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# Classification and Creation of New Media Design Element Based on Reinforcement Learning

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**Abstract.** The application of artificial intelligence technology in new media design not only improves the efficiency of design but also improves the quality of design. However, with the increasing requirements of new media design, the accuracy and efficiency of some artificial intelligence element classification methods cannot meet the needs of new media design. Therefore, this paper builds a new media design element classification and intelligent creation model based on convolutional neural networks and reinforcement learning. Aiming at the problems of classification accuracy and efficiency, this paper combines two kinds of convolutional neural networks to improve the classification accuracy and retrieval efficiency of elements. At the same time, personalized and intelligent element recommendation is realized through reinforcement learning to help designers achieve intelligent optimization. The experimental results show that Compared with other models, the proposed model has the best classification accuracy, stability, and adaptability, which can effectively shorten the retrieval time of different elements and show better performance in intelligent creation. The experimental results show that the proposed model can realize intelligent optimization on the basis of the existing design, increase the sense of design hierarchy, and improve the design layout and overall effect.

**Keywords:** Convolutional Neural Network; Reinforcement Learning; New Media Design; Element Classification; Intelligent Creation
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## 1 INTRODUCTION

The development of information technology and network technology not only provides a broad space for the development of new media technology but also provides a huge amount of design resources [1]. The constant development of new media technology has brought about a new level of development in the field of graphic design. With the rapid increase in communication skills, the graphic design industry urgently needs to find a new way out. As the main graphic design content, graphic design elements should also be innovated and integrated with new design elements [2]. With the development and changes in communication media, graphic designers should engage in new thinking and research on new design methods and ideas in both design and conceptualization. In the new media environment, the speed of information dissemination is rapid, the methods of dissemination are extensive, and the content of information dissemination is constantly increasing [3]. With the development of technology, the ways of information transmission are also changing [4]. The dynamic design of graphic design elements is a new category of design creativity that has emerged in the new media environment. Its emergence has promoted the development of graphic design and brought about new changes in the design scope of graphic design. From ancient postal vehicles and horses to paper media, it has evolved into today's PC and mobile media. While analyzing excellent dynamic design works at home and abroad, we searched for the advantages of dynamic design and carried out design project practice. Perfectly combining dynamic design and graphic design elements in various fields of graphic design, expanding the development trend of dynamic design research on graphic design elements from multiple perspectives. The rapid development of new media technology has significant implications for exploring dynamic design elements in graphic design [5]. Dynamic design techniques enrich the transmission of information content, enhance visual expression, and broaden the dimensional expression of graphic design elements. The article mainly analyzes the characteristics of graphic design elements, starting from the design itself, and elaborates on the methods and research modes of dynamic design of graphic design elements. Dynamic design focuses on the human-machine experience, and humanized user experience is the foundation of dynamic design. We strive to achieve true design effects by combining experience with design. The development of new media technology has a profound impact on the field of graphic design, and the dynamic design research of graphic design elements in the new media environment is a classification and extension of graphic design. Some scholars mainly guide the emergence of practice through theoretical analysis, based on data collection and literature summary [6]. Through literature search, design practice, case analysis and other methods, a dynamic design method for graphic design elements with practical significance is derived. The application of dynamic design in practical projects demonstrates the profound impact of dynamic design research on graphic design elements in the field of graphic design, providing reference value for the development of graphic design.

In contrast, the application of artificial intelligence technology in new media design has greatly changed the development of new media design and greatly improved the development of new media design. Artificial intelligence technology can automatically complete a large number of repetitive tasks and complete the classification of design elements quickly and accurately according to corresponding requirements [7]. At the same time, based on the classification results, designers can quickly select and generate elements that meet the design, reducing a lot of time and labour costs. However, with the deepening of the application of artificial intelligence technology, some researchers have pointed out that new media design elements contain multiple element data such as vision, hearing and text, especially the rapidly expanding scale of design elements such as images and videos, which makes it difficult for some artificial intelligence models to efficiently extract useful feature information when processing new media design elements such as images or videos. It is inefficient and costly. At the same time, in the future development of new media design, it is more necessary to fully consider users' behaviour habits and preferences, and emphasize personalized design and recommendation. It is difficult for some models to balance the needs of the market and customers while adapting to the complex and changing environment to ensure that the design works remain competitive [8]. In view of the above problems, this paper combines convolutional neural network and reinforcement learning to build an intelligent creation model for classifying new media design elements. In other words, the convolutional neural network is used to improve the accuracy of the model's extraction and classification of design element features, and an intelligent design module is built in combination with reinforcement learning to realize intelligent design optimization.

In digital media art creation, precise classification of design elements is the key to improving the quality and innovation of works. Arduino, as a hardware platform, provides artists with the flexibility to implement circuit design and programming, making the integration of technology and art closer [9]. Convolutional neural networks (CNNs) provide technical support for this process with their powerful image recognition and classification capabilities. This deep integration not only enriches the forms of expression of new media art but also opens up vast space for the future development of art. By training CNN models, the system can automatically learn and recognize basic design elements such as color, shape, texture, etc., in artworks and even further understand the combination rules and emotional expressions of these elements in the works [10]. The intelligent creation system combining CNN and RL can not only achieve precise classification and intelligent combination of design elements but also continuously promote works to higher levels of artistic expression through real-time interactive feedback. In the field of new media art, applying RL to the creative process can enable artworks to self-adjust and optimize based on audience feedback or preset aesthetic standards. Reinforcement learning (RL), as a branch of machine learning, enables agents to continuously try and optimize their environment to achieve specific goals [11]. This intelligent classification method not only improves creative efficiency but also provides artists with more diverse sources of creative inspiration. For example, in interactive works, the audience's touch behaviour can be seen as an "evaluation" of the work. By analyzing this feedback through RL algorithms, the work can dynamically adjust the display content, colour matching, or interactive logic on the LED screen to provide a more personalized and immersive artistic experience.

## 2 RELATED WORK

With the continuous advancement of technology and the diversified development of design, the classification methods of new media design elements are becoming increasingly rich and perfect. In the early days, the classification task of new media design elements required manual completion, which was not only costly but also had relatively low classification accuracy. Liu and Yang [11] applied machine learning algorithms to new media design, which can automatically identify and classify design elements such as colours, fonts, images, etc., through random forests or decision analysis of large amounts of design work data. These algorithms can learn the features of design elements and effectively classify them based on these features. Song [12] cites a clustering algorithm that clusters similar design elements into a category to help designers discover design trends and styles, understand the intrinsic connections between design elements, and provide inspiration and direction for creativity. In addition, some researchers start from the semantic information of elements, introduce semantic analysis models, and use natural language processing techniques to convert the semantic information of design elements into computable data for classification and induction. This can delve deeper into the deeper meanings of design elements, improving the accuracy and depth of classification. Based on the development of new media, some researchers believe that design elements usually exist in various forms, such as images, videos, audio, etc. By integrating CNN and RL technologies, Tang et al. [13] achieved deep exploration of design space and intelligent layout optimization, thereby overcoming the limitations of traditional (semi-automatic) methods. In the initial stage of visualizing the storyline, CNN can play a crucial role in efficiently and accurately classifying design elements such as characters, scenes, props, etc. By automatically learning image features, CNN can recognize and distinguish subtle differences between different design elements, providing a rich material library and accurate references for subsequent story plot construction. This step not only improves design efficiency but also ensures visual coherence and consistency of the storyline.

Therefore, multimodal fusion methods are used to extract and fuse design elements from different patterns, forming a unified representation and then classifying them. In this way, the information of design elements can be captured more comprehensively, improving the comprehensiveness and accuracy of classification. In the context of the information explosion and pan-entertainment era, the modern dissemination of traditional cultural elements is even more difficult. Immersive experience not only subverts the audience's previous experience of artworks but also enhances the distance between the audience and the works through continuous communication and feedback, while also having a very efficient dissemination function. Previously, passive display methods such as text, images, and videos were no longer sufficient to meet people's current experiences and aesthetic needs. In order to better utilize the advantages of immersive experiences to help modernize the dissemination of traditional visual elements, Wang and Cai [14] start from the perspective of new media context: firstly, by summarizing and discussing the characteristics, principles, and trends of immersive experiences. Focusing on the application methods and future trends of integrating traditional Eastern visual elements with immersive experiences. In order to achieve better dissemination effects and a wider range of dissemination dimensions for the immersive experience of traditional elements, this article objectively discusses the problems and future prospects of integrating traditional Eastern elements into immersive experiences in current art creation with a speculative attitude. It summarizes and generalizes the development and challenges of traditional visual elements in traditional media and concludes the significance of combining immersive experience with traditional visual elements.

The development and transformation of science and technology in the 1960s promoted the rapid development of information technology and had a huge impact on people's production and daily activities. Traditional graphic elements are especially a concrete manifestation of the Chinese spirit. Therefore, the development of information technology has also promoted the development of the art field. The emergence of various new technological tools, such as various recording devices and multimedia CDs, has provided convenience for artists' continuous innovation. As a traditional art culture that carries thousands of years of Chinese culture and its artistic creation and expression forms, it carries the wisdom of Chinese ancestors and reflects the national characteristics and ideological concepts of the Chinese nation. However, in the process of the vigorous development of new media art, it is facing the gradual decline of traditional culture and traditional art forms. Xin et al. [15] mainly analyzed the definition of the concept and connotation of new media. Comparative research on new media and traditional media, as well as analysis of the connotation of new media art, in order to deepen our understanding of new media art. Therefore, with the help of various new media technology tools, new media art naturally emerged and gradually replaced traditional media as the mainstream art trend at present.

## 3 INTELLIGENT CREATION MODEL OF NEW MEDIA DESIGN ELEMENT CLASSIFICATION

### 3.1 New Media Design Element Classification Module Based on Convolutional Neural Network

New media design elements contain diverse forms of data, so the classification of design elements is relatively difficult, especially the feature extraction of image and video data. In addition, new media design has strong timeliness; that is, the designer's design time is shorter than that of other designs, and the design content information is extensive, which requires the model to have high-precision classification performance and rapid retrieval ability. A convolutional neural network (CNN) is a feedforward neural network with deep structure, which has strong image data processing performance and can meet the needs of new media design element classification. Its structure is composed of multiple layers of different networks stacked together in a specific order and way to realize the processing of input data and feature extraction. However, due to the complexity and abstractness of new media design elements, the feature extraction of CNN has certain limitations, and it is difficult to achieve accurate element capture. At the same time, the training effect and generalization ability of CNN have high requirements on the quality of annotated data, and the complexity of the model will also affect the speed of element classification and retrieval. Therefore, in combination with the characteristics of element classification in new media design and the actual needs, this paper chooses VGG and YOLOv5, variants of CNN, to build the element classification model. Figure 1 shows the schematic diagram of the new media design element classification process based on a convolutional neural network.

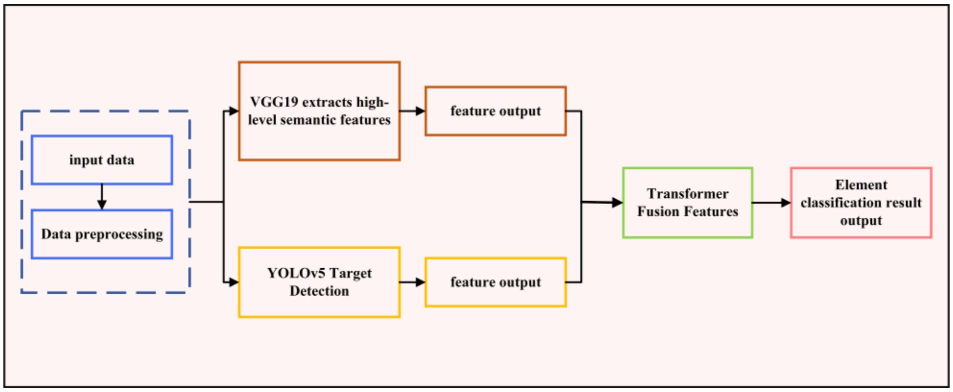


**Figure 1**: Schematic diagram of new media design element classification process based on convolutional neural network.

As can be seen from the figure, VGG19 is adopted in this paper, which is a deep variant of CNN. It is mainly composed of a convolutional layer, pooling layer, and fully connected layer, including 19 convolutional layers and 3 fully connected layers. On the basis of convolutional neural networks, VGG networks enhance the feature extraction capability and overall performance of convolutional neural networks by significantly increasing the depth of the network, that is, stacking more convolutional layers and pooling layers while maintaining or fine-tuning the size of convolutional nuclei to maintain an appropriate receptor field size. This strategy of increasing depth allows VGG to learn more complex and abstract image features, resulting in better performance in tasks such as image classification.

In the convolution layer, the input feature graph is convolved with a set of learnable convolution kernels, To produce an output feature map. Let the feature map position be represented as $(i,j)$ The convolution kernel is denoted as $k$ The convolution operation is shown in formula (1):

$$y_{ijm}=\sum_{p=0}^{k-1}\sum_{q=0}^{k-1}\sum_{n=0}^{C_{in}-1}w_{pqnm}\cdot x_{(i+p)(j+q)n}+b_m \tag{1}$$

Where the channel value of the sequence number is expressed as $y_{ijm}$ The number of input channels in the feature graph is expressed as $C_{in}$. In the convolution kernel of sequence number, $(p,q)$ The position and sequence number of channel connection weights are denoted as $w_{pqnm}$. Position $(i+p,j+q)$ The channel value of the sequence number is expressed as $x_{(i+p)(j+q)n}$, the offset term is expressed as $b$.

The maximum pooling is shown in formula (2):

$$y_{ijm}=\max_{(p,q)\in R_{ij}} x_{pqm} \tag{2}$$

Where the pooling regions corresponding to the positions of the input and output feature maps are represented as $R_{ij}$, within the area $(p,q)$ Where the sequence number is $m$ The value is expressed as $x_{pqm}$.

The fully connected layer flattens all the output feature graphs of the previous layer into a one-dimensional vector multiplied by the weight matrix of that layer, plus bias terms, and finally activates the function, usually via ReLU. As shown in formula (3):

$$y_i = ReLU(\sum_{j=0}^{N-1} w_{ij} \cdot x_j + b_i) \tag{3}$$

Where the value of the output vector element whose sequence number is expressed as $y_i$ the length of the input vector is expressed as $N$ the sequence number is $j$ The number of input vectors and sequences are $i$ The output vector connection weight is expressed as $w_{ij}$ the corresponding offset term is $b_i$.

The feature extraction expression is shown in (4):

$$Features = VGG19(Design\_Image) \tag{4}$$

The input data of the new media design image is expressed as $Design\_Image$ VGG19 The forward propagation process is expressed as $VGG19$.

The classification layer and classification decision are represented as:

$$Scores = Dense\_Layers(Features) \tag{5}$$

$$Probabilities = softmax(Scores) \tag{6}$$

$$Predicted\_Class = \underset{i}{argimax}(Probabilities_i) \tag{7}$$

Where one or more fully connected layers are represented as $Dense\_Layers$. The probability distribution conversion function is $softmax$, by function $\underset{i}{argimax}$ Implement the selection of the highest probability category.

In order to reduce the possibility of overfitting in model training, the parameters of VGG19 in this paper are static parameters, and the VGG19 network structure is shown in Table 1.

| *Serial number* | *Layer Structure* | *Number of layers* | *Serial number* | *Layer Structure* | *Number of layers* |
|---|---|---|---|---|---|
| 1 | Conv3-64 | 1 | 22 | Conv3-512 | 10 |
| 2 | Relu | | 23 | Relu | |
| 3 | Conv3-64 | 2 | 24 | Conv3-512 | 11 |
| 4 | Relu | | 25 | Relu | |
| 5 | Maxpool | | 26 | Conv3-512 | 12 |
| 6 | Conv3-128 | 3 | 27 | Relu | |
| 7 | Relu | | 28 | Maxpool | |
| 8 | Conv3-128 | 4 | 29 | Conv3-512 | 13 |
| 9 | Relu | | 30 | Relu | |
| 10 | Maxpool | | 31 | Conv3-512 | 14 |
| 11 | Conv3-256 | 5 | 32 | Relu | |
| 12 | Relu | | 33 | Conv3-512 | 15 |
| 13 | Conv3-256 | 6 | 34 | Relu | |
| 14 | Relu | | 35 | Conv3-512 | 16 |
| 15 | Conv3-256 | | 36 | Relu | |
| 16 | Relu | | 37 | Maxpool | |
| 17 | Conv3-256 | 7 | 38 | fc(4096) | 17 |
| 18 | Relu | | 39 | Relu | |
| 19 | Maxpool | | 40 | FC(4096) | 18 |
| 20 | Conv3-512 | 8 | 41 | Relu | |
| 21 | Relu | | 42 | fc(1000) | 19 |

| | | |
|---|---|---|
| | 43 | softmax |

**Table 1**: VGG19 network structure.

In terms of new media design elements, this paper adopts the YOLOv5 model to realize the purpose of fast retrieval and classification of design elements. YOLOv5 relies on the strong foundation of CNN and cleverly uses the "single-stage detection" strategy to realize rapid and high-precision identification and positioning of target objects in images. The architecture design of the model shows a high degree of modularity, allowing developers or researchers to customize and optimize according to the actual application scenario easily. At the same time, YOLOv5 pays attention to the lightweight design and effectively reduces the consumption of computer resources by streamlining the network structure and parameters, making it stable operation and excellent performance on a variety of devices, even in an environment with relatively limited resources. Figure 2 shows the network structure diagram of YOLOv5s.

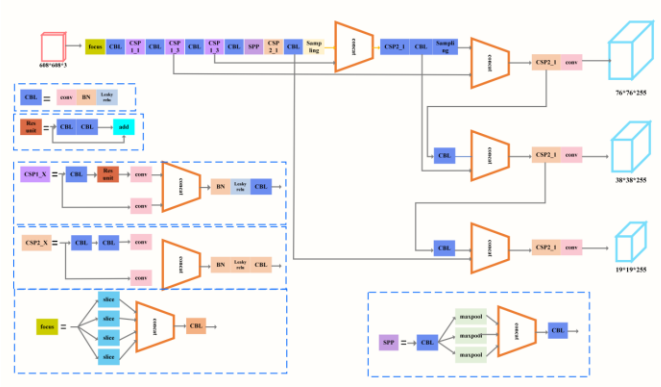

**Figure 2**: YOLOv5s network structure diagram.

In the output stage of the model, in order to accurately evaluate its classification performance, the binary cross entropy loss function is selected to calculate the error between class probability and confidence score carefully. This strategy ensures that the model accurately reflects the predictive power of the target class. At the same time, in order to improve the positioning accuracy of the target in the image, the model innovatively introduces the border loss function, which is specially optimized for the prediction of the target boundary box and effectively reduces the positioning error. By combining these two methods of loss calculation, a multi-scale problem solution is adopted. As shown in formula (8) - (10):

$$v = \frac{4}{\pi^2}(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h})^2 \tag{8}$$

$$\alpha = \frac{v}{1 - IoU + v} \tag{9}$$

$$GIoU\_Loss = 1 - IoU + \frac{p^2(b, b^{gt})}{c^2} + \alpha v \tag{10}$$

In the formula, the Euclidean distance between the real box and the prediction box is expressed as a central point $p^2(b,b^{gt})$ The diagonal distance of the minimum external matrix of the two is expressed as $c$, and the weight parameter is expressed as $a$, The measurement index of aspect ratio consistency is $v$.

In order to improve the integration of VGG19 and YOLOv5 feature data, the Transformer model is adopted in this paper. With its unique sequence processing capability, the Transformer model becomes a bridge to integrating multiple design elements and deep logic relationships. This model is good at crossing the physical distance between elements and accurately capturing and analyzing the intricate dependencies between them. This ability is particularly critical in new media design because it requires designers not only to pay attention to the presentation of individual elements but also to deeply understand how elements interact with each other to build a design work with rich levels and depth. The core of the Transformer model is its self-attention mechanism, which gives the model extraordinary flexibility when working with serial data. In the process, the self-attention mechanism forces the model to consider each element in the input sequence as a potentially related object, to be compared and considered one by one. Through this comprehensive interaction, the model can deeply understand the meaning and role of each element in different contexts, so as to make more accurate processing decisions. The calculation expression is shown in (11):

$$attention(Q,K,V) = soft\max(QK^T \Big/ \sqrt{d_k})V \tag{11}$$

Among them, the input word vector of the self-attention mechanism will have a query vector, a key vector and a value vector, and their corresponding matrices are respectively expressed as $Q,K,V$ the key vector dimension is expressed as $d_k$ .

### 3.2 New Media Intelligent Creation Module Combined With Reinforcement Learning

Intelligent design creation of new media is based on the needs and preferences of users, and also needs to take into account the market competitiveness, so designers need to choose elements that meet the corresponding needs when designing and creating, and realize diversified combinations to provide users with a variety of personalized choices. In addition, on the basis of the existing design, the intelligent design should realize the modification and optimization of the design in a short time according to the specific requirements. Therefore, based on the classification of design elements, this paper combines reinforcement learning to enhance the intelligent creation performance of the model. Reinforcement learning has good autonomous learning ability, dynamic implementation and efficient optimization ability. It learns independently through continuous trial and error and receives feedback from the environment. This ability enables it to gradually optimize its decision-making strategy without explicit guidance. In new media design, this means that the system can automatically explore different combinations of design elements and adjust them based on user feedback to create designs that are more in line with user preferences. At the same time, it can quickly evaluate the advantages and disadvantages of different design schemes, and choose the best design scheme, so as to improve the design efficiency and the quality of the work. In this paper, Q learning in reinforcement learning is adopted to build a new media intelligent design module, which aims to maximize the expected cumulative returns obtained by the agent from the environment, as shown in formula (12):

$$W^*(i) = E\left(\sum_{t=0}^{\infty} \lambda^t l_t\right) \tag{12}$$

Where the discount rate is denoted as $\lambda$ The expectation is described as $E$ , the instant reward at each moment is recorded as $l_t$ , $W^*(i)$ Conforms to the Bellman equation, as shown in (13):

$$W^*(i) = l(i,a) + \lambda \sum_{i'=I}^{+\infty} P_{ia,i'} W^*(i') \tag{13}$$

Where the state transition possibility is denoted as $P_{ia,i'}$ .

The update strategy of Q learning is to maximize the Q-value function to obtain an optimization strategy, and its update rule is shown in (14):

$$\begin{cases} Q(i,a) = l(i,a) + \lambda \sum_{i' \in I} P_{ia,i'} \max_{a} Q^*(i',a') \\ Q(i,a) \leftarrow Q(i,a) + \delta(l + \lambda - Q(i,a)) \end{cases} \tag{14}$$

Where the value function corresponding to the current state and action is denoted as $Q(i,a)$ The learning efficiency is denoted $\delta$. When the value function reaches the optimal value, its optimal management strategy is shown in (15):

$$\pi^*(i) = \arg\max_{a} Q(i,a) \tag{15}$$

## 4 EXPERIMENTAL RESULTS OF APPLICATION OF INTELLIGENT CREATION MODEL

### 4.1 Experimental Results of Model Design Element Classification

In order to test the classification performance of model design elements, this paper mainly tests the accuracy of design elements classification and the retrieval speed of design elements. In the experiment, this paper selected another three models for comparison, including the classic CNN model, CNN-LSTM and Faster R-CNN. The test data were classified into 8 groups, and each group of data contained design elements of various data types such as new media text, image, video and audio. Figure 3 shows the comparison results of extraction and classification accuracy of different new media design elements. The data in the figure shows that in terms of classification accuracy, the classical CNN model has the lowest classification accuracy and there is a large gap between its classification results in different data groups, that is, it lacks certain adaptability and stability. Cnn-lstm and Faster R-CNN are both improved on the basis of the classical CNN model, and their classification accuracy has been improved to some extent, with little difference between them. But in terms of stability, CNN-LSTM performs better. Compared with the other three groups, the element classification accuracy of this model is the highest, and the stability and adaptability of this model are the best. This indicates that the proposed model can effectively improve the quasi-determination of design element classification and enhance the stability and adaptability of the model in different data.

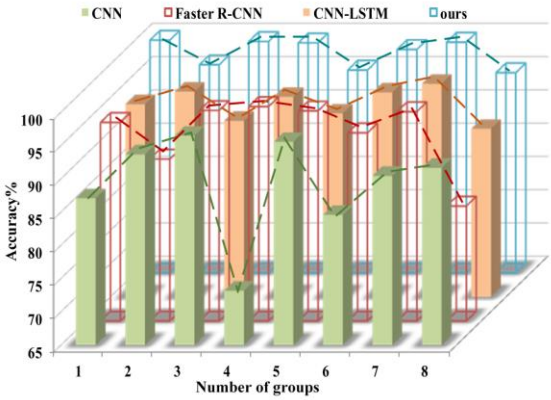


**Figure 3**: Comparison results of extraction and classification accuracy of different new media design elements.

Figure 4 shows the results of classification and average time percentage of the search for different new media design elements. In the experiment, text elements, image elements, colour elements, layout elements and dynamic elements of new media were mainly compared in the average time percentage of search. It can be seen from the results that in the same element classification and retrieval, the average time of the proposed model is significantly shorter than that of the other three models, that is, the retrieval efficiency is higher. This indicates that the proposed model can improve the element retrieval time while maintaining a high classification accuracy, and can provide better data support for the intelligent design of new media.

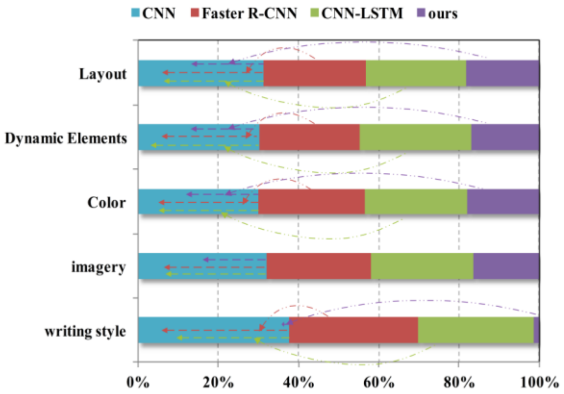


Figure 4: Results of the average percentage of time for classification and retrieval of different new media design elements.

### 4.2 Experimental Results of Intelligent Model Creation

Intelligent creation is carried out according to the needs and preferences of users, and it is also an intelligent optimization achieved in the design of designers. An important performance of intelligent creation is that the model can realize the recommendation of diversified new media design elements according to the needs of users. Therefore, the results of the REINFORCE algorithm in reinforcement learning were used as the reference line for performance comparison, and the results are shown in Figure 5. The results show that compared with the baseline, the accuracy of this model is significantly improved, and the recall rate and FI value are higher than the baseline model. This indicates that the model presented in this paper has good performance improvement in new media intelligent design creation, that is, it can provide better design optimization effects for designers and users in practical applications

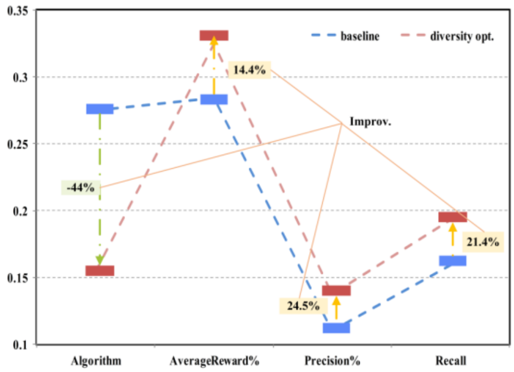


Figure 5: Test results of model recommendation performance of diversified new media design elements.

## 4.3 Experimental Results of the Practical Application of the Model

In order to further test the performance of the model in practical applications, this part mainly detects the optimization effect of the model on existing new media designs and the design results according to user preferences. Figure 6 shows the results of intelligent optimization of new media design by the model based on user preferences and relevant information. It can be seen from the results that the model in this paper can select elements that are more in line with users' needs and preferences on the basis of the original new media design for design optimization. The model increases the colour layer on the basis of the AB and AB designs, and the B design increases the colour saturation and adds new colours. In terms of layout, the optimized design layout is more stretched and can better present visual effects. This shows that the model in this paper can realize the performance of intelligent design creation of new media and improve the quality of design creation in practice.

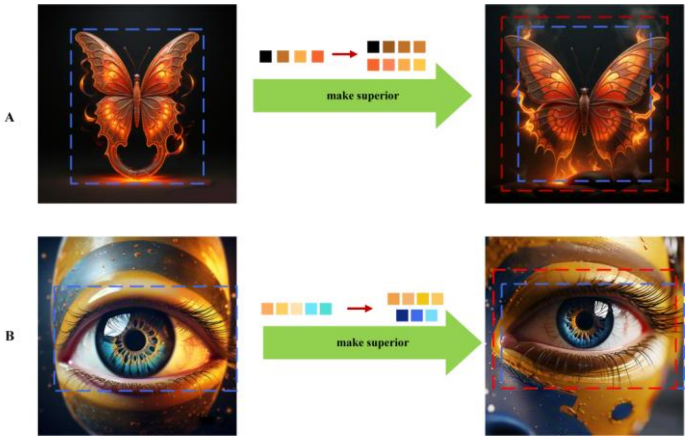


**Figure 6**: Results of model intelligent optimization of new media design.

In terms of intelligent design, different designs are selected for testing in this paper. The model will select corresponding design elements according to the relevant information provided by users and designers to help designers complete the new media design, as shown in Table 2.

| | *style* | *use* | *element* | *preference* |
|---|---|---|---|---|
| A | Ink painting | Tourism periphery | Lakes, mountains, courts, Bridges | Misty rain Jiangnan, cool, exquisite |
| B | freshness | logo | Highlighting handwork, combined with embroidery, wool, crochet | With a sense of layer, full content, soft tone |
| C | Modern + dreamy | Activity publicity | Trees, books, children | The picture is harmonious and soft |
| D | Ink painting | inset | Mountains, trees, pavilions | It has a sense of ethereality and a grand atmosphere |

**Table 2**: Information about new media design and creation.

Figure 7 shows the creation results designed based on the model in this paper. The results show that the utilization rate of elements in the design creation of the four groups can reach more than 80%, and the colour harmony of the A group is more than 85%. The A group belongs to the ink style, which is less in colour itself, and the colour is more in line with the current aesthetic. The layout effect of the four groups of design reached more than 80%, and the overall design effect reached more than 90%. This shows that the model can help designers improve the application and design quality of design elements and realize the purpose of intelligent design in practical application.

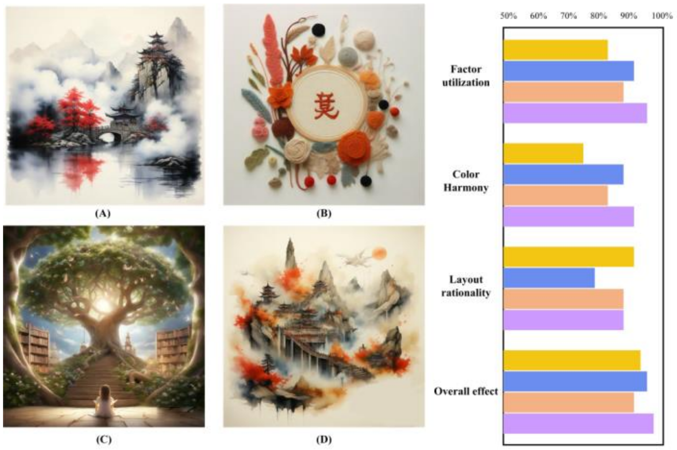


**Figure 7**: Results of new media design and effect analysis.

## 5 CONCLUSIONS

The classification of new media design elements is an important way to improve the quality of new media intelligent design. Improving the accuracy of classification and the speed of element retrieval can not only help designers improve design efficiency but also improve design quality. Compared with traditional methods, the application of artificial intelligence technology has accelerated the development of element classification methods, but the classification accuracy of some artificial intelligence classification methods is relatively low, and the efficiency of element retrieval cannot meet the needs of constantly developing new media designs. Based on this, this paper combines a convolutional neural network and reinforcement learning algorithm to build a new media design element classification and intelligent design model and improves the classification accuracy by combining the extraction and fusion effect of enhancer features with a variety of convolutional neural networks. At the same time, YOLOv5 is used to improve the efficiency of element retrieval. On this basis, this paper also combines reinforcement learning to realize personalized element recommendations and realize the purpose of intelligent design. The results show that the classification accuracy of the proposed model is greatly improved compared with other models, and it shows good adaptability and stability in different data. At the same time, for the same type of element retrieval, the average percentage of retrieval time of this model is lower, that is, the element retrieval time can be greatly shortened. Compared with the benchmark model, the accuracy rate, recall rate and F1 value of the intelligent design are improved, that is, the intelligent design performance of the model is enhanced. The application experiment results show that the model in this paper can be intelligently optimized based on the original new media design according to the preferences and needs of users, increase the sense of design hierarchy, improve the accuracy of element selection, and significantly improve the design layout and overall effect. In addition, this model can also help designers to carry out personalized selection and intelligent design of elements according to the needs of users, and improve the finishing effect of design elements, colour, layout and other aspects.

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