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Research on Automatic Generation and Presentation of Visual Symbols in Poster Design in Streaming Media Era Based on Image Recognition and Segmentation Algorithm

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Abstract It has become common for AI techniques to generate visual symbols to provide inspiration for designers. Therefore, in this paper, two attention mechanism modules, SE and CA, are integrated into the FPN feature network to propose an improved visual symbol recognition algorithm. Structural improvements are made in the original style migration network, and style migration is utilized for visual symbol generation. Combining the recognition and style migration algorithms, an intelligent design system for streaming media posters is established. It can meet the requirements of easy and fast poster generation and real-time presentation. The results of simulation experiments show that the improved algorithm converges faster than the original algorithm loss function, and the number of training times is less. The recognition rate of both the improved visual symbol detection and style migration algorithms can reach more than 86%, with good recognition effect. The mean values of the streaming posters designed by applying the method of this paper are all above 3.6 points in the four aspects of symbol location appropriateness, overall color harmony, text readability and design creativity, respectively. Therefore, the design results have location diversity, color diversity, aesthetic properties and creativity.

Index Terms attention mechanism, style migration, visual symbols, recognition algorithm

I. Introduction

In today's society, poster design has become an important way of publicity, and the application of visual symbols plays an important role in poster design [1], [2]. Visual symbols can attract the audience's eyes, convey information, and evoke emotional resonance, thus improving the promotional effect of posters [3], [4]. Designers need to properly utilize the skills of visual symbols, striving to convey information in a concise and clear manner and echoing the theme of the poster [5], [6]. Through continuous practice and experience accumulation, designers are able to make better use of visual symbols and create more attractive and expressive posters [7], [8]. And in the context of the streaming media era, the automatic generation of visual symbols has become the mainstream form of poster design [9]. Under the background of streaming media, the way of information dissemination is changing day by day, and the emergence of new media changes the way of dissemination that used to rely mainly on traditional media such as paper and broadcasting, which influences people's way of life and improves the speed of receiving information dramatically [10]-[13]. As far as visual communication design is concerned, the impact of emerging media is the most extensive [14], [15]. Posters that used to be posted only on bulletin boards and poster boards can be disseminated through digital media, traditional two-dimensional graphic design can be transformed into a multidimensional animation mode, and packaging can be used as recycled and environmentally friendly household products [16]-[18].

With the help of new media technology and dynamic expression, the boundless integration of time and space conceptual design is added on the basis of traditional posters, which can make various fields interact together without barriers, make the creative space become broader, and realize a variety of creative expression effects such as automating and "moving" visual symbols in poster design [19]-[22].

This paper combines image recognition, segmentation algorithm and style migration algorithm to establish a poster intelligent design system for automatic generation and presentation of different types of poster visual symbols. In order to solve the current problem of high difficulty and poor quality in acquiring image visual symbols, this paper combines traditional image processing methods with deep learning methods, and incorporates two attention mechanism modules, SE and CA, into the FPN feature extraction network of DB algorithm to detect visual symbols. The inclusion of the mask map of the content map in the lower part of the fast style migration network makes the boundary contour of the output visual symbols clearer, and provides new ideas for the innovative design of streaming media posters. The image display module of the system can reflect the changes in visual symbol generation at any time. Finally, the Logo dataset is used as a research sample to conduct simulation experiments to verify the effectiveness of the method in this paper.

II. Visual aesthetic value in the age of streaming media

In the Internet era, theories and technologies related to streaming media have developed rapidly, and the ways of obtaining and exchanging information are richer and more direct, and this way of obtaining information through viewing has become mainstream. Ubiquitous commodities, advertising slogans, views, sales, etc., are invading the public's vision, and the amount and frequency of information received daily are far more than in any past era; however, when this visual stimulation is too common and frequent, it is also silently raising the consumers' visual stimulation threshold [23]. As proposed, the paradox of visual culture: on the one hand, the ecosystem of visual culture has become increasingly rich and complex, and contemporary society lives in a cultural atmosphere of visual stimulus overload. On the other hand, the excess of visual stimuli is also raising people's aesthetic threshold, so much so that people still feel some kind of visual scarcity and lack in such a visually stimulating cultural atmosphere. The direction of design often cycles back and forth between the extremes of the two opposing attributes, and then the birth of graphic design, which is the method of automatic generation and presentation of visual symbols, is a new opportunity for visual design.

III. Methods of visual symbol recognition and generation

III. A. Improved visual symbol recognition methods

In this experiment, through the algorithm improvement mentioned above as well as the network structure improvement, the overall algorithm flow is shown in Fig. 1, where the image input is first passed through the pre-processing operations such as image noise reduction and image enhancement, and then input into the improved network for detection to get the detection results.

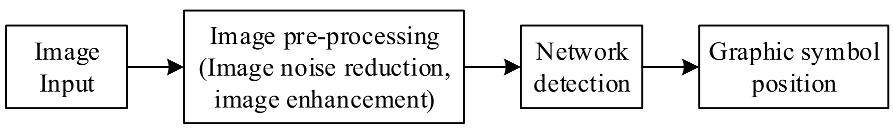

Figure 1: Sign detection process

III. A. 1) DB Segmentation Algorithm

In the feature extraction of images, the lower level features contain less semantic information, but due to the mapping relationship of sensory field, the lower level features often provide more accurate target location information than the higher level features. Therefore, in the graphical symbol detection algorithm, the DB algorithm uses the FPN feature extraction network.The network structure of the DB algorithm, first of all, in the feature extraction part of the FPN structure is used [24].

For the feature map obtained from the feature extraction layer, two parts are generated, one part is the probability map and the other part is the threshold map. The probabilistic map labels are generated mainly by shrinking the polygons describing the text region by Vatti clipping algorithm and the shrinkage offset D is calculated as shown in equation (1):

$$D = \frac{A\left(1-r^2\right)}{L} \tag{1}$$

where L is the perimeter of the original polygon, A is the area of the original labeled box, and r is the shrinkage rate, the method is designed after the PSENet method.

After obtaining the probability map and the threshold map, the two results are combined to obtain the binary map, and the binary map is used to generate the text area. In the traditional approach, the binary map is generated with the probability map and threshold map as shown in equation (2):

$$B_{i,j} = \begin{cases} 1 & P_{i,j} \geq t \\ 0 & otherwise \end{cases} \tag{2}$$

When the probability $P_{i,j}$ of (i, j) position is greater than the threshold t, the value there is 1, otherwise it is 0. Although this approach is feasible inside the traditional method, as applied to network training, this kind of binarization cannot be optimized in network learning due to its non-differentiable nature. Therefore the authors use a differentiable step function to approximate instead of this binarization operation, the step function is shown in equation (3):

$$\hat{B}_{i,j} = \frac{1}{1+e^{-k(P_{i,j}-T_{i,j})}} \tag{3}$$

$\hat{B}$ is the approximate binarized graph, T is the threshold value obtained by learning through network training, and k is a tuning factor to regulate the shape of the curve, such that the function can be differentiated to obtain the purpose of back propagation and network optimization.

The loss function of the DB algorithm consists of three parts and its formula is shown in equation (4):

$$L = L_s + \alpha \times L_b + \beta \times L_t \tag{4}$$

where L_s, L_b, and L_t are the loss of probability, binary, and threshold maps, respectively, and α and β are the weight factors. The loss function of the three parts is shown in equation (5):

$$\begin{cases} L_s = L_b = \sum_{i \in S_l} y_i \log x_i + (1-y_i)\log(1-x_i) \\ L_t = \sum_{i \in R_d} \left| y_i^* - x_i^* \right| \end{cases} \tag{5}$$

where L_s and L_b both use BCE (Binary Cross Entropy) Loss, S_l is a dataset with a 1:3 ratio of positive and negative samples, y_i is the true value and x_i is the predicted value. In contrast, L_t uses L1loss, which refers to the sum of the distances between the predicted and true values.

III. A. 2) SE module

The main attention mechanism modules used in this section are the SE module and the CA module.

SE module is a lightweight channel attention mechanism module, which has been applied in MobileNetV3 network and has shown good performance.The network structure of SE module, the process from feature X to feature U is already existed in the previous structure, and the authors mainly carry out the attention mechanism operation after the feature U [25].

The SE module is divided into two operations, Squeeze and Excitation, in the Squeeze part, the input U is compressed along the direction of the spatial dimension, and the feature map of each channel is turned into a real number, and in terms of mapping relations the real number obtained by compression has a global sensory field, so that the layer close to the input can also have a global sensory field, and finally $(1 \times 1 \times C)$ size feature map, Squeeze operation formula is shown in equation (6):

$$F_{sq}(u_c) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i, j) \tag{6}$$

where u_c represents each layer of the input feature map. The output obtained by Squeeze operation is further subjected to Excitation operation, which is similar to the mechanism of gates in RNN networks, w is a parameter describing the correlation between the feature channels, which is used to assign weights to the features of each channel, and then the output after Excitation is obtained, and the formula for the Excitation operation is shown in Eq. (7) is shown:

$$F_{ex}(z, W) = \sigma(g(z, W)) = \sigma(W_2 \delta(W_1 z)) \tag{7}$$

where σ is the sigmoid function, δ is the ReLU function, z is the output of Squeeze, W is the learned weight, and W_1 and W_2 are obtained from the decomposition of W on the network specifically as two fully-connected layer operations.

The final Scale is actually the operation of redistributing the weights, the output obtained from the previous operation is redistributed to the importance of each channel, the Scale formula is shown in Equation (8), u_c is the feature of each layer, and s_c is the weight, the obtained weight is multiplied by the original feature channel by channel to get the purpose of redistributing the importance of the original feature on the channel:

$$F_{scale}(u_c, s_c) = s_c u_c \tag{8}$$

III. A. 3) CA module

The CA module is also a lightweight attention mechanism module, which mainly incorporates the position information into the channel attention, making the attention mechanism of the lightweight network act on a larger area.The network structure of the CA module is divided into two steps, which are coordinate information embedding and coordinate attention generation [26].

In the coordinate information embedding part, the authors decompose the input features for pooling, using convolution kernels of dimensions $(H,1)$ and $(1,W)$ to encode each channel of the feature in the horizontal coordinate direction and the vertical coordinate direction, the XAvgPool module and the YAvgPool module, respectively. For input X, the output of the feature in the c th channel at height h is shown in Eq. (9), and the output at width w is shown in Eq. (10), and the two transformations aggregate the features in the two directions, respectively, thus generating a two-direction perceptual feature mapping:

$$z_c^h(h) = \frac{1}{W}\sum_{0\le i<W} x_c(h,i) \tag{9}$$

$$z_c^w(w) = \frac{1}{H}\sum_{0\le j<H} x_c(j,w) \tag{10}$$

In the coordinate attention generation part, the authors followed three criteria in their design, namely, the need to be able to be simply and efficiently applied in mobile environments, to be able to make full use of the position information to achieve precise positioning, and to be able to efficiently obtain the relationship between channels. After obtaining the output of the coordinate information embedding part, the output is first spliced and then transformed by the convolution kernel of 1×1 with the following transformation formula:

$$f = \delta\left(F_1\left([z^h, z^w]\right)\right) \tag{11}$$

where $[\cdot,\cdot]$ represents the splicing operation, F_1 represents the convolutional transform function, and δ is the nonlinear activation function. Then the transformed result is decomposed along the spatial dimension to obtain two tensors, and then the two tensors are operated by two 1×1 convolution kernels to finally obtain two tensors with the same number of channels, and the specific transformation formula is as follows:

$$\begin{cases} g^h = \sigma(F_h(f^h)) \\ g^w = \sigma(F_w(f^w)) \end{cases} \tag{12}$$

where f is the output of the previous step, F_h and F_w are the two convolutional transform functions respectively, and σ is the sigmoid function. Finally, the above two outputs are expanded to obtain the attention weights, and the final output of the CA module can be expressed as shown in equation (13), where x is the feature map of the original input, g is the attention weights, and y is the output:

$$y_c(i,j) = x_c(i,j)\times g_c^h(i)\times g_c^w(j) \tag{13}$$

III. B. Visual Symbol Style Migration Method

In the actual operation process, it is found that the original style migration algorithm is used for two problems: first, the visual symbols are rich in color, and the effect diagrams generated by the original style migration algorithm are often unclear, mixed colors, blurred outlines and other problems, which greatly affects the effect of style migration. Secondly, the structure is also a very important component, the original style migration algorithm will almost not retain the original structure of the visual symbols in the migration process. These problems are caused by the algorithm itself: in the convolutional neural network the information such as object and layout of the input image is usually expressed by the high-level features, while in the original style migration algorithm, the method used in calculating the loss of content is to compare the high-level features of the effect image with the content image, so that the effect image will be close to the content image in terms of object and layout. And the method of multi-layer feature fusion is used in calculating the style loss, which attenuates the influence of the object and layout information of the style map on the effect map. It is experimentally proved that even if the weights of the high-level features in calculating the style loss are exponentially increased, the effect on the structure of the effect map is minimal. Based on the above problems, this section proposes an improved style migration method based on the original style migration algorithm [27]. The structure of the proposed improved network is shown in Fig. 2.

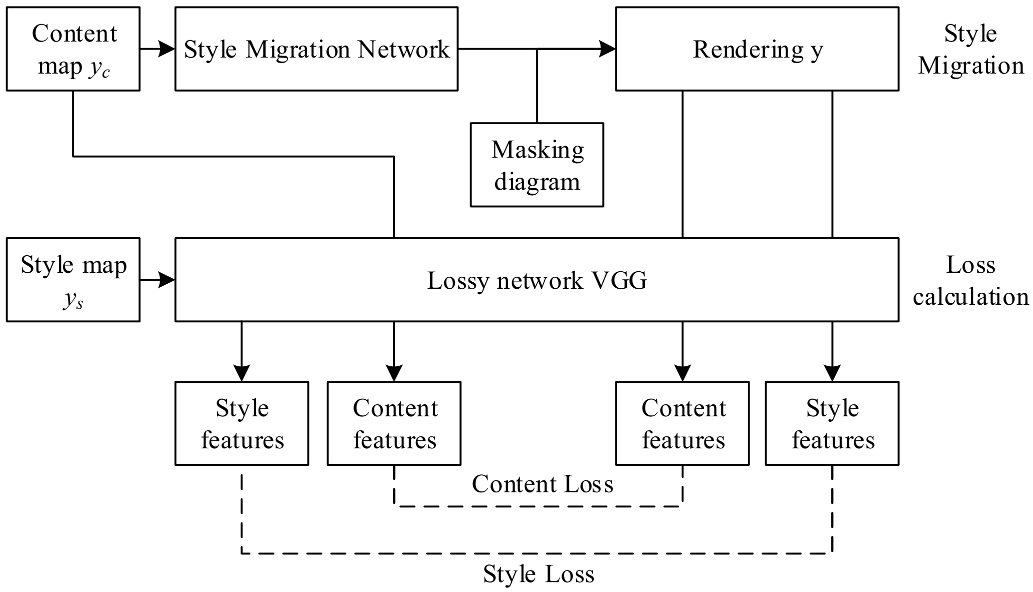

Figure 2: Improved network structure

Similar to the fast style migration, the proposed network is also divided into two parts, the lower half is the loss network, while the upper half of the style migration network incorporates the mask map of the content map in generating the effect map. In the training process, the first input is the style migration network, and the initial effect map $\hat{y}$ will be obtained after the migration network, and the effect map $\hat{y}$ obtained for the first time is usually a noisy picture due to the initial weights of the style migration network are randomized. Each time the generated effect image $\hat{y}$ is fed into the loss network, the effect image will be computed in the loss network with the content image to compute the content loss, and with the style image to compute the style loss, respectively, and subsequently weighted to find the total loss. The total loss will be updated by back propagating the weights of the style migration network. This process is repeated until the total loss converges. At this point, the weights of the style migration network are basically stable. After training, the style migration network can be used directly for re-migration of the same styles without re-training. Due to the combination of the mask map, the style migration network will focus the style migration on the main body of the pattern when generating the effect image, and will not migrate the style of the background, which makes the boundary contour of the output effect image clearer.

IV. Intelligent design system for streaming posters

The core functions to be implemented in the system are summarized below:

Operation mode selection. Users are able to select corresponding modes according to different style migration methods to meet the diversified visual symbol style migration mode switching and adapt to different generation methods.

Self-selected data input. According to the model iteration, iteration of different ways, can be free to pass the pre-trained model parameters, content, style in order to carry out different generation.

Perform parameter passing. Can pass in the corresponding parameters according to the model, and then run the corresponding style migration for different generation.

Visual symbol display. The visual symbols can be displayed at any time according to the user's needs, in order to reflect the changes in the graphical interface at any time, so as to meet the user's needs in the visual symbols generation process of intuitive viewing.

According to the different algorithms and the needs of use, the main steps are organized as follows: first, after entering the interactive interface, the first step should be to switch to the corresponding mode according to the different algorithm operation modes. Second, according to the relevant mode for the corresponding parameter input, for example, to carry out the corresponding mode of operation for the content, style input, for the model iteration can enter the corresponding parameters of the pre-training model, at the same time, corresponding to different content, style should be synchronized with the corresponding display, in order to meet the user's interactive experience. Again, according to the relevant algorithm selection can input the corresponding network parameters, weight value parameters, so as to realize the corresponding operation. Again, the corresponding image display is performed. Finally, due to the uncertainty of the style migration to generate visual symbols itself, it is best to carry out the corresponding post-processing so that the acquired posters can be as diverse and excellent as possible. In addition, corresponding to the human-computer interaction process, since the use process involves non-professionals, the corresponding operation error prompts should be handled correspondingly in order to make the interaction experience better, so the corresponding human-computer interaction, layout, usage instructions, and operation prompts of the system should be designed reasonably as well. Therefore, the overall framework of the corresponding system is shown in Figure 3.

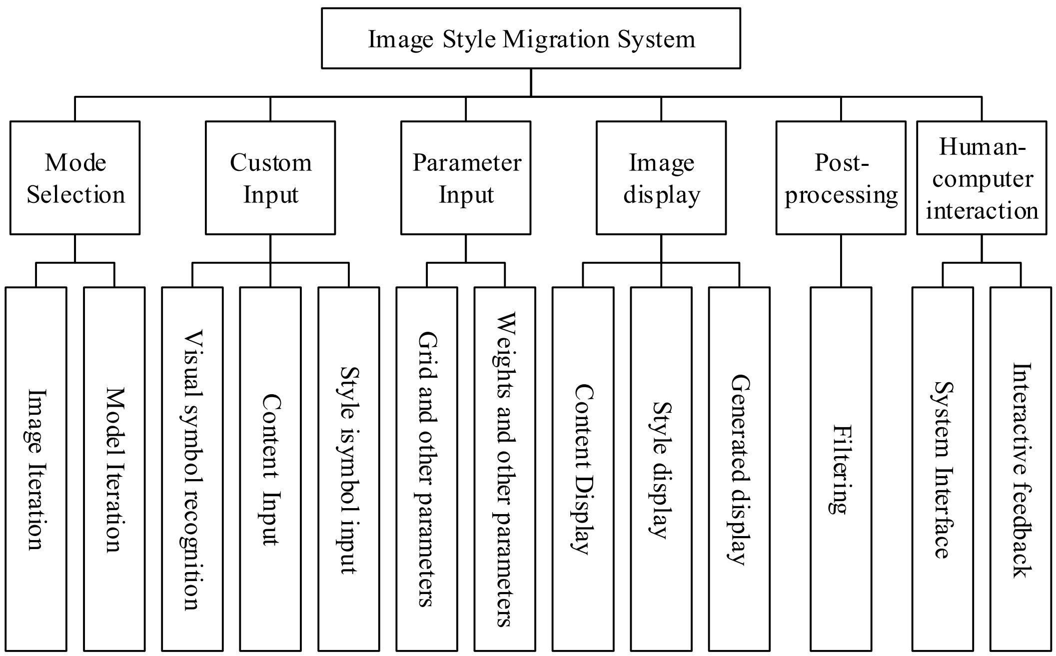

Figure 3: System framework

V. Analysis of the application of automatic symbol generation and presentation techniques in poster design

V. A. Experimental results and analysis

In this paper, a lightweight model is obtained by preprocessing and improving the FPN network structure in improving the recognition accuracy and reducing the number of parameters, and the real-time performance of the model is improved by reducing the computational cost. Separately, the SE module and CA module embedded in the DB algorithm of the two FPN network structure, using Logo dataset for network training, for the DB algorithm and the improved DB algorithm training process comparison is shown in Fig. 4, in which CA-FPN1 represents the original algorithm, CA-FPN2 represents the improved algorithm, as can be seen from the figure, the improved algorithm is faster than the original algorithm convergence speed.

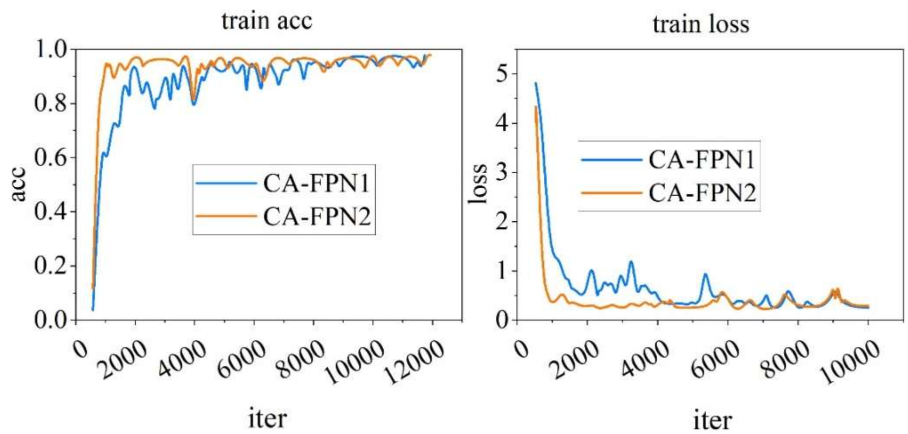

Figure 4: Training process contrast diagram

The same Logo dataset is utilized for the original algorithm and the improved algorithm training results are compared as shown in Fig. 5, where SE-FPN1 denotes the original algorithm, and SE-FPN2 denotes the improved algorithm, from which it can be seen that the improved algorithm's loss function converges faster, and fewer trainings are required to achieve the best results.

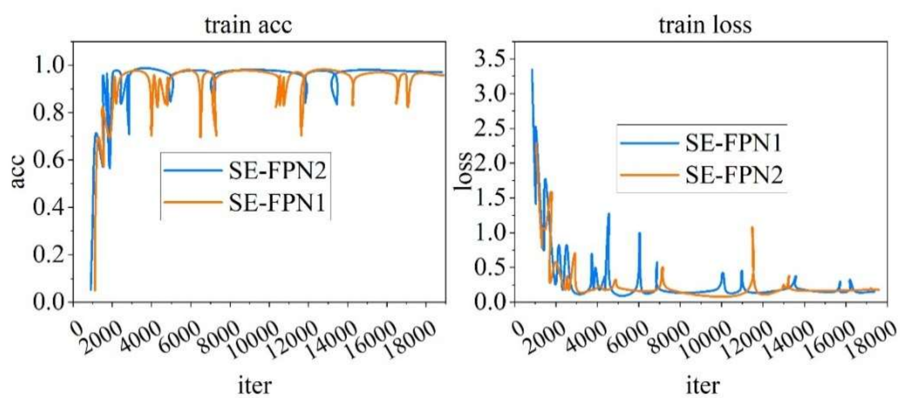

Figure 5: The comparison between SE-FPN1 and SE-FPN2 training

For testing the improved visual symbol recognition and segmentation algorithm, 10,000 sheets of the Test dataset from the MNIST dataset are selected. 19021 sheets from CCTSDB dataset are selected for training and 2114 sheets for testing. 5355 sheets from the Graphical Symbols dataset are selected for training and 362 sheets for testing. 2988 sheets in FlickrLogos-32 dataset are selected for training and 332 sheets for testing. Their test results are shown in Table 1, from which it can be seen that the improved two algorithms can achieve more than 86% recognition rate on all the datasets.

Table 1: Test results of different data sets

Data set	Test quantity	Test error number	Recognition rate	Test speed (FPS)
CA-FPN2				
MNIST	10000	80	99.324%	54
CCTSDB	2114	8	99.678%	46
Graphic symbol	362	4	99.435%	52
FlickrLogos-32	332	35	90.473%	33
SE-FPN2				
MNIST	10000	78	99.327%	46
CCTSDB	2114	15	99.417%	42
Graphic symbol	362	4	99.436%	54
FlickrLogos-32	332	49	86.472%	36

Comparison for CA-FPN1 and improved CA-FPN2 algorithms is shown in Fig. 6, Fig. 6(a) shows the result of comparison of recognition rate, and Fig. 6(b) shows the result of comparison of test recognition rate, it can be seen that the algorithm's recognition rate does not have a large change, but there is a significant improvement in the recognition rate.

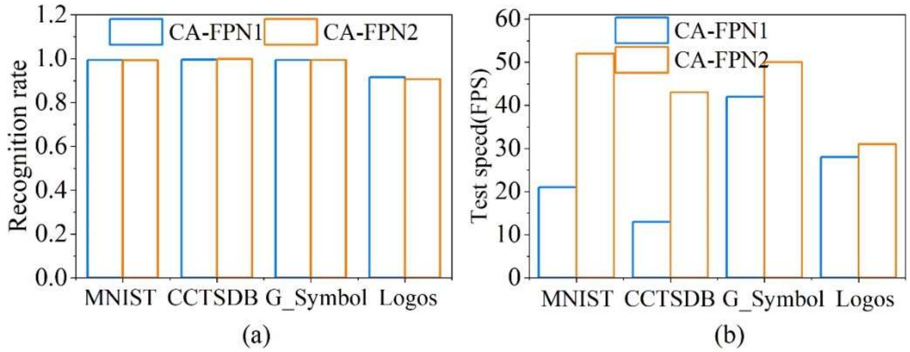

Figure 6: The CA-FPN1 and the CA-FPN2 algorithm are compared

Comparison of SE-FPN1 and improved SE-FPN2 algorithms is shown in Fig. 7, Fig. 7(a) shows the result of comparison of recognition rate, and Fig. 7(b) shows the result of comparison of test recognition rate, which shows that the recognition rate of the algorithms also does not have a large change, but it can be seen that there is a significant improvement in the recognition rate.

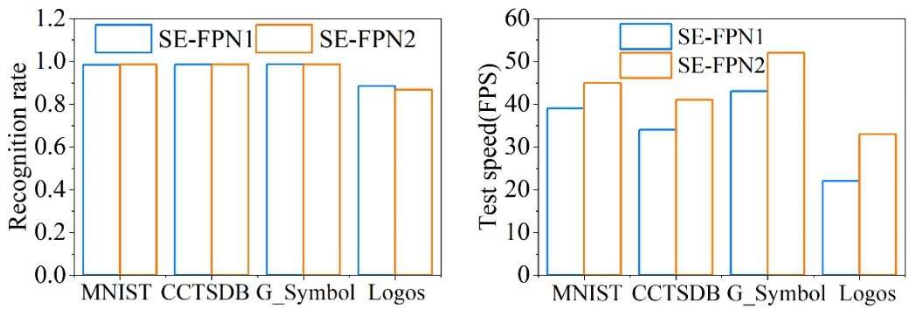

Figure 7: Compared to SE-FPN1 and SE-FPN2 algorithm

The results of the tests performed on the graphical symbol samples are shown in Table 2, with a sample of 375 sheets.Test_error denotes the number of incorrectly recognized sheets in a single symbol sample, and Test_acc denotes the accuracy rate of a single symbol sample.Err_pic denotes the number of incorrectly recognized sheets in the sample (including the scribbling recognition error), and PRE denotes the recognition correctness rate of the symbol sample, and Test_speed is the recognition speed. As can be seen from the table, the method proposed in this paper for the MNIST dataset not only improves the accuracy of classification recognition on the basis of the original algorithm, but also reduces the size of the model, improves the recognition speed of the model, and achieves the optimization of the model.

Table 2: Use this article to improve the algorithm to identify the symbols

Pretreatment	Test_error	Test_acc	Err_pic	PRE	Test speed (FPS)
CA-FPN 1	52	99.24%	52	87.21%	12
SE-FPN 1	20	99.63%	21	95.33%	14
SE-FPN 1+cleaning	11	99.86%	13	98.24%	14
SE-FPN 1+enhancement	3	100%	3	99.86%	16
Preprocessing+ CA-FPN 2	3	99.98%	3	99.58%	16
Preprocessing + SE-FPN 2	2	100%	2	99.87%	22

Comparison results of recognition and segmentation of visual symbols by traditional methods and deep learning methods are shown in Table 3, using the MNIST dataset after performing image preprocessing to train the model, in the recognition results of graphic symbols, the average recognition correct rate of the improved method of this paper is much higher than that of the traditional method. And the improved method in this paper has 9.1% higher average correct recognition rate than the original method, and the speed is also improved, which can meet the test requirements.

Table 3: The recognition algorithm is compared

Algorithm	Model size (M)	Recognition accuracy	Test speed (fps)
SVM	28.4	66.41%	334
MLP	8.35	76.56%	14
CA-FPN 1	58.7	86.43%	12
SE-FPN1	2.56	94.78%	15
CA-FPN 2	40.2	99.58%	16
SE-FPN 2	1.97	99.83%	22

The results of the quantitative effect analysis of the improved style migration algorithm using several evaluation algorithms are shown in Table 4.The lower the FID value, the more convergent the generated visual symbols are with the original distribution, thus reflecting the better quality of the generated visual symbols. A higher PSNR value indicates that the difference between the generated visual symbols and the original visual symbols at the pixel level is smaller, i.e., the fidelity of the visual symbols is higher. The SSIM value measures the structural similarity between the generated visual symbols and the original visual symbols, and a higher value indicates that the two images are visually close to each other.

It can be learned from the judging indexes of all the above comparison results that the improved model in this paper is lower than other models in terms of FID indexes, which is lower on average than the second lowest model in each of the four types of datasets, which indicates that the improved model is closer to the real visual symbols in terms of contour, and color backgrounds, e.g., there are many inconsistencies in the horse contour, and morphology generated by the original model in the ink painting dataset with the real visual symbols, and the improved For example, the original model in the ink painting dataset has many inconsistencies between the horse outline and form and the real visual symbols. Secondly, the PSNR and SSIM indexes are mostly higher than those of other models, which indicates that the improved model handles the line and texture details of the symbols better, and can restore the structure of the content map well. Overall the results generated by the improved model in this paper achieve better results in background color, line texture, local details, and contour morphology.

Table 4: Data set comparison experiment

Model	Monet			Ukiyoe		
Dataset	FID ↓	PSNR ↑	SSIM ↑	FID ↓	PSNR ↑	SSIM ↑
U-GAT-IT	210.53	16.47	0.65	139.04	12.07	0.53
CUT	163.78	18.85	0.62	118.07	12.14	0.68
Stable Diffusion	148.47	22.68	0.78	115.36	11.57	0.69
Cycle Diffusion	140.36	24.57	0.68	110.75	11.53	0.6
Ours	132.84	25.78	0.79	103.46	12.48	0.65
Model	Ink			Oil		
Dataset	FID ↓	PSNR ↑	SSIM ↑	FID ↓	PSNR ↑	SSIM ↑
U-GAT-IT	175.46	11.85	0.62	96.84	16.78	0.54
CUT	152.24	14.28	0.78	99.54	19.27	0.56
Stable Diffusion	152.36	16.27	0.74	90.94	17.68	0.64
Cycle Diffusion	133.61	14.92	0.67	84.15	22.63	0.59
Ours	127.48	17.84	0.87	82.64	20.78	0.68

V. B. Evaluation of Streaming Media Dynamic Poster Design

From the perspective of poster's expression technique, graphics are not only an important visual element for information dissemination, but also can symbolize abstract information and communicate visual semantics in different cultural backgrounds without any obstacles, which has a universality that cannot be reached by language and text.

In the experiment, free licensed photos were downloaded from the Pixabay photo sharing website, together with photos collected by ourselves, to create a background image dataset containing 1226 photos. 10,000 design results related to 1000 background images were randomly selected from the dataset as the training dataset, and 2260 design results related to 226 background images were used as the test set.

For the synthesized results output from the various methods, the experiment recruited 20 evaluators for user rating, their ages ranged from 21 to 35 years old, there were 13 females and 7 males, 11 personnel had design experience □□ while the other 9 had no relevant design experience. The experimental data for the evaluation are as follows: 20 designers' works were randomly selected from the test set in the experiment, and the overall poster synthesized by the method of MM'12, TOMM'16 experimental baseline and the method mentioned in this paper as the experimental results to be evaluated. The evaluation results are shown in Figure 8, and the evaluation indexes are defined as follows:

(1) Symbol location suitability: that is, the symbol results generated by each method, the symbols are located in the location of the suitability of the evaluation, the assessment of the dimensions are many, whether to block the important objects, whether the layout is reasonable without appearing to be too centralized, whether to appear cluttered, through the comprehensive assessment of the consideration of the location of the suitability of the score, from 1 to 5 points represent respectively very unreasonable, some clutter, acceptable, skillful and Very suitable.

(2) Overall color harmony: rendering on the text color and the overall image is harmonious, with a certain aesthetic sense, the score from 1 to 5 points, respectively, representing very disharmonious, disharmonious like, harmonious, and very aesthetically pleasing.

(3) Text readability: the figure of the individual text to read, in maintaining the same viewing distance and image height, whether the text can be seen clearly, see the text can be easily identified, a comprehensive score from 1 to 5 points respectively represent completely unreadable, can read part of it, can be read need to focus, can be relatively easy to read, the eye can read all the text.

(4) Design creativity: this is a qualitative and relatively new evaluation index, because the method based on constraints and templates usually leads to a relatively fixed design format, so based on image recognition and segmentation of the method whether the design creativity can be obtained from the historical data, embodied in the diversity of the location and color design, borrowed from other designers to the design experience of other designers, this data scored from 1 to 5 points respectively, representing a very archaic, lack of flexibility, average, somewhat fancy and rich in design creativity.

The mean values of this paper's methodology for symbol placement appropriateness, overall color harmony, text readability, and design creativity were 3.64, 3.93, 3.69, and 4.26, respectively.

The method proposed in this paper obtains a very high design creativity score, due to some generalization capabilities of deep learning, the network is able to tap into some intrinsic design mechanisms originally embedded by designers, and when these mechanisms are reacted in the automatic generation of visual symbols for poster design works, there will be a very large number of positional diversities and color diversities, and at the same time, it possesses aesthetic properties that are not found in randomly generated methods, so as to to obtain a creative design sense.

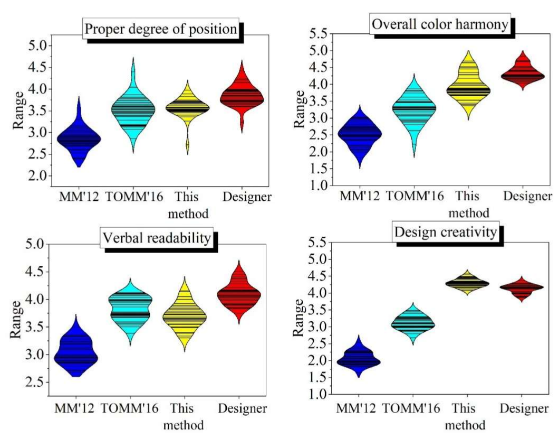

Figure 8: The comparison results of the score

VI. Conclusion

This paper utilizes an improved visual symbol recognition method with an improved style migration algorithm to establish an intelligent design system for streaming posters. It realizes the generation of posters of different styles with the changes of generation presented at any time. After experimental testing and case study analysis, it can be seen that for different datasets, the convergence of the loss function of the improved visual symbol recognition algorithm and the recognition speed are both improved, and the recognition correct rate is above 86%. Compared with other methods, the results generated by visual symbols achieve better results in terms of background color, line texture, local details, and contour morphology. The poster design results of this paper's method obtain better harmony and readability, and have better creativity and design sense than traditional methods.

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References

[1] Gray, A. L., Curtis, C. W., Young, M. R., & Bryson, K. K. (2022). Innovative poster designs: A shift toward visual representation of data. American Journal of Health-System Pharmacy, 79(8), 625-628.

[2] Hamza, L. D. H. A. (2024). SYMBOLIC CONNOTATIONS AS AN INPUT TO THE DESIGN OF THE ADVERTISING POSTER. American Journal Of Social Sciences And Humanity Research, 4(10), 114-132.

[3] Pedwell, R. K., Hardy, J. A., & Rowland, S. L. (2017). Effective visual design and communication practices for research posters: Exemplars based on the theory and practice of multimedia learning and rhetoric. Biochemistry and Molecular Biology Education, 45(3), 249-261.

[4] Huang, Y., & Wang, C. (2024). Image, Symbol, and Philosophy: Meaning Construction and Semiotic Analysis in Graphic Design. Cultura: International Journal of Philosophy of Culture and Axiology, 21(2).

[5] Chun, C. H. (2020). A Study on the Elements of Moving Poster Design. Journal of Korea Multimedia Society, 23(2), 361-367.

[6] Hajjaj, M. H. M. (2024). The iconic signs in the design of posters (Analy. Journal of Arts & Applied Sciences (JAAS), 11(3), 1-10.

[7] Gökalan, M., & Sevindik, O. (2022). Mengü Ertel's design style (sample of poster designs). Meriç Uluslararası Sosyal ve Stratejik Araştırmalar Dergisi, 6(17), 259-279.

[8] Leyla, H. (2023). GRAPHIC RHETORIC: THE ART OF PERSUASION IN POSTER DESIGN. Scientific Work, (2).

[9] Rowe, N. (2017). Poster Design and the Viewer Perspective. In Academic & Scientific Poster Presentation: A Modern Comprehensive Guide (pp. 61-77). Cham: Springer International Publishing.

[10] Oyighan, D., & Okwu, E. (2024). Social media for information dissemination in the digital era. RAY: International Journal of Multidisciplinary Studies, 10(1), 1-21.

[11] Anggraeni, N. C., Yusrizal, M., & Mayesti, N. (2024). Analysis of Information Dissemination Strategies through Mass Media to Build a Knowledge Society: A Case Study of NU Online. Technology and Education, 178.

[12] Xu, W. (2022, January). Discussion on the development trend of new media information dissemination methods in the 5G Era. In International Conference on Innovative Computing (pp. 333-340). Singapore: Springer Nature Singapore.

[13] Majeed, M. F., Ahmed, S. H., Muhammad, S., Song, H., & Rawat, D. B. (2017). Multimedia streaming in information-centric networking: A survey and future perspectives. Computer Networks, 125, 103-121.

[14] Günay, M. (2021). Design in visual communication. Art and Design Review, 9(02), 109.

[15] Yu, G., Akhter, S., Kumar, T., Ortiz, G. G. R., & Saddhono, K. (2022). Innovative application of new media in visual communication design and resistance to innovation. Frontiers in Psychology, 13, 940899.

[16] Barik, A. L., Rizki, A. P., & Astuti, D. (2019). The effectiveness of traditional media (leaflet and poster) to promote health in a community setting in the digital era: A systematic review. Jurnal Ners, 14(3), 76.

[17] Tien, C. Y. (2024). THE USE OF TRADITIONAL AND DIGITAL POSTER PRESENTATIONS AMONG UNIVERSITY STUDENTS. European Journal of Research and Reflection in Educational Sciences, 12(2).

[18] Guan, X., & Wang, K. (2022). Visual communication design using machine vision and digital media communication technology. Wireless Communications and Mobile Computing, 2022(1), 6235913.

[19] Fan, X., & Sun, Y. (2024). Poster Design Research Based on Deep Learning Automatic Image Generation Algorithm. Journal of Information & Knowledge Management, 23(05), 2450069.

[20] Liu, P. (2018, July). Study of Dynamic Poster Design. In 4th International Conference on Arts, Design and Contemporary Education (ICADCE 2018) (pp. 471-473). Atlantis Press.

[21] GULA, Y., MAZNICHENKO, O., PODLEVSKYI, S., OSADCHA, A., & DEREVIANKO, Y. (2024). EVALUATING THE IMPACT OF 3D PRINTERS FOR CREATING INNOVATIVE POSTER DESIGNS. Journal of Theoretical and Applied Information Technology, 102(24).

[22] Ahmed, R. M., & Dakhel, S. K. (2024). Hyperrealism and its representations in artificial intelligence poster design. Al-Academy, 345-368.

[23] Nissim Katz. (2025) .“It’s not us, it’s the government”: Perceptions of a national minority of their representations in the mainstream media during a global pandemic – the case of Israeli Arabs and COVID-19. Communications,50(1),5-25.

[24] Valentin Gonay,Michael P Dunne,Javier Caceres Delpiano & Andrey V Kajava. (2025) .Developing machine-learning-based amyloidogenicity predictors with Cross-Beta DB. Alzheimer's & dementia : the journal of the Alzheimer's Association,21(2),e14510-e14510.

[25] Elif Yusufoğlu,Hüseyin Fırat,Hüseyin Üzen,Salih Taha Alperen Özçelik,İpek Balıkçı Çiçek,Abdulkadir Şengür... & Numan Halit Guldemir. (2024) .A Comprehensive CNN Model for Age-Related Macular Degeneration Classification Using OCT: Integrating Inception Modules, SE Blocks, and ConvMixer. Diagnostics,14(24),2836-2836.

[26] Zhihao Guo,Dongmei Ma & Xiaoyun Luo. (2024).A lightweight semantic segmentation algorithm integrating CA and ECA-Net modules. Optoelectronics Letters,20(9),568-576.

[27] Johannes Haubold,Olivia Barbara Pollok,Mathias Holtkamp,Luca Salhöfer,Cynthia Sabrina Schmidt,Christian Bojahr... & René Hosch. (2025) .Moving Beyond CT Body Composition Analysis: Using Style Transfer for Bringing CT-Based Fully-Automated Body Composition Analysis to T2-Weighted MRI Sequences.. Investigative radiology.