and trained by backpropagation. This PatchGAN design processes each patch efficiently and in parallel, which preserves the local detail discrimination of the IP image of agricultural and sideline products brand and also takes into account the global judgment.

2.3. Effectiveness Analysis of BicycleGAN Modeling

2.3.1. Quantitative assessment. The comparison methods are "pix2pix, Cyclegan and CUT", three traditional style migration algorithms.

Experimental dataset: dataset 1 contains the comic IP character images of different agricultural and sideline products, and dataset 2 contains the matching images of agricultural and sideline products brand images in Jilin province obtained from Google Maps. In this research work, 800 images from datasets 1 and 2 are taken as the experimental datasets respectively, 600 images in each dataset are used as the training set and 200 images are used as the test set.

In order to objectively reflect the effectiveness of the generated images from different models, Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) metrics are used to evaluate the generated images. These two metrics are commonly used as evaluation metrics for image processing. A higher PSNR value between two images indicates less distortion between the generated image and the original image, i.e., higher quality of the generated image.SSIM reflects the similarity of the generated image to the real image in terms of brightness, contrast and structure.The closer the SSIM is to 1, the higher the similarity between the two images, which indicates that the generated image is more in line with the public's visual perception effect.

PSNR is an objective standard for evaluating the quality of color images. The calculation formula is as follows:

$$PSNR = 10\log_{10}\frac{\left(2^n-1\right)^2}{MSE} \tag{16}$$

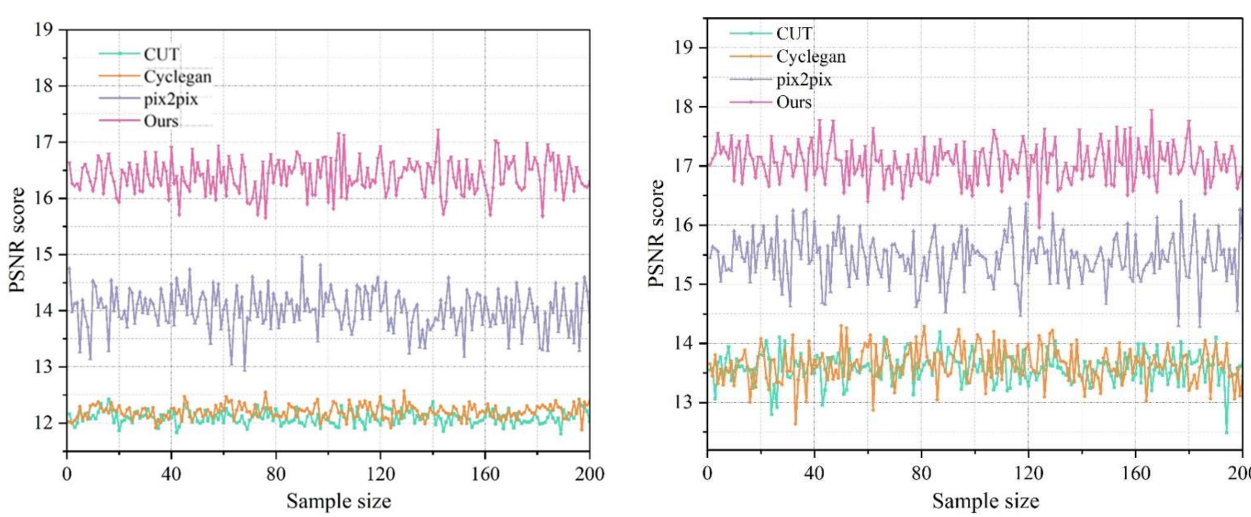
$$MSE = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W}[X(i,j)-Y(i,j)]^2 \tag{17}$$

where H and W represent the width and height of the image respectively, (i,j) represents each pixel point, n represents the number of bits of the pixel, and X and Y represent the two images respectively. Since the PSNR index also has its limitations and does not fully reflect the consistency of image quality and human visualization, the SSIM index is used for further comparison.SSIM is a measure of similarity between two images. The validity and accuracy of the algorithm is verified by comparing the model-drawn image with the original color image. The calculation formula is as follows:

$$SSIM = \frac{\left(2\mu_x\mu_y+c_1\right)\left(2\sigma_{xy}+c_2\right)}{\left(\mu_x^2\mu_y^2+c_1\right)\left(\sigma_x^2\sigma_y^2+c_2\right)} \tag{18}$$

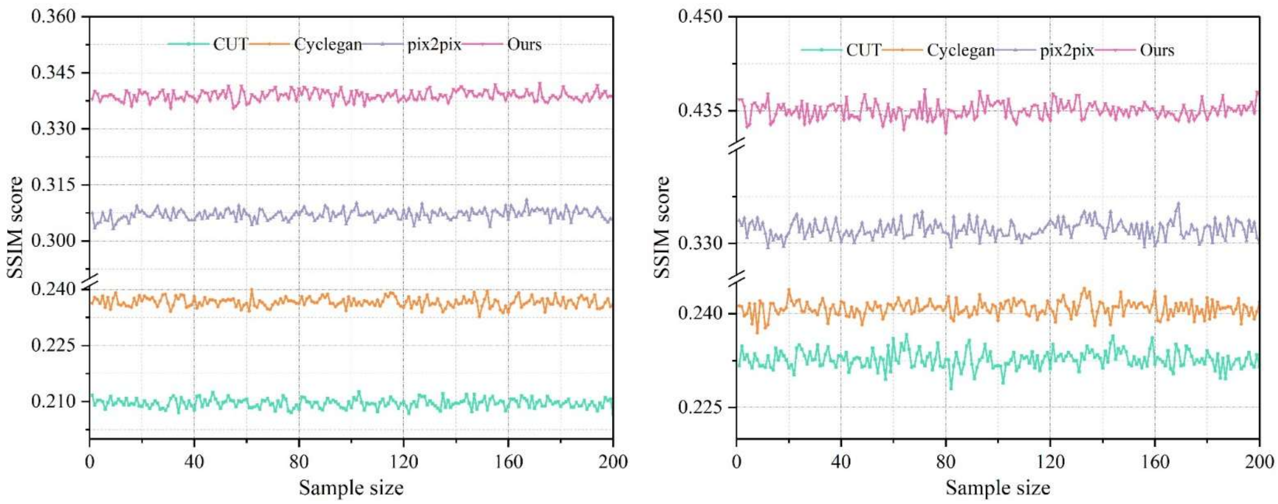
where, μ_x and μ_y denote the mean of the real and generated images respectively, σ_x^2 and σ_y^2 denote the variance of the real and generated images respectively, σ_{xy} denotes the covariance of the real and generated images, $c_1=(k_1,L)^2$ and $c_2=(k_2,L)^2$ are constants to maintain stability, L is the dynamic range of the pixel values, $k_1=0.01$, $k_2=0.03$.

The results of score comparison of PSNR under different methods are shown in Fig. 4, and the results of score comparison of SSIM under different methods are shown in Fig. 5, where (a) and (b) represent dataset 1 and dataset 2, respectively. It can be seen that the PSNR score and SSIM score of this paper's method are higher than the other three methods, indicating that the proposed method is able to generate richer and more vivid image content. On dataset 1, the mean PSNR and SSIM values of this paper's method are 2.375 dB and 0.0309 higher than the second highest pix2pix model, respectively. On dataset 2, the mean PSNR value of this paper's method is 17.36 dB and the mean SSIM value is 0.4349; 2.2094 dB and 0.1107 higher than the second highest pix2pix model, respectively. The pix2pix model enables the generator to produce agricultural products that meet both relevance and diversity, but it makes the image outline unclear when the sample size is large and it ignores the difference part between two domains. The method in this paper introduces a multi-attention mechanism to enhance the connection between distant pixels of multiple samples, which can make the style-migrated images obtain clearer edges. In terms of PSNR and SSIM metrics, the image generated by this paper's method is of higher quality, with less distortion between it and the original image. And its generated image is more similar to the real image in terms of brightness, contrast and structure.



(a)Data set 1 (b)Data set 2

Fig. 4. The results of the PSNR score in different methods

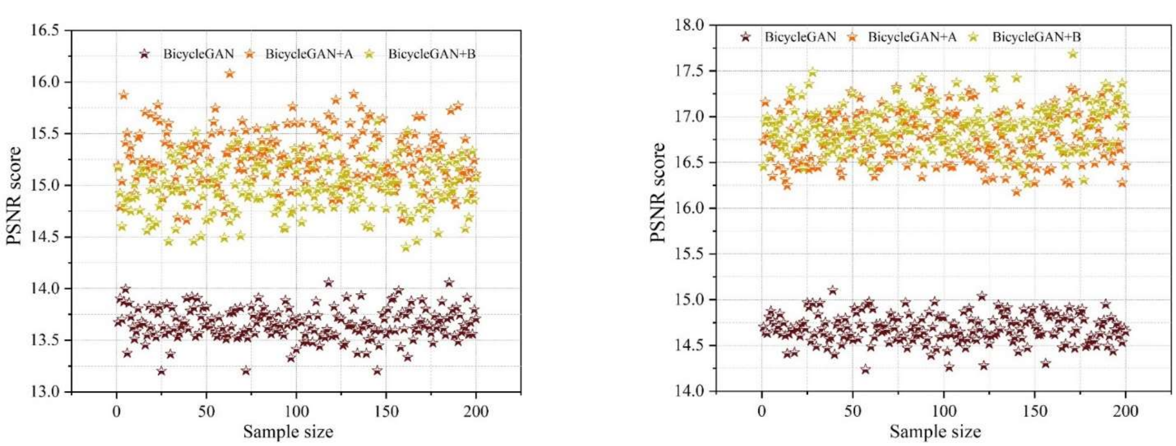


(a)Data set 1 (b)Data set 2

Fig. 5. The results of the fraction of SSIM in different methods

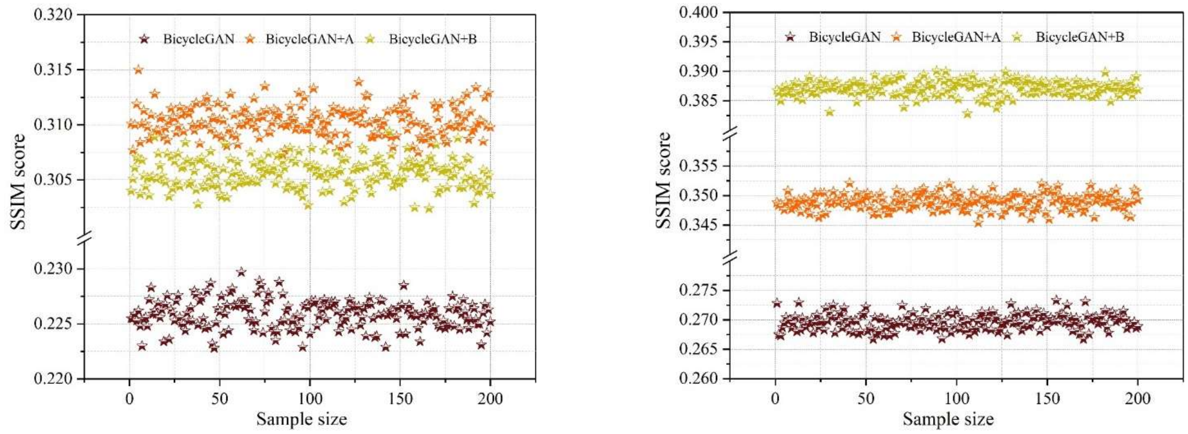
2.3.2. Ablation experiments. In order to verify the effectiveness of the multi-head self-attention mechanism and the bilinear interpolation method on the style migration effect, a set of ablation experiments are designed. The method in this paper is improved by adding self-attention mechanism, spectral normalization and perceptual loss to the original BicycleGAN. The experiments are carried out using the control variable method, and the 2 improvement schemes of the multi-head self-attention mechanism, and the bilinear interpolation method are named A and B respectively, and 3 sets of experiments are designed for comparison.

The comparison results of PSNR scores of ablation experiments are shown in Fig. 6, and the comparison results of SSIM scores of ablation experiments are shown in Fig. 7, where (a) and (b) represent dataset 1 and dataset 2, respectively. It can be seen that the improvement of both the multi-head self-attention mechanism and the bilinear interpolation method helps to improve the PSNR and SSIM scores on both dataset 1 and dataset 2, and there is a significant increase in the effect of improving the image style migration. It shows that the bilinear interpolation method is effective in improving the quality and fidelity of image style migration, and the images generated by using the method of this paper are more realistic and the details of the style migrated images are richer.



(a)Data set 1 (b)Data set 2

Fig. 6. The comparison results of the experiment PSNR score



(a)Data set 1 (b)Data set 2

Fig. 7. The results of the analysis of the SSIM scores of the ablation experiment

3. AI-driven IP design and recommendation effect of agricultural and sideline products in Jilin Province

3.1. IP Image Design for Agricultural Product Brands in Jilin Province

This paper takes rice in Jilin Province as an example to develop the design of its agricultural products comic IP image characters.

3.1.1. IP Image Design Positioning:

1) Brand culture connotation positioning. Jilin's excellent regional public brand Jilin rice has a long history, which is a natural topic for government propaganda to increase trust. In the brand narrative part, Jilin rice has a long history of background stories, Emperor Kang Xi second east patrol, ate rice in the Songhua River basin, it will be sealed only for the royal family to enjoy the "Tribute Rice", enough to the core values of the Jilin rice brand close to the quality of the representative of the rice. The Jilin provincial government can amplify the brand characteristics of Jilin rice publicity, choose the characteristics that distinguish it from similar agricultural products, apply the aura of historical stories, the "emperor certification" and the quality of the qualities as a binding impression of the words appear, deepen the positive subconscious impression of consumers on the brand, so that consumers in the purchase of the product to receive product information, suggestive effect. This deepens consumers' positive subconscious impression of the brand and makes them receive the product's implied effect when buying the product.

2) Layered positioning of sales targets. Under the same type of brand needs different levels of products to meet the needs of more consumers, Jilin rice as a necessity of life, can be appropriate to break through the inherent thinking of solving the problem of food and clothing, the quality of life and the details of life information into the value of the product, to create a multi-level product categories for consumers, to enrich the different consumer demand, such as cost-effective high quality rice and the convenience of the exquisite between the petit package, it is can simultaneously meet the needs of middle-aged and young people's lives.

3) Use of media to promote brand development. At present, Jilin rice has not appeared in the traditional official media with high influence in terms of traditional media publicity. Prior to this, Wuchang rice also chose the famous variety show "XXX", which shows that Wuchang rice has a rich choice of paths in brand promotion, and has invested a huge amount of money in the process of branding, accumulating fame, laying a good foundation for the future development of the enterprise and its brand, and bringing lucrative potential benefits.

4) Brand differentiation and positioning. The development of Jilin rice and Jilin fresh corn relies more on government promotion. With the intensification of agricultural brand competition, differentiated positioning plays a positive role in enhancing brand competitiveness, such as brand image differentiation to create, product differentiation in production, differentiation of publicity methods, etc., which is the most obvious way to enhance brand image. Agricultural products have similar natural characteristics, and rice and corn are not the unique crops of Jilin, so there is a strong need to Therefore, it is urgent to find new angles to enhance brand uniqueness.

3.1.2. Jilin Rice IP Styling Refinement. In terms of species selection for IP image, there are four common ways. First, capture the species information already contained in the brand name; second, capture the brand positioning keywords; third, capture the brand product features; fourth, capture the brand LOGO features. The design methods are all based on the retention of species prototypes for artistic processing, and can be combined with clothing and accessories and other elements to enhance the expression of the character characteristics. This paper mainly adopts the method of "capturing brand positioning keywords" to complete the selection of IP species. On the basis of the preliminary research on Jilin rice brand and brand target users' preferences, two rice images that can reflect the green and safe Jilin rice brand tone and meet the consumers' demand for cute and warm IP images are selected for the character processing of the cartoon IP image.

The IP image combines traditional and modern elements, combines the brand characteristics and culture of "Jilin rice" to create a 3D IP image, and the overall design style of the popular "moe" elements, to create a cute and adorable IP image that heals people's hearts and induces consumers' emotions and stirs up their hearts and minds. The overall design style is popular with "cute" elements, creating a cute and cuddly IP image that heals people's hearts, induces consumers' emotions, and stirs up their hearts and minds. Considering the brand recognition and the accuracy of information dissemination, IP image design is generally based on the retention of species prototypes for artistic processing, combined with brand characteristics and culture to create a unique IP image, to strengthen the recognition and memory of the visual image.

3.1.3. Character Design of Jilin Rice Brand IP Image:

1) Rice Xiaoji. Image design: the shape is a round and lovely image of a rice grain, the head is a full grain of rice, the body is small, the limbs are short, the overall color tone is white and light yellow, symbolizing the purity and high quality of Jilin rice. Dressed in a traditional northeastern flower cotton jacket, the head wears a small hat with a snowflake pattern characteristic of Jilin, reflecting the regional culture of Jilin Province.

Lively, cheerful and energetic, he likes to dance and sing, symbolizing the warmth and affinity of Jilin rice.

Background story: Mi Xiaoji is the guardian spirit of Jilin rice, growing in the rice fields at the foot of Changbai Mountain. His daily task is to guard the rice fields and make sure that every grain of rice is full and sweet. He enjoys working with the farmers and introducing the story of Jilin Rice to visitors.

2) Rice Little Spirit. Image design: the shape is a light and agile rice sprite, the body consists of a bunch of golden rice ears, the head is a crystal grain of rice, the eyes are big and bright, the overall tone is

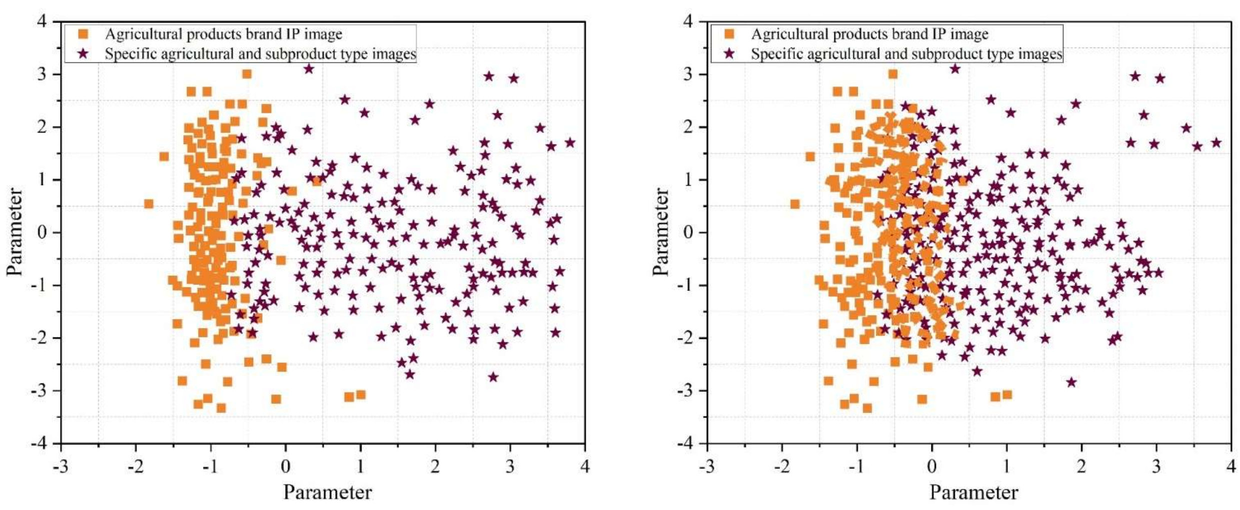
golden yellow and green, symbolizing the harvest and vitality. Wearing a lightweight green cloak with a pattern of rice ears on it, and a pair of small boots with the Changbai Mountain pattern logo. The character is a smart mechanism that likes to explore and adventure, symbolizing the nature and health of Jilin rice.

Backstory: Rice Little Spirit is the wise spirit of the rice field, she has the magical power to make the rice grow fast. She likes to travel through the rice fields to help the farmers solve their planting problems, and she also likes to tell children stories about the growth of rice.

3.2. Effect of IP Image Migration of Agricultural Product Brands in Jilin Province

The starting point of the deep feature migration method is to achieve the migration of image content through the migration of features, in order to intuitively illustrate the method in this paper, we use the visualization of the distribution of image features before and after the migration to illustrate. We use the discriminator used in the domain of agricultural and sideline products in the trained model as the model for image feature extraction to obtain the feature vector of the image. The output of the discriminator is a 30×30 probability matrix, which is used as the feature of the image in the discriminator. Afterwards, the image features before and after the carving are subjected to principal component analysis, and the image feature distribution is obtained by downscaling to a 2-dimensional plane.

The feature distribution of the image before and after the narrowing is shown in Figure 8, where (a) represents the feature distribution of the original image and (b) represents the feature distribution of the narrowed image. It can be intuitively seen that the real agricultural and sideline product brand IP image and the real specific agricultural and sideline product type image are linearly separable in the space of the discriminator. After migration, the feature distribution of the brand IP image gradually converges to the feature distribution of the specific agricultural and sideline product types, and becomes less distinguishable.

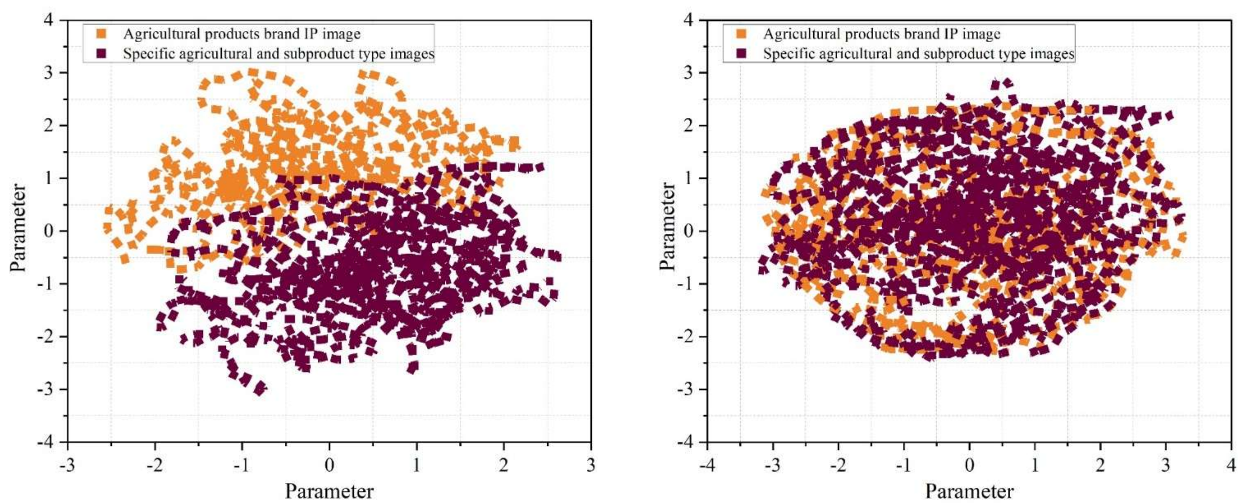


(a)The characteristics of the original image (b)The characteristics of the migration image

Fig. 8. The image is distributed in the discriminator

If the BicycleGAN-based pre-trained Flatten is used as the model for feature extraction, and the reshape processed vectors are taken as the feature vectors of the images, the distribution results of the images before and after the migration in the feature space of Flatten are shown in Fig. 9, where (a) represents the feature distribution of the original image and (b) represents the feature distribution of the migrated image. The two real image collections of agricultural and sideline product brand IP and specific agricultural and sideline product types are linearly divisible two clusters in Flatten's feature space. After migration, the distributions of the generated brand IP image and the specific agricultural product category image in Flatten's feature space almost overlap. This indicates that the generated brand IP image has the image features of the specific agricultural and sideline product category and has a similar distribution with the features of the specific agricultural and sideline product category image, thus becoming linearly indistinguishable from the specific agricultural and sideline product category image in the feature space in the classification network.

Since the discriminator dynamically learns from the brand IP images of agricultural and sideline products and synthetic images of agricultural and sideline products, the generated images of agricultural and sideline products cannot completely “deceive” the discriminator; whereas Flatten learns from the samples of real brand IPs and specific agricultural and sideline products, and therefore generates specific images of agricultural and sideline products from a distributional perspective. Flatten learns from real brand IPs and specific agricultural product types, and therefore generates specific agricultural product types images that can almost completely “deceive” the classifier in terms of distribution.



(a)The characteristics of the original image (b)The characteristics of the migration image

Fig. 9. The image is distributed in the flatten feature space

3.3. Case study of agricultural and sideline products recommendation in Jilin Province

3.3.1. RecGAN-based personalized recommendation:

1) Personalized recommendation model based on implicit feedback. The goal of the RecSimu model is to simulate the behavior of real users and then use the simulation results to train and evaluate other recommendation algorithms. The main idea of the model is to use Generator G to learn the user's current preferences from the user's browsing history and predict the agricultural products that the user may be interested in, and Discriminator D not only distinguishes whether the input recommended agricultural products are real or predicted by Generator G, but also outputs the user's feedback on the recommended agricultural products.

2) Personalized recommendation model based on explicit feedback. CoFiGAN, a collaborative filtering model incorporating GAN, is similar to IRGAN applied in the field of information retrieval, in which generator G generates false data similar to the real data, and discriminator D discriminates whether the data is real or false. Considering the discrete nature of the data, discriminator D directly guides the training of generator G by specifying positive and negative samples.The overall optimization objective of CoFiGAN is shown below:

$$J^{\theta^*,\phi^*} = \min_\theta \max_\phi \sum_{u=1}^{n} (\mathrm{E}_{i\sim p_{true}}[logD(i\,|\,u) + \mathrm{E}_{d\sim p_\theta(i|u)}[log(1-D(i\,|\,u))] \tag{19}$$

In the above equation $d \sim p_\theta(i\,|\,u)$ represents the probability distribution of the agricultural product sampled by user u, p_{true} represents the distribution of user u's true preferences, and the output of $D(i\,|\,u)$ represents the probability that the agricultural product i belongs to user u's true preference distribution. Because the real data is discrete, it is not possible to optimize G using gradient descent method i.e:

$$\theta^* = argmin\sum_{\theta}^{n}(\mathrm{E}_{S^G\sim p_\theta(S|u)}[Dist(S^G, S^D)]) \tag{20}$$

where: S^σ is the positive sample generated by G, S^D is the positive sample considered by D. The distance function $Dist(S^G, S^D)$ is used to measure the gap between S^G and S^D. The smaller the gap is, the better the rewards obtained by G and the closer the generated S^σ is to the real data.

3) Personalized recommendation model based on implicit feedback and explicit feedback. RecGAN effectively simulates the long and short-term behaviors of users and the potential characteristics of agricultural and sideline products in Jilin Province, which improves the recommendation effect. The overall optimization formula of the model is as follows:

$$\begin{aligned} &Q^* = min\max_{Gen}\max_{Dis} V(D,G) \\ &= \Sigma_{t=1}^{T}\Sigma_{i=1}^{N}\Sigma_{j=1}^{M}\mathrm{E}_{r\sim D(r|i,j)_{real|t}}[logDis(r\,|\,i,j,t)] \\ &+\mathrm{E}_{r\sim D(r|i,j)_{gen|t}}[log(1-Dis(r\,|\,i,j,t))]) \end{aligned} \tag{21}$$

Gen and Dis represent the generator and discriminator respectively, i represents the i nd user, j represents the j th agro-product, and t represents the t th moment.The Gen-generated ratings of the user i on the item j at moment t are denoted by $(r\,|\,i,j,t)$, the learned user preference distribution is denoted by $D_{gen|t}$, and the user's true preference distribution is denoted by $D_{real|t}$.

In this paper, a personalized recommendation model (RecGAN) based on implicit feedback and explicit feedback is adopted to complete the recommendation of the following content from the perspective of helping rural revitalization through the cartoon IP image character design of agricultural and sideline products in Jilin Province.

Datasets: In this paper, three mainstream datasets of agricultural and sideline products in Jilin Province, namely Jilin rice, Jilin corn and Jilin black fungus, are selected to evaluate the performance of the algorithm. Each dataset consists of two parts: dataset S1 contains users, agricultural and sideline products, ratings, etc., and dataset S2 contains agricultural and sideline products' metadata information, and in this paper, category, price, and brand are selected as the attributes of agricultural and sideline products. The category attribute consists of multiple words, and through observation, it is found that the word coverage level is from large to small, and the 2nd level is selected as the final category attribute. The data in each dataset will be used 80% for training and 20% for testing.

Comparison methods:

1) Drmud: a diversity recommendation method based on user preferences and dynamic interests, which improves the traditional matrix decomposition algorithm, introduces a time decay function to dynamically adjust the user ratings, and integrates the fatigue function of agricultural and sideline products with matrix decomposition, thus increasing the recommendation of cold products to improve diversity.

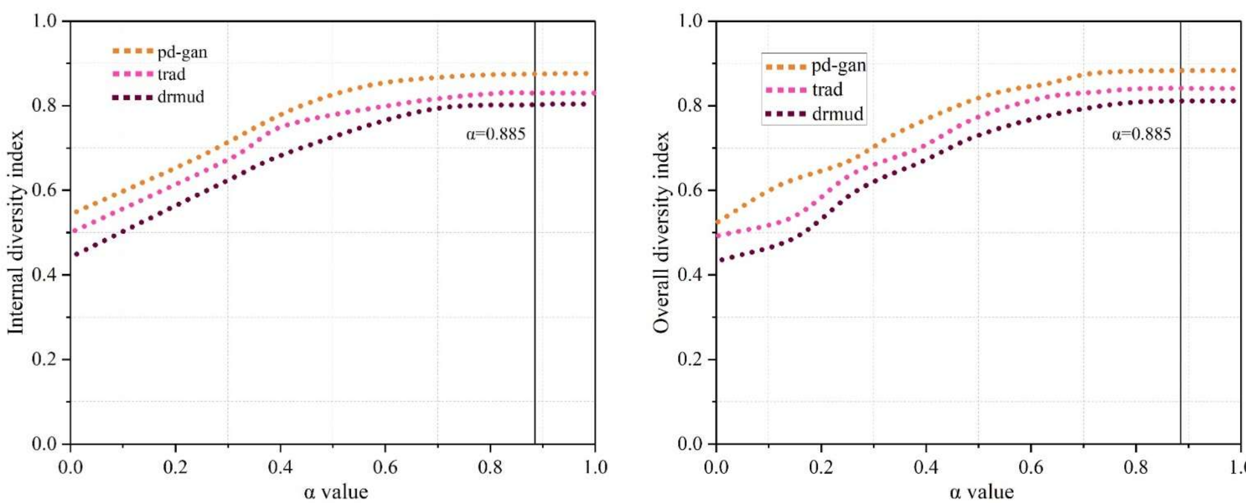
2) trad: an adaptive trust-aware recommendation method for user agricultural and sideline products bipartite graph, utilizing the trust relationship between users to quantify user diversity

needs, which makes it possible to reduce the resources for popular agricultural and sideline products and increase the resource transfer for trusting users in the process of resource allocation.

3) pd-gan: combining the DPP algorithm with a generative adversarial network to simultaneously learn user preferences for a single item and diversity preferences for a set of items, making the generator-generated agricultural by-products conform to relevance as well as reflect diversity.

3.3.2. Diversity analysis. For the category generator, it focuses on all the agricultural and sideline product categories, so that the final recommended agricultural and sideline products cover a sufficiently rich variety. For the brand generator, considering the user demand, the percentage of brands that have not interacted is set to α, and the percentage of brands that have interacted is set to 1 - α.

In order to choose the appropriate α value in the brand generator, the length of the recommendation list is selected to be 15 for the experiment, and the results of the distribution of the α value of the brand generator are shown in Fig. 10, where (a) and (b) represent the results of the distribution on the internal diversity and the overall diversity, respectively. It is reasonable that the larger the α value is, the more diverse the final recommended agricultural and sideline products are, but it is found that the diversity indicator no longer rises when α > 0.885. By analyzing the dataset, it is found that each brand contains multiple categories of agricultural and sideline products, and for new brands, the categories of agricultural and sideline products it includes have already appeared in previous brands, so it does not result in a further increase in diversity. At the same time, the brands that users have interacted with represent the user's brand preferences, which should be reflected in the final recommended brands.



(a)Internal diversity (b)Overall diversity

Fig. 10. Distribution of the brand generator α value

The performance of this paper's method and the comparison method on diversity indexes is shown in Table 1, and the Top-N list lengths of 10 and 20 were selected to conduct experiments on three datasets, respectively. The results show that the diversity recommendation performance of all the methods proposed in this paper is better than the other methods, in which the best results are achieved due to the fact that the Jilin rice dataset has the largest variety of agricultural and sideline products. In contrast, Drmud, which improves the traditional matrix decomposition algorithm, is found to be overall ineffective in diversity recommendation performance, due to the fact that it only improves the recommendation proportion of cold agricultural and sideline products, and does not help much in the category diversity of the overall recommendation list.

Material diffusion algorithm is currently the basis of most diversity recommendation algorithms selected, trad through the establishment of trusted users to enhance the resources allocated by trusted users to achieve the purpose of diversity recommendation. The process is the transfer of resources from users to agro-products and then to users, and the enhancement of diversity by boosting the weight of resource transfer in a certain step exists one-sidedness and is not enough to apply to every user.

The Pd-gan method introduces the game idea of GAN into the field of diversity recommendation, and maximizes the probability of dissimilarity of recommended agricultural and sideline products through the DPP probability model, so as to achieve the purpose of diversity, but the diversity should not only include the dissimilarity between agricultural and sideline products, but also include the diversity of attributes and so on.

The method proposed in this paper focuses on different attributes of agricultural and sideline products through different generators, and each generator is aimed at diversity, which not only realizes the diversity of categories but also the diversity of brands, and at the same time analyzes the user's price demand to meet the user's consumption level, so that the final recommended list not only meets the user's needs, but also recommends a rich variety of agricultural and sideline products, whether for individuals or between users, the recommended Agricultural products can achieve the purpose of diversity.

Table 1. The method and comparison method in the diversity index

Data set	Method	Top=10		Top=20	
		Internal diversity	Overall diversity	Internal diversity	Overall diversity
Jilin rice	Drmud	0.3393	0.4443	0.3954	0.5107
	Trad	0.5473	0.6867	0.5922	0.6931
	Pd-gan	0.6703	0.7011	0.6847	0.788
	Ours	0.8347	0.8843	0.8909	0.9531
Jilin corn	Drmud	0.3513	0.4385	0.4041	0.4763
	Trad	0.5563	0.6663	0.5932	0.7211
	Pd-gan	0.6841	0.7011	0.6952	0.7942
	Ours	0.8012	0.8769	0.8309	0.9001
Jilin black fungus	Drmud	0.3487	0.4567	0.4058	0.4796
	Trad	0.553	0.6873	0.6045	0.6914
	Pd-gan	0.6732	0.7067	0.6933	0.7875
	Ours	0.8059	0.8879	0.8848	0.9344

3.3.3. Accuracy analysis. The method in this paper aims at diversity recommendation and takes accuracy into account. In order to improve the diversity of recommendation results without decreasing the accuracy, we consider the combination of user needs. The method in this paper fully considers the user's needs in terms of diversity and accuracy in the brand generator and the price generator. For the brand generator, the brands of agricultural and sideline products that the user has purchased and the brands of agricultural and sideline products that the user has not purchased are analyzed at the same time, so that they are recommended according to the optimal ratio. For the price generator, it is divided by the category of agricultural and sideline products, and analyzes the ratio of high-priced agricultural and sideline products to low-priced agricultural and sideline products purchased by the users in that category, so that the prices of the final recommended agricultural and sideline products are in line with the consumption habits of the users.

In order to verify whether the consideration of user needs is helpful to improve the accuracy of recommendation, experiment 2 selects Jilin corn dataset to conduct comparison experiments on the accuracy index recall, and the length of the recommendation list is selected as 10 and 20. The accuracy comparison results of different methods are shown in Fig. 11, and the results of the recommendation combined with the user's needs are indeed improved in terms of accuracy when compared with other methods. Because the consideration of user needs can make the recommendation results more catering to user preferences, whether it is the user's choice of brands of agricultural and sideline products or the consumption habits of the price, it can be done according to the person, to meet the needs of different users, and to realize the recommendation that takes into account the accuracy and diversity. It can be seen that the IP image promotion of agricultural and sideline products constructed by the method proposed in this paper enhances the popularity of agricultural products, is chosen by more users, and provides a great help to the best-selling agricultural and sideline products and rural revitalization in Jilin Province.

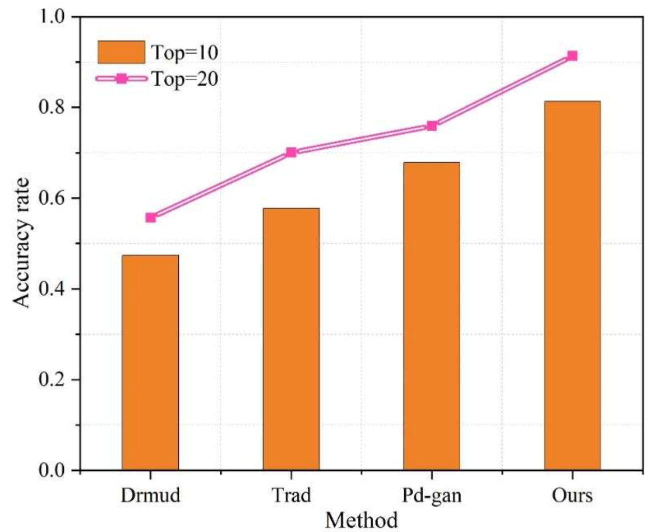


Fig. 11. Comparison results of different methods

3.4. *Agricultural products cartoon IP image character design to help rural revitalization*

One of the key material bases for rural revitalization lies in agricultural products, and the foundation of industrial revitalization is the upgrading of agricultural development, which requires major ideological upgrading and reality testing. Adopting the three strategies of designing and promoting the empowerment of agricultural products by socialist civilization, designing and promoting the creation of agricultural products with special characteristics, and designing and promoting the service of agricultural products by the network can effectively promote the renaissance of rural production, the renaissance of civilization, the renaissance of the community system, and the renaissance of environment and education revitalization.

In order to increase the value of agricultural products, their intrinsic value must be reflected in their interaction with consumers. Design and culture are symbiotic in rural revitalization. By adopting the cultural empowerment strategy of art-driven rural development, the cultural added value of agricultural products can be effectively increased, and the persuasive function of agricultural culture can then be used to realize the cultural value of agricultural products. The regional design of IP image of agricultural and sideline products brand by combining local characteristics and market demand, product packaging positioning, and put forward the marketing concept, and then visual creativity, so as to drive the marketing of agricultural products, and then help the local rural revitalization development.

4. Conclusion

Taking agricultural and sideline products in Jilin Province as the research object, this paper proposes an improved generative adversarial network based on multi-head self-attention and bilinear interpolation method for the design of cartoon IP image characters of agricultural and sideline products in Jilin Province, which helps local rural revitalization. The results show that:

1) The BicycleGAN method proposed in this paper improves the quality of image generation and visual effect compared with the traditional “pix2pix, Cyclegan, CUT” style migration model; when the recommendation list is 15, the average values of PSNR score and SSIM score can be improved by 26.14% and 46.4% respectively compared with the traditional method. When the recommendation list is 15, the average values of PSNR score and SSIM score can be maximized by 26.14% and 46.55% than the traditional method.

2) According to the method proposed in this paper, we design two rice brands with the characteristics of Jilin Province from the image and character of agricultural and sideline products as well as regional characteristics, with the brand names of “Rice Xiaoji and Rice Xiaoling”, and elaborate the story background of the brand's creation, so as to pave the way for the promotion of the brand.

3) The personalized recommendation method based on RecGAN proposed in this paper helps to analyze the diversity of users at the multi-attribute level, and the incorporation of user needs will further improve the accuracy of recommendation while meeting the diversity of recommendation, providing technical support for the promotion of agricultural and sideline products and the revitalization of the countryside.

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References

[1] Hongqin, W. A. N. G., Lijia, W. A. N. G., Chen, L. I. U., & Yanling, J. I. A. N. G. (2022). Brand Building of Agricultural Products in China: A Review. Journal of Agriculture, 12(12), 76.

[2] Chunying, W. (2024). Exploration of Brand IP Strategy for Geographical Indication Agricultural Products of Rice in Jilin Province. Academic Journal of Humanities & Social Sciences, 7(8), 188-192.

[3] Wang, Q., & Tai, Y. (2023). Study on Countermeasures for Regional Brand of Agricultural Products Embedding Regional Cultural Elements. Frontiers in Business, Economics and Management, 9(2), 153-156.

[4] Zhang, L., Zhao, Z., Zhang, J., & Ding, L. (2020, January). Research on the strategic choice of brand development of agricultural products in Jilin Province driven by financial service innovation. In 2019 International Conference on Management Science and Industrial Economy (MSIE 2019) (pp. 328-331). Atlantis Press.

[5] Liu, K., & Lu, H. (2020, December). Research on the design and development of animation cultural and creative products in Jilin province under the Internet big data. In IOP Conference Series: Earth and Environmental Science (Vol. 619, No. 1, p. 012074). IOP Publishing.

[6] Luo, S., Ma, Y., & Wang, T. (2023). What Determinants Will Enhance or Constrain the Spatiality of Agricultural Products with Geographical Indications in Northeast China? An Interpretable Learning Approach. ISPRS International Journal of Geo-Information, 12(11), 442.

[7] Liu, L., Zhang, F., & Yang, Y. (2019, April). Study on the Influence of Agricultural Eco-Environment on the Competitiveness of Agricultural Products E-Commerce Brands in Jilin Province. In IOP Conference Series: Earth and Environmental Science (Vol. 252, No. 5, p. 052056). IOP Publishing.

[8] Zhang, Q., Xie, Y., Ma, S., & Yang, S. (2022). Discussion on Creative Design of Art and Design for Rural Revitalisation. World Scientific Research Journal, 8(10), 155-161.

[9] Qiu, L., Ahmad, R. A. R., & Dolah, M. S. B. (2024). Innovative design of agricultural tourism souvenirs to promote the inheritance and promotion of intangible cultural heritage. Pakistan Journal of Agricultural Sciences, 61(1), 359.

[10] Peng, H., Yang, F., & Yue, O. (2024). How Rural Industry Revitalization Affects Farmers' Incomes in China. Sustainability, 16(21), 9182.

[11] Chen, T., Pang, B., Ma, C., & Shao, W. (2024). Exploration of Brand Visual Communication Innovation Design Method Based on AIGC Technology. Procedia Computer Science, 247, 519-528.

[12] Kwaku, A. R., & Fan, Q. (2020). Effect of good product design and packaging on market value and the performance of agricultural products in the Ghanaian market. Open Access Library Journal, 7(9), 1-14.

[13] Liao, Y., Chen, M., Wu, J., & Huang, S. (2021). Analysis on the Marketing Strategy of Regional IP Brands. JOURNAL OF SIMULATION, 9(1), 1.

[14] Chien, H. H., & Huei, H. S. (2024). Research on the packaging design of local cultural specialties in Taiwan—taking Chiayi Xingang Candies as an example. In System Innovation for an Artificial Intelligence Era (pp. 279-286). CRC Press.

[15] Zhan, Q., & Khiatthong, T. (2024). The Cartoon IP Image Design and Management Strategies for Guilin Cultural Tourism Brands in China. Journal of Roi Kaensarn Academi, 9(12), 3451-3463.

[16] Wei, X., & Zhang, S. (2021, January). Analysis on the application of cartoon characters in brand image design. In The 6th International Conference on Arts, Design and Contemporary Education (ICADCE 2020) (pp. 688-692). Atlantis Press.

[17] Li, Q. L., Huang, X. Y., & Xu, J. L. (2022). The Characteristics of Cartoon IP Images in the New Media Context. In Knowledge Innovation on Design and Culture: Proceedings of the 3rd IEEE International Conference on Knowledge Innovation and Invention 2020 (IEEE ICKII 2020) (pp. 335-338).

[18] Wang, Y., Wang, Z., & Mu, R. (2024). Modern Design Thinking and AIGC Intervention. In Design Studies and Intelligence Engineering (pp. 850-862). IOS Press.

[19] Huang, K. L., Liu, Y. C., Dong, M. Q., & Lu, C. C. (2024). Integrating AIGC into product design ideation teaching: An empirical study on self-efficacy and learning outcomes. Learning and Instruction, 92, 101929.

[20] Jin, J., Yang, M., Hu, H., Guo, X., Luo, J., & Liu, Y. (2025). Empowering design innovation using AI-generated content. Journal of Engineering Design, 36(1), 1-18.

[21] Wang, S. F., & Chen, C. C. (2024). Explore the driving factors of designers' AIGC usage behavior based on SOR framework. Frontiers in Computer Science, 6, 1417016.

[22] Shreyas, S., Elangovan, S., Viknesh, G., Mitra, S., Unjhawala, H. M., Kumar, N., ... & Nandigana, V. V. R. (2021). Product Design of Cartoon Characters for Software Feature Film. American Journal of Software Engineering and Applications, 10(2), 36-38.

[23] Lin, Y., & Liu, H. (2024, June). The Impact of Artificial Intelligence Generated Content Driven Graphic Design Tools on Creative Thinking of Designers. In International Conference on Human-Computer Interaction (pp. 258-272). Cham: Springer Nature Switzerland.

[24] Li, J., & Liu, Q. (2024). Application of Generative Artificial Intelligence AIGC Technology Under Neural Network Algorithm in Game Character Art Design. Journal of the Knowledge Economy, 1-32.

[25] Mi, X., Cao, Y., & Li, Q. (2023, October). The Application Path of AIGC in Assisting Game Character Design-A Case Study of the Black Bear Monster from Journey to the West. In 2023 4th International Conference on Intelligent Design (ICID) (pp. 275-282). IEEE.

[26] Yan, H., Tan, S., Zhang, K., & Wang, D. (2024). A New Paradigm for Contemporary Film and Television Characters Design in the Context of Artificial Intelligence. Advances in Education, Humanities and Social Science Research, 11(1), 194-194.

[27] Li, X. (2024). Innovative Design Applications of AIGC in Costume Design for Drama and Film: A case study of opera Turandot. Advances in Engineering Technology Research, 12(1), 615-615.

[28] Tang, M., & Chen, Y. (2024). AI and animated character design: efficiency, creativity, interactivity. The Frontiers of Society, Science and Technology, 6(1).

[29] Park, H. (2024, June). Researching Character Design with Generative AI: –Focusing on Creating Five Probiotic Characters. In International Conference on Human-Computer Interaction (pp. 249-256). Cham: Springer Nature Switzerland.

[30] Xiaoying Pan,Han Chen,Zizheng Zhang & Wulin Wen. (2025). NBIGAN: Automatic nasopharyngeal white light and narrow band imaging transformation based on feature aggregation and perceptual generative adversarial networks. Expert Systems With Applications126509-126509.

[31] Zhongyuan Qin,Jiarong Fan,Xujian Liu,Zeru Li & Xin Sun. (2025). Effective fuzzing testcase generation based on variational auto-encoder generative adversarial network. Engineering Applications of Artificial Intelligence110094-110094.

[32] Jiawei E,Yinglong Zhang,Xuewen Xia & Xing Xu. (2025). TANGNN: A concise, scalable and effective graph neural networks with Top-m attention mechanism for graph representation learning. Expert Systems With Applications126599-126599.

[33] Muhammmad Bilal,Zahid Ullah,Omer Mujahid & Tama Fouzder. (2024). Fast Linde–Buzo–Gray (FLBG) Algorithm for Image Compression through Rescaling Using Bilinear Interpolation. Journal of Imaging(5),124-.