Optimization of Visual Communication Design Scheme by Combining Computer-Aided Design and Deep Learning

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Abstract. This article uses CAD's computer-aided visual reinforcement method to optimize integrated design comprehensively. By enhancing the process of visual communication, we have carefully expanded on the basic principles and conducted a comprehensive inspection and analysis. Optimizing the design of visual communication has built the basic visual design advantages of CAD. The study emphasizes the fundamental knowledge challenge analysis of visual communication driven by DL in design and constructs an optimization model for CAD transmission design under the visual strategy. By optimizing transmission design models in different fields, their respective strengths were constructed. The research results indicate that the integrated design innovation research process of CAD and DL greatly reduces the repetitive tasks of design. At the same time, the model integrates the current visual design communication efficiency and attractiveness, providing huge reference value for promoting the industry of visual communication.

Keywords: Computer-Aided Design; Deep Learning; Visual communication Design; Design Optimization; Combination Strategy
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1 INTRODUCTION

At present, deep learning and analysis of visual communication have become an indispensable strategic value for media. In the analysis interface process of mobile platforms, Cho and Kim [1] constructed the textual transmission value of decision-making behaviour. It deeply explores its application in English teaching applications, especially in the expansion analysis of visual communication. This handwriting input method is not only more convenient than the step-by-step selection buttons or menu items in traditional graphical user interfaces (GUI) but also more in line with the user's natural writing habits. To achieve accurate recognition of handwritten text, an interactive technique that combines is proposed. In terms of visual communication, we further analyzed how the visual elements of the handwritten text interface effectively convey information and promote user behaviour. Based on the above interface and technology, we have created an English teaching application. In addition, the interface design of the application program has been optimized through the principle of visual communication, making it more in line with user visual habits and cognitive processes. Teaching machine learning in schools is crucial in helping students better adapt to the rapidly changing society caused by artificial intelligence. Combining the perspective of visual communication, Gresse et al. [2] found that visual elements and images play a crucial role in helping students understand and master machine learning concepts. In this study, 16 student-oriented tools were discovered, mainly as part of short-term extracurricular activities, guiding students to explore machine learning through visual means. It supports embedding the created machine learning models into games or mobile applications, allowing students to see the practical application of their learning outcomes in a real environment. Considering the cognitive development of students, adopting age-appropriate teaching tools and methods is crucial to ensure that students can fully understand machine learning and stimulate their potential in visual language during the K-12 stage, we systematically mapped emerging visual tools that support machine learning teaching in this educational stage and conducted a decade long in-depth analysis of them. This process of visualizing and concretizing learning outcomes is one of the important applications of visual communication in education. The research results indicate that these tools can effectively utilize visual elements and images to enhance students' machine-learning understanding. This design not only encompasses traditional sectors like advertising, packaging, and display but has also found its way into emerging fields such as web design, interfaces, and multimedia. Consequently, exploring the refinement and novelty of visual communication design holds immense importance in elevating design quality and catering to user needs.

On the basis of in-depth research on non-contact depth of field-based 3D measurement methods, Guo and Wang [3] further explored the application of visual communication in digital sculpture art. This method achieves approximate 3D reconstruction of submicroscopic object shapes through the analysis and processing of digital images without increasing hardware costs. It has the advantages of simple hardware, non-contact, and high-precision measurement. It involves the visual expression, transmission, and understanding of information. In digital sculpture art, the role of visual communication is particularly important. By restoring the three-dimensional shape (defocus depth) from a focused image, we can use a regular microscope to capture a series of images with different focus depths, and then calculate the shape of the three-dimensional object. Digital sculpture art, as a product of computer-aided modelling, not only overcomes the drawbacks of low production efficiency, difficult modification, and limited preservation in traditional manual carving art but also provides new possibilities for artistic creation with its unique advantages such as high precision and replicability. Through visual communication, designers can present their creativity and ideas in a three-dimensional form. Through examples of folk craft modelling, they validated the methods for reasonable wiring and demonstrated the practicality of computer sculpture modelling methods in art design. CAD, a pivotal instrument in modern design, finds extensive application across multiple design disciplines, visual communication design being one of them. By leveraging digital tools, CAD significantly bolsters design efficiency and precision, thereby expanding the creative horizons for designers. Nevertheless, its usage in visual communication design still faces certain constraints, particularly in generating and refining intricate design elements and expediting design iteration.

He [4] proposed a pattern interactive visual teaching mode based on an intelligent classroom environment and conducted an in-depth expansion analysis with visual communication. Through the application of intelligent cloud service technology, it has collected, transmitted, and analyzed teaching data such as concept maps, and developed a personalized set of course learning resources. These resources are presented in a visual form, which can better meet the learning needs of students and improve learning efficiency. In the stage of guiding conceptual cognitive integration, we use interactive tools provided by the intelligent classroom environment to guide students to integrate their learned knowledge through discussions, collaboration, and other means, deepening their understanding of the knowledge points. In the stage of establishing a cognitive map, we use the principle of visual communication to concretize abstract knowledge through visual elements such as graphics and images, helping students form intuitive cognitive structures. The study also employed a

Flanders interaction analysis system with multiple encoding types and combined it with an intelligent classroom environment to improve the interaction between humans and technology. The recent surge in DL technology has opened up new avenues for optimizing visual communication design. By simulating the workings of the human brain's neural network, DL can autonomously acquire and extract characteristics from images, texts, and other data, facilitating inference and prediction based on these attributes.

In the domain of visual communication design, DL can facilitate the automated generation of design elements, swift iteration, and refinement of designs, ultimately equipping designers with more efficient and intelligent tools. When creating electronic content, in order to attract users and ensure that they better understand the information provided, we have adopted a series of advanced visualization technologies. Ince [5] has broken through tradition by utilizing deep learning and popular artificial intelligence technologies to develop an automated intelligent content visualization system. Although these methods are effective, they still have limitations in handling complex information and creating intuitive visual experiences. Visual communication emphasizes the dynamic transmission and perception process of visual information. The birth of design art has always been accompanied by the development of technology and manufacturing techniques. Since the Bauhaus period, the level of design to a certain extent reflects the level of scientific and technological development at that time. At the same time, science and technology and process technology also directly affect the development trend of design, and the two interact with each other. The concept and form of modern brand visual identity design have gradually broken our traditional understanding of a single logo effect. Designers should not stay at the level of racking their brains for a simple individual graphic but should consider using various forms, means, and forms to express the entire system. The traditional two-dimensional static logo has been unable to meet the market competition of brands and the needs of mass communication [6]. The systematic dissemination of brand visual image recognition requires increased interaction with the audience and sensory experience, in order to strengthen the brand's extended application and dissemination in the new media environment. Data visualization not only illustrates complex analysis results through intuitive graphical forms, reducing the difficulty of learning statistics, but also provides valuable learning opportunities for students with different learning styles at the level of visual communication. By analyzing real-world data, such as financial and business statistics, students can gain the operational mechanisms of the business world. Introducing teaching methods in business statistics to enhance the practical skills and business insights of business school students.

However, at present, there is still relatively little research on the application of the combination of CAD and DL in visual communication design. Therefore, this article will discuss the research status and challenges of the combination of CAD and DL in visual communication design, and try to propose an optimization method for a visual communication design scheme based on CAD and DL. Then, DL's application in refining visual communication designs is explored, discussing various methodologies and case studies. Following this, the integration of CAD and DL in optimizing visual communication design schemes is detailed, introducing an optimized method rooted in these technologies. The article concludes with a summary of the research findings, its limitations, and suggestions for future directions.

2 RELATED WORK

Interaction design is an indispensable part of web design. Interaction design focuses on the interaction process between users and web pages, including navigation design, button design, form design, and other aspects. An excellent interaction design can ensure that users can easily and smoothly complete various operations while using web pages, improving the user experience and satisfaction. Information design also plays an important role in web design. Information design focuses on how to present complex information in a clear and intuitive manner, enabling users to quickly understand and obtain the information they need. Kiu [7] proposed a series of suggestions to enhance effective communication of web design information. In web design, factors such as the visual presentation of information, the rationality of interaction design, and the clarity of information architecture have a significant impact on the effectiveness of information communication. It first provides a comprehensive overview of web design and explores the key factors that affect information exchange in web design. In this context, visual communication expansion analysis provides a new perspective for web design. Visual communication not only focuses on the static presentation of information but also emphasizes the dynamic transmission of information at the visual level and the user's perceptual experience. Information reception, and processing processes when browsing web pages. Thus optimizing the layout and presentation of information, and enhancing effective communication of information. Designers should pay attention to the visual habits and psychological expectations of users, guide their visual flow through reasonable visual layout and colour matching, and improve the readability and comprehensibility of information. Interactive visualization systems are not only tools for displaying data but also platforms for providing users with in-depth insights. This challenge often stems from a lack of professional experience and insufficient data analysis skills, which is particularly significant for non-professionals. This method aims to provide diverse and insightful interactive recommendations to novice users in real time by capturing their interactive behavior and visual state. However, public users who are new to multi-view visualization often face the challenge of how to effectively operate interactions and explore which parts of data to obtain maximum value [8]. In this system, users can explore the works, life stories, and influence of poets through various views and interactive methods. These vectors not only contain real-time operational information of the user but also reflect the user's behaviour patterns throughout the entire conversation process. At the same time, we will also combine recommendations with current visual content, providing users with more intuitive and easily understandable feedback through animation, transition effects, and visual prompts. In terms of visual communication, our method further expands the analysis. By updating and displaying recommended interactive options in real-time, we can guide users' gaze and attention, helping them explore data more focused and efficiently.

Liu et al. [9] conducted an in-depth analysis using two classics, with the aim of selecting appropriate datasets to capture and predict landscape trends. It proposes a novel machine learning-based landscape visualization scheme, which particularly emphasizes the extension analysis of visual communication. Through the analysis of a large amount of historical data and on-site research data, we comprehensively analyze multiple dimensions such as ethnic culture, society, ecology, and aesthetic emotions, in order to establish a unique landscape indicator system for the Lai ethnic village. Through carefully designed visual interfaces and interactive charts, we can enable users to intuitively see the evolution trend, spatial distribution, and ecological characteristics of the landscape of the Lai ethnic village. In terms of visual communication expansion analysis, we focus on transforming landscape data into intuitive and easily understandable visual elements. Research has shown that conducting machine learning-based visual system research on the landscape of Lai ethnic villages can not only accurately reflect the cultural landscape characteristics of Lai ethnic villages, but also contribute. Ma and Ding's [10] research work is committed to improving the quality and efficiency of talent cultivation in universities. This system utilizes deep-learning neural networks to process and parse large amounts of educational data. Deep learning neural networks have powerful feature extraction and pattern recognition capabilities. It can automatically learn and extract valuable information from raw data, providing strong support for subsequent data analysis. Through data mining, the system can discover the inherent connections between different data items, providing more comprehensive and detailed guidance for talent cultivation in universities. This indicator system not only covers traditional academic performance and course completion, but also incorporates multi-dimensional evaluation indicators such as practical skills, innovative thinking, and professional competence. Through various presentation forms such as interactive charts, dynamic maps, and 3D simulations, users can intuitively see various aspects of talent cultivation, including student academic performance, development of practical skills, employment trends, etc.

With the widespread deployment of machine learning models in real-world applications such as healthcare, bank loans, and other critical decision-making areas, the accuracy and reliability of their prediction results have become crucial. Ma et al. [11] proposed a visual analysis framework that combines visual communication extension analysis, aiming to help users explain and explore model vulnerabilities in adversarial attacks. The visual analysis community has made some progress in revealing the operational mechanisms within machine learning models. This framework not only adopts various visualization schemes, but also integrates the design concept of visual communication, and analyzes the performance of the model under different attack strategies. Through visual communication, the vulnerabilities and potential risks of the model are under attack. Specifically, our framework starts from multiple perspectives such as models, data instances, features, and local structures, and provides users with rich analytical tools through carefully designed visual interfaces and interactive tools. The study also combines visual communication methods such as animation, gradients, and interaction, allowing users to explore different parts and levels of the model through interactive operations, thereby gaining a deeper understanding of the working mechanism and sources of vulnerabilities of the model. Mao [12] introduced an image quality evaluation algorithm, which can automatically filter out relatively high-quality images. Based on the calculated saliency and clarity values, this method further eliminates objects whose saliency and transparency have not reached the preset threshold. In terms of object extraction, this method adopts a deep learning model to determine the saliency and clarity values of the image. Because only high-quality images can provide accurate and rich information for subsequent analysis. By analyzing this feature information, the model can accurately identify salient objects in the image and calculate their clarity values. Combined with visual communication expansion analysis, make the presentation of oil painting art teaching more intuitive, vivid, and effective. These standards not only help us identify objects with poor quality and low ratings but also expand analysis through visual communication, enabling students to have a more intuitive understanding of the application of these aesthetic principles in oil painting creation. In this process, we use visual communication technology to present the matching process to students in a dynamic and intuitive form, helping them better understand the relationships and combinations between image elements. In the stage of object extraction and fusion, we extended the regions with high saliency and matched the contours of segmented image elements with those drawn by students to return the optimal matching value.

Industry 4.0 is leading the innovation of the design process, not only a wave of technological change but also a deep reshaping of the way ideas are conceived. In this context, visual communication extension analysis provides new ideas for computer-aided participatory design. Digital technology, especially 3D simulation technology, endows designers with the ability to simulate complex systems, such as human-machine collaboration (HRC), enabling change to be implemented with higher time and cost-effectiveness [13]. By visualizing, we can present complex industrial environments, workplaces, and processes in a more intuitive and easily understandable form, thereby reducing the participation threshold for non-professional users. The research results show that in order to achieve effective computer-aided participatory design, software tools need to meet a series of basic requirements.

Xiao and Ni [14] The application of these technologies was explored, and the role of visual communication extension analysis was analyzed in depth. A convolutional neural network-based image enhancement algorithm for industrial design products was proposed. Compressing the CNN model, not only improves the stability and anti-overfitting performance of the network but also reduces the computational complexity and runtime of the algorithm. Visual communication extension analysis plays a crucial role in image processing, as it simulates the working mechanism of the human visual system to process images more finely and efficiently. It applies visual communication extension analysis to image enhancement algorithms in industrial design products to optimize the visual quality and detail expression of images. This optimization enables the algorithm to adapt more quickly to different industrial design scenarios and improves the efficiency of the CAID design process. This model can be quickly trained and achieve target accuracy in a short period of time, supporting the feature extraction and modelling stages of CAID. Compared with traditional single-user verification methods, parallel verification methods can more comprehensively evaluate the stability and generalization ability of the model, thereby ensuring the effectiveness of the model in practical applications. Through simulation experiments, we have verified the excellence of the CAID image processing task. Zhang [15] delves into the development history, application fields, and related technologies of visual interaction from the perspective of technical personnel and further expands the analysis of the concept of visual communication and its application in design. This requires us to focus not only on the implementation of technology in the creative process but also on understanding the needs and expectations of users deeply. Secondly, as an important component of visual interaction, Visual communication involves the transmission, processing, and reception of visual information. The development of visual interaction is not only reflected in technological innovation but also in how it closely integrates with the psychology, behavior, and perception of users. In the context of the development of digital media art, it is necessary to pay more attention to how to integrate visual interactive experiences with creative design, creating works that are both aesthetically pleasing and interactive. Therefore, it has established a more comprehensive visual communication model, utilizing advanced image processing techniques and cross-information fusion techniques. Extract and enhance the edge contour features of visual communication information to achieve clearer and more accurate visual communication. Especially in the field of visual interaction art design and related technologies, although the development of visual interaction and its applications in various fields have shown great potential, in-depth research and practice are still insufficient.

3 THEORETICAL BASIS OF VISUAL COMMUNICATION DESIGN

3.1 Basic Concepts of Visual Communication Design

Visual communication design, as an important branch of design discipline, mainly focuses on how to convey information, emotions and ideas through visual elements. It covers many fields such as print advertising, packaging design, corporate identity systems, brand planning, publication design, web page and interface design. Visual communication design is not only a combination of aesthetics and technology but also a comprehensive embodiment of cultural, economic, and technological development.

In visual communication design, designers need to use various visual elements, such as words, graphics, colours, lines, shapes, etc., to construct design works with visual impact, attraction and appeal (as shown in Table 1). These visual elements can quickly and accurately convey the theme, information and emotion of the design work through the clever combination and layout of designers.

Element	*Describe*	*Function*
Characters	One of the most important information carriers in visual communication design.	Directly express the intention and theme of the design works.
Graph	One of the most intuitive and vivid elements.	Quickly attract the attention of the audience and convey the emotion and atmosphere of the design works.
Colour	One of the most important emotional factors.	Resonate with the audience and create a specific atmosphere.
Layout	The process of orderly combination and layout of visual elements such as words, graphics and colours.	Determine the visual effect and overall aesthetic feeling of the design works.

Table 1: Overview of visual communication design elements.

4 APPLICATION OF CAD IN VISUAL COMMUNICATION DESIGN

4.1 Overview of CAD Technology

CAD technology is a general term for designing, drawing, analyzing, and compiling documents through computers and related software. Its basic principle is to use the powerful computing power of a computer and combine it with professional software to realize the digital processing of design data. In visual communication design, CAD technology is widely and deeply applied. For example, in the field of advertising design, designers can use CAD to quickly draw an advertising layout with accurate size and proportion, and make the advertising works more vivid through functions such as colour filling and material mapping. In the field of packaging design, CAD technology structure drawings, and make simulation analysis on materials, colours and printing processes to ensure the practicality and aesthetics of packaging design.

CAD plays an important role in improving design efficiency and quality. Through CAD software, designers can quickly complete design conception and scheme optimization, and avoid repeated work and mistakes. Furthermore, CAD technology can also provide accurate design data and simulation analysis functions, help designers better grasp the design details and effects, and ensure the accuracy and high quality of design works.

4.2 The Limitations of Cad in Visual communication Design

Although CAD technology has a wide range of applications and significant advantages in visual communication design, there are also some problems and shortcomings (as shown in Table 2).

Existing problems and deficiencies	*Specific description*
Learning cost	CAD software usually requires high learning costs and operating skills, which constitutes a threshold for non-professional designers.
Dealing with complex design elements	There may be limitations in dealing with complex design elements and creative ideas, and it is difficult to meet the creative needs of designers fully.
Fast iteration and optimization	CAD technology is insufficient in the rapid iteration and optimization of design schemes, so it needs to be combined with other technologies.

Table 2: Challenges of CAD technology in visual communication design.

In view of the problems and shortcomings of CAD technology in visual communication design, some improvement measures can be taken. For example, strengthen the user-friendly and easy-to-use design of CAD software, reduce the learning cost and operating skills requirements, Combine DL and other advanced technologies, and improve the ability of CAD software to deal with complex design elements and creative ideas Through the incorporation of novel technologies, including cloud computing, swift iteration and refinement of the design plan is achieved. These advancements will enhance the efficacy and worth of CAD technology within visual communication design.

5 THE METHOD OF DL IN VISUAL COMMUNICATION DESIGN OPTIMIZATION

5.1 Optimization of Visual Communication Design Based on DL

The fundamental concept behind DL lies in creating a multilayer framework that mimics the neural network of the human brain. This structure enables a profound comprehension and extraction of input data features through gradual abstraction and amalgamation. DL technology shines in image processing and generation due to several notable strengths. Firstly, DL excels at automatically learning and extracting image features, often yielding richer and more precise details than traditional manual methods. Secondly, DL models can handle vast amounts of image data, continuously refining their parameters through training to bolster processing accuracy and efficiency.

Our RNN model comprises an input layer, a hidden layer, and an output layer. While the input layer receives feature vectors from the design elements, the hidden layer utilizes loop units to capture sequences' dependencies. Finally, the output layer produces the refined design sequence. Consider a sequence, for instance:

$$X = x_1, x_2, x_3, \ldots, x_T \tag{1}$$

Where x_t represents the input at time step x_t ; T is the length of the sequence. Output sequence of RNN:

$$Y = y_1, y_2, y_3, \ldots, y_T \tag{2}$$

Where: y_t is the output at time step t. The basic formula of RNN can be expressed as:

$$h_t = \sigma \; W_h h_{t-1} + W_x x_t + b \tag{3}$$

$$y_t = \sigma \; W_{hy} h_t + b_y \tag{4}$$

In the RNN model, this article uses the way of stacking multi-layer circulating units to capture more complex design rules and dependencies. Furthermore, the attention mechanism is introduced into the model, so that the model can pay attention to the important parts of the design sequence and improve the pertinence and accuracy of the design, as shown in Figure 1.

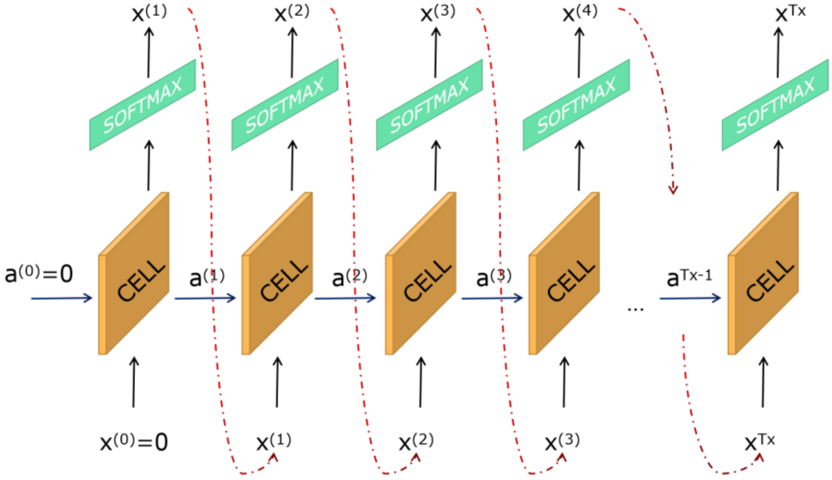

Figure 1: RNN model.

The MSE loss function is a commonly used indicator in regression tasks, as it can quantify the difference between the predicted and true values of the model. When training RNN models, The MSE loss function can help us evaluate the accuracy of the model in each prediction step. This method of squared error gives higher weight to larger differences, making it more sensitive to capturing larger errors in model predictions. Specifically, MSE calculates the average square of the difference between the predicted value and the true value. Therefore, by minimizing the MSE loss function, we can ensure that the model's predictions are accurate throughout the entire sequence. Due to the ability of RNN to process sequence data, each step of prediction relies on previous information. Therefore, having only a loss function is not enough, we also need a suitable optimizer to guide the parameter updates of the model. These optimizers use different strategies to update model parameters to minimize the loss function. The selection of optimizers has a significant impact on the training effectiveness of the model. Common optimizers include Random Gradient Descent (SGD) Adam, RMSprop, etc.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \; Y_i - \hat{Y}_i \; ^2 \tag{5}$$

Where n is the number of samples; Y_i is the i real tag; $\hat{Y}_i$ is the i th predicted value. A smaller MSE indicates a better model prediction, as it signifies a narrower gap between predicted and actual values.

The optimizer is used to adjust the parameters of the model to minimize the loss function, and we choose the Adam optimizer. Adam optimizer is a widely used DL optimization algorithm. This optimizer combines the ideas of Momentum and RMSProp and aims to achieve more efficient network training by dynamically adjusting the learning rate of each parameter. Adam's optimizer has fast convergence speed and good generalization ability. Adam optimizer uses the following two main estimators: the first-moment estimation of gradient (that is, mean value): β_1 and second-order moment estimation of gradient (i.e. non-centralized variance): β_2. The update rule of the Adam optimizer can be expressed by the following formula:

Update of the first-moment estimate (gradient mean);

$$\theta := \theta - \frac{\alpha \cdot \hat{m}}{\sqrt{\beta_1} + \in} \tag{6}$$

Where θ is the model parameter to be updated; $\hat{m}$ is a deviation-corrected version of the first-order moment estimator, which is calculated as follows:

$$\hat{m}_t := \frac{\beta_1}{1 - \beta_1^t} \cdot m_t \tag{7}$$

First-order moment estimation is commonly used in Adam optimizers to simulate the average value of gradients. Specifically, it stores the exponential decay average of the previous gradient, which can smooth out the changes in the gradient and make the adjustment of the learning rate more robust. So in the initial stage of training, the values of first-order moment estimation and second-order moment estimation tend to lean towards 0, causing them to underestimate the true gradient and gradient variance. This formula is actually a recursive exponential weighted average that can give greater weight to recent gradients.

$$\beta_2 := \frac{\beta_2 \cdot \ 1 - \beta_2^t}{1 - \beta_2^t} \tag{8}$$

In practical application, when designers need colour matching, they can input information such as design theme and design goal into the colour matching model.

5.2 Simulation of DL Optimal Design

Early stopping and regularization techniques are employed to prevent overfitting. Through numerous trials and parameter adjustments, a high-performing RNN model is achieved. The training outcomes of the RNN model are illustrated in Figure 2.

The horizontal axis Epoch in Figure 2 represents the number of times the entire training dataset has been traversed by forward and backward propagation. In each Epoch, the model will see all samples in the training dataset once. Through training with multiple Epochs, the model has the opportunity to learn patterns and structures in the data. The loss on the vertical axis is a function that measures the difference between the predicted and actual values of a model. In the training process of RNN models, the goal is to optimize (minimize) this loss function. Different tasks and models may use different loss functions, but the usual goal is to make the model's predicted values as close as possible to the actual values. In Figure 2, the trend of Loss with increasing Epoch can be observed to determine the training status of the model. The continuous decline of Loss and its tendency to stabilize at a certain point is usually a good sign that the model is effectively learning patterns in the data. The accuracy of the RNN model is shown in Figure 3.

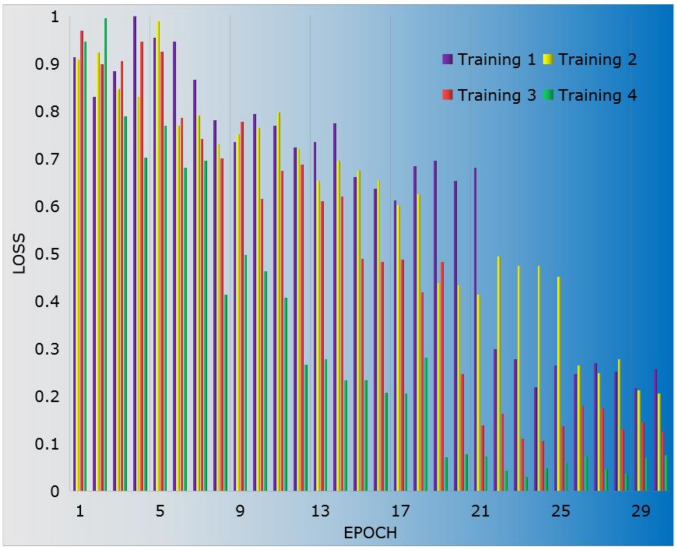

Figure 2: Training results of RNN model.

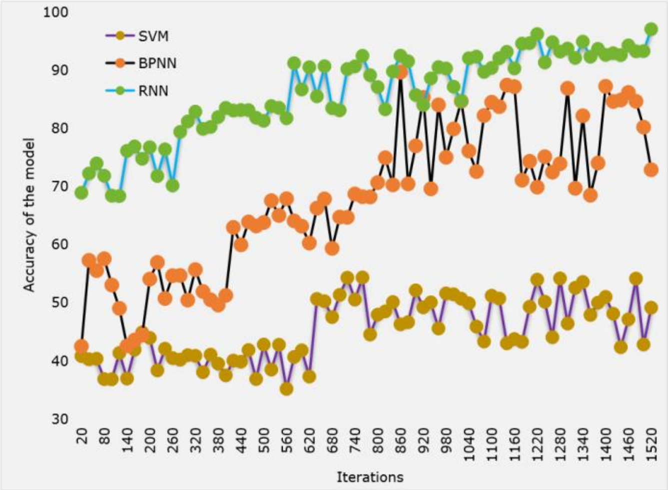

Figure 3: Accuracy of RNN model.

In Figure 3, we expect to demonstrate the accuracy comparison of SVM (Support Vector Machine), BPNN (Backpropagation Neural Network), and RNN (Recurrent Neural Network) models on specific tasks. In order to explain the content of Figure 3 more clearly and conduct further analysis, the horizontal axis represents the number of iterations, and the vertical axis represents the accuracy of the model on the test set, that is, the proportion of samples correctly classified or predicted by the model. The performance differences of these models in visual communication design optimization tasks. From the graph, it can be seen that the RNN model has the highest accuracy. Secondly, the accuracy of the BPNN model is relatively high. Finally, there is the SVM model. If the accuracy of the RNN model is significantly higher than other models, it indicates that the model is more suitable for this task. The model has achieved high accuracy and low loss on the test set, which proves its effectiveness in visual communication design optimization. As shown in Table 3 and Figure 4, the user's rating of the optimized design works is shown.

User ID	*Design work number*	*Grade*	*Feedback*
001	DW-001	9.2	The design is more in line with my aesthetics and the details are handled better
002	DW-001	8.5	Colour matching is more harmonious, but some elements still need improvement
003	DW-001	9.0	Overall, I feel very good and the operation is also more convenient
004	DW-002	8.8	The layout is more reasonable, but font choices can be more diverse
005	DW-002	9.5	This is one of the best designs I have ever seen, very satisfied
006	DW-002	8.0	Functionally improved, but visually monotonous
007	DW-003	9.3	Highly innovative and user-friendly interface
008	DW-003	8.7	The functionality is very powerful, but I hope to see more personalized options
009	DW-003	9.1	The details are well-handled, and the overall style is also very consistent

Table 3: User rating statistics for optimized design works.

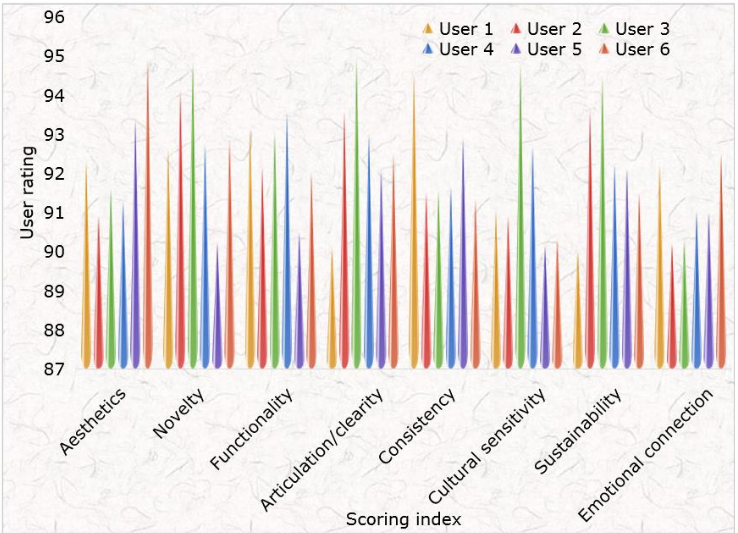

Figure 4: User's rating of design works.

The horizontal axis in Figure 4 lists the different indicators used by users to evaluate design works. These indicators include aesthetics, innovation, functionality, clarity (which may be a repetition of clarity but to explain why we assume it is effective, it may refer to different aspects of clarity, such as visual clarity or content clarity), consistency, cultural sensitivity, and sustainability. Figure 4 shows a bar chart where each indicator corresponds to a column, and the height of the column represents the average score of the user on that indicator. By analyzing the user's rating of the optimized design works, we can find that the model can capture the dependencies and rules between design elements and generate new design works that meet the aesthetic and design norms. These new designs are innovative and practical in colour matching and graphic combination.

Taking a fashion brand as an example, the brand collects a large number of fashion pictures and trend data and uses the DL model to learn the characteristics and laws of fashion elements. When designing new clothes, designers can input design requirements and constraints, and the DL model will automatically generate design schemes that meet fashion trends and user needs, and make continuous optimization and improvement. The favourable rate before and after optimization and improvement is shown in Figure 5 and Figure 6.

Figure 5: Positive review rate before optimization and improvement.

In Figure 5, we show the positive evaluation rate of fashion brands' design works based on traditional design methods and personal experience of designers before designing new clothes. These evaluations typically come from target customer groups, market analysts, or fashion experts who provide feedback on the fashion, innovation, practicality, and brand style of the design work. From the graph, it can be seen that although design works based on traditional methods and designer experience have a certain market acceptance, the positive evaluation rate shows certain fluctuations and limitations. This may be because traditional methods are difficult to fully capture and predict the complexity and variability of fashion trends, and the personal experience and style of designers may also limit the innovation and diversity of design to some extent.

However, by introducing deep learning (DL) models, we can expect to achieve higher positive evaluation rates during the design process. The DL model has strong learning and generalization capabilities, which can automatically learn and extract the dependency relationships and rules between fashion elements, thereby generating new design works that meet aesthetic and design standards. These works have higher innovation and practicality in color matching, graphic combination, and other aspects, which can better meet fashion trends and user needs.

In Figure 6, we demonstrate the positive reviews received by fashion brands for their design works after applying deep learning (DL) models for optimization and improvement. This data significantly demonstrates the powerful potential and value of DL models in the field of design. From the graph, it can be seen that the positive feedback rate after optimization and improvement has reached over 92%, which is a very optimistic result.

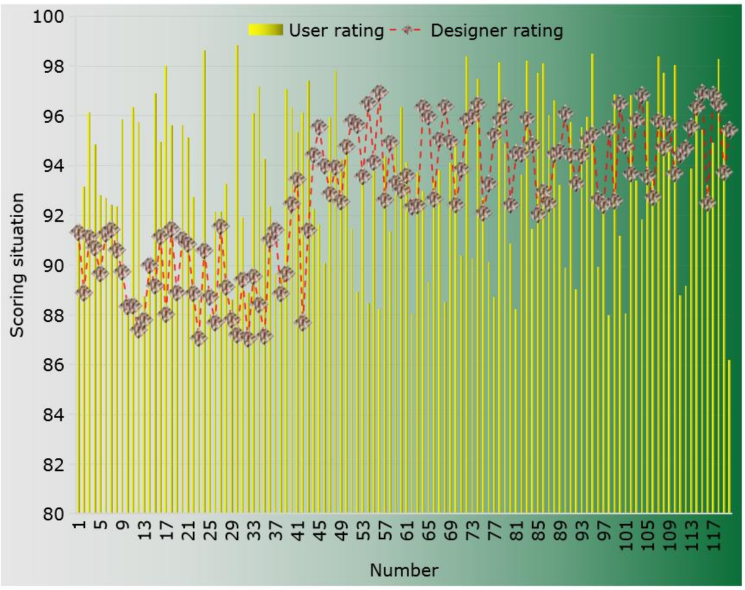

Figure 6: Positive review rate after optimization and improvement.

This means that the vast majority of users have a positive attitude towards design works processed by DL models, which demonstrate a high degree of innovation and practicality in color matching, graphic combination, and other aspects. This improvement is mainly attributed to the DL model's ability to capture complex dependencies and rules between design elements, thereby generating new works that are more in line with aesthetics and design standards. Compared to traditional design methods and personal experience of designers, DL models can better predict and grasp fashion trends, and meet the personalized needs of users. The favourable rate after optimization and improvement is obviously better than that before optimization and improvement, and the favourable rate after optimization and improvement has reached more than 92%, which is an optimistic result.

Through the case study, we can find the great potential of DL in visual communication design optimization. However, it should also be noted that there are still some challenges and limitations in the practical application of DL technology, such as data collection and processing, model training and optimization. Therefore, in future research, we need to continue to explore and improve the application methods and technical means of DL technology in visual communication design optimization, so as to better serve the design industry and meet the needs of users.

6 OPTIMIZATION OF VISUAL COMMUNICATION DESIGN SCHEME

The combination of CAD and DL technology aims to make use of their advantages and jointly promote the optimization and development of visual communication design. The core of the combination strategy is to integrate the intelligent analysis and processing ability of DL into the design process of CAD, so as to realize the automation, intelligence and accuracy of the design process.

In this article, a large number of design cases are studied and analyzed through the DL model, and the laws and characteristics of design elements, colour matching and typesetting layout are extracted. These rules and characteristics can be used as reference or guidance in CAD design software to help designers find suitable design schemes quickly. The specific design example is shown in Figure 7.

Figure 7: Example of visual communication design.

The above example uses CAD software to draw visual communication and intelligently analyzes and processes visual content through DL models. The DL model can automatically extract key visual information, emotional colors, and style features, and provide corresponding design suggestions and optimization solutions. This can help designers quickly complete visual design, ensuring accurate, vivid, and attractive advertising content.

7 CONCLUSIONS

This study successfully combines CAD with DL technology and explores its application in visual communication design optimization. Through the in-depth analysis of the basic principle and development of DL technology, this article puts forward the strategy of an effective combination of CAD and DL and discusses in detail the specific application of this method in colour matching, font selection, design element generation and optimization. The findings reveal that integrating CAD and DL technology notably enhances design efficiency, enables the automatic processing of vast amounts of design data, and produces a design plan that adheres to design specs and fulfils aesthetic criteria. Furthermore, by intelligently analyzing and refining the DL model, notable enhancements have been achieved in the quality of design works, specifically in terms of colour coordination, font suitability, and innovative design components.

This research not only affirms the viability and potency of merging CAD and DL in visual communication design but also introduces a novel design approach and instrument for designers. It is anticipated that this combined approach will gain increasing significance in the realm of visual communication design in the future.

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