An Intelligent Advertising Creative Generation Method Based on CAD Collaborative Design

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Abstract. The traditional advertising design mode can not meet the increasing competition in the advertising industry on the demand for personalization and efficiency; designers, in a short period of time, can not quickly accumulate design experience and materials to improve the efficiency and quality of advertising creative design. Therefore, this paper combines a convolutional neural network and Teamcenter to construct an intelligent advertising creative generation model based on computer-aided design (CAD) and collaborative design to realize the automation and personalization of advertising design. The experimental results show that the model has a fast performance convergence speed and high accuracy and can effectively classify elements and ensure high accuracy. At the same time, the extracted creative elements have the lowest error, which is more in line with the aesthetic needs of designers and customers, and it can provide effective and accurate data information for the generation of advertising creativity. In addition, compared with the other two creative generation models, this model can keep a relatively short time in generating creative ideas of different difficulties and obtains the highest degree of recognition from designers and clients.

Keywords: CAD; Collaborative Design (Co-Design); Intelligence; Convolutional Neural Network; Advertising Creative; Idea Generation
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1 INTRODUCTION

The programmatic creativity of information flow advertising in the digital media era, as a new form of advertising creativity, has its own characteristics and development laws. Chen et al. [1] conducted a visual comparison between artificial intelligence technology and traditional advertising. Focusing on user-centered communication, creative advertising, and performances have been completed through interaction with users. It has various forms of expression, can trigger different user preferences, and further improves platform construction through user feedback. Conducting research on the programmatic creativity of information flow advertising can promote the symbiotic prosperity of advertising forms. This module is responsible for processing CAD model data, including data format conversion, model optimization, and simplification. Through data processing, it is possible to ensure efficient loading and smooth presentation of the model in multi-view visualization. This is the core part of achieving multi-view visualization. A visualization engine can render and display multiple views of advertising products in real time according to user needs. Interactive functions can enhance user engagement and experience. Users can freely operate and explore advertising products by configuring interaction modes such as mouse drag and drop, keyboard shortcuts, etc. Traditional advertising design often relies on the personal experience and inspiration of the designer, and although this method can sometimes produce unique works, it is inefficient and the generation of ideas is highly contingent. Driven by the digital wave, social media advertising has become an important tool for brand communication and market promotion. In the era of intelligent digital and online communication, advertising creative production faces problems such as insufficient accuracy, lack of scene connectivity, and efficiency. The above issues are becoming increasingly apparent in the face of cyberized users. Faced with the continuous digitization of users, products, and scenarios, the generalization and deconstruction of creative production entities have led to the "small group creativity" model. Advertising is gradually incorporating intelligent machines with data and algorithms as the core solution in creative production. While improving efficiency, gradually penetrating into various aspects of creative production, promoting the restructuring and intelligent transformation of the advertising industry. In the development process of intelligent advertising creativity, Corry et al. [2] summarized the intelligent advertising creative model. It optimizes combination creativity, augmented reality creativity, and human-machine co-creation creativity. It exhibits the characteristics of machine participation, dynamism, diverse connectivity, and diverse presentation. Collaborative design, on the other hand, breaks the limitations of the traditional design mode, enabling multiple designers to participate in the design process together and inspire more creative sparks through brainstorming. Computer graphics processing technology has become an indispensable part of intelligent advertising creative visual communication design. The emergence of this technology has greatly enriched the expression forms of advertising design and improved the attractiveness and dissemination effect of advertising. Traditional advertising design often relies on manual drawing or photography, making it difficult to achieve precise and accurate results. Computer graphics processing technology can achieve precise modification, stitching, and synthesis of images through digital processing, thereby creating more exquisite and realistic advertising images. Fan and Li [3] enhanced the visual impact of advertisements through computer graphics processing technology. By utilizing techniques such as colour adjustment, light and shadow rendering, and dynamic effects, computer graphics processing can transform ordinary images into creative and dynamic visual works. So as to attract the attention of consumers and stimulate their desire to purchase. The intelligent advertising creative generation method based on CAD and collaborative design can not only improve the design efficiency and reduce the design cost but also produce more diversified and creative advertising works. Intelligent advertising creative visualization can also help designers better understand and grasp advertising effects. Through real-time feedback and user interaction data, designers can understand the audience's reactions and preferences towards advertisements, thereby further optimizing advertising creativity and presentation methods. In advertising creativity, automatic imaging segmentation can help designers quickly and accurately extract desired objects from complex backgrounds, providing high-quality materials for subsequent creative design and visualization processing. Through AR technology, González et al. [4] integrated virtual elements into real-life scenes to create stunning visual effects. VR technology can create a completely immersive virtual environment for users, making them feel like they are in an advertising scene. This method combines the experience and inspiration of designers with the precision of computer technology, injecting new vitality into the advertising industry. Therefore, in-depth research and promotion of this intelligent advertising creative generation method based on CAD and collaborative design is of great significance in promoting the innovative development of the advertising industry.

Some problems and challenges are inevitably encountered in the in-depth study of intelligent advertising creative generation methods based on CAD and collaborative design. First of all, CAD co-design involves communication and collaboration among multiple designers, and how to ensure the accurate transfer of information and real-time updating is an urgent problem to be solved. He [5] discussed the application and practice of graphic interactive visual design based on intelligent advertising environments in art courses. An intelligent advertising environment refers to an advertising communication environment that utilizes technologies such as artificial intelligence and big data to intelligently manage and optimize advertising content, form, and delivery. Graphic interactive visual design, on the other hand, is based on visual elements such as graphics, images, colours, and text. Through interactive design, it achieves effective communication of information and a good user experience. Introducing graphic interactive visual design based on an intelligent advertising environment in art courses not only helps to enhance students' creative design abilities but also enables them to better adapt to the needs of the advertising industry in the digital age. Through the study and practice of the course, students can master how to use the intelligent advertising environment for data analysis, and user profile construction, and how to use the principles of graphic interactive visual design to conceptualize and implement advertising creativity. If the information exchange between designers is poor, it may lead to misunderstanding and duplication of efforts in the design process, affecting the design efficiency. Secondly, CAD collaborative design involves the collaboration of multiple designers, and there may be differences in design concepts and styles between different designers, which may lead to differences in opinion during the collaborative design process, affecting the design progress and results. Finally, the information interactivity of CAD software itself is relatively weak, and it is necessary to realize the purpose of collaborative design through the collaborative design platform, and the compatibility, stability and security of the platform become one of the direct factors affecting the creativity of collaborative design advertising. Based on this, this paper combines the convolutional neural network in the intelligent advertising creative generation model based on CAD and collaborative design, improves the model to carry out intelligent elements of advertising creative elements, realizes accurate positioning and layout through the CAD model, and then realizes multi-people collaborative design, information interaction and sharing through the support of heterogeneous CAD collaborative design platform to make the advertising creative elements organically combined and jointly perfect the advertising creativity to meet customers' individualized demand for creativity.

2 RELATED WORK

The application of CAD and collaborative design in fashion advertising provides new research objects and perspectives for multimodal analysis methods. By combining CAD-generated fashion product models with creative discussion records during the collaborative design process, Ikhlef and Awad [6] gain a deeper understanding of the design philosophy and implementation process of fashion advertising. It is necessary to supplement academic research on the programmatic creativity of information flow advertising. In practical application fields, the programmatic creativity of information flow advertising is gradually being accepted by the advertising industry. At present, companies in China that specialize in programmatic creativity include Chopstick Technology, Cheer Network, Baidu Nishang, Sizmek, and others. There are professional agency companies as well as companies that promote media platforms. They focus on the production of programmatic creativity in information flow advertising, which is fundamentally different from the production model of traditional advertising. The manifestations of programmatic creativity are also becoming diverse with the widespread application of programmatic creativity. At present, various forms of media information flow, such as graphic, video, and textual, have emerged, enriching the content of programmatic creativity. The programmatic creativity of information flow advertising constantly adapts to user needs in its interaction with users and becomes increasingly presented based on user preferences. Kang and Kim [7] used the SICAS user consumption behaviour model as a theoretical basis to compare the production of information flow advertising programmatic creativity with traditional advertising creativity. It provides an in-depth analysis of the characteristics of the programmatic creative effects of information flow advertising on users. At the same time, empirical research is used to analyze user preferences for programmatic creativity, and a construction plan for a programmatic creativity platform is proposed. Provide development suggestions for the production mechanism, mode of action, and platform construction of programmatic creativity in information flow advertising.

Li et al. [8] abstractly summarized the application model of artificial intelligence in the field of creative production by integrating and analyzing case data. The intelligent creation of text advertising is based on natural language processing technology, and its intelligent production follows the path of understanding the content of the copy text and extracting user and product features. The intelligent creation of image advertising is based on computer vision technology, forming a system model of requirement extraction and image design framework learning, visual image generation, evaluation, and feedback. The intelligent creation of video advertisements requires the comprehensive application of various artificial intelligence technologies such as natural language processing, computer vision, speech recognition, and processing. Li et al. [9] conducted research on the programmatic creativity of information flow advertising. It can supplement the theoretical materials on programmatic creativity in the academic community and enrich the theoretical foundation of programmatic creativity. The application of the SICAS theoretical model in the study of programmatic creativity in information-flow advertising will enable people to have a clearer understanding of the user reactions caused by programmatic creativity in information-flow advertising and the effects achieved. This provides theoretical support for programmatic creativity, a unique form of digital advertising creativity. At present, there is relatively little academic research on programmatic creativity. Through this research, it can help the academic community to explore programmatic creativity and make its development more mature. Ma et al. [10] conducted research on CAD and collaborative design of advertising programmatic creativity, which will further clarify the differences between traditional advertising creativity and collaborative design advertising creative production processes. It helps companies select advertising agents in different directions based on product characteristics, providing guidance for the correct application of information flow advertising.

At the level of creative communication, the connection between media platforms and scenes is becoming increasingly close, and IoT technology has expanded the touchpoints with users. The continuous integration of virtual and physical scenes makes the reach of creativity diverse and efficient. Singh et al. [11] analyzed the flow of data between users and scenarios. The machine has strengthened its ability to obtain and analyze user data, resulting in an improvement in the effectiveness of advertising creativity, gradually approaching zero time difference from insight to reach conversion. Based on XR technology, cross-scene interaction that breaks through temporal and spatial limitations can be achieved, and the user's creative experience can also be enhanced. At the level of creative content production, there will be stronger integration between humans and machines, and human-machine collaborative production will become a norm. The connection between humans and machines becomes closer, forming a benign complementarity, and with the development of brain-computer interface technology, it continues to move towards human-machine integration. The creative and data capabilities of advertising have ushered in a turning point with the help of big data and artificial intelligence technology. The generalization and deconstruction of creative production entities have led to the "small group creativity" model. Intelligent machines flowing with data blood are also involved in advertising creative production, which makes creative production more focused on efficiency. Programmatic creativity is applied in copywriting, image creation, video creation, and even interactive design. Creativity is no longer exclusive to humans, and in future advertising creative production, machines will become an indispensable part [12].

As a preliminary expression of advertising creativity, hand-drawn advertising sketches have always been an important tool for designers to express their creativity and ideas. However, traditional hand drawing methods are limited by the designer's skill level and time cost, making it difficult to present advertising effects quickly and accurately. Creativity, as the leading force in realizing cultural and product values, has completed the transformation of culture in a subtle social process. At the same time, creativity is also an effective tool to stimulate social and economic vitality. Almost all fields cannot abandon the important position of creativity. However, compared to the forward-looking approach in practice, there is a certain lag in theoretical research related to creativity. In this era of rapid rise and development of artificial intelligence, it has driven the improvement of productivity and the transformation of production modes, including creative production. Due to the accelerated flow of information, the production of creative content has deviated from market demand, and machine intelligence has joined the ranks of creative production. However, there are still unclear issues in the academic field regarding machine creativity, and there are still doubts about the thinking of human-machine relationships. The discipline of journalism and communication has not established a relatively integrated and complete research framework with disciplines such as artificial intelligence and systems science. Xu et al. [13] hope to comprehensively organize the research on artificial intelligence technology and its application in advertising creative production. And propose a theoretical model combining multiple perspectives, providing a basis and optimization for the creative mode of intelligent advertising. Zhang et al. [14] studied the creative production process in advertising operations and analyzed it under the guidance of kinesthetic schema theory. It studied the impact of artificial intelligence technology on advertising creative production under the background of intelligent advertising development, including the impact of the intelligent wave on traditional advertising creative production models. After the intervention of CAD technology, there has been a revolution in advertising creative production, and artificial intelligence technology has been widely used in the advertising creative production process. Based on the analysis and summary, it extracts a general model of an intelligent advertising creation system and explores possible paths for the future development of intelligent advertising creativity. Zhong [15] discovered that the distributed feature representation of data can be directly applied to intelligent advertising design. Simply put, deep learning uses neural networks as an optimization algorithm to decompose raw data into nested hierarchical systems. Extract hidden layers with abstract features from relatively simple and intuitive data, and then progressively complete the process from simple to complex, general to abstract.

3 CONSTRUCTION OF INTELLIGENT ADVERTISING CREATIVE GENERATION MODEL BASED ON CAD AND COLLABORATIVE DESIGN

Through the review and summary of the above literature, it can be seen that scholars' research on advertising in the digital media era relies more on the interactivity of digital media communication. The forefront of digital media technology requires the study of user dominance in advertising communication. Scholars have studied information flow advertising and programmatic creativity, emphasizing the personalized matching and precise reach characteristics of programmatic creativity in information flow advertising. It indicates that the programmatic creativity of information flow advertising is centered on user perception and experience and reveals that the interaction between advertising and users, as well as user participation, are the key points in the production of programmatic creativity in information flow advertising. It is an important prerequisite for programmatic creativity to achieve good dissemination effects. In addition, scholars have also paid attention to the technical issues of programmatic creativity in information flow advertising in the digital media era. It explores the technical characteristics of digital media, information flow advertising, and programmatic creativity. Most scholars have affirmed the convenience and efficiency that technology brings to the programmatic creativity of information flow advertising. However, most literature only describes the effects and effects of programmatic creativity in information flow advertising on users. However, there has not been an effective theoretical sorting and exploration of the relationship between the two. Therefore, this article analyzes the characteristics and mechanisms of programmatic creative production of information flow advertising in the digital media era.

3.1 Convolutional Neural Network-Based Model for Recognizing and Classifying Advertising Creative Elements

Convolutional Neural Networks (CNNs) are an important model in the field of deep learning, especially suitable for processing data with a grid structure.CNNs automatically extract local features of the data by simulating the processing of the visual cortex of the human brain and performing convolutional operations on the input data. These features are further combined and abstracted at deeper layers of the network to form a global representation of the input data. Advertisement design contains rich visual elements that can attract and convey effects, such as colours, shapes, textures, etc. Convolutional neural networks can automatically learn the feature representations of these elements and accurately identify innovative elements in advertisements, thus helping designers better understand the visual composition of advertisements. In addition, after training on a large number of advertisement samples, CNN can learn the commonalities and differences between different innovative elements, and then automatically categorize new advertisement works into the corresponding categories. This not only improves the efficiency of advertisement design but also enables designers to obtain design inspiration from similar advertisements more quickly, thus promoting the innovative development of advertisements. Compared with traditional neural networks, convolutional neural networks also have a strong generalization ability, which can be applied to new and unseen advertising data to effectively identify and classify innovative elements.

Convolutional neural networks are connected by local weight connection and parameter sharing, i.e., the correlation information between image pixels is retained through local sensing for higher dimensional feature extraction to obtain other rich information in the image. The number of network parameters can then be reduced through weight sharing and downsampling steps to increase the number of hidden layers by increasing the robustness of the model and making the model sustainable in terms of depth. The two most important network layers in a CNN are the convolutional layer and the downsampling layer, where the downsampling layer is also known as the pooling layer. The convolutional layer is the most important core of the CNN neural network, its feature extraction is accomplished through the convolutional kernel, and a convolutional layer usually contains multiple high-dimensional convolutional kernels and is generally consistent with the number of input bits, the size of the convolutional kernel is inconsistent with the extracted features are also different. As shown in Figure 1 is a simple structure of the convolutional neural network schematic model.

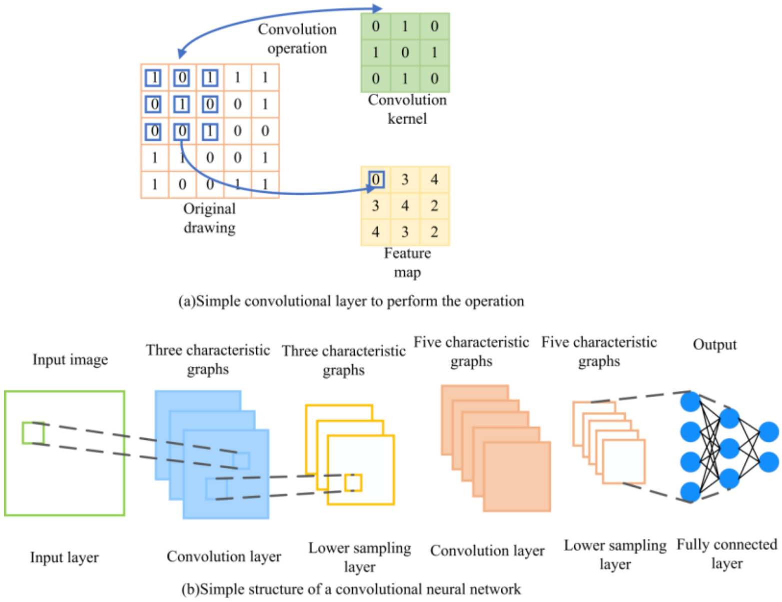

Figure 1: Simple structural schematic model of convolutional neural network.

Let the input image be X , the convolution kernel be K and the size is $m*m$, then the final output feature map Y is shown in equation (1):

$$Y_j(j \in p*q) = f(\sum\nolimits_{i \in m*m} X_i * K_i + b) \tag{1}$$

where the bias is denoted as b and the final output map size is denoted as $p*q$.

The pooling layer removes the redundant information from the feature map extracted by the convolutional layer and keeps the most important information to realize the purpose of dimensionality reduction of the feature map. The pooling layer generally contains maximum pooling, average pooling, and summing deficit, the first two are the most commonly used types of pooling. Suppose the first j output feature map in the $L-1$ layer is denoted as a_j^{L-1}, after the pooling layer as shown in equation (2).

$$a_j^L = f(down(a_j^{L-1}) + b_j^L \tag{2}$$

The bias in Eq. is denoted as b_j^L and the pooling function is $down(\cdot)$.

The CNN activation function is shown in equation (3):

$$relu(x) = \max(0, x) \tag{3}$$

The loss function is shown in equation (4):

$$loss(Y, \hat{Y}) = \frac{1}{N}\sum_{i=1}^{N}(\overset{\wedge}{y_i} - y_i)^2 \tag{4}$$

Although convolutional neural networks with depth can be used to mitigate problems such as gradient dispersion by the above methods, there is still the problem of insufficiency, so in this paper, the activation function used in the deep learning model is normalized to the standard normal distribution by the given batch inputs when the model is being trained, so as to achieve the purpose of model enhancement.

Although the deep convolutional neural network is able to alleviate problems such as gradient dispersion to a certain extent by virtue of its powerful feature extraction capability, it still has some inherent limitations in practice. In order to further improve the performance and stability of the model, this paper adopts an innovative approach in the process of model training, i.e., standard normal distribution normalization is performed for the activation function used in the deep learning model. The introduction of this normalization process aims to optimize the parameter distribution within the model, enabling the model to converge faster during training and reducing the risk of overfitting. By giving a batch of inputs, it ensures that each batch of data is processed uniformly and efficiently, which in turn improves the generalization ability of the model. In this way, the performance of the model can be successfully enhanced so that it can show better performance in the face of complex and variable datasets. Let the size of the batch $Batch$ be m, where the sample with sequence number i is denoted as x_i, and the output of the batch normalization layer is denoted as y_i, which is calculated as shown in Eqs. (5)-(8):

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{5}$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \tag{6}$$

$$\hat{x}_t = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{7}$$

$$y_i = \alpha \hat{x}_t + \beta \tag{8}$$

Among them, the batch $Batch$ mean is denoted as μ_B, the corresponding variance is denoted as σ_B^2, the random very small number set to prevent the denominator from going to zero is recorded as

ε, the normalized value is denoted as $\hat{x}_t$, and the corresponding pull-up and offset parameters are denoted as a and β, respectively.

There is no obvious correlation between the data content features extracted by the general recognition and classification model and the recommendation task, so the feature extraction results obtained in the unsupervised learning mode have a large error. Therefore, in this paper, the recognition and classification model of advertising creative elements based on a convolutional neural network adopts the recommendation task correlation method for the extraction of advertising creative element features, i.e., the mean value of advertising creative element features outputted from the fifth layer of the convolutional neural network Z_j will be fused with the framework of Bayesian personalized sorting algorithm, so as to optimize the feature extraction model under the impetus of the recommendation task. In addition, different designers and clients have large differences in aesthetics, style, experience, knowledge, etc., so there will be rarely used creative elements recommended, and then $\mathbf{Q}_j$ will be replaced Z_j for the calculation of the client's or designer's preference for the creative elements of the advertisement, which is obtained by Bayesian formula as shown in Eq. (9):

$$P(\theta \middle| > u) = \frac{P(> u \middle| \theta) P(\theta)}{P(> u)} \tag{9}$$

Where θ denotes the parameter. Since any advertising creative element is the same for both design and client, Equation (10) is simplified as shown in Equation (6):

$$P(\theta \middle| > u) \propto P(> u \middle| \theta) P(\theta) \tag{10}$$

The objective function in Eq. (6) is viewed as two parts i.e. $P(> u|\theta)$ which is related to D and $P(\theta)$ which is not related to D. The simplification $P(> u|\theta)$ is shown in Eqs. (11) and (12):

$$\prod_{u \in U} P(\theta \middle| > u) = \prod_{(u,i,j) \in D} P(i > u \ j \middle| \theta) = \prod_{(u,i,j) \in D} \sigma(\bar{x}_{ui}(\theta) - \bar{x}_{uj}(\theta)) \tag{11}$$

$$\bar{x}_{ui}(\theta) = w_u \bullet h_i = \sum_{f=1}^{k} w_{uf} h_{if} \tag{12}$$

where the degree of preference of the client or designer for the creative elements of the advertisement is denoted as $\bar{x}_{ui}(\theta)$, and w_u and h_i are vectors of latent factors.

In $P(\theta)$ if the parameter θ belongs to the Positron distribution, then it is shown in equation (13):

$$\ln P(\theta) = \lambda \|\theta\|^2 \tag{13}$$

The final objective function $\ln P(\theta|> u)$ is simplified as shown in Equation (14):

$$\ln P(\theta \middle| > u) \propto P(> u \middle| \theta) P(\theta) = \prod_{(u,i,j) \in D} \ln \sigma(\bar{x}_{ui}(\theta) - \bar{x}_{uj}(\theta)) + \lambda \|\theta\|^2 \tag{14}$$

3.2 Support for Heterogeneous CAD Co-Design Platforms

Multi-CAD is a CAD system that can support a variety of different CAD systems, which has strong compatibility and integration and can support the data import and format conversion of a variety of CAD software, realize the seamless connection between different design tools, realize the seamless docking and sharing of data, and break the barriers between traditional CAD software. Designers are able to utilize various design software and tools more flexibly in the process of collaborative design of advertising creativity to improve design efficiency. In addition, Multi-CAD with efficient co-design capabilities can support multi-person online collaboration, designers can share design data and ideas in real-time, and jointly participate in all aspects of advertising design. This not only speeds up the design process but also promotes communication and exchange among team members, which helps to stimulate more creative inspiration. Its accurate data processing and analysis capabilities can accurately measure and analyze design data, helping designers better grasp the details and key points of advertising design. Therefore, this paper chooses Teamcenter software and Multi-CAD to realize the CAD co-design integration function.

Teamcenter, a powerful product lifecycle management software, has the outstanding ability to automatically convert multiple CAD parts (PARTs) into source CAD-independent.JT format. This feature greatly broadens the scope of design data, allowing designers to freely reuse, create, share and modify component designs in their preferred CAD system, providing an integrated and collaborative work environment for advertising designers, and effectively improving the flexibility and efficiency of the design process. Teamcenter also has a powerful merging function that can merge these converted. JT format components into multiple CAD components or product designs, designers can integrate components or product designs from different sources and formats to form a complete design solution, which greatly simplifies the design process and provides great convenience for the generation of advertising ideas. Designers can easily draw on and integrate different design elements to create more innovative and attractive advertising works. Teamcenter's visualization features also provide designers with an intuitive window to view and edit design data, providing a deeper understanding of the details and structure of the design. This intuitive design approach helps stimulate designers' creative thinking, allowing them to adjust and optimize their design solutions more flexibly, and improving the quality and effectiveness of their advertising ideas. A schematic of how Multi-CAD works in conjunction with Teamcenter is shown in Figure 2.

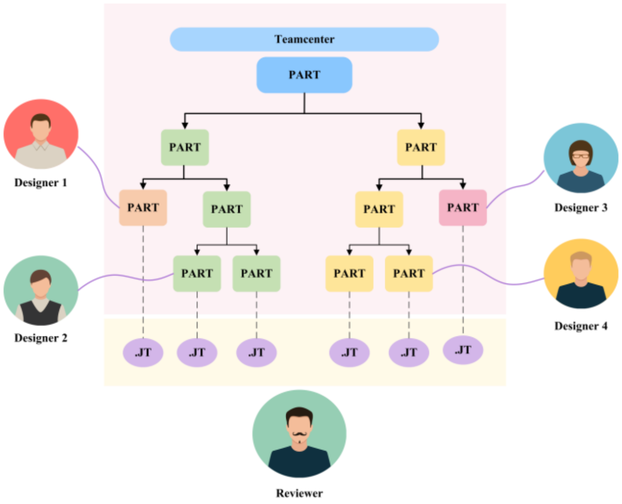

Figure 2: Schematic diagram of how Multi-CAD works in conjunction with Teamcenter.

4 TEST RESULTS OF INTELLIGENT ADVERTISING CREATIVE GENERATION MODEL BASED ON CAD AND CO-DESIGN

The performance of the convolutional neural network-based recognition and classification model of advertising creative elements has a great influence on the advertising innovation generation model. Therefore, in this paper, the performance of this module is tested first, and two other advertising innovation element recognition and classification models are selected for comparison, which contains the recognition and classification models based on the BP neural network and RNN neural network. The results of error and accuracy visualization of the three models on the two training sets are shown in Figure 3. The error data in the figure shows that on the training dataset 1, the convergence trend of the three models has high consistency, and the convergence accuracy of the three is not much different, especially since the other two models are close to each other, while the model in this paper has the lowest convergence accuracy. On the training dataset 2, the convergence speed of the BP neural network model is much lower than that of the other two models, and the convergence accuracy is the worst, mainly because the BP neural network is easy to falls into the local optimization problem. The convergence speed and accuracy of the model in this paper are the best among the three models. In terms of test-level accuracy, the BP neural network converges faster than the RNN neural network on dataset 1, but performs the worst in terms of accuracy, and the overall accuracy of the two is not much different. The model in this paper still has the best convergence speed and accuracy and requires the least number of iterations. In dataset 2, the accuracy of the BP neural network is much smaller than that of the other two models, and there is little difference in convergence speed and accuracy between this paper's model and the RNN neural network model. In summary, the model in this paper has the best overall performance in terms of convergence speed and accuracy both in terms of error and precision.

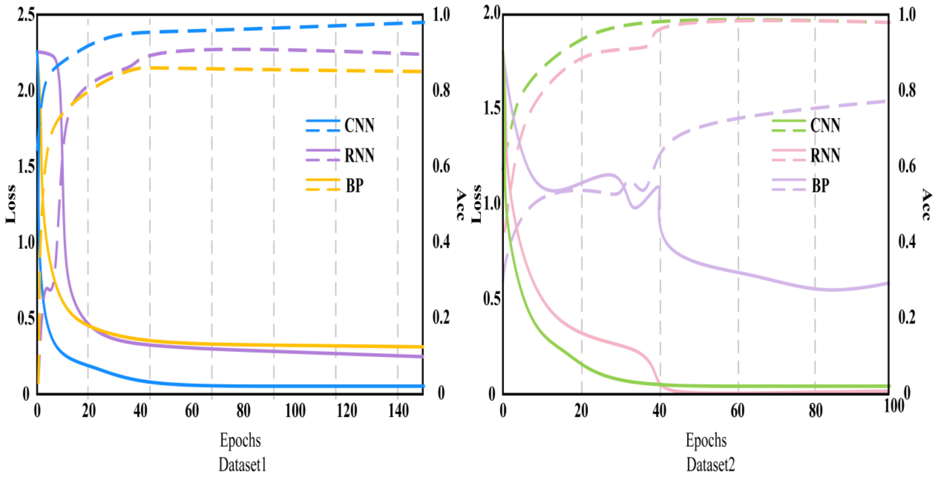

Figure 3: Error and accuracy visualization results for the three models on two training sets.

In order to further verify the application performance of the intelligent advertising creative generation model based on CAD and co-design, this paper compares the advertising creative feature extraction of different models, as shown in Figure 4 for the advertising creative feature extraction indexes as well as the initial and measured parameter standards, which is used as the basis for the comparative evaluation of the feature extraction of the three models.

As shown in Figure 5 for the three models of advertising creative elements feature extraction results in comparison, the results show that the three models extracted by the average value of the advertising creative elements feature AUC fluctuations within a certain range, in which the BP neural network fluctuation amplitude is the largest, and there are only a few features of the AUC value is higher than 0.65. The RNN neural network feature extraction results in the early stage of the performance of the performance of the poorer, lower than 0.65, and the performance of the later stages gradually improved to reach above 0.65. The AUC value of the feature extraction results of the model in this paper basically reaches above 0.65, which indicates that the model is more in line with the needs of designers and customers in the feature extraction of creative elements in advertisements and shows higher extraction accuracy.

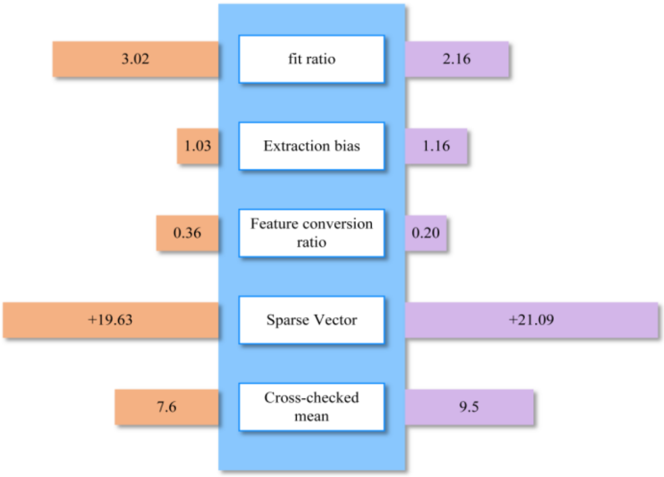

Figure 4: Advertising creative feature extraction indexes and initial and measured parameter criteria.

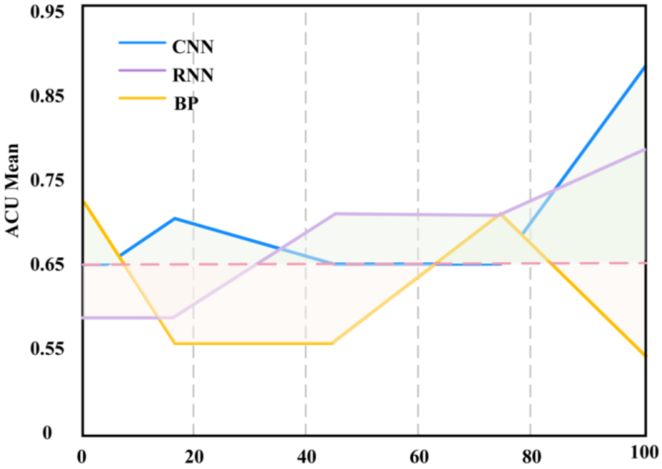

Figure 5: Comparison of feature extraction results of three models of advertising creative elements.

As shown in Figure 6 the three models advertising creative elements classification results, which contain the number of recognized categories and accuracy. The experiment mainly uses five categories of advertising creative elements as test samples, and the results show that the BP neural network only completes the classification of four categories of elements, and the recognition accuracy is relatively low. Both the RNN neural network and this model recognize five categories of elements, but in terms of recognition accuracy, this model performs better than the RNN model, which indicates that the model can effectively recognize and do the classification task according to the needs of designers and customers, and provide more error data for the subsequent generation of advertising creativity. This shows that the model can effectively recognize and do the corresponding classification task well, and provide data with less error for the generation of advertisement creativity afterwards.

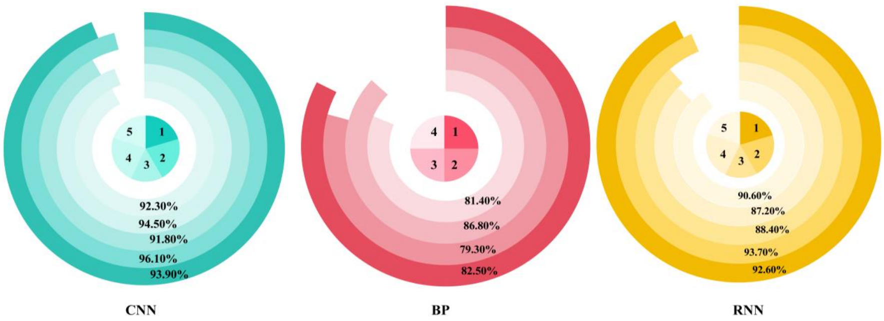

Figure 6: Classification and recognition accuracy results of three models of advertising creative elements.

As shown in Fig. 7, the generation time of the three advertisement idea generation models and the satisfaction level of the designers and clients with the preliminary designs are shown. The data results in the figure show that the advertisement idea generation model time of the three models increases gradually with the difficulty of the advertisement. However, in the case of the same level of difficulty, the generation time of this paper's model is significantly lower than that of the other two models, and the designers and clients have the highest level of satisfaction with the advertisement creativity generated by it.

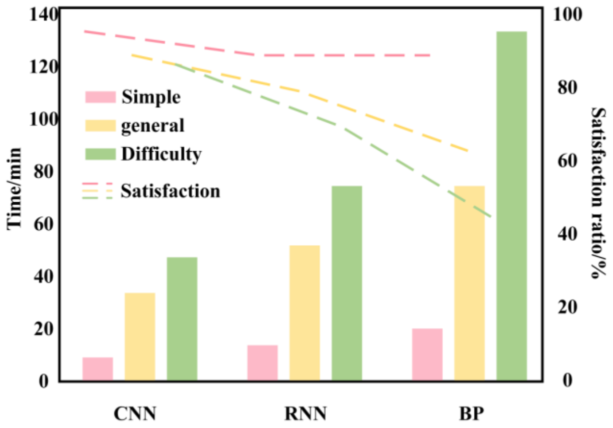

Figure 7: Generation time of the three advertisement idea generation models and the level of satisfaction of designers and clients with the preliminary designs.

5 CONCLUSION

The development of the advertising industry and the constant change of customers' aesthetic demands make the demand and requirement for advertising creativity increase; designers need to complete the advertising design and ensure the quality of creativity in a short period of time, which can not be satisfied by the traditional advertising creative design. The intelligent advertising creative generation method based on CAD and collaborative design brings new development opportunities for the advertising industry. In this paper, the recognition and classification of advertising creative elements are realized by combining the convolutional neural network model, and the automation and personalization of multi-person collaborative design and advertising design are realized by Teamcenter and Multi-CAD, which provide strong support for the innovative development of the advertising industry. The research results show that the recognition and classification model of advertising creative elements based on a convolutional neural network is the fastest in terms of both error and accurate convergence speed compared with other models, and the convergence accuracy is higher and shows good classification ability and high accuracy in the element classification and recognition experiments, and is able to provide accurate and effective data support for the generation of advertisement creativity. In addition, the intelligent advertisement idea generation model based on CAD and co-design shows faster speed in different difficulties of advertisement idea generation and is recognized by most designers and clients.

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