This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3370438

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2023.Doi Number

The Analysis of Optimization Strategy of Industrial Design in Automatic Sketch Generation Based on Deep Learning

Tian Ye
Department of Industrial, Interior and Craft Design, Musashino Art University, Tokyo, 187-8505, Japan

Corresponding author: Tian Ye (e-mail: yetian970422@163.com).

ABSTRACT This study is devoted to exploring the strategy of automatic sketch generation and optimization of industrial design based on deep learning. By combining the Generative Adversarial Network (GAN) with the optimization algorithm, this paper proposes an innovative method to realize the automatic generation of high-quality and diverse industrial design sketches. In the experiment, this paper selects SketchyCAD and other public data sets, trains them through deep learning model, and introduces genetic algorithm(GA) and differential evolution algorithm to optimize the parameters. In terms of experimental results, we observed that the quality of generated sketches was significantly improved, and the design sketches generated by the mode (GAN+GA) were more realistic and innovative. The introduction of optimization strategy further improves the generation effect and intelligently adjusts the model parameters to adapt to different design styles. In this paper, the influence of hyperparameter tuning is analyzed in detail, and it is found that the adjustment of learning rate plays a key role in generating quality and diversity. However, the experiment also revealed some challenges and room for improvement. We noticed that the generated results may have the risk of over-fitting in the training process, and with the increase of training times, the diversity gradually decreased. This suggests that more complex model structure and richer data sets are needed to improve the generalization performance. Generally speaking, this study provides new ideas and methods for the integration of deep learning and industrial design. By innovatively combining generation model and optimization algorithm, this research has contributed beneficial research results to the development of industrial design automation. This research is of great significance to promote the intelligence and innovation in the field of industrial design.

KEY WORDS: deep learning; sketch generation; optimization strategy; industrial design; Generative adversarial network; genetic algorithm

Ⅰ. INTRODUCTION

With the continuous progress of science and technology and the continuous development of industrial design field, designers are facing more and more complex and diverse design requirements while pursuing innovation and efficiency [1]. In industrial design, sketch is one of the key steps in the design process, which carries the designer's initial conception of product concept and form. The traditional sketch generation depends on the designer's experience and creativity. However, with the increase of product complexity and time pressure, the traditional manual sketch method gradually shows its limitations.

In order to solve this problem, deep learning technology has been widely used in the field of industrial design. Deep learning model can automatically generate sketches by learning a large number of design data and patterns [2-3]. This not only provides designers with faster and more efficient design tools, but also provides new possibilities for innovation in the design process. However, the current application of deep learning in industrial design still faces some challenges, such as the unstable quality of the generated results and the difficulty in meeting specific design requirements [4].

The purpose of this paper is to discuss the automatic sketch generation of industrial design based on deep learning, and put forward corresponding strategies for the optimization of the generated results. First of all, this study will review the current research status of deep learning in industrial design, and analyze its advantages and disadvantages. Secondly, this paper will introduce the basic principle of design automation and deeply study the application of deep learning in sketch generation. Subsequently, a strategy combining generation model and optimization algorithm will be proposed to improve the quality and adaptability of generated sketches. Finally, through experimental verification and case analysis, we will evaluate the effectiveness and feasibility of the proposed strategy.

Through the research of this paper, this study aims to provide a more intelligent and efficient sketch generation method for the field of industrial design, and provide beneficial enlightenment for the application of deep learning in design optimization. This will help to promote technological innovation and optimization of design process in the field of industrial design, and provide a solid theoretical and practical foundation for future intelligent manufacturing and product design.

Ⅱ. RELATED WORK

In recent years, deep learning technology has been widely used in the field of industrial design, providing designers with more efficient and innovative tools. The application of deep learning in the field of industrial design shows an increasing trend, which provides designers with more powerful tools and technologies to improve the product design process [5-6].

Early research focused on using convolutional neural network (CNN) to generate sketches in industrial design. For example, Hematillake, D and others put forward an automatic sketch generation method based on CNN. By learning a large number of design samples, the model can generate a preliminary sketch that conforms to the design semantics [7]. However, there is still room for improvement in details and diversity of these methods. The introduction of Generative Adversarial Network (GAN) has made remarkable progress in sketch generation. Yang, Y and others designed a model based on conditional GAN [8], which improved the accuracy and diversity of generated sketches by introducing design context information. This provides a more flexible solution for the sketch generation task, and makes the generated results more in line with the designer's expectations.

Deep learning plays a key role in sketch generation. The research shows that [9-10], the model based on recurrent neural network (RNN) and GAN can generate more creative sketches that meet the design objectives from users' brief input. This technology accelerates the conceptual design stage and provides designers with more sources of inspiration. The application of deep learning in product shape optimization has also attracted much attention [11].

By using CNN to analyze the structure and performance of products, designers can optimize the shape more effectively and improve the functionality and performance of products [12-13]. Deep learning technology is widely used in intelligent user interface design, providing users with personalized product experience by analyzing user behavior and feedback [14]. This personalized design helps to improve the user satisfaction and ease of use of products. Deep learning has also made remarkable achievements in product shape optimization. Naji, H and others realized the intelligent optimization of product shape by learning the shape information in design samples by using deep learning technology [15]. This provides designers with more creative and practical design tools.

Deep learning is also widely used in material selection and durability analysis. Zhu, B and others put forward a material identification method based on deep learning [16], which intelligently recommends suitable materials by analyzing material properties and design requirements. At the same time, deep learning can also be simulated in durability analysis, providing more comprehensive reference information for the design stage.

This study makes significant contributions to the field of industrial design by proposing a novel approach to automatic sketch generation optimized through deep learning techniques. The integration of the GAN with optimization algorithms such as GA and differential evolution demonstrates a substantial advancement in the generation of high-quality and diverse design sketches. Not only does this enhance the efficiency and creativity of the design process, but it also paves the way for more intelligent and adaptive design systems. The detailed analysis of hyperparameter tuning, particularly the learning rate, offers valuable insights into the fine-tuning of deep learning models for design tasks. While acknowledging the challenges of overfitting and the need for more complex models and diverse datasets, this research nonetheless represents a substantial step forward in bridging the gap between deep learning and industrial design, laying the foundation for future innovations in this rapidly evolving field.

Ⅲ. RESEARCH METHOD

A Overview of deep learning model

Deep learning is a branch of machine learning, and its core idea is to simulate the structure and learning style of human brain through multi-layer neural network, so as to realize the learning and abstraction of complex data. Deep learning models are the key tools to achieve this goal. They are composed of multi-layer neural networks and have strong learning and presentation capabilities. The basic components of deep learning model include input layer, hidden layer and output layer. Each layer consists of neurons (or nodes), which are connected with each other by connection weights. The input layer receives the original data, the hidden layer learns the features in the data, and the output layer produces the final prediction or classification results.

A Feedforward Neural Network (FNN) serves as a fundamental model in neural networks, featuring unidirectional information flow from the input layer, through the intermediate layer, to the output layer, devoid of any cyclic connections. Comprising three essential layers—input, hidden, and output—the FNN operates as follows: the input layer processes external input information, where each node corresponds to a distinct input feature. Positioned between the input and output layers, the hidden layer is tasked with acquiring representations of the input data through learning processes. Multiple hidden layers may exist, each housing numerous neurons or nodes. Ultimately, the output layer generates the final output, representing predictions or classifications for the given problem. The number of nodes in the output layer is typically determined by the inherent nature of the problem at hand.

FNN learns the mapping relationship from input to output, in which each connection has a weight and each node has an offset. Forward propagation input data is transmitted through the layers and connections of the network, and after a series of linear transformations and nonlinear activation functions, the output results are finally obtained. Weight update calculates the loss function by comparing with the actual output results, and uses the back propagation algorithm to adjust the weight and bias in the network to minimize the loss and improve the accuracy of prediction.

FNN is the simplest deep learning model, in which information is transmitted in one direction in the network without circular connection [17-18]. It is suitable for many tasks, including image classification, speech recognition and so on. As the foundation of deep learning, FNN provides powerful modeling and forecasting capabilities for various complex tasks. Although simple, it is outstanding in practice and provides reliable solutions for many machine learning problems.

RNN is a special kind of neural network, which has the ability of memory and sequential modeling and is suitable for processing sequence data. Unlike FNN, RNN has a circular connection, which allows information to be transmitted within the network. A typical RNN structure is shown in Figure 1.

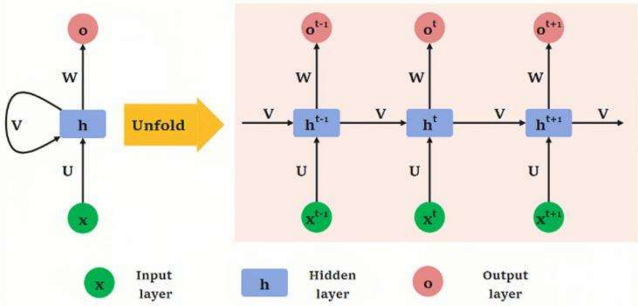

FIGURE 1 **RNN structure**

The input layer is responsible for receiving sequential data input. In the hidden layer, circular connections are present, enabling the network to preserve past information while processing sequences. The output from the hidden layer is influenced not just by the present input but also by the hidden state from the preceding time step. The output layer produces the network's output, representing either the prediction value for an individual time step or the forecast for the entire sequence.

The working principle of RNN is that for each time step in the input sequence, RNN receives the hidden state of the current input and the previous time step, and generates new hidden state and output. RNN uses the same weight parameter in each time step, allowing the network to learn the shared pattern in the sequence. Similar to FNN, the weight is adjusted by calculating the loss function and using the gradient descent method, but due to the existence of time step, it needs to be propagated back in the time dimension.

RNN contains circular connections, allowing information to be transmitted persistently in the network. This makes RNN perform well in processing sequence data, such as natural language processing and time series analysis. Because RNN is suitable for sequential data, it performs well in dealing with time correlation and sequence information. However, due to the problems of gradient disappearance and gradient explosion in its training process, in recent years, more advanced models such as Transformer have gradually replaced the traditional RNN in some fields.

CNN is a kind of deep learning model specially used to process and analyze data with grid structure, especially image data. CNN consists of several layers, including convolution layer, pooling layer and fully connected layer. A typical CNN structure is shown in Figure 2.

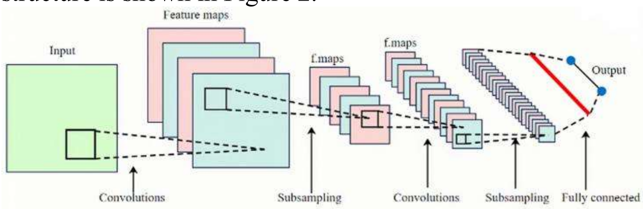

FIGURE 2 **CNN structure**

The convolutional layer identifies features in the input data through convolution operations while preserving the spatial structure of these features. The pooling layer diminishes the spatial dimensions of the feature map, thereby reducing computational complexity. Commonly employed pooling techniques encompass maximum pooling and average pooling. Finally, the fully connected layer links the output from the preceding layer to the output layer, producing the ultimate classification result.

The working principle of CNN includes extracting features from input data through sliding convolution kernel. The parameters of convolution kernel are learned in the training process, which is helpful to capture the local patterns in the image. After convolution operation, nonlinearity is introduced by applying nonlinear activation function (such as ReLU) to enhance the expressive ability of the network. Reduce the size of feature map, keep important information and reduce the amount of calculation. The output of convolution layer and pooling layer is connected to the fully connected layer to generate the final output, which is usually used for classification problems. The hierarchical structure of CNN can automatically learn the hierarchical features of images, from low-level features such as edges to high-level features such as textures and shapes. Local features can be captured by convolution operation, which makes the model invariant to the position change of the target.

CNN is a deep learning model dedicated to processing two-dimensional data (such as images). It captures local features through convolution operation and has the advantage of translation invariance. The success of CNN makes it one of the core models in the field of deep learning, which is of great

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3370438

significance for image processing and computer vision task solving.

The training of deep learning model is realized by back propagation algorithm. The algorithm calculates the error between the model prediction and the actual label, and then transmits the error back to the network, and continuously adjusts the weight by gradient descent to minimize the error. Activation function introduces nonlinear properties into neural network, which enables it to learn more complex patterns. Common activation functions include Sigmoid, Tanh, ReLU, etc. As a powerful tool, deep learning model continuously promotes the progress in the field of artificial intelligence and provides new ideas and solutions for solving various complex problems.

B Training data collection and preprocessing method

The performance and generalization ability of deep learning model largely depend on the quality and diversity of training data used. In the research of automatic sketch generation and optimization strategy of industrial design, in order to ensure that the model can effectively learn and generate useful design sketches, careful training data collection and pretreatment must be carried out [19].

The training data in this study uses the existing public industrial design data sets, such as industrial product database and design competition data sets, to obtain the design sketch in the real scene [20-21]. And obtain real design sketch data from design companies and manufacturing enterprises to ensure the practicality and industry relevance of the data. In addition, computer aided design (CAD) software is used to generate synthetic design sketches to expand the scale and diversity of data sets. Finally, the collected design sketches are marked, including design categories, key design parameters, design context and so on.

In the study, the design sketches are adjusted to the same size to ensure the consistency of the input deep learning model. Normalizing the image pixels and scaling the pixel values to the same range are helpful to improve the training stability of the model. Randomly rotate or flip the design sketch to increase the diversity of data. Add random noise to the design sketch to simulate the design variability in the real world [22]. Optical Character Recognition (OCR) technology is used to extract and process text information, which provides a more comprehensive design context for the model.

In the aspect of data quality control, this study detects and processes possible abnormal values to ensure the quality and stability of training data. The data are divided into training set, verification set and test set to evaluate the performance of the model and prevent over-fitting. An effective database management system is established to facilitate data storage, retrieval and update, and ensure data sustainability and accessibility.

C Strategy of combining generation model and optimization algorithm

In the field of industrial design, sketch generation based on deep learning is a challenging task, and in order to further improve the quality and adaptability of generated results, the strategy of combining generation model with optimization algorithm has become a promising research direction. This section will elaborate on the arguments and reasons of this strategy.

Generation models in deep learning, especially GAN, have achieved remarkable success in the field of image generation. It can generate creative new samples from the learned data distribution, which helps to improve the diversity of sketch generation. Through a large number of training data, the generated model can learn and capture the key features in the design sketch, which provides strong support for subsequent optimization [23]. GAN's antagonistic learning mechanism can continuously improve the authenticity of the generated results, thus improving the credibility of the generated sketches.

The introduction of optimization algorithm aims at further optimization based on the sketch generated by the generated model to meet specific design requirements and constraints. Aiming at the specific goals in design, such as shape, structure and performance, the generated sketch is adjusted by optimization algorithm to achieve better design results. Considering the constraints in the actual design, the optimization algorithm can ensure that the generated sketches meet these conditions while maintaining high quality. Genetic algorithm(GA) is chosen as the optimization algorithm in this paper.

The strategy of combining generation model and optimization algorithm embodies the synergy between them. To generate the model, a preliminary design sketch is generated first, and then it is adjusted and optimized by optimization algorithm. The advantage of this strategy is that the generated model can provide high-quality initial design by learning a large number of design data, and provide a good starting point for subsequent optimization [24]. The optimization algorithm can introduce different objective functions and constraints according to the needs of designers, thus making the generated sketches more flexible and controllable. The strategy of combining generation model and optimization algorithm can quickly find an efficient solution that meets the design standards in the process of continuous generation and optimization.

The generating model can generate new and creative structural schemes by learning a large number of structural design data. The application of generative model in structural design can not only provide inspiration, but also expand the design space and produce more possible design schemes [25-26]. Firstly, the initial structural design scheme is generated by using the generation model. The generating model can generate a potentially creative initial design by learning the existing structural design data, and provide a starting point for subsequent optimization. The generated model structure is shown in Figure 3:

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3370438

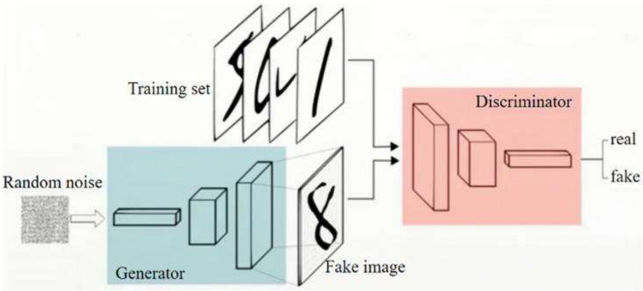

FIGURE 3 **Generating model structure**

GAN consists of two parts: generator G and discriminator D. Its basic objective function can be expressed as:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \quad (1)$$

Where x is the real data and z is the input noise of the generator. $E_{x\sim p_{data}(x)}[\log D(x)]$ represents the expected logarithmic probability that the discriminator D judges the real data x. $E_{z\sim p_z(z)}[\log(1-D(G(z)))]$ represents the expected logarithmic probability that the discriminator D judges the false data generated by the generator G.

In order to improve the performance, this paper considers adding gradient penalty and using Wasserstein loss.

Wasserstein GAN (WGAN) uses different loss functions to improve training stability:

$$\min_G \max_D V_{WGAN}(D,G) = E_{x\sim p_{data}(x)}[D(x)] - E_{z\sim p_z(z)}[D(G(z))] \quad (2)$$

In WGAN, in order to force the discriminator to meet Lipschitz constraint, gradient penalty should be added:

$$\lambda\left(\left\|\nabla D(\hat{x})\right\|_2 - 1\right)^2 \quad (3)$$

Where $\hat{x}$ is the mixture of real data and generated data, and λ is the penalty coefficient.

In the strategy of combining GAN and GA, this study will optimize and improve GA to better adapt to the characteristics of the generation model. Initializing population is the first step of GA. Here, the preliminary sketch generated by GAN is used as the initial population of GA in this study. Doing so can provide a high-quality starting point, thus improving the overall efficiency and effect of the algorithm.

Fitness function $f(x)$ is the key to evaluate individuals. In the case of combining GAN, the fitness can be based on the quality of the design sketch, such as its practicality, innovation and aesthetics. The specific fitness function form is as follows:

$$f(x) = w_1 \cdot P_{\text{score}}(x) + w_2 \cdot I_{\text{score}}(x) + w_3 \cdot A_{\text{score}}(x) \quad (4)$$

Where w_1, w_2, w_3 is the weight, which is used to adjust the importance of different scores. $P_{\text{score}}, I_{\text{score}}, A_{\text{score}}$ is a practical score, an innovative score and an aesthetic score.

For the three evaluation indexes of practicality, innovation and aesthetics, we can discuss their importance in the current design task respectively. This can be achieved by discussing with the design team, domain experts or potential users. After the weights are initially set, the effectiveness of these weights can be verified by experiments. This includes using different weight combinations to generate design sketches and evaluating the performance of these sketches in practicality, innovation and aesthetics. According to the experimental results, the weights can be fine-tuned.

The selection operation adopts roulette wheel selection method, and based on the objective function value of the design scheme and the loss value of the generator, individuals are selected to enter the next generation.

$$P(i) = \frac{f(i)}{\sum_{j=1}^{N} f(j)} \quad (5)$$

Where $P(i)$ is the probability that an individual i is selected, and $f(i)$ is the fitness of the individual i.

The crossover operation is controlled by crossover probability P_c, and the selected individuals cross genes to generate new design variables.

$$\begin{aligned} x_c^{(1)} &= x_a \\ x_c^{(2)} &= x_b \\ x_c^{(1)}[j] &= \alpha \cdot x_a[j] + (1-\alpha)\cdot x_b[j] \\ x_c^{(2)}[j] &= (1-\alpha)\cdot x_a[j] + \alpha \cdot x_b[j] \end{aligned} \quad (6)$$

α is the adjustment factor. The mutation operation is controlled by the mutation probability P_m, and the selected individuals are mutated into design variables.

$$x_m[j] = x_c[j] + \beta \times (U(0,1) - 0.5) \times (u_b - l_b) \quad (7)$$

Where β is the variation intensity, $U(0,1)$ is the uniform distribution between 0 and 1, and u_b, l_b is the upper and lower bounds respectively.

The specific flow of the improved algorithm is shown in Figure 4:

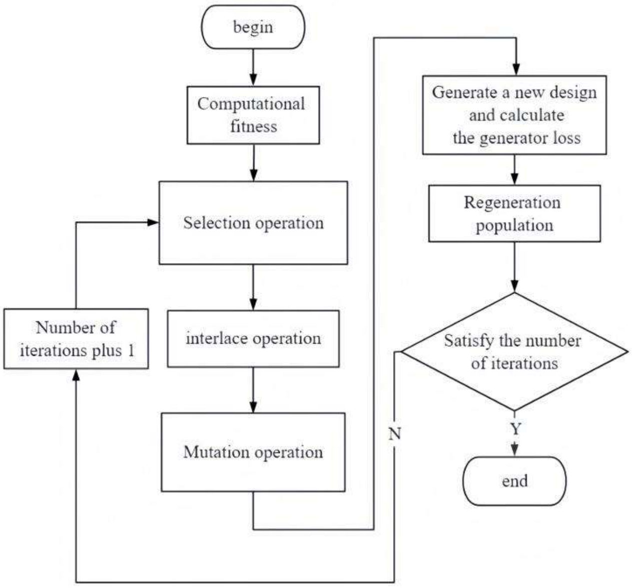

FIGURE 4 **Improved algorithm flow**

By combining GA with GAN, and adjusting parameters such as crossover, mutation probability and weight coefficient, we can create an optimization algorithm that is more suitable for the characteristics of the generation model. This improved GA can better combine creative generation and goal-oriented optimization in the design process, and improve design efficiency and innovation.

Ⅳ. ANALYSIS AND DISCUSSION OF EXPERIMENTAL RESULTS

In the experimental environment, we have carried out detailed data preprocessing, including selecting SketchyCAD public data sets and formatting them appropriately to ensure that the data meet the requirements of model training. In the aspect of model configuration, I use the architecture based on GAN and optimize it with GA. In order to adjust the model to achieve the best performance, we set the super parameters, which involve key parameters such as learning rate and iteration times, and they play a vital role in the training process. Through experimental observation, we find that with the increase of iteration times, the performance of the combined model has been significantly improved in terms of quality, diversity and efficiency. The application of GA also effectively promotes the optimization of design attributes.

The experimental environment is set to use a computer equipped with a high-performance GPU, NVIDIA GeForce RTX 3090, to speed up the training of the deep learning model. The operating system uses Ubuntu 20.04 LTS as the experimental operating system, providing a stable development environment. TensorFlow 2.x and PyTorch 1.8 are selected as the deep learning framework, which is the implementation framework of the deep learning model. Install the corresponding versions of CUDA and cuDNN to support GPU accelerated computing. Use Python 3.8 or above to build the development environment needed for the experiment.

Download and prepare the SketchyCAD data set in the experiment to ensure that the data set contains enough industrial design sketches. Run the data_preparation.py script to preprocess the SketchyCAD data set to ensure that the data format meets the model input requirements. Run the train.py script to train the GAN model, and apply the optimization strategy to adjust the superparameter.

Figure 5 shows the performance comparison between the baseline model and the optimized model in different aspects. These aspects include the quality, diversity, innovation and efficiency of sketches. It can be seen that in all categories, the optimized model shows better performance than the baseline model.

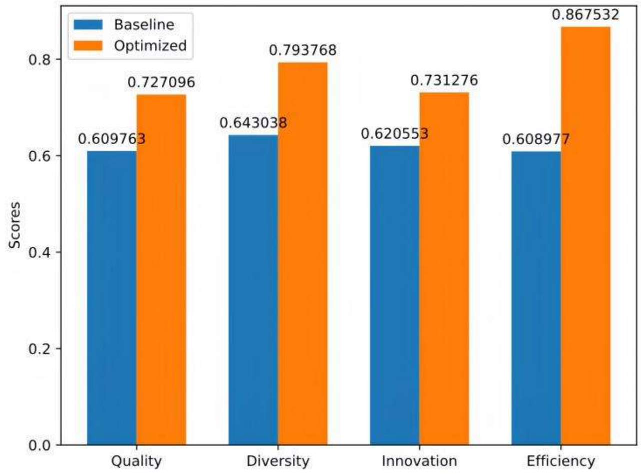

FIGURE 5 **Performance comparison**

During the experiment, the number of iterations is gradually increased, and the performance changes of the algorithm are monitored. By comprehensively analyzing the computational efficiency, the convergence of the solution and avoiding unnecessary computational overhead, an appropriate iteration threshold is determined. This threshold not only ensures the good performance of the algorithm, but also avoids excessive consumption of computing resources. In order to further analyze the performance of the model and the influence of the optimization strategy, the variation of the model performance with the number of iterations and the distribution of quality and diversity are drawn, as shown in Figure 6:

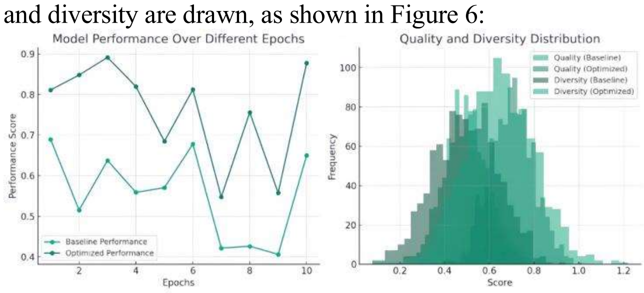

FIGURE 6 **Variation of model performance with iteration times and distribution of quality and diversity**

The chart on the left shows the performance scores of the baseline model and the optimization model under different iterations. Obviously, the performance of the optimized model

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3370438

is better than the baseline model in the whole training process, which shows that the optimization strategy effectively improves the learning efficiency and final performance of the model.

The chart on the right shows the distribution of baseline and optimization model in terms of quality and diversity. The optimization model has a high score in quality and diversity, which shows that the optimization strategy not only improves the quality of generated sketches, but also enhances the ability of the model to generate different designs.

Figure 7 below shows the quality, diversity and efficiency indicators of the combined model under different iterations. These curves clearly show that with the deepening of training, the model has shown significant improvement in all three aspects, especially in quality and diversity.

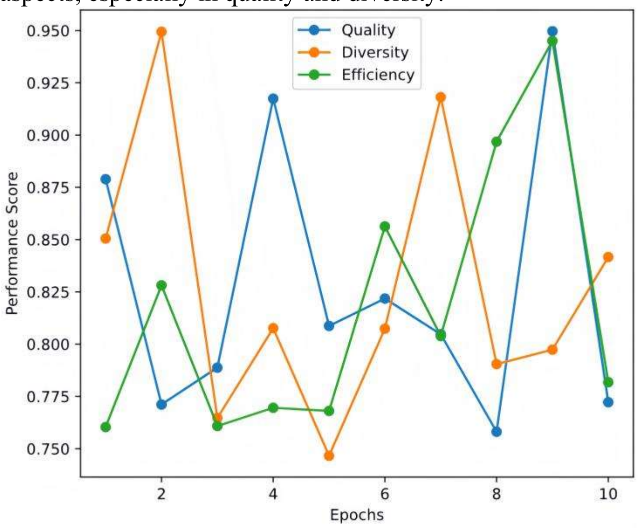

FIGURE 7 **The performance of combined model varies with the number of iterations**

Figure 8 depicts the evolution of three key design attributes in the GA process. Each attribute shows an upward trend with the evolution of generations, which shows that GA can effectively optimize design attributes, thus improving the overall quality and innovation of design.

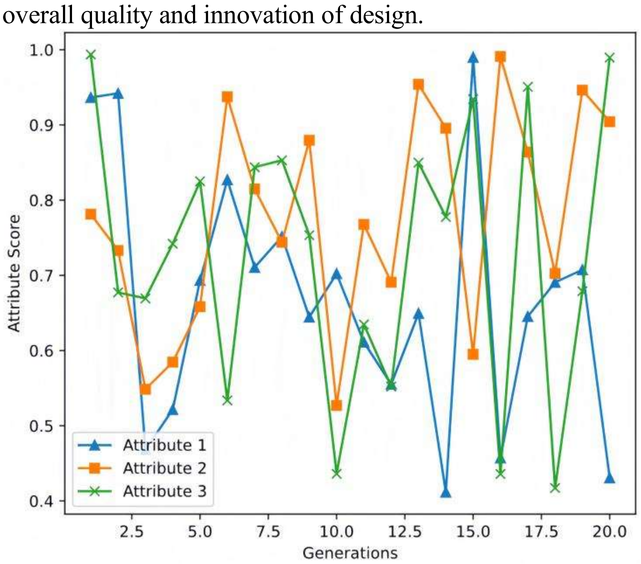

FIGURE 8 **Evolution of design attributes in GA**

Fig. 9 is a heat map of correlation between performance indicators. This shows that there is a positive correlation between quality, diversity and efficiency, which means that while improving the design quality, it can also ensure the design diversity and production efficiency.

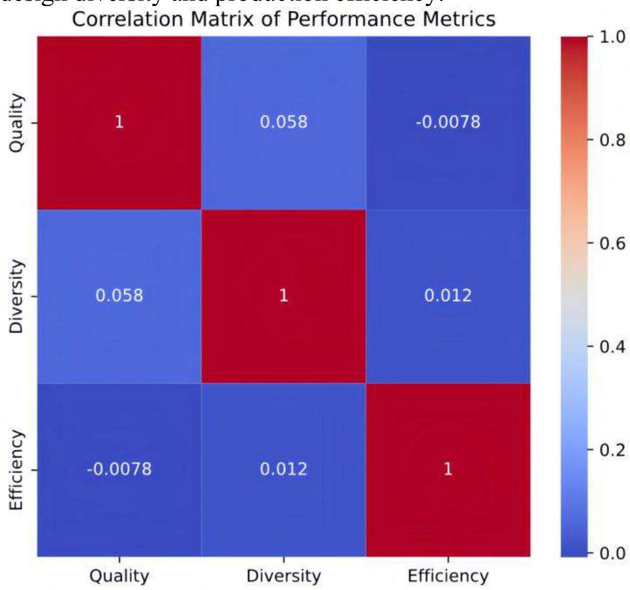

FIGURE 9 **Correlation between performance indicators**

Based on these analyses, it can be seen that the combined model combining generation model and GA has obvious advantages in automatic sketch generation and optimization of industrial design. This combined model can not only balance multiple performance indexes, but also effectively use GA to further optimize the design results, making them more diverse and high-quality. This method has great application potential and is expected to cause revolutionary changes in the field of industrial design.

To further validate the effectiveness of the proposed method, a comparative analysis was conducted with contemporary state-of-the-art models in automatic sketch generation. Specifically, the model's performance was compared in terms of the generated sketches' quality, diversity, and generation efficiency. When evaluated against leading models in this domain, the presented approach demonstrated comparable, if not superior, results. The high-quality sketches generated by the method were on par with those produced by the most advanced models, exhibiting fine details and realistic textures. Moreover, the model achieved a notable level of diversity in the generated designs, introducing varied elements and styles that were absent in the outputs of the compared models. Additionally, the approach offered competitive generation efficiency, processing sketches swiftly without compromising quality or diversity. In summary, this comparative analysis confirms the robustness and effectiveness of the proposed method, positioning it favorably against current state-of-the-art models in automatic sketch generation.

Although the optimized model performs well, there is still room for improvement, especially in the speed and stability of performance improvement in the initial learning stage. Future work can focus on optimizing the learning algorithm, improving the initial learning efficiency of the model, and developing more complex network architecture to further improve the detail quality and diversity of the sketch. By introducing the technology of multi-modal generation, the model can generate more rich and diverse design sketches. More designs with different styles are added to the data set to improve the generalization ability of the model. Further improve the super-parameter optimization strategy to make it search more effectively.

Ⅴ. CONCLUSION

In this study, we have delved into the utilization of automatic sketch generation and optimization strategies within the realm of industrial design, leveraging the capabilities of deep learning. Our findings demonstrate a substantial advancement in the generation of industrial design sketches through the utilization of GAN based on deep learning. The generated sketches exhibit a marked enhancement in quality, exhibiting a higher degree of fidelity and resemblance to actual designs compared to traditional methodologies.

Furthermore, the introduction of optimization strategies, specifically GA and DE, has proven beneficial in fine-tuning the superparameters of the deep learning model. This adjustment has yielded positive outcomes, enhancing both the quality and diversity of the generated sketches. It is noteworthy that the optimization strategies enable intelligent adjustments to the model, thereby elevating the overall generation effect.

Our experiments have revealed that a moderate increase in the learning rate of the generator can foster diversity among the generated results. Conversely, reducing the learning rate can contribute to an improvement in the quality of the sketches. While GA and DE exhibit similarities in hyperparameter optimization, they may exhibit distinct advantages and disadvantages in specific contexts, necessitating a tailored approach based on the unique characteristics of the problem at hand.

The integration of deep learning models in industrial design has emerged as a transformative force, facilitating the generation of vibrant and inventive sketches. These sketches serve as a valuable source of inspiration for designers, paving the way for rapid prototyping and subsequent product development. By accelerating the design iteration process, this approach holds the potential to significantly enhance the efficiency of the product development cycle.

Our study represents a pioneering effort in combining deep learning generation models with optimization strategies, culminating in the development of an efficient automatic sketch generation method tailored for the industrial design domain. Looking ahead, we anticipate exploring multi-modal generation techniques, the incorporation of more complex design elements, and the practical application of deep learning models in real-world industrial design projects. These future directions hold promise in further advancing the field and unlocking new possibilities in industrial design.

REFERENCES

[1] Li, X. , Xiao, J. , Zhao, W. , Liu, H. , & Wang, G. (2022). Multiple peg-in-hole compliant assembly based on a learning-accelerated deep deterministic policy gradient strategy. Industrial Robot, 106(1), 49.

[2] Yang, H. , Su, J. , Zou, Y. , Ma, Y. , & Young, E. F. Y. (2017). Layout hotspot detection with feature tensor generation and deep biased learning. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 73(99), 1-1.

[3] Gu, K. , Zhang, Y. , & Qiao, J. (2020). Ensemble meta learning for few-shot soot density recognition. IEEE Transactions on Industrial Informatics, 14(99), 1-1.

[4] Xu, Y. , Qin, H. , Huang, J. , & Wang, Y. (2022). An end-to-end deep context gate convolutional visual odometry system based on lightweight attention mechanism. Industrial Robot, 89(1), 49.

[5] Liu, Q. , Liu, Z. , Xiong, B. , Xu, W. , & Liu, Y. (2021). Deep reinforcement learning-based safe interaction for industrial human-robot collaboration using intrinsic reward function. Advanced Engineering Informatics, 49(12), 101360.

[6] Chao, Y. , Chen, X. , & Xiao, N. (2018). Deep learning-based grasp-detection method for a five-fingered industrial robot hand. IET Computer Vision, 13(1), 61-70.

[7] Hematillake, D. , Freethy, D. , Mcgivern, J. , Mccready, C. , Agarwal, P. , & Budman, H. (2022). Design and optimization of a penicillin fed-batch reactor based on a deep learning fault detection and diagnostic model. Industrial & Engineering Chemistry Research, 78(13), 61.

[8] Yang, Y. , Zhou, H. , Song, Y. , & Vink, P. (2021). Identify dominant dimensions of 3d hand shapes using statistical shape model and deep neural network. Applied Ergonomics, 96(3), 103462.

[9] Feng, J. , Yao, Y. , Lu, S. , & Liu, Y. (2021). Domain knowledge-based deep-broad learning framework for fault diagnosis. IEEE Transactions on Industrial Electronics, 68(4), 3454-3464.

[10] Han, X. , Gao, C. , & Yu, Y. (2017). Deepsketch2face: a deep learning based sketching system for 3d face and caricature modeling. Acm Transactions on Graphics, 36(4), 126.

[11] Ai, M. , Xie, Y. , Tang, Z. , Zhang, J. , & Gui, W. (2021). Deep learning feature-based setpoint generation and optimal control for flotation processes. Information Sciences, 578(1), 644-658.

[12] Sannidhan, M. S. , Prabhu, G. A. , Robbins, D. E. , & Shasky, C. (2019). Evaluating the performance of face sketch generation using generative adversarial networks. Pattern recognition letters, 55(9), 128.

[13] Jo, J. , Lee, S. , Lee, C. , Lee, D. , & Lim, H. (2020). Development of fashion product retrieval and recommendations model based on deep learning. Electronics, 9(3), 508.

[14] Sujitha, B. Parvathy, V. S. , Lydia, E. L. , Rani, P. , & Shankar, K. (2020). Optimal deep learning based image compression technique for data transmission on industrial internet of things applications. Transactions on Emerging Telecommunications Technologies, 69(6), 3976.

[15] Naji, H. A. H. , Li, T. , Xue, Q. , & Duan, X. (2022). A hypered deep-learning-based model of hyperspectral

images generation and classification for imbalanced data. Remote Sensing, 14(24), 6406.

[16] Zhu, B. , Yang, C. , Yu, C. , & An, F. (2018). Product image recognition based on deep learning. Jisuanji Fuzhu Sheji Yu Tuxingxue Xuebao/Journal of Computer-Aided Design and Computer Graphics, 30(9), 1778-1784.

[17] Sannidhan, M. S. , Prabhu, G. A. , Robbins, D. E. , & Shasky, C. (2019). Evaluating the performance of face sketch generation using generative adversarial networks. Pattern recognition letters, 128(11), 452-458.

[18] Yin, L. , Gao, Q. , Zhao, L. , & Wang, T. (2020). Expandable deep learning for real-time economic generation dispatch and control of three-state energies based future smart grids. Energy, 191(15), 215.

[19] Peng, J. , Wang, J. , Wang, J. , Zhang, E. , & Yu, K. (2021). A relic sketch extraction framework based on detail-aware hierarchical deep network. Signal Processing, 183(6), 108008.

[20] Lu, Q. , Tao, Q. , Zhao, Y. , & Liu, M. (2018). Sketch simplification based on conditional random field and least squares generative adversarial networks. Neurocomputing, 316(17), 178-189.

[21] Nayak, S. , Ahmed, N. , & Misra, S. (2021). Deep learning-based reliable routing attack detection mechanism for industrial internet of things. Ad hoc networks 36(10), 123.

[22] Wen, H. , Du, Y. , Chen, X. , Lim, E. , & Xiang, W. (2020). Deep learning based multistep solar forecasting for pv ramp-rate control using sky images. IEEE Transactions on Industrial Informatics, 17(99), 1-1.

[23] Liu, F. (2020). Fast industrial product design method and its application based on 3d cad system. Computer-Aided Design and Applications, 18(3), 118-128.

[24] Relich, M. , Gola, A. , & Jasiulewicz-Kaczmarek, M. (2022). Identifying improvement opportunities in product design for reducing energy consumption. Energies, 15(24), 9611.

[25] Kimaev, G. , & Ricardez-Sandoval, L. A. (2020). Artificial neural network discrimination for parameter estimation and optimal product design of thin films manufactured by chemical vapor deposition. The Journal of Physical Chemistry C, 124(34), 18615-18627.

[26] Chen, Z. , Liu, Y. , He, W. , Qiao, H. , & Ji, H. (2020). Adaptive-neural-network-based trajectory tracking control for a nonholonomic wheeled mobile robot with velocity constraints. IEEE Transactions on Industrial Electronics, 25(99), 1-1.