Graphic Design Effect Evaluation Based on CAD and Collaborative Design

Yanfang Wei[1] and Jisi Pan[2]

[1]College of Art and Design, Guangxi Science & Technology Normal University, Laibin, Guangxi 546199, China, 201908013@gxstnu.edu.cn
[2]School of Mechanical and Electrical Engineering, Guangxi Science & Technology Normal University, Laibin, Guangxi 546199, China, Panh5888@163.com

Corresponding author: Yanfang Wei, 201908013@gxstnu.edu.cn

Abstract. Initially, this article delves into the obstacles encountered in graphic design, particularly the difficulties in anticipating design outcomes, along with the pivotal role played by CAD (Computer-Aided Design) technology and collaborative design in shaping the design process. To overcome these obstacles, we introduce a predictive model that seamlessly integrates CAD parametric modelling, parameters from the collaborative design environment, and the GNN (Graph Neural Network) algorithm. This model leverages design elements from the CAD system and real-time data from the collaborative design environment to deliver precise predictions of graphic design outcomes. When compared to other predictive models, our proposed model demonstrates superior predictive accuracy. Experimental results confirm its excellence, particularly when tackling intricate and nonlinear design challenges, where it exhibits remarkable adaptability and generalization capabilities. In essence, our CAD and collaborative design-based predictive model for graphic design outcomes offers a novel and efficient forecasting tool to the graphic design community. This model not only enhances design efficiency but also elevates design quality, empowering designers and decision-makers with more informed and precise design support.

Keywords: Computer-Aided Design; Graph Neural Network; Collaborative Design; Graphic Design; Prediction Model
DOI: https://doi.org/10.14733/cadaps.2024.S26.142-157

1 INTRODUCTION

With the rapid development of commerce, graphic design has become ubiquitous today. Graphic design is a visual communication tool that creates and combines elements such as graphics and text in various forms to convey information to users. Common graphic designs in social life include magazines, posters, web design, and so on. Layout is an important consideration factor in graphic design. The quality and effectiveness of graphic design often depend on the quality of the layout, and having a good layout can often achieve the goal of attracting user attention and promoting user experience. Layout design usually relies on graphic designers using intuition and experience to artificially complete. Excellent professional graphic designers are able to design creative and visually appealing layouts. But there is also a lot of simple and repetitive work involved. If we can extract some commonalities in layout design to preliminarily generate layouts, it will greatly reduce their workload. They can redesign on this basis and fully unleash creativity. For amateur graphic designers, it is difficult to design aesthetically pleasing and effective layouts, and automatically generating good layouts through certain methods will help them solve this obstacle. Therefore, it is necessary to study how to automatically generate planar layouts [1]. Boluki and Mohanna [2] analyzed the important role of optimal Gabor filters in video processing. In practical applications, planar image and video processing techniques based on optimal Gabor filters have achieved significant results. For example, in medical image analysis, this technology can help doctors more accurately identify lesion areas. Traditional classification methods often fail to fully utilize the spectral-spatial information of images, resulting in low classification accuracy. Therefore, Han et al. [3] proposed a hyperspectral image classification method based on spectral-spatial joint features and principal component analysis network, aiming to improve the accuracy and efficiency of classification. Hyperspectral images not only contain rich spectral information but also contain rich spatial information.

Given the outstanding performance of GAN in the field of image processing, Han et al. [4] selected a dataset of animated character avatars. Use these six models for image synthesis experiments, and improve the network structure of some models during the experiment. Then, human eye observation and score calculation are used to compare and analyze the generation effects of various models. So as to summarize the loss function and network structure with excellent birth ability. The training process of generative adversarial networks is difficult to control. Through conducting image synthesis experiments on six models, some methods to improve model training are also attempted. Jing and Song [5] further extended GAN to the field of graphic design and attempted to conduct preliminary experiments on the MNIST dataset using the LayoutGAN model. Debug a network structure and hyperparameters with good generation effect, providing a reference for subsequent experiments. Then conduct experiments on the room layout maps in the SUNCG dataset, in order to achieve automatic generation of floor plans. Chapter 3 is about image synthesis based on generative adversarial networks. Firstly, a theoretical analysis was conducted on DCGAN, WGANWGAN-GP, LSGAN, and CGAN. Next, select GAN and these five models to generate new anime character avatars. By improving the network structure of the model to achieve better image generation results, then conducting a horizontal comparative analysis of the image generation effects of these six models, and finally summarizing

The innovations presented in this article are threefold: (1) the integration of CAD technology with collaborative design theory to propose a novel approach for predicting graphic design effects; (2) the utilization of the GNN algorithm to construct a prediction model that enables quantitative forecasting of design outcomes; and (3) the validation of the model's effectiveness and practicality through simulation experiments. These innovations enrich the theoretical and methodological landscape of graphic design, providing practical guidance and reference for professionals in the field.

The article begins by outlining the research background, significance, current state and trends, research content, innovations, and structural arrangement. It then delves into the relevant theoretical foundations and technologies, covering CAD technology, collaborative design principles, graphic design effect assessment methods, prediction model construction techniques, and simulation experiment methodologies. Subsequently, the article details the construction process and methodology of the graphic design effect prediction model. Following this, it introduces the design and implementation of the simulation experiments, presenting a comprehensive analysis and discussion of the experimental results. Finally, the article summarizes the key achievements and contributions of the study, offering recommendations and prospects for future research.

2 RELATED WORKS

As a fundamental element of design, flat patterns have unique artistic charm and visual impact. In CAD, designers can use pattern libraries or custom tools to quickly create and edit various flat patterns. These patterns can be applied to multiple fields such as product design, interior design, clothing design, etc., adding unique style and personality to the work. At the same time, the precise drawing and editing functions provided by CAD software make the production of flat patterns more precise and accurate, meeting the designer's pursuit of details. Kang and Kim [6] save the created patterns as CAD files for easy retrieval and modification at any time. This not only improves design efficiency but also ensures consistency and accuracy of the design. In addition, through the data exchange function of CAD software, designers can also share pattern resources with other team members or suppliers, achieving rapid transmission of design information and collaborative work. As an important component of design elements, the accurate extraction of texture features is of great significance for design innovation, collaboration, and optimization. Keyvanpour et al. [7] analyzed and reviewed feature extraction methods for planar texture design based on CAD and collaborative design, and explored their current development status and future trends. Khaldi et al. [8] summarized the encoding rules for multi-line text in AutoCAD software through in-depth research and analysis. Using this encoding rule, implement multi-line text input and editing functions in JHCAD, and achieve a bidirectional interface between JHCAD and AutoCAD for multi-line text input and extraction. By utilizing the functions of the Skin++interface library, the function of customizing user interface styles can be achieved, making the program window unique and meeting the different needs of different users for software interface styles. Add a 256-color true-color toolbar to the program to make the interface more aesthetically pleasing. After in-depth learning and research on the process of creating multi-document application windows, as well as the functions of the BCGControlBar library, a multi-document tab display mode was implemented on the JHCAD engineering drawing software system platform, replacing the traditional multi-window mode. Complete the function of automatically hiding the parking information window, making it more convenient to provide a large amount of information for drawing personnel. By fully utilizing object-oriented technology, the rapid drawing function and the simple editing function of tables in JHCAD engineering drawing software have been achieved.

For any engineering drawing software, text and graphics processing function is essential, which is determined by the importance of text and graphics themselves. In the process of engineering drawing, sometimes relying solely on drawings cannot clearly express the designer's thoughts and intentions. The necessary text needs to be added to the design to illustrate the information that the graphics cannot express, as well as the rich part information and relevant information of the drafter contained in the title and parts lists. The drawings will also include technical requirements, assembly requirements, drawing proportions, and so on. These all require a large amount of text resources to implement. The input and editing of text will accompany the entire drawing process [9]. The drawing software CAXA, its multi-line text processing function is very different from AutoCAD. The text editing window is designed to be very complex, with cumbersome operations and simple functions. Only one text style can exist in its multi-line text editing window. Each style change will apply to all text in the window, so it is not possible to set the style for specific text. This has brought great inconvenience to the drawing work. This also makes CAXA incompatible with AutoCAD's DWG files in multi-line text editing processing. At the same time, changes in text style cannot be displayed at any time in its text editing window, making it difficult for users to control the text style. Reska and Kretowski [10] capture global and local features of a graph by transmitting information between nodes and edges. Traditional damage detection methods often rely on manual inspection, which is inefficient and easily influenced by subjective factors. Therefore, automated damage detection methods based on image processing technology have received widespread attention. Shahabian et al. [11] constructed a matrix that reflects the texture features of an image by calculating the frequency of pixel pairs at different grayscale levels in the image. This matrix not only contains the grayscale information of the image but also the spatial relationship information between grayscales, so it can comprehensively describe the texture structure of the image. Calculate the grayscale co-occurrence matrix of the image and extract statistics that reflect the texture features of the image, such as energy, contrast, entropy, etc. Finally, based on these statistics, the image is classified or segmented to identify damaged areas.

The application of image processing and image design in various fields is becoming increasingly widespread. Especially in the fields of art design, advertising creativity, product display, etc., content-based image design technology has become an indispensable tool for designers. Traditional image design often relies on the subjective experience and manual adjustments of designers, while content-based image design can automatically or semi-automatically generate images that meet design requirements by analyzing the inherent properties of images, such as texture and colour. Tadi and Fekri [12] extracted texture features of images through various algorithms. It utilizes the grayscale co-occurrence matrix to statistically analyze the spatial relationships between pixels of different grayscale levels in an image, thereby describing the texture structure and directionality of the image. Wu et al. [13] explored the optimal Gabor filter design for planar detection based on particle swarm optimization. Convolutional layers are the core modules of convolutional neural networks, used to extract high-level semantic features from input images. It uses convolution kernels to perform convolution operations on images to obtain feature maps, where the number in the convolution kernel is the weight. Due to the use of the same convolutional kernel during a complete convolution operation on an image, convolutional neural networks have weight-sharing characteristics.

JHCAD adopts a true Windows multi-window and multi-document all-Chinese environment, allowing users to open any drawing simultaneously without any impact on performance. It provides a complete and unique set of graphic drawing and editing tools. In the process of drawing, the correlation, symmetry, and continuity of the graphics are fully considered, resulting in high efficiency in drawing. The practical size driving function and engineering dimension annotation that fully comply with national standards make the addition, modification, and editing of annotations convenient and easy to use. By establishing and managing the library, it is easy to establish and operate fixed symbol libraries and variable size libraries, achieving parameterized design functions. Users can also modify and expand the national standard parts library to establish a standard parts library that meets their own needs. It provides drawing aids and convenient positioning input methods, such as dynamic navigation, three-view navigation, feature point capture, grid setting, and various convenient and fast input methods for position points [14]. In the process of drawing two-dimensional drawings, relying on the drawn pattern can generally clearly express the designer's thoughts and intentions. However, it is often necessary to add necessary text in the design to explain the information that the graphics cannot express. For example, the title bar and parts list contain rich part information and relevant information about the drafter. The drawings will also include the technical requirements required for part processing and the assembly requirements for later stages. Dimensioning in engineering drawings, drawing proportions, and so on. These all require a large amount of text resources to implement. As the drawing process continues, the input and editing of text will accompany the entire drawing process [15].

3 THEORETICAL BASIS AND RELATED TECHNOLOGIES

3.1 Principle and Application of Collaborative Design

Online collaborative design workshops are a new trend, and there is relatively little theoretical research in this area, and the practical results have not been systematically and relatively dispersed. Studying online collaborative design workshops requires fully utilizing the theoretical foundations of other related disciplines, analyzing and finding commonalities from the underlying logic, and outputting a reasonable model framework, which poses certain difficulties. The construction of the participation model in the online collaborative design workshop not only involves collaborative design in the design discipline but also involves customer integration theory in the marketing management discipline. If the two are integrated from a theoretical perspective, a large amount of literature reading is needed to supplement the key knowledge points of customer integration theory. It fosters better communication and teamwork, encouraging innovative ideas and resulting in enhanced design quality.

3.2 Assessment Method of Graphic Design Effect

The assessment of graphic design effect refers to the objective and comprehensive assessment of the quality and effect of graphic design works. The commonly used assessment methods of graphic design effect mainly include subjective assessment method and objective assessment methods.

The subjective assessment method mainly depends on the personal experience and aesthetic standards of the appraiser, and judges its effect through the intuitive feeling and assessment of the design works. The objective assessment rule is based on certain assessment indicators and quantitative methods to objectively evaluate the effect of design works, as shown in Table 1.

Appraisal procedure	*Describe*	*Characteristic*
Subjective assessment method	Depending on the appraiser's personal experience and aesthetic standards, the effect of design works can be judged through intuitive feeling and assessment.	1. Simple and easy to implement, quickly obtain assessment results 2. Subjective factors have a significant impact on the evaluator, making it difficult to ensure objectivity and accuracy
Objective assessment method	Based on the assessment index and quantitative method, the effect of design works is objectively evaluated.	1. The assessment results are relatively objective and accurate
	Commonly used assessment indicators include innovation, practicality and aesthetics.	2. Need certain assessment indicators and quantitative methods to support
	Quantitative analysis can be carried out by means of a questionnaire survey and expert scoring.	3. The assessment process may be relatively complex and require some time and resources

Table 1: Assessment method and characteristics of graphic design effect.

3.3 Prediction Model Construction Technology

Predictive model construction technology refers to the use of mathematical, statistical, machine learning, and other methods to analyze and mine historical data and construct models that can predict future trends or results. In predicting graphic design outcomes, predictive modelling techniques enable designers to foresee the potential impacts of various design approaches, leveraging existing design datasets and guidelines. Standard predictive modelling methods encompass regression analysis, neural networks, decision trees, and support vector machines, among others. Depending on the data types and prediction objectives, these methods can be strategically chosen and integrated to build models tailored for graphic design effect prediction. This article employs the GNN model to study and anticipate the combinations and arrangements of design elements, thereby attaining feasible design outcomes.

4 CONSTRUCTION OF A PREDICTIVE MODEL FOR GRAPHIC DESIGN EFFECTS

4.1 Model Construction Requirements Analysis

Before constructing the prediction model of graphic design effect, it is needed to analyze the requirements of the model in depth. These demands mainly come from the challenges and problems faced by designers in the actual design process, as well as their expectations and requirements for the design effect prediction model.

On the one hand, designers hope that the model can accurately predict the effects of different design schemes, so as to help them make correct decisions in the early stage of design and avoid the trouble of later modification and adjustment. On the other hand, designers also hope that the model can adapt to the collaborative design environment, support multiple people to participate in the design at the same time, share design resources, and provide feedback on the change of design effect in real-time. Therefore, the demand for graphic design effect prediction models can be summarized as four points in Table 2.

Demand point	*Description*
Accuracy	The model should be able to accurately predict the design effect, provide a reliable reference for designers and reduce the design risk.
Real-time	The model needs to be able to feedback on the change of design effect in real-time, help designers adjust the scheme in time and improve the design efficiency.
Synergy	The model should support a multi-person collaborative design function, realize the sharing of design resources and the real-time transmission of design intentions, and promote teamwork.
Usability	The model should have a friendly user interface and simple operation mode, which is convenient for designers to get started quickly and reduce the difficulty of use.

Table 2: Demand for graphic design effect prediction model.

4.2 Extraction of Graphic Design Elements Based on CAD

The construction of a graphic design effect prediction model needs to extract key design elements from CAD design documents. These elements include graphic elements (such as lines, shapes, colors, etc.), layout structure, design style, etc. They are the basic components of graphic design works and also an important factor affecting the design effect. When extracting design elements, we can use the graphic processing and data analysis functions of CAD software to analyze and process design documents. In this article, the characteristic parameters related to the design effect are extracted by identifying and analyzing the attributes, positions and sizes of graphic elements. Through the analysis and comparison of the layout structure, the characteristic indexes reflecting the design style and aesthetic feeling are extracted.

For each graphic element i in the CAD design file, extract its attribute set A_i, such as colour, line type, material, etc. These attributes can be obtained through the built-in functions of CAD software. The drawing element attribute extraction formula is as follows:

$$A_i = \text{color}_i, linetype_i, material_i, \ldots \tag{1}$$

Each graphic element has a definite position in the design file, which can be represented by two-dimensional or three-dimensional coordinates. The position information P_i may include the coordinates of the center point, the coordinates of the boundary point, etc., of the element. The formula for extracting the position of graphic elements is as follows:

$$P_i = \ \mathrm{x}_{i1}, y_{i1}\ ,\ \mathrm{x}_{i2}, y_{i2}\ ,\ \mathrm{x}_{i3}, y_{i3}\ , \ldots\ \mathrm{x}_{im}, y_{im} \tag{2}$$

The size of a graphic element can be calculated by the width and height of its bounding box or measured by its area and volume. The drawing element size extraction formula is as follows:

$$S_i = \ \mathrm{w}idth_i, height_i \quad or\ S_i = \ area_i, volume_i \tag{3}$$

The size information S_i is very important to predict the design effect. In order to extract the characteristic indexes reflecting the design style and aesthetic feeling, we can calculate the similarity between different layout structures. The formula for calculating the similarity of the layout structure is as follows:

$$Similarity\ \ L_1, L_2\ = \frac{\sum_{i \in L_1} \sum_{j \in L_2} f\ \ dist\ \ P_i, P_j\ \ , size\ \_diff\ \ S_i, S_j}{\sqrt{|L_1| \cdot L_2}} \tag{4}$$

Among them, f is a function to measure the difference between positions and sizes, $f\ \ dist\ \ P_i, P_j$ calculates the distance between positions, and $f\ \ size\ \_diff\ \ S_i, S_j$ calculates the difference between sizes.

The above characteristic parameters and indicators will be used as input variables of the prediction model for subsequent model training and prediction.

4.3 Effect Prediction Algorithm in Collaborative Design Environment

In the collaborative design environment, the graphic design effect prediction algorithm needs to be able to deal with the situation that multiple designers participate in the design at the same time, give feedback on the change of design effect in real-time, and consider the interaction between different designers. In order to achieve this goal, a prediction algorithm based on machine learning -GNN can be adopted. GNN can deal with complex relationships in data structures, such as social networks and molecular structures, and can also be applied to the relationship modelling between design elements. In the process of learning and predicting the combination and layout of design elements by using the GNN model, several key steps need to be clarified first: data preparation, model construction, training and optimization, and prediction and assessment. Firstly, this article collects a data set containing various combinations and layouts of design elements. These data come from historical design projects, online design platforms, or competitions. Each data sample should include the type, size, location, color, and other attributes of design elements, as well as the corresponding design effect label or score. After the raw data is prepared, the preprocessing operation is carried out to convert the raw data into a format that can be processed by the neural network model.

This article constructs a GNN model (as shown in Figure 1), takes the extracted design elements as the input layer, and outputs the predicted design effect through the calculation and processing of the hidden layer.

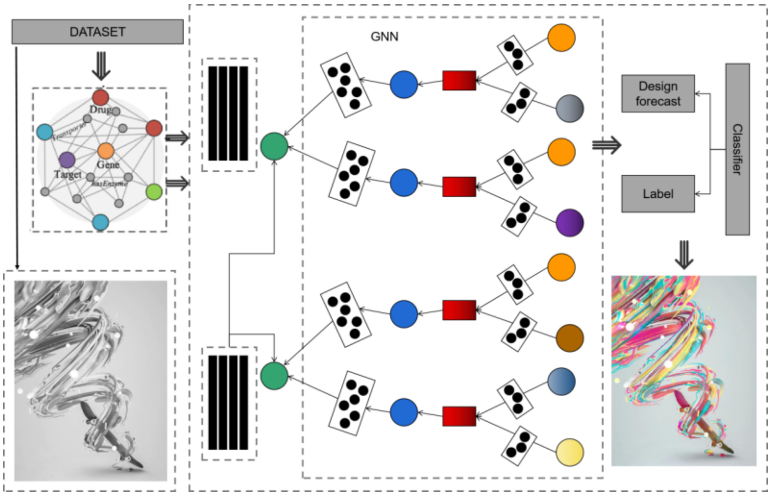

Figure 1: GNN model.

Feature mapping is the output data obtained by convolution operation in GNN, and each feature mapping can be regarded as the "abstraction" of input data in GNN, which extracts different features from the input data. All neurons in the same feature mapping plane share the same filter; that is, they use the same convolution kernel for convolution operation. In this way, GNN can detect the same features in different spatial positions, thus realizing the translation invariance of features. The convolution kernel formula is as follows:

$$h_{ij}^{k} = \tanh\left(W^{k} * x_{ij}\right) + b_{k} \tag{5}$$

Where W^k denotes the weight and b_k denotes the offset. This article computes the standard deviation $s \in R^c$ between the two-dimensional characteristic maps of c channels and retains the channel characteristic maps exhibiting significant deviation values. The formula is given below:

$$s = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2\right)^{1/2} \tag{6}$$

$$x_k = \sum_{i=1}^{w}\sum_{j=1}^{h} T_{i,j}^{k} \tag{7}$$

Here s, N, x_k denotes the standard deviation vector, the count of images in the training dataset, and the convolutional feature activation map preserves the c -dimensional feature vector, which is derived by summing other dimensions along with the channel dimension c .
Furthermore, this article explores the incorporation of an attention mechanism to bolster the model's expressive capabilities (refer to Figure 2).

Once the model is constructed, the next step involves training it using the gathered datasets. During this training phase, historical design data paired with their corresponding real-world outcomes serve as training samples. The neural network's weights and biases are fine-tuned through the backpropagation algorithm, enabling the model to progressively grasp the correlation between design components and their impact on the overall design.

When it comes to GNN training specifically, the gradient descent approach or its variations are commonly employed for updating the weights. The standard gradient descent method only considers the gradient information of the current step to determine the updated direction of the decision value.

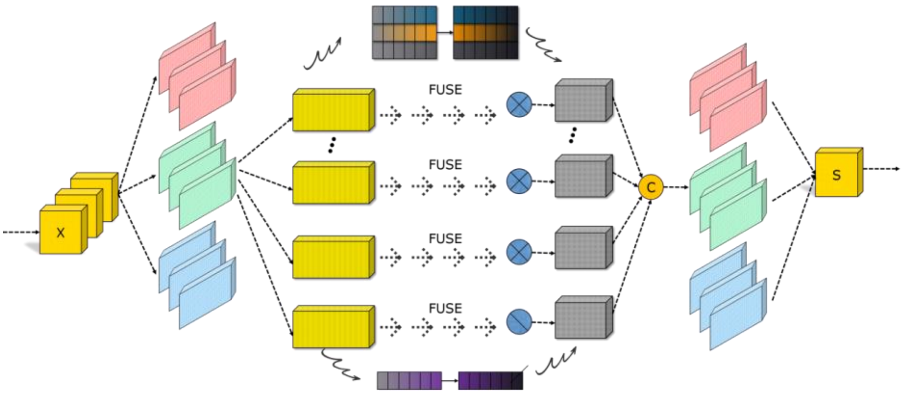

Figure 2: Attention mechanism.

However, sometimes this method may cause the training process to oscillate in some directions in the optimization space, especially when there are high curvature areas, narrow valleys or multiple local minima. In order to alleviate this problem, a momentum term can be added to the weight update rule. The momentum term is actually a weighted average of the previous gradient, which helps to accelerate the gradient descent process and may help the algorithm jump out of the local minimum. The weight updating rule with momentum term can be expressed as:

$$\Delta w_{ji}\ n = -\eta\sum_{t=0}^{n}\alpha^{\eta-t}\frac{\partial\varepsilon\ t}{\partial w_{ji}\ t} = -\eta\frac{\partial\varepsilon\ n}{\partial w_{ji}\ n} - \eta\sum_{t=1}^{n}\alpha^{\eta-t}\frac{\partial\varepsilon\ t}{\partial w_{ji}\ t},\ \ 0<\alpha<1 \tag{8}$$

The present gradient holds the greatest significance in $\Delta w_{ji}\ n$, consistently carrying a coefficient of one. Meanwhile, the impact of the preceding gradient $\Delta w_{ji}\ n$ diminishes exponentially as $\alpha^{\eta-t}$ increases. In this way, the momentum term actually introduces a kind of "inertia" or "memory" in the weight update, which helps the algorithm move more smoothly and efficiently in the optimization space.

The error function is often used to describe the cumulative probability density function of normal distribution in mathematics. Its formula can be expressed as:

$$E_p = \frac{\sum_t \ t_{pi} - o_{pi}\ ^2}{2} \tag{9}$$

Where t_{pi} and o_{pi} are the expected output and the actual calculated output of the network, respectively.

In order to consider the influence of a collaborative design environment, this article adds the designer's weight factor to the model to reflect the degree of influence of different designers on the design effect. In this way, when multiple designers participate in the design at the same time, the model can comprehensively consider their design intentions and contributions according to their respective weight factors, thus obtaining more accurate and comprehensive prediction results.

4.4 Realization of Prediction Model and Parameter Optimization

During the model implementation phase, selecting the right programming language and development tools is crucial for coding and debugging the prediction model. In this research, Python stands out as an ideal choice due to its user-friendliness, versatility, and extensive library support. Moreover, employing an integrated development environment like PyCharm can enhance development productivity. Additionally, to optimize the model's predictive capabilities, it's essential to fine-tune its parameters. These parameters encompass various aspects such as the number of GNN layers, node count, learning rate, and other relevant factors. Furthermore, adjusting parameters like the number of iterations during training, batch size, and more (refer to Table 3) is also critical for achieving optimal performance.

Parameter name	*Set value*	*Explain*
Neural network layer number	6	Comprises an input layer, a hidden layer and an output layer.
Number of hidden layer nodes	256,128,128,128, 64, 32	The number of nodes in each hidden layer gradually decreases from the first layer to the last layer.
Learning rate	0.01	Control the step size of the model weight update.
Batch size	32	The number of samples used for each weight update.
Dropout probability	0.5	The probability of randomly discarding some neurons in the training process is used to prevent over-fitting.

Table 3: GNN model parameter setting and optimization.

In order to optimize these parameters, this article uses cross-validation and grid search methods to select and adjust the parameters. By constantly adjusting the parameters and comparing the accuracy index of the model under different parameter combinations, the optimal parameter combination can be found to make the model achieve the best prediction effect on the test set. The experiment of parameter setting is shown in Figure 3.

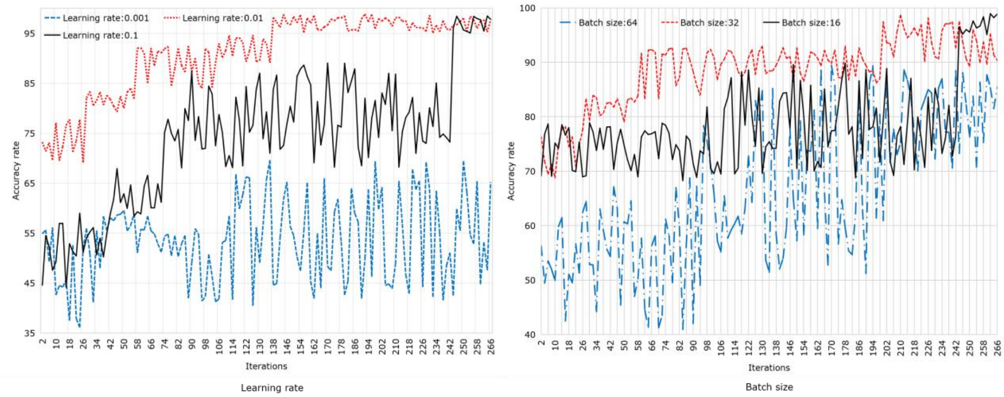

Figure 3: Experimental situation of parameter setting.

In addition, in the process of model realization, we need to consider the issues of data expansibility and model universality so as to apply the model to the task of graphic design effect prediction in different fields and scenes.

5 SIMULATION EXPERIMENT DESIGN AND RESULT ANALYSIS

The main purpose of this simulation experiment is to verify the accuracy of the prediction model of the graphic design effect. By simulating the real design environment, the predicted results of the model are compared with the actual design results to evaluate the performance of the model in practical application. The experimental environment is equipped with high-performance computers and professional graphic design software to support complex graphics processing and data analysis tasks. Furthermore, in order to simulate the collaborative design environment, a network platform is built to realize real-time interaction and data sharing among multiple designers. In terms of data set preparation, the experiment collected a large number of graphic design works and their corresponding design elements and actual effect data. These data are obtained through historical design projects, design competitions and online design platforms. When collecting data, we pay attention to the diversity, integrity and accuracy of the data to ensure the reliability of the experimental results. The control factors include the parameters of the model, the number of training iterations, the batch size and so on. These factors need to be consistent or adjusted in a controlled way during the experiment to eliminate their influence on the experimental results.

In this article, the output data of the model in each stage and the actual design effect data are collected. These data will be used to evaluate the prediction performance and accuracy of the model. The influence of design factors on prediction performance is shown in Figure 4.

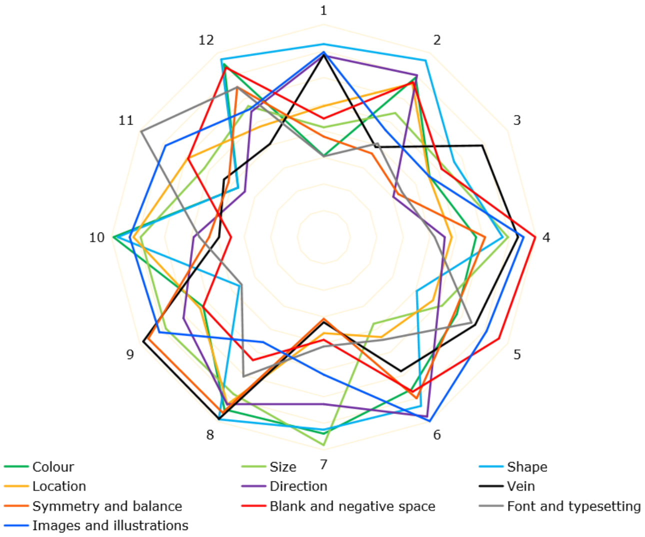

Figure 4: Influence of design factors on prediction performance.

By comparing the prediction data corresponding to different design elements, we can intuitively see that layout structure and element size have a greater influence on prediction performance. This means that this design element plays an important role in improving the prediction performance. Therefore, in the design process, we should focus on these factors that have a great influence on performance.

The influence of the designer's weight factor on the prediction results is shown in Figure 5. By observing the trend of a line chart, we can analyze how the designer's weight factor affects the prediction results. The broken line in the figure shows an upward trend, which shows that increasing the designer's weight factor can improve the prediction results. It should be noted that the fluctuation in the line chart reveals the optimal value and sensitive area of the weight factor, and the setting of the weight factor corresponding to these points is more effective in practice. The influence of collaborative design environment parameters on design efficiency is shown in Figure 6.

In some cases, the reduction of communication delay will significantly improve the design efficiency, but when the number of concurrent users reaches a certain level, this improvement may be weakened. In order to verify the superiority of the prediction model constructed in this study, this section will be compared with other related research models. These models include prediction models based on statistical methods, decision tree algorithms and simulated annealing algorithms. The comparison of the prediction accuracy of different methods is shown in Figure 7.

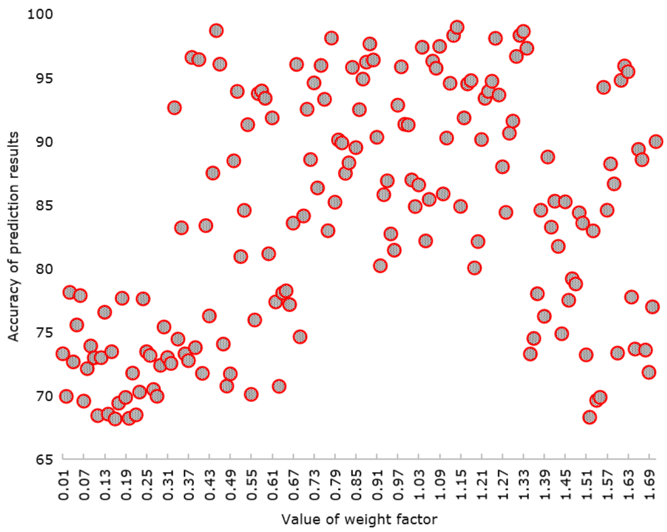

Figure 5: Influence of designer's weight factor on prediction results.

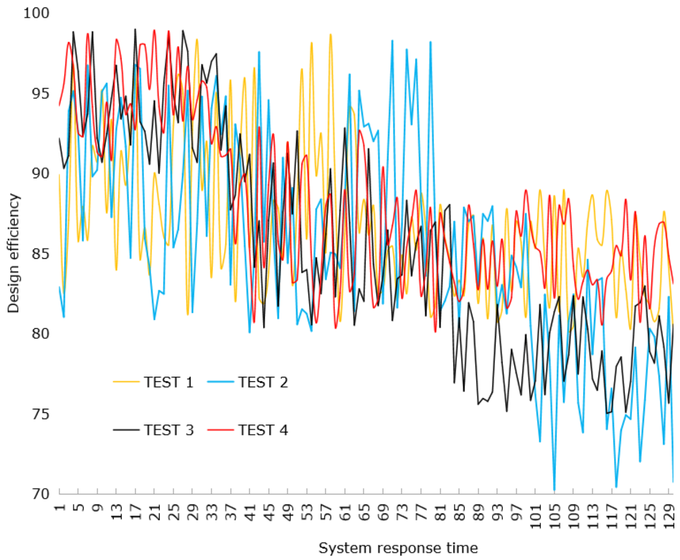

Figure 6: Influence of collaborative design environment parameters on design efficiency.

By comparing and analyzing the prediction accuracy of different methods, we can find that the prediction model constructed in this study has certain advantages in performance. This is because this article combines GNN and specific optimization strategies for design problems, so as to capture the deep relationships and patterns in data more accurately and provide more powerful support for design decisions.

This article also collected feedback from designers and experience data so as to further optimize and improve the model. The feedback from designers is shown in Table 4.

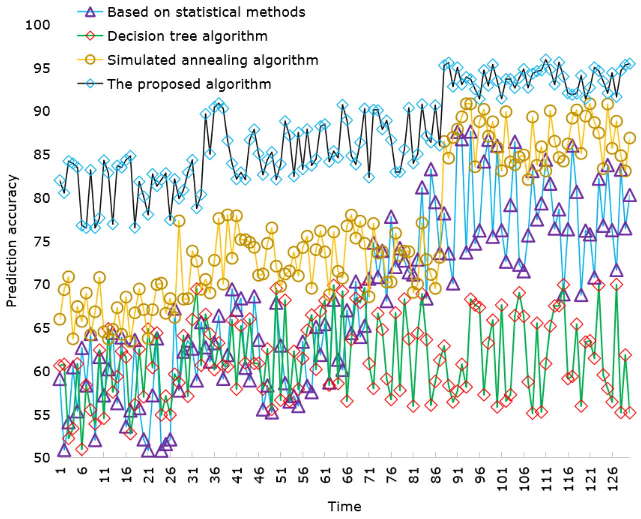

Figure 7: Comparison of prediction accuracy of different methods.

Designer number	*Project name*	*Feedback aspect*	*Specific feedback*	*Has it been resolved*	*Satisfaction rating*
1	Graphic design A	Prediction accuracy	The prediction of colour matching is quite accurate, which is consistent with the feedback from the end customers.	Yes	4.9
2	Graphic design B	Real-time feedback	When the font size is adjusted, the model can feedback on the typesetting effect in real-time, which greatly improves the design efficiency.	Yes	4.8
3	Graphic design C	collaborative design	Edit with team members in the cloud at the same time, and synchronize changes in real-time, and the collaborative experience is very smooth.	Yes	4.9
4	Graphic design D	User Interface	The interface design is clear, the icons are intuitive and easy to	Yes	4.7

			understand, and the novice guidance is also in place.		
5	Graphic design E	Industry-specific forecast	The prediction of design style for specific industries (such as food packaging) is not accurate enough, so it is suggested to increase relevant training data.	Yes	4.2
6	Graphic design F	Operational fluency	When performing complex operations (such as the multi-layer superposition effect), the model is a little stuck.	Yes	4.5

Table 4: Feedback from designers.

Note:

A satisfaction score of 1 means very dissatisfied, and 5 means very satisfied. Scoring can help quantify the satisfaction of designers for subsequent analysis and improvement.

The designer's experience data is shown in Figure 8.

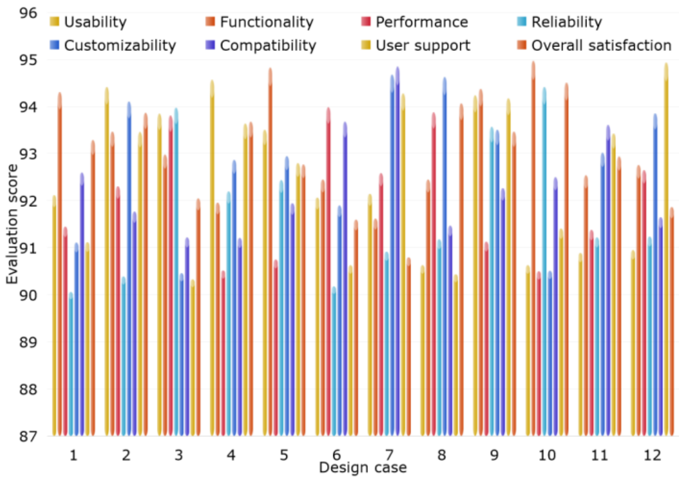

Figure 8: Designer's experience data results.

The designer's feedback in Table 4 covers many aspects of the model, including prediction accuracy, real-time feedback, collaborative design, user interface, industry-specific prediction, and operational fluency. This shows the designer's comprehensive assessment of the model. From Figure 8, the designer has a positive assessment of the overall performance of the model, especially in the aspects of prediction accuracy, real-time feedback, collaborative design and user interface. However, there are also some problems that need to be improved, such as the accuracy of prediction and the fluency of operation in specific industries. These problems provide directions and suggestions for the subsequent improvement of the model.

6 CONCLUSIONS

In the stage of model construction, this article deeply analyzes the requirements of model construction, extracts the elements of graphic design based on CAD, designs the effect prediction algorithm under the collaborative design environment, and constructs the framework of the prediction model. In the design and implementation stage of the experiment, the purpose and hypothesis of the experiment are defined, the experimental environment and data sets are prepared, the experimental variables and control factors are determined, the experimental process and data collection are recorded in detail, and the experimental results are analyzed preliminarily. Through simulation experiments, we have confirmed the prediction model's validity and precision. The outcomes indicate that the model can precisely anticipate the impacts of various design approaches, offering designers a dependable reference. Additionally, the model is adaptable to collaborative design settings, facilitating simultaneous participation by multiple individuals, sharing of design resources, and real-time feedback on design changes. This advancement presents fresh ideas and techniques for pushing the boundaries of graphic design innovation.

This article introduces a novel prediction technique to the realm of graphic design, addressing a previous void in effect prediction. Simulation tests have affirmed the model's efficacy and accuracy, providing valuable insights for researchers and professionals alike. Moreover, it has catalyzed innovative advancements in graphic design, enhancing both efficiency and quality and making significant contributions to the industry's progress. We anticipate that more researchers will delve into the study of graphic design effect prediction, collectively fostering sustainable growth, innovation, and progress in this thriving field.

Yanfang Wei, https://orcid.org/0009-0005-9455-8738
Jisi Pan, https://orcid.org/0009-0000-8187-1008

REFERENCES

[1] Asadi, A.-S.; Mohammadpoory, Z.; Nasrolahzadeh, M.: A Novel Content-based Image Retrieval System using Fusing Color and Texture Features, Journal of AI and Data Mining, 10(4), 2022, 559-568. https://doi.org/10.22044/jadm.2022.12042.2353

[2] Boluki, M.; Mohanna, F.: Inspection of textile fabrics based on the optimal Gabor filter, Signal, Image and Video Processing, 15(7), 2021, 1617-1625. https://doi.org/10.1007/s11760-021-01897-3

[3] Han, Y.; Shi, X.; Yang, S.; Zhang, Y.; Hong, Z.; Zhou, R.: Hyperspectral sea ice image classification based on the spectral-spatial-joint feature with the PCA network, Remote Sensing, 13(12), 2021, 2253. https://doi.org/10.3390/rs13122253

[4] Han, Z.; Shang, M.; Liu, Z.: SeqViews2SeqLabels: learning 3D global features via aggregating sequential views by RNN with attention, IEEE Transactions on Image Processing, 28(2), 2019, 658-672. https://doi.org/10.1109/TIP.2018.2868426

[5] Jing, Y.; Song, Y.: Application of 3D reality technology combined with CAD in animation modeling design, Computer-Aided Design and Applications, 18(S3), 2020, 164-175. https://doi.org/10.14733/cadaps.2021.S3.164-175

[6] Kang, M.; Kim, S.: Fabrication of 3D printed garments using flat patterns and motifs, International Journal of Clothing Science and Technology, 31(5), 2019, 653-662. https://doi.org/10.1108/IJCST-02-2019-0019

[7] Keyvanpour, M.-R.; Vahidian, S.; Mirzakhani, Z.: An analytical review of texture feature extraction approaches, International Journal of Computer Applications in Technology, 65(2), 2021, 118-133. https://doi.org/10.1504/IJCAT.2021.114990
[8] Khaldi, B.; Aiadi, O.; Kherfi, M.-L.: Combining colour and grey-level co-occurrence matrix features: a comparative study, IET Image Processing, 13(9), 2019, 1401-1410. https://doi.org/10.1049/iet-ipr.2018.6440
[9] Li, F.; Yuan, L.; Zhang, K.; Li, W.: A defect detection method for unpatterned fabric based on multidirectional binary patterns and the gray-level co-occurrence matrix, Textile Research Journal, 90(7-8), 2020, 776-796. https://doi.org/10.1177/0040517519879904
[10] Reska, D.; Kretowski, M.: GPU-accelerated image segmentation based on level sets and multiple texture features, Multimedia Tools and Applications, 80(4), 2021, 5087-5109. https://doi.org/10.1007/s11042-020-09911-5
[11] Shahabian, R.; Sahaf, A.; Mohammadzadeh, M.-A.; Pourreza, H.: Statistical texture analysis of asphalt pavement distress images based on grey level co-occurrence matrix, Road, 30(111), 2022, 69-82. https://doi.org/10.22034/ROAD.2022.110866.1670
[12] Tadi, B.-N.; Fekri, E.-S.: Content-based image retrieval based on combination of texture and colour information extracted in spatial and frequency domains, The Electronic Library, 37(4), 2019, 650-666. https://doi.org/10.1108/EL-03-2019-0067
[13] Wu, H.; Xu, X.; Chu, J.; Duan, L.; Siebert, P.: Particle swarm optimization-based optimal real Gabor filter for surface inspection, Assembly Automation, 39(5), 2019, 963-972. https://doi.org/10.1108/AA-04-2018-060
[14] Yang, G.; He, Y.; Li, X.; Liu, H.; Lan, T.: Gabor-GLCM-based texture feature extraction using flame image to predict the O2 content and NoX, ACS omega, 7(5), 2022, 3889-3899. https://doi.org/10.1021/acsomega.1c03397
[15] Zitouni, A.; Benkouider, F.; Chouireb, F.; Belkheiri, M.: Classification of textured images based on new information fusion methods, IET Image Processing, 13(9), 2019, 1540-1549. https://doi.org/10.1049/iet-ipr.2018.6256