# Application and Effect Evaluation of Deep Learning and Computer Aided Design in Product Design

Rong Guo

School of Art and Science, Chengdu college of University of Electronic Science and Technology of China, Chengdu 611731, China, guorong@cduestc.edu.cn

Corresponding author: Rong Guo, guorong@cduestc.edu.cn

**Abstract.** The combination of deep learning (DL) and computer aided design (CAD) provides new possibilities for product design. How to effectively integrate DL technology into CAD system and how to ensure that the generated design scheme meets both functional and aesthetic requirements are all problems that researchers need to solve. In this article, DL and CAD are applied to product design and optimization, a product image feature detection model based on lightweight convolutional neural network (CNN) is constructed, and its practical application effect is evaluated and tested by experiments. The results show that the method proposed in this article can improve the quality of product images and deal with the challenges brought by angle changes to some extent. DL can learn hidden design rules and user needs from a large amount of data, thus assisting designers to create products that are more in line with market demand. The use of DL and CAD in product design shows great potential and value.

**Keywords:** Deep Learning; Computer Aided Design; Product Design; Application Effect
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## 1 INTRODUCTION

With the continuous promotion of technology and innovation, product design has undergone tremendous changes. The traditional product design method mainly depends on the designer's experience and intuition. Although it can produce certain results, it often seems inadequate when dealing with complex and diverse design requirements. With the rapid development of industrial automation and intelligent manufacturing, the application of industrial robots (IR) in production lines is becoming increasingly widespread [1]. The application and effectiveness evaluation of deep learning and computer-aided design in product design is an important research field. With the continuous development of artificial intelligence technology, deep learning has become one of the effective methods to solve complex problems in many fields. In terms of product design, deep learning can analyze and learn from a large amount of data, extract the laws and features hidden behind the data, and apply them to the actual product design process. Firstly, applying deep learning in product design can help designers better understand user needs. By analyzing user behavior, preferences, and feedback data, deep learning can uncover potential user needs and guide the product design process based on these needs. For example, on e-commerce platforms, analyzing user shopping records and browsing behavior can predict the types of products that users may be interested in. And recommend similar or related products to users based on these predicted results. Secondly, deep learning also plays an important role in product innovation [2]. Traditional artificial innovation methods typically rely on professional knowledge and experience accumulation, while deep learning can automatically extract valuable information from a large amount of data and generate novel and creative ideas. For example, in the field of automotive design, deep learning technology can be used to obtain various styles, styles, colors, and other elements from a massive database of automotive images. And combined with market research data for comprehensive analysis and model training, the final generation of a brand new and market demand compliant car exterior design solution.

In addition, introducing computer-aided design (CAD) technology in the production and manufacturing process can greatly improve efficiency and accuracy. CAD software combines functions such as graphic processing and numerical calculation, which can quickly complete tasks such as complex drawing and 3D modeling. It also supports parameterized modeling, making it easy to modify and optimize. Through CAD software, designers can not only quickly present the ideas they have come up with in their minds, but also easily share and collaborate with other team members to edit project files. Overall, in addition to our ability to discern customer needs, it also makes it easier for us to identify hidden but popular or cutting-edge fashion trends. The introduction of CAD technology also makes the entire process more efficient and flexible [3]. The rapid development of artificial intelligence (AI) and deep learning (DL) technology has brought new possibilities to product design. Among them, the application of deep learning in the field of computer-aided design (CAD) is particularly eye-catching. By combining deep learning, CAD can enable more efficient and accurate product design. In furniture design, deep learning can help designers learn and optimize design plans from a large amount of historical design data [4]. For example, designers can use convolutional neural networks (CNN) to train historical furniture design data, allowing AI to learn which designs are aesthetically pleasing and practical. Then, designers can innovate on this basis, thereby saving a lot of time and energy. In automotive design, deep learning can help designers optimize the shape and structure of car bodies. For example, using generative adversarial networks (GAN) to train automotive design data can enable AI to learn to generate car shapes that meet the requirements of the designer. At the same time, deep learning can also help designers predict and analyze the performance of cars, thereby better optimizing design solutions [5].In consumer product design, deep learning can help designers learn and optimize design solutions from a large amount of user feedback data. For example, using Natural Language Processing (NLP) technology to train user comment data can help AI learn to understand user preferences and needs. Then, designers can optimize the appearance and functional design of the product based on these feedback data.

However, traditional topology optimization methods often only find one or several feasible design solutions, and cannot guarantee the performance of these solutions in terms of design diversity. In recent years, reinforcement learning has been applied to solve this problem. Reinforcement learning is a machine learning method that uses trial and error learning to find the optimal behavior strategy in a complex environment. In topology optimization design, reinforcement learning can be used to guide the design process and increase design diversity. Jang et al. [6] trained a reinforcement learning model. This model can learn how to take the optimal behavior in a given environment to achieve maximum reward. In topology optimization design, rewards may include improving structural performance, reducing costs, or improving aesthetics. For example, how to effectively integrate DL technology into CAD system and how to ensure that the generated design scheme meets both functional requirements and aesthetic requirements are all problems that researchers need to solve. In this article, DL and CAD are applied to product design and optimization, a product image feature detection model based on lightweight CNN is constructed, and its practical application effect is evaluated and tested by experiments, which proves that the proposed optimization method is feasible in product design.

The combination of DL and CAD can significantly improve the design efficiency and enable designers to put forward more design schemes in a shorter time. DL can learn hidden design rules and user needs from a large amount of data, thus assisting designers to create products that are more in line with market demand. Technological innovation will enable enterprises to respond to market changes more quickly and design more popular products, so as to stand out in the fierce market competition. The research includes the following innovations:

(1) Lightweight CNN model is introduced into product design. Compared with the traditional CNN model, the lightweight CNN model has fewer parameters and higher operation efficiency while maintaining high performance, which is especially suitable for product design environment with limited resources.

(2) This article not only studies the application of DL in product design, but also discusses how to combine DL closely with existing CAD tools, so that designers can use these tools more conveniently and improve work efficiency.

(3) This article assesses the effect of the proposed method of combining DL with CAD. The assessment content includes design efficiency, quality of design scheme, feasibility of method and so on, which proves that the proposed optimization method is feasible in product design.

This article first introduces the research background and purpose, then expounds the theoretical basis of DL and CAD, and puts forward a product image feature detection model based on lightweight CNN, then describes the experimental process and effect assessment in detail, and finally discusses the results, summarizes the full text and looks forward to the future research direction. The whole article aims to discuss the combination and application of DL and CAD in product design, so as to improve the design efficiency and accuracy.

## 2 THEORETICAL BASIS

With the intensification of global market competition, the design speed and innovation ability of industrial products have become key factors determining the competitiveness of enterprises. Traditional design methods often rely too heavily on the experience and skills of designers, which cannot meet the needs of modern industrial design. Therefore, Liu [7] explores the rapid design methods and applications of industrial products based on 3D CAD systems. Modular design is a method of decomposing products into independent modules for design. Designers can decompose products into different functional modules through modularization, and then design and optimize them separately. This design method can greatly improve the efficiency and flexibility of the design. Parametric design is a method of changing design by adjusting parameters. In a 3D CAD system, designers can set parameter relationships for various elements in the model through parameterization modules. In this way, when the parameters of an element change, the parameters of other related elements will also be automatically adjusted to maintain the coherence and consistency of the design. By utilizing the simulation and optimization functions of 3D CAD systems, designers can predict and evaluate their performance in the early stages of product design. Through continuous simulation and optimization, designers can find the best design solution to improve product performance and quality. Virtual reality (VR) technology has gradually integrated into our daily lives. The field of product design is no exception, as VR technology provides designers with new possibilities to conduct product design and evaluation in a virtual environment. Lorusso et al. [8] explore the importance and application of conceptual modeling in product design in virtual reality environments. Conceptual modeling is a key step in the product design process, helping designers transform creativity and ideas into meaningful product models. In virtual reality environments, the importance of conceptual modeling is becoming more prominent. Firstly, virtual reality technology enables designers to model in a three-dimensional environment, which is more intuitive and flexible than traditional two-dimensional CAD systems. Secondly, virtual reality technology can simulate the real usage scenarios of products, helping designers evaluate the design and performance of products, thereby better identifying problems and improving design. Virtual reality technology can simulate the real usage scenarios of products, helping designers evaluate the performance and user experience of products. For example, designers can simulate the actions and behaviors of users when using a product, in order to identify potential problems and make improvements. By simulating usage scenarios, designers can evaluate the design and performance of products, identify potential problems, and optimize them. For example, designers can evaluate whether the appearance of a product meets user needs and expectations, or whether the functionality of the product meets user needs.

Lu et al. [9] introduced a product optimization design method driven by user review data. This method collects and processes user review data, establishes a user review database, and uses data-driven methods to analyze the data, construct a product optimization model, and achieve product optimization design. Case analysis shows that this method can effectively improve the pertinence and market competitiveness of product design, providing new ideas and methods for enterprise product research and development. Taking an e-commerce website as an example, there are common issues such as unreasonable page layout and cumbersome shopping processes in user reviews. To address these issues, researchers adopted a user review data-driven product optimization design method. Firstly, collect user review data through online surveys and user interviews. Secondly, through data analysis, identify key factors that affect user experience, such as page layout, shopping process, etc. Then, an optimization model is constructed using machine learning algorithms to predict user satisfaction with different page layouts and shopping processes. Finally, based on the analysis results of the optimization model, the website was redesigned and optimized, improving the page layout and shopping process. After verification and evaluation, the optimized website has significantly improved in terms of user satisfaction and conversion rate. Meng et al. [10] explored the application of machine learning technology in clinical drug therapy. Unsupervised learning is a learning method that discovers its inherent laws by analyzing input data without a known output. In drug design, unsupervised learning can be used for clustering analysis, such as classifying drug molecules or predicting their potential biological activities. Reinforcement learning is a learning method that learns how to perform tasks by interacting with the environment and optimizing strategies. In drug design, reinforcement learning can be used to optimize the structure of drug molecules to improve their efficacy and reduce toxicity. Researchers use deep neural networks to predict the properties of drug molecules, such as efficacy and toxicity. By training models to learn the inherent relationship between drug molecules and biological activity, rapid prediction and screening of new drug molecules can be achieved. Researchers use reinforcement learning methods to optimize the structure of drug molecules to improve their efficacy and reduce toxicity. By combining with a virtual screening platform, candidate drug molecules with excellent efficacy and low toxicity can be quickly screened. 3D factory simulation software plays an important role in computer-aided participatory design of industrial workplaces and processes. Pelliccia et al. [11] explored the applicability and advantages of 3D factory simulation software in the industrial field. 3D factory simulation software can quickly create and modify models, while performing parametric design and optimization, greatly improving design efficiency. Designers can use 3D factory simulation software to showcase design solutions, communicate effectively with team members or clients, and ensure understanding and recognition of the design solutions by all parties. 3D factory simulation software can simulate the actual production environment, evaluate equipment layout, process flow, etc., identify and solve potential problems in advance, and reduce the cost and risk of later modifications. Using 3D factory simulation software, designers can simulate and evaluate different factory layout plans, optimize equipment placement, channel width, etc., and improve production and management efficiency. Through 3D factory simulation software, designers can simulate and optimize the process flow in a virtual environment, ensuring the smooth and efficient production process. With the help of 3D factory simulation software, designers can simulate and evaluate safety facilities to ensure the safety and health of employees.

In today's engineering and design, computer-aided design (CAD) systems have become indispensable tools. With the continuous development of technology, artificial intelligence and machine learning technology have gradually penetrated into various fields, including CAD. Rapp et al. [12] aim to review the research progress of machine learning in CAD themed papers, explore its applications, challenges, and development trends. Machine learning can automate the design process and reduce manual intervention. For example, using generative adversarial networks (GANs) for innovative design involves learning a large amount of data to generate new and valuable solutions. Machine learning can help predict the performance and results of a design. For example, using deep learning for simulation and analysis to predict the mechanical behavior of structures. Machine learning can provide intelligent auxiliary tools and suggestions for designers. For example, using natural language processing (NLP) and machine vision technology to understand the needs and intentions of designers, providing real-time feedback and suggestions. Although machine learning can provide auxiliary tools and suggestions, human designers still play a crucial role in design. With the rapid development of technology, additive manufacturing (AM) has become an indispensable part of modern manufacturing. AM constructs objects by adding materials layer by layer, which requires a deep understanding and control of materials, structures, and processes. In order to better improve the efficiency and performance of AM, machine learning technology has gradually been introduced into this field. Sarkon et al. [13] will review the current application status of machine learning in additive manufacturing, explore from design, manufacturing to property control, and analyze its development prospects. In additive manufacturing design, machine learning can help designers better understand product performance and optimize design solutions. By training machine learning models to learn patterns from historical design data, designers can quickly screen and optimize design solutions, improving product performance and reliability. For example, using neural networks for structural optimization design can predict the optimal design solution by learning patterns from historical data. In the additive manufacturing process, machine learning can help optimize printing parameters and processes, improve printing efficiency and product quality. For example, using deep learning technology to analyze images during the printing process to predict potential problems and take measures in advance. In addition, machine learning can also predict future trends in the printing process by learning patterns in historical printing data, thereby better controlling the printing process.

With the continuous development of additive manufacturing (AM) technology, the creation and management of design libraries has become a key link. Although there are currently many design and optimization tools available, they often cannot fully meet the complexity and uniqueness of AM. 3D Convolutional Neural Network (3D CNN), as a deep learning technology, has powerful feature learning and classification capabilities and has shown its potential in many fields. Williams et al. [14] explored the potential of 3D CNN in evaluating and optimizing the effectiveness of design libraries, as well as its application in additive manufacturing. The effectiveness of a design library usually depends on the quality and diversity of its content. 3D CNN can accurately evaluate the feasibility and performance of models in the design library by learning complex patterns and relationships. For example, training 3D CNN to predict the mechanical performance, printing feasibility, or aesthetics of a model can help designers better screen and optimize their designs. In addition, 3D CNN can also help designers better understand and meet market demands by learning historical design data and predicting future design trends. Wu and Zhang [15] explored how to use deep learning technology for style recognition and intelligent design of oil paper bamboo umbrella images. By training CNN models to recognize image styles and training GAN models to generate new designs, we can greatly improve design efficiency and quality. At the same time, combining deep learning technology with computer-aided design systems can provide more comprehensive and effective solutions for the design and manufacturing of oil-paper bamboo umbrellas. In the future, with the further development of deep learning technology, we have reason to believe that it will play a greater role in the field of computer-aided design and application. After recognizing and understanding the image style of oil-paper bamboo umbrellas, deep learning technology can also be used to optimize the design process. We can train a generative adversarial network (GAN) model to automatically generate oil paper bamboo umbrella designs that meet the design requirements. Specifically, we can train the GAN model into two parts: a generator and a discriminator. The generator is responsible for generating new oil paper bamboo umbrella designs, while the discriminator is responsible for determining whether these designs meet the requirements. In this way, GAN models can gradually learn and generate designs that meet people's expectations. Yoo et al. [16] utilized deep learning technology to construct a model that automatically generates three-dimensional concept wheels.

Firstly, by training a large number of 3D concept wheel datasets, the model can learn the geometric features and design rules of different types of concept wheels. Then, using this model, the designer can input some parameters or constraints according to the requirements, such as wheel size, material type, etc. The model will automatically generate a three-dimensional conceptual wheel model that meets the requirements. Through deep learning technology, we can construct an evaluation and optimization model to evaluate and optimize the generated 3D concept wheel. Firstly, the model can be trained using existing datasets to learn standards and rules for evaluating 3D concept wheels. Then, input the generated 3D concept wheel model, which will automatically evaluate its quality and performance, and provide improvement suggestions. In addition, deep learning can also be used for structural optimization and multidisciplinary optimization, such as automatically adjusting the shape and size of wheels and spokes to improve performance and efficiency.

## 3 MATERIALS AND METHODS

DL is a branch of ML, and its theoretical basis is mainly based on neural network. Neural network constructs a network structure containing multiple neurons by simulating the connection mode of human brain neurons. Each neuron receives inputs from other neurons, and calculates according to certain weights and activation functions to generate output signals. Through the stacking of multi-layer neural networks, DL model can abstract the characteristics of data layer by layer and realize the learning of complex functions. In DL, CNN is a common model structure. It has the characteristics of local perception and weight sharing, and is suitable for processing images, voices and other types of data. Through the stack of convolution layer and pooling layer, CNN can automatically learn the feature representation of images and achieve excellent results in tasks such as classification and identification. CAD is a method of product design using computer technology. It helps designers to design, analyze and optimize products better by transforming design ideas into digital models that can be processed by computers. CAD system usually includes several functional modules such as modeling, rendering and simulation. The modeling function is used to build a 3D model of the product, which can be represented by wireframe model, surface model and solid model. The rendering function is used to present the visual effect of the product model, and improve the realism of the model by means of material mapping and lighting settings. The simulation function is used to verify the performance of product design, such as structural analysis and fluid analysis.

The combination of DL and CAD is mainly reflected in two aspects: on the one hand, the application of DL in the process of CAD modeling and rendering, on the other hand, CAD provides data and application scenarios for DL. In the process of CAD modeling and rendering, DL can learn a lot of design data, extract design features, and assist designers in more efficient and accurate modeling and rendering. For example, the design rules generated by DL can guide the CAD system to carry out automatic modeling. Using the image generation technology of DL, the optimization of product rendering results can be realized. Through a large quantity of product design data generated by CAD system, DL model can be trained to learn more design features and rules. As the core tool of product design, CAD also provides a broad application space for DL, such as automatic design, design optimization and design assessment. CAD technology can realize the visualization and optimization of design scheme, so that designers can better understand and improve the design.

In order to get the utmost out of DL technology in product design, this section proposes a product image feature detection model based on lightweight CNN. The model adopts lightweight CNN structure, which reduces the model complexity and calculation cost while ensuring performance, and is suitable for product design environment with limited resources. These hierarchical structures can abstract the features of product images layer by layer and generate representative feature vectors. By training the model, it can learn the ability to extract effective features from a large quantity of product images and provide key information for subsequent CAD optimization. Figure 1 shows the principle of 3D object voxel modeling based on lightweight CNN model in this article.

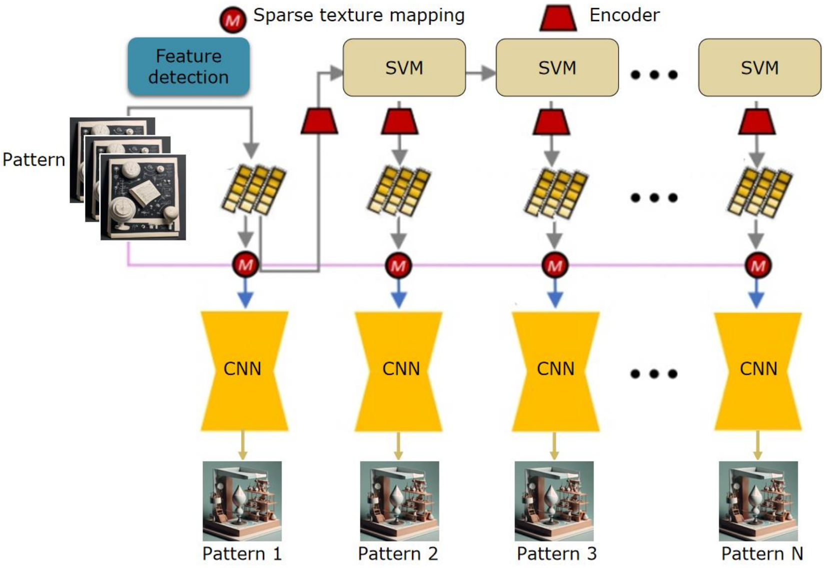


**Figure 1**: 3D object voxel modeling.

Voxel modeling of 3D objects is a data representation method based on voxels, which is used to describe the shape and structure of 3D objects. Different from the traditional modeling method based on surface mesh, voxel modeling uses discrete 3D mesh to represent objects, and each mesh unit is called a voxel, which is similar to pixels in two-dimensional images. Firstly, a 3D object is represented as voxel data. This is usually achieved by converting the surface mesh of a 3D object into a voxel mesh, in which each voxel can have a binary value indicating whether the object substance exists at the position. Next, the proposed lightweight CNN model is used to process the voxel data. After inputting the voxel data, the model extracts and learns the feature representation in the voxel data through a series of convolution, pooling and nonlinear activation operations. After the lightweight CNN model is processed, each voxel will get a feature vector, which describes the attributes of the voxel and its relationship with neighboring voxels. Based on these feature vectors, the classification algorithm can be used to determine the category of each voxel, and then the voxel model of the whole 3D object can be obtained.

In the case of deep learning application in product design, the application of CNN model mainly focuses on optimizing image quality. In the process of product design, images are a crucial medium for presenting and expressing the appearance and details of the product. In furniture product design, CNN models can be used to identify and classify images of furniture design, helping designers quickly find the required reference images or optimize design details. In automotive product design, CNN models can be used to optimize the appearance of cars to improve their aerodynamic performance or enhance their appearance quality. Research requires training a large number of product design images to obtain a model that can recognize and classify product designs. Then use this model to evaluate and optimize the designer's design. The network structure of product image feature detection usually adopts CNN model in DL. This network structure is specially used to process image data, and can automatically learn and extract advanced feature representation from images. Convolution layer is the core component of CNN, which is responsible for learning and extracting features from input images. It contains a series of convolution kernels (or filters), and each convolution kernel can learn and detect certain features in the input image, such as edges and corners. Activation function is used to introduce nonlinearity, so that the network can learn and represent more complex features. Pooling layer is used to reduce the dimension of features, reduce computational complexity and improve the robustness of features. At the end of CNN, there are usually several fully connected layers, which are used to combine the learned local features into global features for the final classification or regression task. For the task of product image feature detection, the design of network needs to balance the feature detection ability and computational complexity. Therefore, the lightweight CNN model is a good choice, which can reduce the consumption of computing resources and memory while maintaining sufficient feature detection ability, and is more suitable for use in resource-constrained environments. The network structure of product image feature detection is shown in Figure 2.

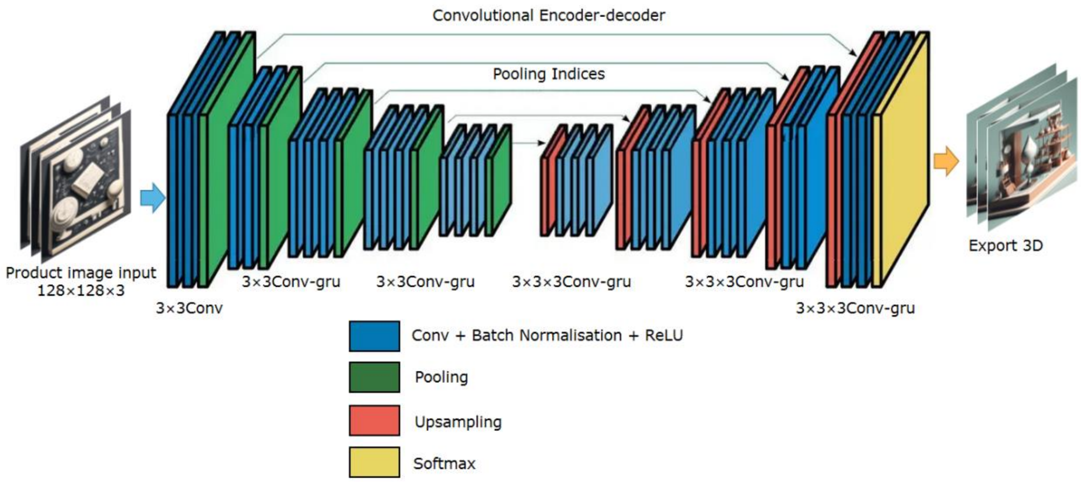


**Figure 2**: Network structure of product image feature detection.

Once the feature vector of product image is obtained, the next step is to apply it to CAD optimization. Specifically, these feature vectors can be used as the input of CAD system to guide the automation and optimization process of product design. In CAD system, feature vectors can be used for parametric design of products. By mapping the relationship between feature vectors and product design parameters, CAD system can automatically adjust the parameters of product design according to the changes of feature vectors and realize the optimization of design. This data-driven design optimization method can not only improve the efficiency, but also reduce human intervention, making the design results more objective and accurate.

Let a straight line on one side of an ideal rectangle corresponding to a segment of the original polygon be $\Delta tp_t u_t\ y$ . The sum of the square errors of the segment and the straight line in the original polygon is:

$$P_{t+\Delta t} = p_t + \Delta tp_t u_t(y) \tag{1}$$

$$P_{t+\Delta t} = p_t\left(1+\Delta tu_t(y)\right) + p_t\left(1+\Delta tu_t(y')\right) \tag{2}$$

$P_{t+\Delta t}$ finds the first-order partial derivative of $y$. When the first-order partial derivative is 0, the error is the smallest, so:

$$s_{t+\Delta t}(y) = \frac{p_{t+\Delta t}}{P_{t+\Delta t}} = \frac{p_t + \Delta tp_t(y)}{p_t\left(1+\Delta tu_t(y)\right) + p_t\left(1+\Delta tu_t(y')\right)} \tag{3}$$

$$s_{t+\Delta t}(y) = \frac{p_{t+\Delta t}}{P_{t+\Delta t}} = \frac{s_t(y)\left(1+\Delta tu_t(y)\right)}{s_t(y)\left(1+\Delta tu_t(y)\right) + s_t(y')\left(1+\Delta tu_t(y')\right)} \tag{4}$$

The fitted straight-line equation for this segment is:

$$s_{t+\Delta t}(y)-s_t(y)=s_t(y)\frac{\Delta tu_t(y)-\Delta t\bar{u}_t^p}{1+\Delta tu_t} \tag{5}$$

In order to realize the bidirectional mapping relationship from graph $G$ to latent variable $z\in R^c$. The loss function of graph variational automatic encoder is defined as:

$$L\ \varphi,\theta;G\ =E_{q_\varphi\ z|G}\left[-\log p_\theta\ G|z\ \right]+KL\left[q_\varphi\ z|G\ |p\ z\ \right] \tag{6}$$

Where $E_{q_\varphi\ z|G}\left[-\log p_\theta\ G|z\ \right]$ is reconstruction loss and $KL$ is Kullback-Leibler divergence. Decomposition of maximum likelihood estimation for each observation;

$$-\log p\ G|z\ =-\lambda_A\log p\ A|z\ -\lambda_F\log p\ F|z \tag{7}$$

In the concrete implementation, a large quantity of product image data needs to be collected and preprocessed to prepare for training the lightweight CNN model. Next, the lightweight CNN is trained by using the collected data, and the model parameters and structure are adjusted to achieve the best performance. Once the model is trained, it can be applied to new product images to extract feature vectors and input them into CAD system to guide the automation and optimization process of product design. Finally, the application effect needs to be evaluated, and the model and method need to be adjusted and improved according to the assessment results to form a closed-loop optimization process.

In order to minimize the influence of the error generated in the feature detection process on the identification results, the fuzzy distribution needs to meet the requirement that the curve drops rapidly when the feature difference value is large. The fuzzy distribution function is expressed as:

$$\mu\ x\ =\frac{1}{2}-\frac{1}{2}\sin\frac{\pi}{a_2-a_1}\left(x-\frac{a_1+a_2}{2}\right) \tag{8}$$

Where $x$ is the magnitude of the characteristic difference.

The matrix $\mu$ between features of the same dimension is constructed by:

$$\mu=\begin{bmatrix}\mu_{11} & \mu_{12} & \cdots & \mu_{1Q}\\ \mu_{21} & \mu_{22} & \cdots & \mu_{2Q}\\ \vdots & \vdots & \ddots & \vdots\\ \mu_{M1} & \mu_{M2} & \cdots & \mu_{MQ}\end{bmatrix} \tag{9}$$

The pixel value $H\ v$ of the product feature distribution is:

$$H\ v\ =L_{xx}\ x,\sigma\ +\frac{1}{\sqrt{L_{yy}}}\exp\left(\frac{j\pi}{4}\right)\exp\left[\frac{-j\pi}{L_{yy}S\ t}\right] \tag{10}$$

## 4 EXPERIMENT AND ASSESSMENT

The purpose of the experiment is to evaluate the effect of DL and CAD in product design. In order to carry out the experiment, this study collected a data set containing various product images. This data set contains images with different angles, lighting conditions and gray levels to simulate the changes in the real world. The experimental process includes the following steps: data preprocessing, model training, model testing, result recording and performance analysis. At different stages of the process, necessary adjustments and optimizations were made to ensure the accuracy of the experiment. As shown in the real scene test results in Figure 3, it can be clearly observed that the method proposed in this article has improved the product image quality, and successfully retained more details.


**Figure 3**: Comparison of visual effects of product design image enhancement.

By comparing the images before and after using this method, it can be clearly seen that the noise in the image has been effectively suppressed. This makes the overall look and feel of the product image clearer and cleaner. For the texture and material of the product, this method successfully preserves these tiny details. This is very important to show the realism and texture of the product.

Test the time required to complete product image processing with different numbers of pictures and different nodes (Figure 4).

When the quantity of processed product images is small, with the increase of the quantity of nodes, the time required for image processing also increases. This is because when the quantity of pictures is small, increasing the quantity of nodes will not improve the processing speed, but will lead to longer processing time because of the communication and management overhead between nodes. As the quantity of product images increases, the processing time increases accordingly. However, in this case, increasing the quantity of nodes can significantly reduce the processing time. This is because multiple nodes can process multiple images at the same time, thus realizing parallel processing and improving the overall processing speed. When the quantity of images increases to a certain extent, the processing time using multiple nodes is obviously less than that using a single node. This proves that using multiple nodes can significantly improve the processing efficiency when processing a large quantity of images.

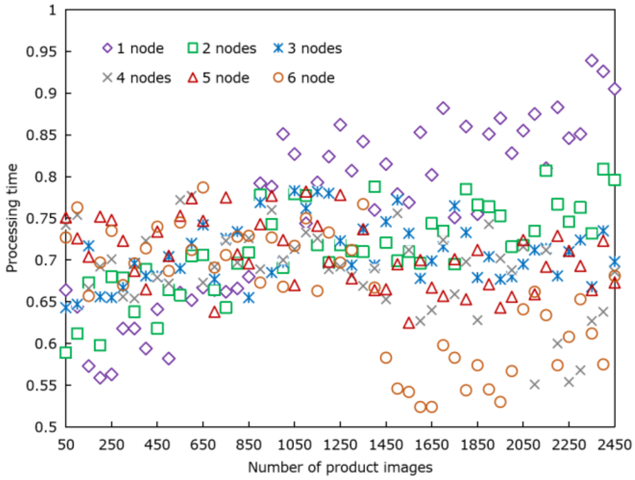


**Figure 4**: Image processing consumes time.

According to the data presented in Figure 5, it is known that the error rate of this algorithm is reduced by 28.37% compared with the traditional ML when the feature detection scheme of directional gradient histogram is implemented. Directional gradient histogram is a very effective feature descriptor, especially suitable for capturing local shape and texture information. In the product image, these local features often carry the most critical information, such as the texture and material of the product. The traditional ML algorithm may be limited in dealing with complex image features, but this algorithm can mine the information in the image more deeply by combining DL and directional gradient histogram, thus achieving a lower error rate.

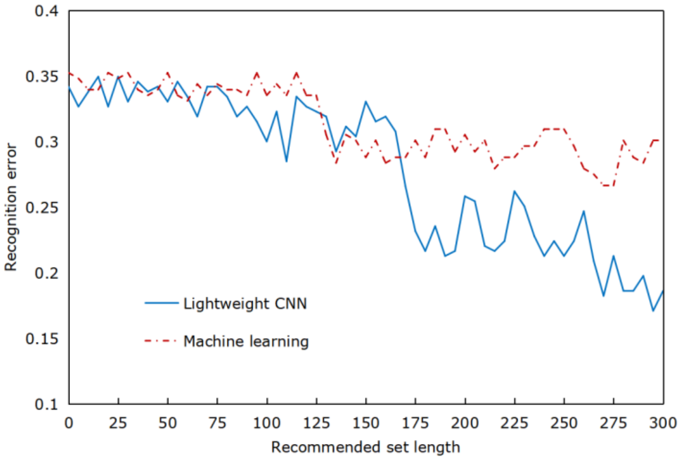


**Figure 5**: Image feature detection error.

Through the well-designed data structure, the algorithm can calculate more efficiently and reduce unnecessary information redundancy. Moreover, choosing the appropriate data type also ensures the accuracy and stability of the calculation. The window parameter is set to 64*128, the block parameter is set to 32*32 and the cell parameter is set to 16*16. These parameter settings play a key role in feature detection. A larger window can capture more contextual information, while a smaller cell unit can capture the local features of an image in more detail. This parameter setting is helpful for the algorithm to capture and represent the features of product images more accurately.

Gray normalization is an important step in image processing. Through gray normalization, the uneven illumination and the change of gray value range of the image can be removed, making the gray values of objects or regions in the image more consistent and comparable. From Figure 6, we can observe the change of accuracy after image gray normalization.

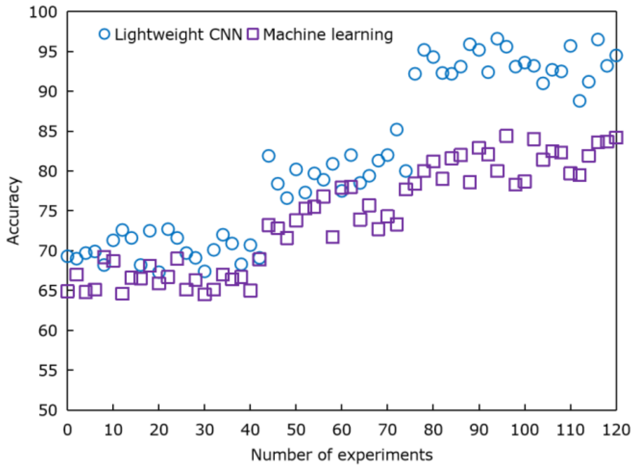


**Figure 6**: Accuracy of image gray normalization.

According to the results of Figure 6, it can be clearly seen that the accuracy of the image is improved after the gray level normalization processing. This shows that the gray normalization processing is effective for improving the performance of image identification or classification tasks. Through normalization, the gray value of the image becomes more consistent, which reduces the influence of illumination and gray value changes on the image identification algorithm, thus improving the accuracy. In practical application, gray normalization can be considered as an image preprocessing step to improve the performance of image identification algorithm. The accuracy under the condition of uncertain angle is shown in Figure 7.

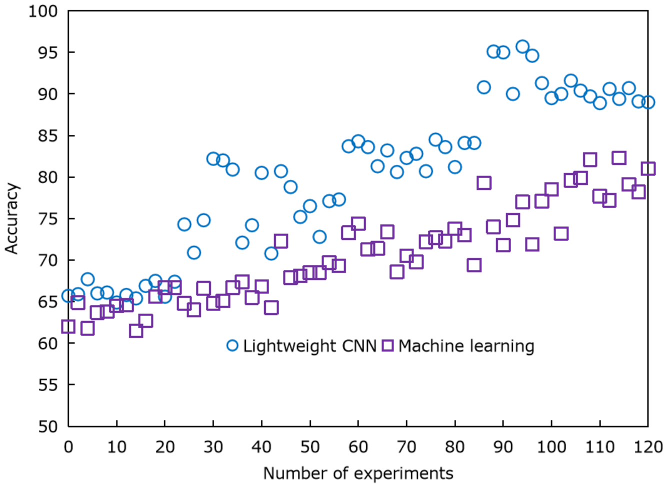


**Figure 7**: Accuracy under the condition of uncertain angle.

With the increase of the quantity of experiments, the accuracy shows an upward trend and tends to be stable, which may indicate that the algorithm gradually learns and adapts to the angle change in many experiments and improves the robustness to the angle.

## 5 DISCUSSION AND FUTURE WORK

The experimental results show that proper image preprocessing, such as gray normalization, can significantly improve the identification accuracy. This emphasizes the importance of image preprocessing for specific tasks in practical applications. The experimental results under the condition of uncertain angle show that angle change is an important challenge in image identification. Although the existing algorithms are robust to angle changes to a certain extent, the fluctuation of accuracy is still a problem to be solved. Future research can further explore how to improve the robustness of the algorithm to angle changes. This may include:

⊖ Synthesizing multi-angle data: Synthesizing images from various angles through data enhancement technology to enhance the adaptability of the model to angle changes.

⊜ Introduce the loss function of angle perception: design a new loss function to make the model give priority to angle change and learn the characteristics of angle invariance in the training process.

⊛ Optimization of real-time image preprocessing: Considering the positive influence of image preprocessing on accuracy, we can study how to preprocess images in real time and efficiently in practical applications in the future to ensure the best performance of image identification algorithms.

④ More complicated scenes and challenges: In the real world, the challenges of image identification are far more than angle change and gray normalization. Future research can consider more factors in the actual scene, such as illumination change, occlusion, background noise, etc.

## 6 CONCLUSIONS

The traditional product design method mainly depends on the designer's experience and intuition, and it often seems inadequate when dealing with complex and diverse design requirements. CAD technology can not only improve the efficiency, but also realize the visualization and optimization of design scheme, so that designers can better understand and improve the design. The combination of DL and CAD provides new possibilities for product design. In this article, DL and CAD are applied to product design and optimization, a product image feature detection model based on lightweight CNN is constructed, and its practical application effect is evaluated and tested by experiments, which proves that the proposed optimization method is feasible in product design. By using CNN to extract features, we can effectively capture and represent the key information of product images, and then optimize product design. This method has achieved satisfactory results in improving product image quality and preserving details. However, there are still some challenges and problems to be solved, such as robustness to angle changes. Future research can further explore how to improve the robustness of the algorithm and expand the use of DL and CAD in product design.

*Rong Guo*, https://orcid.org/0009-0007-9880-6297

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