

Research Article

Exploration and Application of Graphic Design Language Based on Artificial Intelligence Visual Communication

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Graphic design is one of the design disciplines with the longest history in the history of human design. As a marginal discipline, it integrates science and art organically. Graphic design has three basic characteristics: information, art, and economy. Information refers to the fact that graphic design is a carrier of information communication, and graphic design works have the practical function of specific information transmission. Among them, graphic design language is the direct form of information communication, but there is a relative lack of research on the intelligent recognition of graphic design language. To address this problem, this paper focuses on the analysis method of graphic design language based on artificial intelligence visual communication. First, in order to segment different parts of the image more accurately, this paper improves a deep learning-based image segmentation method. The method uses a three-branch network structure to learn semantic information, detail information, and fusion information, respectively. The coding network uses a lightweight convolutional neural network and adds an attention mechanism in the branches to weight the importance of image feature channels, and the features extracted from different perceptual fields of the image are multiscale fused to fuse the features extracted from different stages of the coding network. Then, the salient target regions are detected on the basis of segmented images, the salient target emotions are analyzed by using feature pyramids to improve the convolutional neural network, the emotions expressed by graphic design language are analyzed by constructing a weighted loss convolutional neural network on a multilayer supervised module, and the salient target emotions are fused to obtain the final emotion classification results. The experimental results show that our proposed method outperforms traditional segmentation methods in the dataset, and the sentiment analysis based on segmented images can obtain higher sentiment classification accuracy than the sentiment analysis method that directly identifies the whole image, which is beneficial to the research and application of graphic design language.

1. Introduction

Graphic design is a combination of words, graphics, and imagination, mainly “visual” as a way of communication and expression, but also through design thinking and various techniques to recreate and innovate the symbols, graphics, and words used to convey ideas or convey information visual art. Design language symbols are one of the most important elements of visual art [1]. In the process of creating artworks, designers use the basic language symbols to express the form and formal beauty of the works and use design methods to explore and create new symbolic language to express the ideological connotation

of the works, which is very valuable for research and dissemination in art creation.

Graphic design works are artistic and generally classified as practical art, but graphic design works are different from pure art works, and the biggest difference between the two is that graphic design works are the reproduction of the designer’s “thoughts and emotions of the people for whom he designed the work,” while pure art works express the artist’s thoughts and emotions. The latter has a strong subjective nature, while the former is subject to more objective constraints [2]. As a practical art, graphic design has artistic value, information transmission value, and most of it has commercial value. The

merits of graphic design works are mainly judged from the above three perspectives. The artistic value is mainly assessed from the aesthetic height, while the information transfer value is mainly judged from the perspective of information carrying and cultural identity. The model of graphic design work evaluation is shown in Figure 1.

The most intuitive and main form of communication with the outside world is through visual means, and graphic design is composed of various design form language symbols. The most important way to transmit information is through visual language, and it is because of the existence of formal language symbols that graphic design works have a more special artistic and communicative nature than other forms of artistic expression. Graphic design is not simply to meet the surface aesthetic experience, but to convey a deeper artistic emotion through the rhythmic beauty of the formal language symbols. For graphic design, art works need to use the design form language symbols as a carrier to realize the transmission of emotion, and the form language symbols also need to be expressed through the artistic emotion to become rich in connotation and rhythm [3]. The fusion and reprocessing of design language symbols and artistic emotion will often result in impressive design effects, which will bring people visual and spiritual shock and produce a strong psychological impact.

The analysis of the language of graphic design is mostly manual. The advent of the digital age is changing this traditional approach. A better understanding of the language of graphic design in the digital age, in terms of its basic principles and characteristics, is the basis for mastering this language with new characteristics in the new age. At the same time, the analysis of the overall strengths and weaknesses of graphic design in the visual language of graphic design with the new characteristics of the digital age is conducive to the concretization of understanding. The visual language of graphic design in the digital context itself contains modern and advanced technology, and its automation means the automation of the language expression process. Although the visual language of graphic design in the digital context is not completely automatic in its expression, based on the virtualization characteristics mentioned earlier, the virtualization tool used by human is actually a command button, and after the human operates the button, the rest of the realization process is mostly done automatically by the computer, so it is said that the visual language of graphic design in the digital era reflects a certain degree of automation [4]. At the same time, since these automations are realized under the program edited by computer language, it is also said to have programmatic characteristics.

Using artificial intelligence technology, automatic recognition of graphic design language can be realized, and the technology includes two parts: image segmentation and image sentiment analysis. Among them, the image segmentation algorithm not only needs to be able to segment high-resolution images, the key is to be able to achieve high accuracy segmentation results, especially for the segmentation of graphic design, but also for the algorithm real-time segmentation requirements are relatively high, so there are three problems with the image segmentation algorithm: first, most of the algorithms proposed by the academic community about high-quality image segmentation are for low-resolution images; second, the existing image

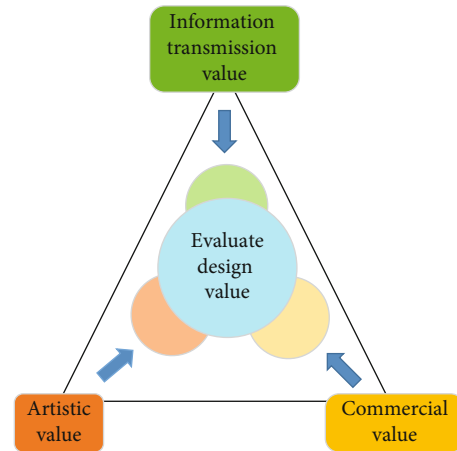


FIGURE 1: Evaluation model of graphic design works.

segmentation algorithms for object or character edge details, hair, and other locations always have low segmentation accuracy problems; third, there are many current deep learning-based image segmentation algorithms, although you can get a better soft segmentation effect in the image of the hair, detail parts, but most of them require human interaction [5]. While the essence of image sentiment analysis is image classification, the main work is feature engineering as well as the extraction of regions conducive to emotional expression. There are three stages: low-level sentiment features of images, mid-level semantic sentiment features, and high-level semantic sentiment features of deep networks. Compared to text sentiment recognition, image sentiment recognition takes some more time. Images may contain salient targets, and these salient target features can more easily express the user's emotion. However, in real life, text and images often do not exist in isolation but often accompany each other, and they are both ways for humans to express emotions. Some images have salient target sentiment features, but some images are not so obvious in their sentiment. Text can express emotion well, but there will be false data [6]. Therefore, in recent years, multimodal sentiment analysis is gaining more and more attention, which takes into account not only image features but also text features, so that when one modality cannot accurately judge emotion, another modality will play a complementary role.

Aiming at the research and application problems of graphic design language, combined with artificial intelligence technology, this paper proposes a recognition method. The method is constructed for graphic design works and contains a total of two parts of structure. The first part is used to segment different parts of the graphic work, and this part improves a deep learning-based image segmentation algorithm, which designs a separate branch to actively learn the significant information of the image and another branch to learn the edge detail information of the foreground of the image, and finally fuses the feature information learned by the two branches and outputs the segmentation results through the fusion branch. The second part is used for image sentiment analysis, firstly, using feature pyramid to improve convolutional neural network to extract multi-scale fusion of salient target sentiment features, then adding a supervised module of weight loss to extract sentiment features,

and finally fusing the salient target sentiment of each region to finally determine the sentiment features of the image.

The unique contribution of the paper includes

- (i) development of a recognition method for graphic design works
- (ii) the first part of the framework segmented different parts of the graphic work using deep learning-based image segmentation algorithm
- (iii) the second part of the framework performed image sentiment analysis using feature pyramid to improve the performance of CNN. This helped to extract multiscale fusion of salient target sentiment features

2. Related Works

2.1. Current Status of Graphic Design Language Research. The design form language symbols and the modern design trend of simplicity and simplicity harmonize with each other and push forward the new ideas. With the advancement of industrial industrialization and production informatization, graphic design gradually begins to become an important way to communicate and exchange information in production and life. People's appreciation level and aesthetic concept also improve with the development and progress of society, while more needs are put forward. As the most widely used form of visual art, graphic design needs to use formal language symbols rationally to create, constantly innovate, improve creative thinking, and create a more beautiful space for the visual aesthetics and psychological feeling needs of the appreciators [7]. A true understanding of the basic meaning and deeper connotations of graphic design will help designers to express their emotions more fully and accurately when creating their works and to design works that will shock people's hearts.

The use of basic symbols in graphic design should take into account the interaction between symbols. For the use of basic design languages such as dots, lines, and surfaces, certain methods and rules need to be followed, which change depending on the form of expression, design theme, or style of the work and ultimately convey information through the work and then convey the inner emotion that the author wants to reflect, presenting a visual effect with beauty and impact. Dots are often used as the center of visual appreciation and gathering in order to reflect more enthusiasm and affinity. For graphic design, point, line, and surface are the main framework and foundation of design, and the use of the overall design form language symbols is based on the basic language symbols of point, line, and surface. The final design effect and design theme also need the overall design form language symbols to integrate information with each other. Graphics, images, words, and colors are the main and most common overall design language symbols in graphic design, and the overall form language symbols are indispensable elements in graphic design and also have very important significance in aesthetics [8]. In the process of design practice, through the artistic processing of graphics, words, and colors, the original independent and scattered points, lines, and surfaces in the picture are integrated to fill the entire visual

space, making the design work more rich and concise, so that the scattered layout forms a whole object, and the information of the work becomes integrated from scattered.

The expression of artistic emotion in design is composed of the designer's subjective emotion and the process of appreciation and criticism of the art work by the appreciators, because the audience of the design work is both the appreciators and the critics. A successful design work cannot only be the expression of the creator's own subjective artistic emotion, but the creator can fully express his creative message, and the appreciator can also feel the emotion contained in the design form language symbols. The purpose of design is not only to look good, but also to carry a sense of mission; firstly, as a medium of information transmission, it has the role of transmitting information; secondly, it carries the responsibility of improving people's quality of life and aesthetic level [9]. Using the design form language symbols of point, line, surface, and geometry unique expression to design, through the creator's free creation, the image often has enhanced visual image of interest and vividness, bringing a strong visual impact, giving people a reverie, so that the appreciators in the appreciation process left a deep impression but also gives the designer full creative space and freedom.

2.2. Current Status of Image Segmentation Research. Since the 1970s, researchers have been attracted by the image segmentation problem and have made great efforts to achieve certain research results. So far, image segmentation algorithms have been researched for decades, and traditional image segmentation algorithms with better segmentation performance have emerged during this period, such as threshold segmentation algorithms, edge detection-based image segmentation algorithms, and region-based image segmentation algorithms. In addition, there are also image segmentation algorithms based on specific theories, such as clustering analysis, active contour model, and graph theory. These methods can be used to solve image segmentation problems in a specific field based on their own characteristics [10]. As the application requirements change, each segmentation algorithm not only optimizes and improves on its own theoretical basis, but also promotes the development of image segmentation theory to a certain extent by integrating theoretical knowledge from other fields. The existing image segmentation algorithms are listed as follows.

- (1) Threshold segmentation method. As a typical algorithm in the field of image segmentation, the implementation principle of threshold segmentation is simple, efficient, and practical. By setting one or more different thresholds and comparing all pixels in the image domain with the set single or multiple thresholds in turn, the algorithm divides all pixels in the image domain into two classes or several classes with different gray level regions [11]. Setting appropriate thresholds can distinguish the images well and get more satisfactory segmentation results
- (2) Image segmentation algorithm based on edge detection. The purpose of image segmentation aims to obtain the target contour, considering that the intensity

values, colors, or textures at the edges connected to different regions in the image domain vary greatly; therefore, the image can be segmented by detecting the edges of different regions [12]. The basic implementation principle is to detect the possible boundaries in the original image based on the discontinuities between image pixel points and to divide the original image into two or more different regions accordingly

- (3) Region-based image segmentation algorithms. For the region growth method as the most basic region segmentation method, its implementation principle is that in the image domain, first select a single or a group of pixel points, use them as seed points, and then compare them with neighboring pixel points in order according to the similarity criterion defined in advance
- (4) Image segmentation algorithm based on active contour model [13]. The main idea of the active contour model is to use continuous curves to represent the target boundary, and at the same time to construct external energy terms with the help of image information, and to combine with internal energy terms to define the energy generalization function
- (5) Image segmentation algorithms based on visually significant regions. Inspired by the biological ability of humans to recognize important information quickly and effectively in complex environments, many visual significant region detection algorithms have been proposed and are widely used in many fields
- (6) Deep learning-based image segmentation algorithms, with the rise of convolutional neural networks [14]. However, the training set requires a large amount of manpower for support, and the underlying features always play an important role in the development of deep learning-based frameworks. Most of the deep learning-based image segmentation algorithms are currently based on code-decode network structures

2.3. Current Status of Image Sentiment Analysis Research.

Generally, there are three types of visual features used for image sentiment analysis: low-level features, mid-level features, and high-level features. SentiWordNet is the first exploration of the connection between image sentiment and visual content. The method first represents images with color distributions and visual bag word models, extracts sentiment values (positive and negative) from textual metadata using a synonym library, then uses information methodology for feature analysis, and finally image classification using machine learning methods such as support vector machines [15]. To address the problem that the VSO-based model cannot indicate which ANP is highly related to the emotional orientation of the visual content, some researchers proposed a visual emotion theme model for visual emotion analysis, as shown in Figure 2. In addition, some researchers have found a “semantic gap” between low-level visual features and image emotions, so they proposed a visual emotion ontology method to discover the connection between low-level visual features and image emo-

tions, which is called an emotion detector. The emotion ontology is a formal representation of emotions that relates to affective phenomena and coincides with the Basic Formal Ontology. It distinguishes “emotions proper” in the form of human emotions such as anger and fear from appraisals and subjective feelings. The content-based image retrieval systems work more on human semantics and aim to reduce the semantic gap between the high-level human experience and low-level visual features of the pictures. The use of codified emotion ontology in global color features of images helps in annotating images at the semantic level. The closest adjective-noun pair of an image is used as an emotion marker.

Because of the effectiveness of CNN models in the image domain, a large number of researchers have also switched from using traditional methods for image sentiment analysis to using deep learning techniques. Researchers have heavily adapted CNN models and released numerous advanced CNN-based models. One researcher designed a PCNN network model by first labeling Flickr images with a baseline sentiment classification algorithm to obtain 500,000 training samples, then initially using these noisy image data to train the CNN, and finally using the already labeled training Twitter data samples to gradually fine-tune the neural network to obtain a better sentiment neural network model [16]. Experiments have demonstrated that the accuracy of using migration learning is significantly better than that of random initialization of weights. Some researchers added the visual self-attention mechanism module to the CNN emotion classification framework; however, the method would ignore the key emotional region part of the image, so the salience target of the image is considered as the emotional prior knowledge to correct the region of visual attention learning, which compensates the shortage of self-attention mechanism to learn emotional features. To mine the regions in images that induce emotion, some researchers use a trained visual attribute detector to detect the emotional attributes that may be contained in images and then use the attention model to automatically mine the local regions of images that are closely associated with emotional descriptors.

Meanwhile, there are also methods combining image segmentation for sentiment analysis. Some researchers use existing target detection methods to obtain N candidate regions, combine sentiment scores and object scores to select the top K sentiment regions, then use CNN to extract features of the whole image and sentiment regions, and finally calculate the sentiment polarity of the image by fusion strategy. Other researchers use object detectors to detect local target regions contained within a pair of images, then use neural networks to extract target region features, and finally combine the overall image features and target region features to train an image sentiment recognition model to predict the sentiment of an image [17]. In addition, to locate the salient target regions in an image using a target detection system, some researchers use VGGNet to train the salient target and the whole image sentiment recognition model separately, and finally fuse the results of both predictions to get the final sentiment polarity, and the experiments show that the salient target can help the whole image to improve the accuracy of image sentiment analysis.

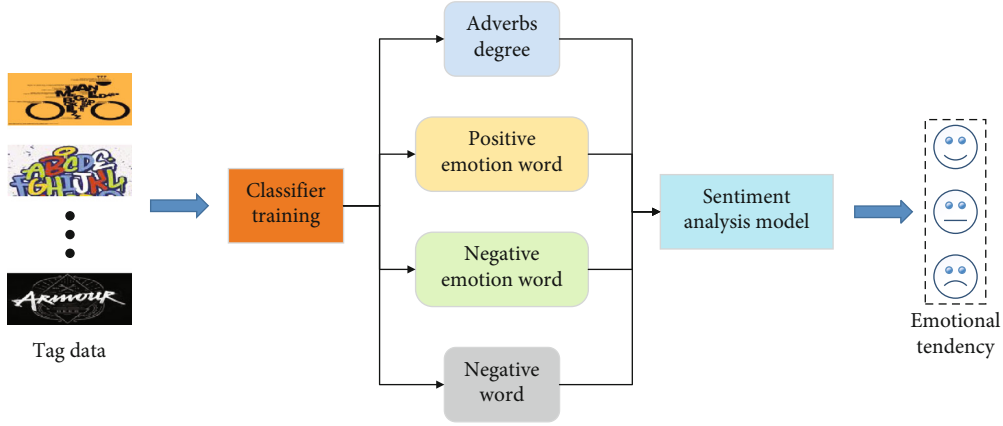


FIGURE 2: Intermediate emotion analysis model.

3. Algorithm Design

3.1. Deep Learning-Based Image Segmentation Algorithm. The segmentation network structure of this paper is divided into three parts: encoding network, transition network, and decoding network, as shown in Figure 3. The encoding network adopts the lightweight network MobilenetV2, the transition network consists of the attention mechanism module and the void space pyramid module, and the decoding network is composed of three network branches. In total, the feature extraction of MobilenetV2 is divided into five parts according to the variation process of the feature extraction size of MobilenetV2 [18]. The transition network consists of two modules. In the decoding network, one part learns the classification of foreground, background, and unknown regions of the image. The other part learns the image edge detail information, i.e., details. The last part aggregates the graphs learned from the previous two parts, i.e., hybrid branching.

The understanding of semantic information of an image is a key step in computer vision tasks. Semantic information is what an image contains, and the semantic information in a segmentation task can be seen as the foreground and background in this image. In the segmentation task, semantic information prediction is crucial because it directly determines the overall effect of segmentation. The semantic branching network is designed based on the idea of classification [19, 20]. The main task of the branching network is to separate the background information, the foreground information, and the unknown area where the background and foreground intersect, that is, the semantic branching is doing a triple classification problem. It is used in performing specialized information retrieval tasks such as in detection of plagiarism. The information is provided on hierarchical relations for employing semantic compression in order to reduce diversity in language. This helps the system to match words with respective meanings independently from set of words being used.

The semantic branch first passes the encoded features through the attention mechanism module, which performs channel importance weighting, and then fuses the features of the first four stages of the encoding network with the different stages of the decoding network, respectively [21]. The specific way of feature fusion is that the features of the first

four stages of the coding network are fused with the features of different stages of the decoding network, respectively. Then a feature map with three channels is finally output by convolution and upsampling operation of the semantic branching network, and each feature map represents one category, respectively. The loss function is

$$L_s = - \sum_{c=1}^C \alpha_g^c \ln S_p^c, \quad (1)$$

where $\alpha_g^c \in (0, 1)$ is the true label of the pixel point, $S_p^c \in (0, 1)$ is the predicted label of the pixel point, and C is the category.

To obtain larger scale contextual information, void space pyramidal pooling is added to the detail branch to capture multiscale information using parallel void convolution layers with different sampling rates. The bootstrap model aggregates feature of different sensory fields, so that the values located in unknown regions can be effectively linked to foreground and background information for more accurate prediction [22]. The detail branch is designed using the idea of feature fusion, with 12 convolutional layers, each followed by a normalization layer and an activation layer, where the activation function of the last convolutional layer is sigmoid, mainly to control the prediction value to between 0 and 1. The detail branching network first extracts the multiscale information of the image from the coded features through the void space pyramid structure. The detail branching loss function is

$$L_d = \sum_i^n \text{smooth}_{L1} \left(m_d^i \left(d_p^i - \alpha_g^i \right) \right), \quad (2)$$

$$\text{smooth}_{L1}(x) = \begin{cases} 0.5x^2 & |x| < 1, \\ |x| - 0.5 & \text{others,} \end{cases}$$

where $d_p^i \in (0, 1)$ is the predicted pixel point value, $\alpha_g^i \in (0, 1)$ is the true pixel point value, and i is the pixel point label.

The hybrid branch is mainly used to predict the final feature map, with two convolutional layers and the last. The hybrid branch fuses the features of the semantic branch

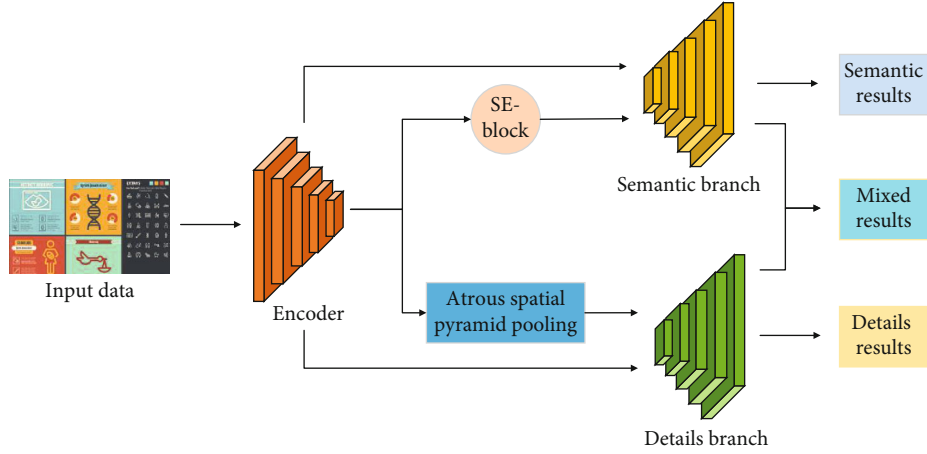


FIGURE 3: Segmentation network structure diagram.

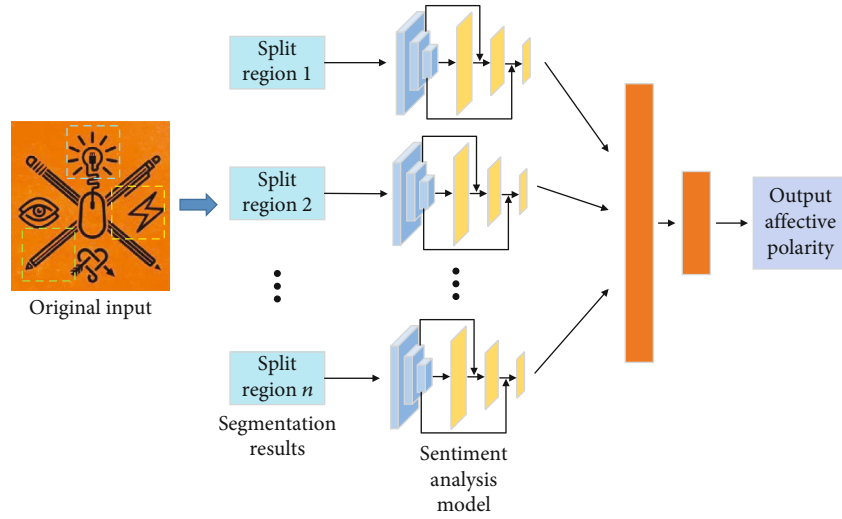


FIGURE 4: Image emotion analysis model.

TABLE 1: Dataset contains the number of emotional images.

Dataset	Negative	Positive	Total number
ArtPhoto	378	428	806
Twitter I	769	500	1269
Flickr and Instagram	16430	6878	23308

and the detail branch, and the fused features are obtained from the last convolutional layer of each branch, and the channels of the two feature maps are concatenated to output a single-channel feature map. The hybrid branch loss function is

$$L = \lambda_s L_s + \lambda_d L_d, \quad (3)$$

where λ_s and λ_d are hyperparameters used to balance the losses of the two branches.

3.2. Significance of Target Sentiment Analysis Algorithm. In order to better explore the emotion conveyed by the image, this paper proposes the framework of salience target sentiment

analysis method as shown in Figure 4, the specific process is firstly, different regions of the image are obtained by segmenting the whole image. Then the target sentiment is identified by the saliency target detection algorithm. The target sentiment analysis helps in extracting targets and performs classification of sentiment classes. It determines the entity-level sentiment for the entities in the input document. This enables analysis of the output data to determine specific products or services that get positive or negative feedback. Finally, the results predicted by each model are fused to obtain the sentiment polarity of the final image. Each part of the framework will be described in detail below.

Salient target detection aims to detect salient target regions in an image, with applications in image understanding, image description generation, semantic segmentation, and other fields. Shortcut connections are added to the deeply supervised layer-hopping structure to extract salient target features at multiple scales per layer. Although the deep side output layer can locate the salient target region well, it also loses some detail information [23]. The shallow side output layer focuses on the low-level features, but the overall information is missing, so

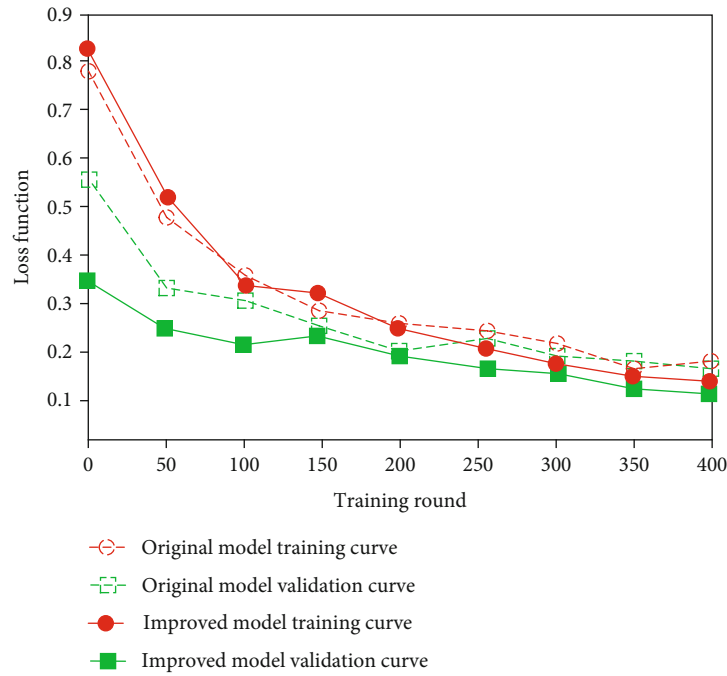


FIGURE 5: Experimental results of segmentation model training.

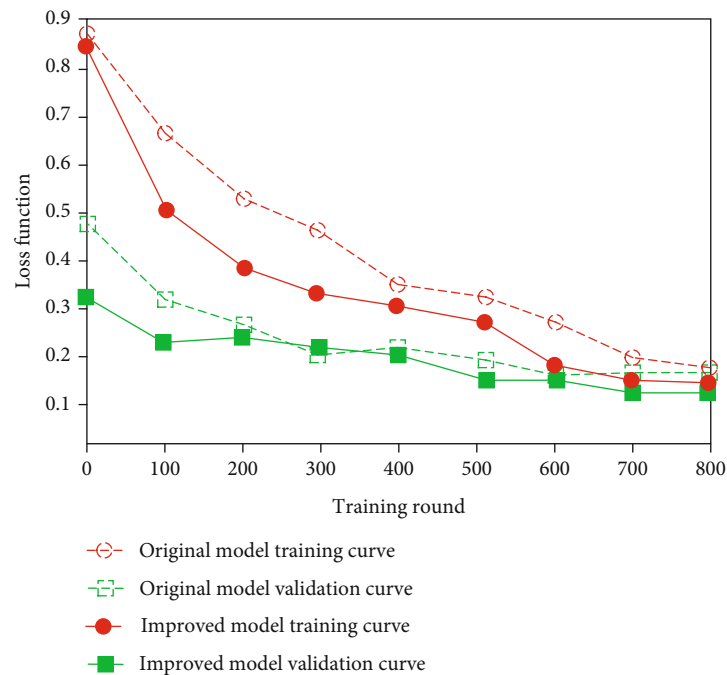


FIGURE 6: Experimental results of emotion analysis model training.

the feature maps of different depths of the side output layer are fused to extract the salient targets.

Considering that multiple target regions grayscale maps may be connected together, the grayscale maps are subjected to an erosion operation, which can separate multiple target regions. Then the target regions whose targets are too small or have too large difference in aspect ratio are filtered out. Since the emotion of an image is not only in the target region,

but also the background around the target region plays a key role in image emotion analysis, the smallest rectangular area pixels surrounding the target are set to 255, and the rest pixels are set to 0 [24]. The obtained binary map is resized to the same size as the original image, and then the original image and the binary map are executed as bit-wise operation. Finally, the contour detection is performed, and the area belonging to the target rectangular box is keyed out. In order to prevent the

TABLE 2: Experimental results of image segmentation.

Model	Overall segmentation accuracy	Detail segmentation accuracy	Segmentation correctness
Learning based	78.53%	75.91%	82.64%
DIM	83.26%	76.38%	79.57%
LFM	87.28%	84.72%	85.32%
MODNet	90.64%	89.85%	86.73%
Ours	94.17%	92.36%	88.65%

hidden layer supervision module from overlearning the hidden layer features and falling into local optimal solutions, a loss function with weights is designed as follows:

$$L_E(W, w) = \sum_{m=1}^M \alpha_m l_m(W, w^{(m)}), \quad (4)$$

where W is the set of parameters of VGG16, each supervised module corresponds to a weight $w = (w^{(1)}, w^{(2)}, \dots, w^{(M)})$, and l_m is the supervised module loss function.

In order to combine the regions to determine the emotional polarity of the images, the results of each emotion recognition model are integrated using a weight fusion strategy:

$$Y = \alpha_1 y_1 + \alpha_2 y_2 + \dots + \alpha_n y_n, \quad (5)$$

where α is the weight coefficient and y is the sentiment recognition result of each region.

4. Experimental Results

4.1. Experimental Datasets. In order to verify the effectiveness of the proposed method, a public dataset including ArtPhoto, Twitter I, and Flickr and Instagram was used for testing. 75% of the three datasets were randomly sampled as the training set and 25% as the test set. ArtPhoto contains 806 artistic photos, and each image is labeled with a real emotion. 1269 images were collected from social networking sites and labeled according to the text describing the emotion filtering the collected 90,000 images, and finally 23,308 images were selected, which contained 8 categories: happy, admiring, content, excited, angry, disgusted, scared, and sad. For the convenience of the study, the first four categories were grouped as positive and the last four as negative. Table 1 shows the number of categories corresponding to each dataset.

4.2. Neural Network Training Results. First of all, the segmentation model is trained, and the neural network training results are shown in Figure 5. As can be seen from Figure 5, the neural network is trained for 400 rounds, and the improved network needs to reach convergence in 350 rounds, while the improved network can converge in 300 rounds, and the mean square error is less than 0.2. When the neural network of branching model is used for image segmentation, the mean square error reaches less than 0.25 after 200 rounds of training. Compared with the original model, the convergence speed is faster, the

number of iterations required is significantly reduced, and the error reduction is faster.

Then the sentiment analysis model is trained, and the neural network training results are shown in Figure 6. As can be seen from Figure 6, the neural network is trained for a total of 800 rounds, and the improved network needs to reach convergence in 800 rounds before the improved network converges in 700 rounds. The error function decreases faster when the neural network with the attention model is used to analyze the image emotion, indicating that the attention model helps to learn the emotion expressed by the image more quickly.

4.3. Comparison of Experimental Results. In order to compare the advantages and disadvantages of the algorithms in this paper, a traditional segmentation algorithm learning based and three deep learning-based segmentation algorithms, namely, the semiautomatic DIM segmentation algorithm based on deep learning, the fully automatic LFM segmentation algorithm, and the fully automatic MODNet segmentation algorithm, are compared in the validation set in this paper. The semiautomatic segmentation is a process in which automatic segmentation is performed by manual checking and editing of the segment boundaries. This type of segmentation is done where segmentation of large databases need to be performed for training comprehensive recognizers. MODNet is used for subobjective consistency from a single input image in real-time when subjected to variability pertinent to scene change. It is designed using neural networks in association with self-supervised strategy and one frame delay to smoothen the portrait sequence. The LFM segmentation algorithm is an LCD algorithm based on binary feature classification matching between similar images using deep learning technique. Table 2 shows the segmentation results of each of the five methods.

As can be seen from Table 2, it can be found that the traditional segmentation algorithms based on learning based are not clearly separated in details. This reason explains that although the learning-based segmentation algorithm has good segmentation results for the regions where the figure clearly belongs to the background and clearly belongs to the foreground, it still needs to rely on the algorithm to predict the unknown regions, so the performance of the hair segmentation results for the unknown regions is not very good; the semiautomatic segmentation method DIM based on deep learning has good segmentation results for the image, but the unknown region is not very good, which is mainly because DIM lacks a large number of portrait dataset training; fully automatic segmentation algorithms based on deep learning, LFM and MODNet, have improved the segmentation effect for the detailed part of the image, but the segmentation effect of occasional details is not very good, which shows that the problem of generalization of deep learning still exists as a difficult problem to solve. In contrast, the algorithm in this paper is more complete in the semantic part of the image; firstly, the segmentation effect of the algorithm in this paper is more complete for these images as a whole, and secondly, the segmentation effect of the detail part is more fine.

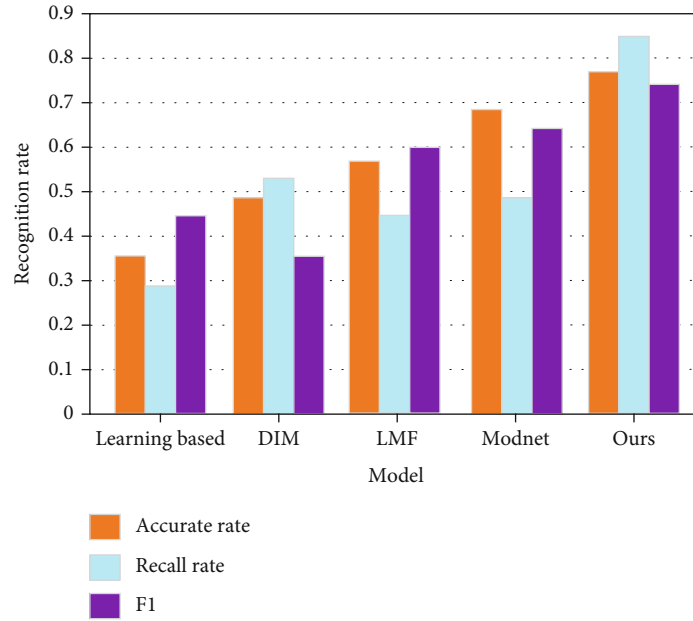


FIGURE 7: Experimental results of segmentation quantization index.

TABLE 3: Experimental results of emotion analysis.

Model	Accuracy on different datasets		
	ArtPhoto	Twitter I	Flickr and Instagram
FCNN	73.82%	75.13%	79.76%
AR+ concatenation	76.35%	80.65%	82.49%
GMEI&LRMSI	75.64%	81.27%	85.32%
Ours	79.76%	84.61%	87.21%

In order to further verify the effectiveness of the algorithm, three commonly used image segmentation evaluation metrics, namely accuracy rate, edge recall rate, and F1 value, are also used for verification. The experimental results are shown in Figure 7, from which it can be seen that the images segmented by the algorithm in this paper are the highest in all three metrics, thus objectively proving that the algorithm in this paper is better than the other two algorithms in image segmentation as a whole. A closer look at the value of edge recall shows that the algorithm in this paper scores higher than the other two algorithms, which is precisely the reason why the algorithm in this paper combines VGG-16 convolutional network, making the algorithm in this paper in absolute advantage in contour segmentation.

The results of the image sentiment analysis comparison experiments are shown in Table 3, and the comparison methods are FCNN, AR+ concatenation, and GMEI&LRMSI. The GMEI&LRMSI technique highlights the fact that all images in the dataset do not contain salient objects, and visual sentiment analysis focuses only on local features. In case of GMEI&LRMSI, global and local modules are implemented, and the decision to use local module is taken on the basis of object detection module. Table 3 reveals that the accuracy of the experiments using AR+ concatenation and GMEI&LRMSI is higher than that of the methods using FCNN, which indi-

cates that it is easier to enter the local sentiment region than just using the whole image to identify the emotion of an image, and incorporating saliency targets to identify image emotion accuracy will be higher. Our method improves the accuracy by 2 to 5 percentage points compared with the GMEI&LRMSI method, indicating that adding the target sentiment region to the fused saliency target can further improve the image sentiment classification accuracy.

5. Conclusions

Today's society has entered the information age, and the role of graphic design language as a carrier of information transmission is becoming more and more important in daily life, both to achieve the purpose of information transmission and to meet people's aesthetic needs. The study of graphic design language plays an important role in the improvement of design level. This paper takes graphic design language as the research object and studies the graphic design language from the perspective of artificial intelligence. First, an image segmentation algorithm is improved in the paper. The algorithm uses two separate branching networks to learn the semantic information and detail information of the image, respectively, and the information of the feature maps learned by both are aggregated together to realize an end-to-end segmentation algorithm. Then, an image sentiment analysis method combining saliency targets is proposed. The saliency target sentiment analysis model is constructed by segmenting images, and the target sentiment analysis model is constructed by a weighted supervised module, and finally the sentiment analysis model of the saliency target in each region is fused to predict the sentiment polarity of images. The experimental results show that the method proposed in this paper can improve the segmentation accuracy of different parts of graphic design, especially the detail segmentation accuracy; it also shows that

the image sentiment analysis method of fusing salient targets can be used to identify graphic design languages. The proposed model could be further implemented on medical image dataset or healthcare dataset to justify its applicability in radiotherapy planning for various diseases.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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